The Brain Drain

Leveling the Playing Field or Widening the North-South Divide?

Hisham Foad
December 16th, 2005
Emory University

1. Introduction

One of the defining features of modern globalization has been increased labor mobility. We observe this both within countries and across borders with increased immigration. Between 1990 and 2000 the total number of international migrants increased from 154 million to 175 million (UN, 2002). While the face of immigration often portrayed in the media is of low-skill worker taking jobs paying low wages, the majority of documented immigration is actually of high skilled labor. Much of this high skilled labor comes from developing countries to developed countries, with developed countries facilitating this movement.

What are the consequences of developing countries losing high skilled workers to the developed world? For example, 70% of all tertiary degree holders from Guyana reside in the United States. This figure is nearly 70% for Jamaica, 25% for Sierra Leone, and 15% in Iran. Nearly 40% of the foreign born population in the US has an advanced degree. Does the US gain from having such a large percentage of these countries' highly educated populace? What does this "brain drain" imply for these countries? Given that human capital has been found to be an important determinant of economic growth, is there any way to stem this brain drain? If not, can we redistribute the gains from high skill workers abroad back to their native countries? This paper will seek to address these questions.

The brain drain presents a development challenge not only because developing countries lose out on the relatively high contributions to total output by high-skill workers, but also because of the positive externalities these workers generate (Bhagwati and Hamada 1974, Miyagiwa 1991.) High skilled workers generally increase the productivity of their co-workers. Much of the brain drain consists of people who could provide key public services such as health and education. For example, when a doctor trained in a developing country emigrates, that country loses not only the income the doctor generates, but also the health benefits he or she provides. A risk taking entrepreneur generates economic opportunity for both themselves and others in the local economy. These positive externalities are not limited to economic benefits. Highly educated people often play an integral role in policymaking and in forwarding social debate within a country. When these people leave their native countries for greener pastures abroad, their level of participation in economic and social issues is diminished.

The brain drain also presents a public finance problem. Governments often subsidize the training of high skilled workers, anticipating the gains to society these individuals will make. When high skill workers emigrate, the human capital investment financed by public resources yields a return to the receiving, rather than host country. For example, Stalker (1994) estimates that Jamaica must train five doctors for every doctor remaining in the country, an 80% brain drain. When developing countries foot the bill for training skilled workers but do not receive the benefits of their training, a strain is placed on their already limited resources.

Despite the loss of positive externalities generated by high-skill workers, some researchers have argued that the brain drain may actually aid in development. When highly educated workers have an opportunity to earn higher wages through immigration, the return on an education in the native country is increased. As a result, more people will seek to attain these skills, leading to stronger educational institutions in the native country. Without the opportunity to earn higher wages abroad, these investments in higher education would never have been made.

Another argument in favor of the positive effects of the brain drain is that workers abroad generally send large remittances to their native countries. While these remittances do not make up for the loss of positive externalities created by these workers, they do mitigate the loss of output from the brain drain.[1] Remittances can be a significant portion of income in developing countries. For example, Gustaffson and Makonnen (1993) find that if we eliminate remittances to Lesotho, an additional 11-14% of households would be

[1] Considering that skilled workers who immigrate generally earn higher wages than those who do not (usually much higher), remittances may actually more than make up for the loss in output.

classified as poor. Adams (2005) finds that the households in the lowest decile group of income in Guatemala receive between 50-60% of their income in remittances. Lucas (1987) finds that increased remittances from workers migrating to South Africa from neighboring countries resulted in greater productivity in the migrants' native countries, implying that remittances are invested in human and physical capital. However, early evidence suggests that remittances are not evenly distributed among sending countries, with remittances having an equalizing effect on incomes for high migration areas, but not in low migration areas (Mora and Taylor, 2004).

The potential benefits of the brain drain to developing countries assume that high skilled workers utilize their skills upon immigration. However, there is strong evidence that high skilled workers from developing countries often take low-skill jobs. Ozden (2005) examines this "brain waste" across immigrant groups, finding that educated immigrants from Latin America and Eastern Europe are more likely to be subject to brain waste than those from Asia, the Middle East, and Sub-Saharan Africa.

This paper makes two contributions to the existing debate over the brain drain. Using data from the 2000 US census, population densities of various immigrant groups across US cities are estimated across skill levels. There is a strong tendency for immigrant groups to agglomerate in a small number of cities. The second contribution of this paper is to set up an experimental design to assess the risk tolerance of various immigrant groups in the US. Studies on economic growth have found that a dynamic entrepreneurial class is a key determinant of growth. One feature common to entrepreneurship is the ability to take risks. Thus, if immigrant groups (specifically high skilled immigrants) display significantly low levels of risk aversion, the potential losses from the brain drain may actually be larger than previously estimated.

The rest of the paper proceeds as follows. Section 2 presents a basic theoretical model in which immigration occurs when the expected benefit exceeds the expected cost. Augmenting this theory, we examine existing studies on brain drain losses and potential gains. We then analyze several proposed policies aimed at turning around or mitigating the effects of the brain drain. Section 3 examines a policy with the greatest potential for mitigating the brain drain, fostering strong networks between skilled labor living abroad and their native countries. Section 4 summarizes the findings from the 2000 US census, identifying the key agglomerations of immigrant groups across a range of native countries. This is useful from a theoretical standpoint – why different immigrant cluster in particular cities – and from a practical standpoint – if we are to develop strong networks, we need to know where large concentrations of immigrant groups are. Section 5 describes the experimental design used to assess risk tolerance across immigrant groups and Section 6 concludes.

2. Theories on Immigration and the Brain Drain

Why do people immigrate? Numerous explanations have been presented for this question ranging from economic explanations to escaping repressive regimes in their native countries to migration for familial reasons. We can capture these dynamics with a simple cost-benefit model of immigration. When considering whether or not to immigrate to a particular country, a potential migrant will only do so when the expected benefit of migration exceeds the expected costs. What are the costs and benefits of immigration? An obvious benefit of immigration is the ability to earn a higher wage abroad. Other benefits could be greater freedom, economic and social mobility, and escaping persecution. The costs of immigration include not only the physical costs of moving, but also the psychological costs of leaving behind family and familiarity, difficulty assimilating into the receiving country, and perceived loss of culture. An implication of this model is that immigrants from countries with high migration costs must have perceived large benefits from immigration. For example, consider two potential migrants to the US from the UK and Germany who have identical skill levels. The costs of immigration from these countries are nearly identical in all respects except for one: language. An immigrant from the UK faces lower immigration costs as English is a common language. Thus, if both people immigrate to the US, we would expect the German immigrant to earn higher wages as they faced a higher cost. Supporting this theory is evidence on immigration and physical distance. For example, immigrants to Europe generally come from Middle East, North Africa, and Eastern Europe. Immigrants to the US generally come from Latin America and the Caribbean.

The cost-benefit theory has several implications for the brain drain. When considering two potential immigrants from the same developing country facing the same set of migration costs, but differing in skill level, which will be more likely to immigrate? A high skilled worker can earn a larger increase in wages by moving to a developed country than an unskilled worker. Thus, we should see more skilled workers immigrating, fueling the brain drain. Coupled with the fact that developed countries often facilitate the migration of skilled workers, developed countries are increasingly subject to losing skilled workers to the developed world.

Receiving countries are generally seen as gaining from the brain drain. These countries gain technical expertise and positive externalities generated by skilled labor. For example, Chelleraj, Maskus, and Mattoo (2005) find that a 10% increase in the number of foreign graduate students in the US raises the university patent applications by 4.7%, university patent grants by 5.3%, and non-university patent grants by 6.7%. Furthermore, the benefits enjoyed by receiving countries were at least partially funded by sending countries. Although there is some evidence that native skilled workers see their wages decline with increased high skill immigration (Borjas 2005), the general consensus is that the brain drain benefits receiving countries, a sentiment reinforced by the policies these countries put in place to facilitate high skilled immigration.

Do the gains to receiving countries necessarily come at the expense of the sending countries? This had been the consensus view in early studies of the brain drain. In addition to the loss of output suffered, sending countries also lose out on the positive externalities generated by skilled labor. Suppose a doctor trained in Mexico emigrates to the US. A first order effect is that income and spending by that doctor now takes place in the US instead of Mexico. However, the loss goes further than this. The doctor provided a key health service which increased the standard of living not only to the doctor, but to those around her. The doctor most likely had a relatively high income in Mexico, and therefore contributed substantially to public finance through tax payments. What if the doctor used her influence to advance local debates on social and political issues? All of these contributions by the doctor are lost to some extent with migration and go beyond a simple loss of income. Thus, even if the doctor sends remittances back to Mexico that offset the loss of her income, Mexico may still suffer a net loss from her migration.

Is there any reason to believe that sending countries may actually benefit from the emigration of skilled workers? The "new" brain drain literature presents a case in which this may occur. The basic argument here is that the potential for high skilled migration to countries that offer greater wages increases the return to education in the sending country. For example, if an engineer from Bangladesh can earn twice as much if they emigrate to the UK, then the return on an engineering degree in Bangladesh increases. As the return on education increases, human capital investment will increase, strengthening educational institutions. Without the prospect for immigration, this increase in investment would not have occurred, implying a potential gain from the brain drain. This theory, proposed by Stark (2004) has found some empirical support. Beine et al (2005) find that the positive effects of the brain drain exceed the negative effects for countries with low levels of human capital and low migration rates of skilled workers. However, as skilled migration rates exceed 20% or when the proportion of people with higher education is greater than 5%, the brain drain has negative consequences on economic growth. This result is consistent with diminishing returns to human capital. In that the brain drain may foster the development of educational institutions that were virtually non-existent before, it may be beneficial as long as a large proportion of the newly education workers stay at home. However, for countries that have established educational institutions, increased investments spurred by the prospect for migration are not enough to offset the losses felt by society from skilled migration abroad. Schiff (2005) picks up on this theme, arguing that Stark's theory is fundamentally flawed because it is static in nature. While increases in human capital investment due to the brain drain are beneficial to growth, they will only be so if a significant proportion of newly educated workers stay in their native countries.

Several policies have been proposed to either stem the migration of skilled labor or mitigate the losses from the brain drain. When examining policies aimed at reducing migration, we need to consider that their effectiveness will depend on the extent to which they lower the expected benefits and/or raise the costs of migration. One such policy has been to delay emigration by making some form of public service mandatory. For example, doctors seeking specialist training in Indonesia are required to serve three years of service in rural areas (Padarath et al 2005). While such a scheme helps delay brain drain migration, it does nothing to address the perceived costs and benefits of migration. In fact, delaying policies may actually exacerbate the situation. Delaying potential migration or increasing training times reduces the return on a human capital investment, reducing the incentive to acquire skills. Second, the presence of mandatory service may actually prevent some repatriation of skilled labor living abroad. For example, the mandatory military service requirement in Turkey was cited as one of the major reasons why Turkish students studying abroad choose not to return to Turkey after completing their studies (Tansel and Gungor 2002).

Another proposed policy is to inhibit immigration in either the source country or to the receiving country. This type of policy was seen in the former Soviet bloc, where labor migration was highly regulated and controlled. Alternatively, migration to a particular destination could be restricted. For example, the US could agree to restrict the immigration of skilled labor from Mexico, raising the cost of migration. However, such a policy depends on the receiving country enacting a policy that goes against its best interests. In fact, this was seen when the US limited migration from Middle Eastern countries following 9/11. The US government issued 74,000 visas for immigrants to work in science and technology in 2002, down from 166,000 in 2001. Some of this was due to heightened security concerns due to 9/11, but the majority of the decline was due to a drop in applications. Skilled immigrants increasingly chose *not* to come to the US, due to a perceived hostile reception. Universities and business leaders, bearing the losses from reduced skilled migration, exerted considerable political pressure on the government to lift restrictions. Even if a bilateral agreement could be made in the receiving country, this would not necessarily reduce the brain drain, as skilled labor could just go to a country without the restriction. Unless these restrictions globally adopted, their effectiveness would be limited. Given the limitations discussed above, some governments have tried to encourage skilled labor to stay through incentives such as subsidies and expanded research budgets. While such a policy would reduce the wage gap between the developed and developing worlds, it would also place a strain on already limited public resources.

In response to the brain drain, we often see countries recruiting skilled workers from even poorer countries. For example, Canada offers foreign doctors in rural areas accelerated immigration status to make up for the loss of Canadian doctors to the US. As a result, a large number of South African doctors have emigrated to Canada. In response, South Africa has actively targeted Cuban doctors. At a certain point, however, this chain must end, likely at the poorest country. There is also an issue of skill portability. Do Cuban doctors exactly offset the loss of South African doctors? Aside from differences in training across countries, there are also language and cultural issues which may reduce the portability of skills.[2]

Repatriation efforts have met with limited success. For example, the South African International Organisation for Migration ran a program called the "return of talent programme" to encourage the repatriation of skilled South Africans living abroad. The program was only able to recruit 52 professionals to repatriate to South Africa, of whom 25% re-migrated after a few years. An explanation for the limited success of this program may be that it offered no incentive to return beyond goodwill. Some countries have attempted to encourage repatriation with financial incentives. However, this kind of policy could actually backfire by raising the benefit of migration, accelerating the brain drain.

3. Diaspora Networks

Given the limitations of policies aimed at reducing the brain drain or repatriation, the most effective policy may be to develop strong networks between skilled workers living abroad and their native countries. Developing strong diaspora networks allows developing countries to return some of the benefits of skilled workers. For example, 80% of foreign investment in China has come from Chinese nationals living abroad. Given that many of these Chinese nationals earn higher wages by living abroad, the pool of available resources for investment may actually be larger than if migration had not occurred. Diaspora networks can also be used to transfer the expertise of skilled labor living abroad.

Another successful diaspora network was between Indian immigrants working in Silicon valley and the development of the tech industry in India. In 1998, Indian immigrants were running nearly 800 tech companies in Silicon Valley accounting for $3.6 billion in sales and employing over 16,000 workers. On average, 1 in 3 Silicon Valley firms was headed by an immigrant from India. The Indian government helped

[2] Cohen (1997) found that malpractice suits against Cuban doctors in South Africa were no higher than native doctors.

facilitate the transfer of this expertise and capital between Indian researchers working abroad and domestic companies through legislative and tax rules.

What conditions are necessary for successful diaspora networks? Can we rely solely on markets to provide these networks? Considering that the gains from these networks extend beyond workers living abroad and the native workers they interact with, a market solution is likely to lead to inefficiently small and disaggregated networks. Another issue here is with who bears the costs of developing strong networks. Diaspora networks are likely to have large fixed costs, but are non-excludable goods (the use of the network by one person does not preclude its use by others). As a result, we are likely to see a free-rider problem, again leading to inefficiently small networks. Therefore, successful diaspora networks need to be supported with public resources. While most diaspora networks remain disaggregated private ventures, governments in developing countries are becoming increasingly aware of the viability and benefits of these networks. The South African Network of Skills Abroad (SANSA) is an effort to connect 22,000 graduates of South African universities living abroad with their alma maters. The Reverse Brain Drain Project (RBDP) is an organization in Thailand founded to address the brain drain. The RBDP has two stated objectives:

1. Identify and attract experienced high-level Thai professional living overseas to participate in mission-oriented projects, and promote development of core teams led by the respective Thai professionals.

2. Promote and facilitate the return of Thai professionals overseas to work in government agencies or in the private sector.

Interestingly, the RBDP strongly emphasizes the first objective over the second, highlighting the limitations of repatriation efforts. To foster strong networks, the organization offers grants to researchers (in Thailand or abroad) and supports collaborative efforts financially.

Given the difficulty of halting the brain drain or encouraging repatriation, the development of diaspora networks appears to be the most effective policy to mitigate its adverse effects.[3] Developing countries can recoup not only the financial losses from the brain drain, but also some of the positive externalities lost through migration with strong diaspora networks. However, these networks are best developed with public support rather than small, private, and disaggregated networks.

4. Agglomerations of Immigrant Groups in the US

Where do immigrants choose to locate when they migrate? Do immigrants follow the same pattern as local residents, or do they cluster in a few locations? Answering these closely related questions has important theoretical and practical considerations. Returning to our theoretical model, we can make a few predictions on an immigrant's location decision. First, locations that are closer to their native countries in terms of distance will be less costly to migrate to than those that are distal. In the US, this is seen with the relatively large number of Mexican immigrants in Los Angeles and Texas or Cuban immigrants in Miami. Certain locations are also closer in terms of language and culture. Immigrants from Spanish speaking countries are more likely to locate in places in which Spanish is commonly spoken. We may also get strong "pull" effects, where the presence of a large immigrant community tends to pull in more migrants. There is also the possibility that immigrant's location decision is not actually a choice. This is seen with relocation communities, such as the high concentration of Ethiopians living in Minneapolis. Finally, certain locations offer unique opportunities to immigrants, especially high skill immigrants. A classic example of this is Silicon Valley, which attracted a large number of skilled workers in the IT industry, particularly in India.

Data from the 2000 US Census is used to assess the location decisions of immigrants. From a sample of 1.2 million immigrant households living in the US, data is collected on birthplace, current location, household income, age, years of education, and familiarity with English.[4] To assess immigrant clustering, an "agglomeration index" is constructed. This index is defined as the total number of immigrants from a particular

[3] The existence of strong networks may actually induce greater brain drain migration, as native workers in developing countries will have contacts in developed countries, facilitating their own migration. McKenzie (2005) finds that the existence of migrant networks raises the probability that other community members will migrate internationally.

[4] The original dataset is taken from the Integrated Public Use Microdata Sample (IPUMS). Any observations with age less than 18 years or no reported education were dropped from the sample.

group living in a particular location relative to the total number of immigrants from that group in the sample divided by that location's population as a percentage of the total population of all the locations in the immigrant sample. For example, suppose that there are 10 Argentinean immigrants in the sample, with 8 living in Miami and 2 living in New York. Thus, 80% live in Miami and 20% live in New York. Now suppose that New York is four times as populous as Miami (Miami represents 20% of potential population in the sample, while New York represents 80%). The agglomeration index would then be defined as 80%/20% = 16 for Miami and 20%/80% = 0.25 for New York. We can interpret the index as how much more likely an immigrant is to live in a particular location than the general population (both immigrants and natives). In the example above, an Argentinean immigrant is 16 times as likely to live in Miami than the average person in America, but only 0.25 times as likely to live in New York.

The data presents a strong case for clustering of immigrant groups. Looking across fifteen countries, we observe significant agglomerations of immigrant groups. For the three Latin American countries (Argentina, Brazil, and Colombia), the strongest agglomerations are in locations with large Spanish speaking populations such as south Florida. The strong language effect is strengthened by the large agglomeration of Brazilian immigrants in Boston, reflecting the large Portuguese speaking community in New England. History and distance appear to play a strong role in agglomerations for the three east Asian countries (China, Korea, and Taiwan). The largest agglomerations are in San Francisco, Oakland, San Jose, Los Angeles, and Honolulu. These cities are all characterized by long histories of thriving Asian communities, underscoring the "pull" effect of immigration. Turning our attention to immigrant groups from four African countries (Egypt, Ethiopia, Nigeria, and South Africa), the underlying reasons behind agglomerations become less clear. For example, Egyptian immigrants appear to be subject to "ghettoization" on the outskirts of major metropolitan areas, notably New York. There are large concentrations of Ethiopian immigrants in Atlanta, Minneapolis, and Seattle, perhaps due to relocation policies (i.e. this was location by choice). Looking at Eastern European immigrants, they tend to be older than the other groups in the sample. This is reflected in their agglomerations, which tend to be in industrial centers such as Cleveland and Chicago. Looking at Indian immigrants, some of the agglomerations can be explained by available opportunity. Reflecting the anecdotal evidence that entire graduating classes at the Indian Institute of Technology took jobs in Silicon Valley, some of the highest agglomerations of Indian immigrants are in the San Francisco Bay area. Finally, the one location that consistently has large agglomerations across groups is Washington, D.C., which should come as no surprise.

5. Measuring Risk Tolerance across Immigrant Groups

In addition to the loss in income suffered by developing countries losing skilled workers to the developed world, there may be a deterioration of the entrepreneurial class in these countries. A dynamic entrepreneurial class is necessary for economic growth, fostering strong domestic industries and serving as a link between the research sector and the market. A defining feature of entrepreneurs is the willingness to take risks.

Why should risk tolerance be any different between people who choose to immigrate and those who remain in their native countries? To see this, consider again the theoretical model of immigration. A person will migrate when the expected benefit of migration exceeds the expected cost. Inherent in this statement is that benefits and costs are forecasted, often times with error. Many migrants do not know with certainty how well they will do after migration nor do they fully realize all of the costs associated with migration. Furthermore, immigration may be at least partially irreversible. In other words, if someone immigrates and then decides that it was a bad idea, they cannot costlessly repatriate. All of these factors imply that immigration is a risky venture. Therefore, those people who do choose to immigrate must have a relatively high tolerance for risk.

If developing countries are losing both high skilled and high risk tolerance people to the developed world, the losses from the brain drain may be higher than previously estimated. The need for strong diaspora networks is highlighted in this case, as entrepreneurial efforts are exactly the kind of activity that these networks can be effective in transferring back to developing countries.

One way to assess risk tolerance across immigrant groups is with economic experiments. Consider the following choice of two lotteries. Lottery A offers a 50% chance of winning $10 and a 50% chance of winning $12. Lottery B offers a 90% chance of winning $0 and a 10% chance of winning $110. Which option would you select? Both lotteries offer the exact same expected payoff of $11. However, most people faced with this choice will go for option A, as it is the safer bet.[5] Now suppose that lottery B offered a 90% chance of winning nothing and a 10% chance of $120? The expected payoff of option B is actually greater than option A, although most people would still choose option A. If we were to keep increasing the payoff of lottery B (to a 10% chance of winning $130, $140, $150, etc.), at what point would you choose lottery B over lottery A? A measure of your risk tolerance could be estimated by looking at the amount with which you had to be compensated for bearing additional risk. For example, if you chose lottery A when both A and B had the same expected payoff, but lottery B when the expected return of B was $16, then you would require $5 to bear the additional risk of lottery B. The higher your risk premium, the lower your tolerance for risk.

A similar experiment could be conducted across immigrant groups in the US. For example, we could gather a sample of immigrants from a particular country and collect information on age, education, occupation, and other demographic characteristics. Their risk premia could be estimated and compared to risk premia in their native countries (using existing studies as a benchmark). Given the simplicity of this experiment, it could either be conducted in a controlled laboratory session or through a mailing. To identify and locate immigrant groups, we could first use the information collected in this study and then make use of local embassies and consulates. If immigrant groups have significantly higher tolerances for risk than people remaining in their native countries (especially after controlling for education and demographic factors), then we will have identified another significant loss from the brain drain. Given the large potential of the diaspora as an entrepreneurial class, strong networks between immigrants and their native countries are even more imperative.

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Agglomerations of Immigrant Groups

Agglomeration Index = (Immigrants in City/Total Immigrants)/(City Pop/Total Pop of Sample Cities)
Avg. Income = Household Income of the respondent, averaged across location and immigrant group
Avg. Age = Average age of the respondent
Education = Average years of schooling.
% Non-English = % of respondents who reported that they could not speak English or could speak "with difficulty."

Argentina

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	0.92	98,340	44	13.2	0.0%
Austin, TX	0.15	83,966	48	11.9	10.0%
Baltimore, MD	0.47	75,624	47	12.2	3.2%
Boston, MA	1.30	97,920	41	13.1	2.5%
Charlotte, NC	0.18	43,830	39	11.0	20.0%
Chicago, IL	0.37	109,345	46	11.6	16.5%
Cleveland, OH	0.27	69,315	51	11.2	0.0%
Dallas, TX	0.35	71,645	44	11.3	4.8%
Daytona Beach, FL	1.69	53,923	48	11.3	9.1%
Denver, CO	0.41	51,742	42	12.4	13.0%
Detroit, MI	0.26	88,236	48	12.6	8.0%
Fort Lauderdale, FL	11.57	62,709	46	11.0	22.3%
Houston, TX	0.65	98,738	47	11.5	22.7%
Jersey City, NJ	3.61	44,414	49	9.4	38.6%
Las Vegas, NV	1.58	47,961	50	9.9	16.9%
Los Angeles, CA	1.86	66,177	48	10.6	20.2%
Melbourne, FL	2.21	38,787	38	10.4	12.5%
Miami, FL	18.88	59,937	43	10.7	27.3%
Minneapolis, MN	0.54	66,137	38	13.2	14.3%
Nassau Co, NY	0.92	113,087	48	11.0	7.2%
New Haven, CT	0.88	93,409	54	12.5	9.1%
New Orleans, LA	0.22	52,762	55	12.4	0.0%
New York, NY	0.68	71,520	47	10.6	18.0%
Newark, NJ	3.13	64,584	45	9.9	22.9%
Oakland, CA	1.50	97,100	44	11.8	4.9%
Orlando, FL	3.81	61,293	47	10.5	15.2%
Philadelphia, PA	0.37	83,670	51	11.1	17.5%
Phoenix, AZ	0.40	70,910	47	11.3	18.8%
Pittsburgh, PA	0.44	178,751	48	14.7	0.0%
Providence, RI	0.57	111,749	40	12.3	0.0%
San Diego, CA	0.53	65,900	46	12.0	6.1%
San Francisco, CA	1.08	94,355	51	10.7	9.4%
San Jose, CA	0.53	115,221	44	12.5	8.3%
Seattle, WA	0.52	60,092	43	11.3	10.0%
St. Louis, MO	0.65	167,784	47	12.3	13.0%
Tampa, FL	1.43	69,742	56	11.0	13.6%
Washington, DC	2.70	104,917	45	12.7	8.3%

Brazil

City	Agglomeration Index	Avg. Income	Avg, Age	Education	% Non-English
Atlanta, GA	2.41	68,741	34	10.6	28.0%
Austin, TX	0.21	62,212	40	12.8	21.0%
Baltimore, MD	0.33	91,739	36	13.2	17.0%
Boston, MA	12.53	54,941	34	9.7	40.0%
Charlotte, NC	0.26	63,662	38	10.8	45.0%
Chicago, IL	0.28	81,984	41	11.5	10.7%
Cleveland, OH	0.31	157,497	43	12.4	4.8%
Dallas, TX	0.44	69,537	38	11.4	17.8%
Denver, CO	0.36	110,996	39	12.5	18.0%
Detroit, MI	0.35	97,638	39	11.5	8.5%
Fort Lauderdale, FL	30.05	53,768	37	10.8	26.8%
Honolulu, HI	0.35	69,627	38	12.7	0.0%
Houston, TX	0.31	75,530	41	12.6	11.0%
Jacksonville, FL	0.21	56,112	37	10.7	13.6%
Jersey City, NJ	5.69	45,155	38	9.5	36.0%
Las Vegas, NV	0.69	50,927	42	10.2	8.7%
Los Angeles, CA	0.62	64,285	38	11.8	11.0%
Melbourne, FL	2.21	55,275	45	12.0	4.5%
Miami, FL	9.55	68,076	38	11.6	19.2%
Minneapolis, MN	0.30	107,860	34	13.9	12.5%
Nassau Co, NY	0.40	67,067	44	11.0	18.9%
New Haven, CT	0.69	37,308	39	12.2	0.0%
New Orleans, LA	0.22	33,906	41	12.9	0.0%
New York, NY	0.59	70,106	40	10.8	15.8%
Newark, NJ	11.77	59,311	36	9.1	42.4%
Oakland, CA	1.70	66,279	38	12.5	8.4%
Orlando, FL	10.31	44,819	37	11.6	21.6%
Philadelphia, PA	0.57	59,263	39	10.3	37.5%
Phoenix, AZ	0.20	84,979	43	13.0	0.0%
Providence, RI	2.64	44,174	39	9.5	25.0%
Raliegh-Duhram, NC	0.65	105,288	34	13.4	8.0%
San Diego, CA	0.58	58,550	36	12.0	6.0%
San Francisco, CA	1.35	81,962	37	11.5	25.0%
San Jose, CA	0.45	107,667	43	12.5	5.0%
Seattle, WA	0.56	59,033	38	12.8	7.0%
St. Louis, MO	0.43	42,914	39	11.8	14.2%
Tampa, FL	2.48	61,740	39	10.5	22.8%
Washington, DC	3.48	91,368	41	11.9	12.9%

Colombia

City	Agglomeration Index	Avg. Income	Avg, Age	Education	% Non-English
Atlanta, GA	2.05	60,752	40	10.8	33.5%
Atlantic City, NJ	3.24	49,263	41	8.8	56.0%
Austin, TX	0.17	62,236	39	12.6	17.1%
Baltimore, MD	0.21	76,733	45	11.3	10.2%
Boston, MA	1.96	54,707	38	9.4	41.0%
Charlotte, NC	0.36	58,749	37	10.4	47.0%
Chicago, IL	0.35	68,854	43	10.7	29.4%

Cleveland, OH	0.16	63,321	40	11.4	25.0%
Dallas, TX	0.27	71,999	42	11.1	26.7%
Daytona Beach, FL	1.45	44,964	45	10.4	24.0%
Denver, CO	0.29	78,171	37	12.3	24.0%
Detroit, MI	0.09	111,345	43	11.8	19.0%
Fort Lauderdale, FL	23.43	58,308	42	10.8	31.0%
Houston, TX	0.71	60,587	44	10.2	34.0%
Jacksonville, FL	0.18	53,465	39	12.1	18.8%
Jersey City, NJ	6.67	47,679	43	9.2	52.0%
Las Vegas, NV	0.31	61,246	41	10.1	14.8%
Los Angeles, CA	0.62	61,419	45	10.2	29.0%
Melbourne, FL	1.53	52,712	47	10.7	22.5%
Miami, FL	24.73	51,200	43	10.4	41.0%
Minneapolis, MN	0.20	53,660	34	10.9	14.3%
Nassau Co, NY	1.32	79,275	43	10.1	27.0%
New Haven, CT	0.73	43,078	41	11.1	42.4%
New Orleans, LA	0.14	74,991	45	11.9	8.0%
New York, NY	1.19	55,579	43	9.5	41.0%
Newark, NJ	9.78	64,947	41	9.3	45.0%
Oakland, CA	0.70	78,206	42	11.8	13.6%
Orlando, FL	7.47	51,356	43	10.2	37.4%
Philadelphia, PA	0.25	57,945	42	10.4	29.0%
Phoenix, AZ	0.18	68,248	42	11.0	13.9%
Pittsburgh, PA	0.11	96,146	45	11.9	15.3%
Providence, RI	4.64	43,984	42	9.2	49.0%
Raliegh-Duhram, NC	0.45	59,980	41	11.4	24.4%
San Diego, CA	0.20	98,669	41	11.8	15.3%
San Francisco, CA	0.37	77,725	44	11.7	22.0%
San Jose, CA	0.16	88,983	42	12.2	18.0%
Seattle, WA	0.29	93,749	42	11.0	23.0%
St. Louis, MO	0.19	79,620	43	12.1	20.8%
Tampa, FL	3.37	48,964	43	10.5	37.0%
Washington, DC	2.14	80,178	43	10.8	29.0%

China

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	1.02	83,315	43	12.9	23.2%
Atlantic City, NJ	2.05	76,768	45	8.9	55.0%
Austin, TX	0.35	70,072	37	13.8	19.1%
Baltimore, MD	0.58	68,464	42	12.3	26.7%
Boston, MA	3.47	69,894	48	10.4	44.0%
Champaign, IL	1.65	37,359	36	14.5	7.6%
Charleston, SC	0.31	85,919	52	11.3	28.6%
Charlotte, NC	0.10	85,230	46	10.4	44.7%
Chicago, IL	0.58	71,116	46	11.2	37.0%
Cleveland, OH	0.49	68,202	45	12.4	29.0%
Dallas, TX	0.45	82,899	43	13.4	22.5%
Denver, CO	0.32	87,277	48	10.9	32.2%
Detroit, MI	0.41	77,278	43	12.0	26.0%
Fort Lauderdale, FL	1.28	45,726	46	10.0	40.8%

Honolulu, HI	1.95	54,229	53	8.3	56.0%
Houston, TX	0.51	64,346	48	12.4	33.0%
Jacksonville, FL	0.05	38,042	48	10.8	40.7%
Jersey City, NJ	1.10	63,703	41	12.1	25.0%
Las Vegas, NV	0.62	79,747	48	10.3	34.6%
Los Angeles, CA	1.91	64,929	53	10.3	51.0%
Melbourne, FL	0.46	59,906	45	12.2	34.6%
Miami, FL	0.58	51,126	50	9.8	40.5%
Minneapolis, MN	0.65	70,161	42	12.8	23.0%
Nassau Co, NY	0.48	102,366	49	11.8	26.9%
New Haven, CT	0.72	58,542	40	13.1	19.3%
New Orleans, LA	0.19	56,849	47	11.2	33.3%
New York, NY	1.48	53,461	47	8.6	59.1%
Newark, NJ	1.85	116,662	46	13.2	25.0%
Oakland, CA	8.54	77,112	50	10.4	43.5%
Orlando, FL	0.96	60,824	43	11.5	30.4%
Philadelphia, PA	0.53	64,592	45	11.5	37.0%
Phoenix, AZ	0.29	72,861	47	11.1	36.0%
Pittsburgh, PA	0.39	62,706	38	13.4	19.8%
Providence, RI	0.65	55,071	46	10.4	30.4%
Raliegh-Duhram, NC	0.92	72,474	41	13.9	22.0%
San Diego, CA	0.43	81,330	48	12.3	24.0%
San Francisco, CA	7.60	74,120	54	8.7	57.5%
San Jose, CA	2.67	109,382	48	12.5	32.6%
Seattle, WA	1.74	70,216	49	10.9	39.7%
St. Louis, MO	0.49	65,011	43	12.0	24.3%
Tampa, FL	0.53	81,414	49	11.7	36.2%
Washington, DC	3.11	83,287	47	12.4	30.0%

Korea

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	2.95	66,203	42	11.3	36.0%
Atlantic City, NJ	0.83	68,433	46	11.0	13.0%
Austin, TX	0.34	51,438	36	12.4	15.0%
Baltimore, MD	1.54	67,798	43	11.2	33.0%
Boston, MA	1.12	69,203	37	13.1	16.7%
Champaign, IL	1.97	40,742	34	13.4	23.7%
Charlotte, NC	0.22	63,750	40	11.0	32.0%
Chicago, IL	0.90	80,399	45	12.1	33.0%
Cleveland, OH	0.28	76,704	45	12.4	23.0%
Dallas, TX	0.73	64,049	43	11.3	35.5%
Daytona Beach, FL	0.53	15,440	38	9.8	20.0%
Denver, CO	0.88	66,583	41	10.8	30.1%
Detroit, MI	0.40	87,439	43	11.9	26.0%
Fort Lauderdale, FL	1.06	56,791	41	11.7	16.7%
Honolulu, HI	3.18	56,545	46	10.2	34.5%
Houston, TX	0.26	57,107	43	11.7	31.3%
Jacksonville, FL	0.11	65,375	48	9.6	27.8%
Jersey City, NJ	0.91	75,623	42	11.8	33.0%
Las Vegas, NV	0.94	60,598	44	10.4	23.5%

Los Angeles, CA	3.41	59,244	45	11.5	43.1%
Melbourne, FL	0.47	60,156	46	10.5	0.0%
Miami, FL	0.23	66,971	44	12.4	8.0%
Minneapolis, MN	0.78	65,860	34	11.3	15.0%
Nassau Co, NY	0.62	108,615	45	12.2	26.6%
New Haven, CT	0.35	80,641	44	12.5	26.0%
New Orleans, LA	0.14	52,790	46	10.0	29.0%
New York, NY	0.71	61,936	42	11.3	43.3%
Newark, NJ	1.54	88,790	44	12.4	33.0%
Oakland, CA	3.26	70,036	43	11.9	29.2%
Orlando, FL	1.06	63,308	45	11.4	13.6%
Philadelphia, PA	0.87	64,361	44	11.4	34.8%
Phoenix, AZ	0.28	51,648	42	11.3	27.0%
Pittsburgh, PA	0.42	69,295	38	12.9	16.1%
Providence, RI	0.58	69,041	37	12.9	15.6%
Raliegh-Duhram, NC	0.64	41,214	37	13.0	19.2%
San Diego, CA	0.58	60,537	42	11.8	31.0%
San Francisco, CA	1.09	81,494	43	12.0	23.0%
San Jose, CA	1.66	92,155	43	12.1	32.0%
Seattle, WA	2.78	64,702	44	11.4	29.9%
St. Louis, MO	0.60	63,052	41	12.3	22.5%
Tampa, FL	0.86	62,451	45	11.2	27.6%
Washington, DC	6.18	77,955	44	11.6	35.8%

Taiwan

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	1.45	92,839	41	12.7	14.7%
Austin, TX	0.47	59,325	34	13.4	2.7%
Baltimore, MD	0.69	83,858	38	13.4	12.3%
Boston, MA	1.73	92,287	37	13.9	7.8%
Champaign, IL	1.00	14,810	29	13.8	18.8%
Charlotte, NC	0.08	116,599	39	13.3	0.0%
Chicago, IL	0.44	112,544	44	13.9	12.3%
Cleveland, OH	0.38	96,212	42	13.6	6.9%
Dallas, TX	0.79	86,939	39	13.3	12.6%
Denver, CO	0.38	68,466	41	11.7	14.0%
Detroit, MI	0.39	118,921	43	14.3	6.9%
Fort Lauderdale, FL	1.13	89,800	43	12.9	19.5%
Honolulu, HI	1.49	71,553	43	11.9	25.0%
Houston, TX	0.77	75,360	42	13.0	18.0%
Jacksonville, FL	0.09	78,324	42	11.7	13.3%
Jersey City, NJ	0.54	90,923	37	12.8	16.0%
Las Vegas, NV	0.58	81,400	40	11.9	10.6%
Los Angeles, CA	3.52	82,100	40	12.5	25.0%
Melbourne, FL	1.24	103,171	43	12.2	14.3%
Miami, FL	0.38	52,019	41	13.4	15.2%
Minneapolis, MN	0.48	87,794	41	13.0	13.6%
Nassau Co, NY	0.50	123,161	44	13.3	13.0%
New Haven, CT	0.58	54,817	35	14.3	6.0%
New Orleans, LA	0.13	52,832	41	11.8	13.3%

New York, NY	0.50	75,834	40	12.1	22.3%
Newark, NJ	3.36	129,313	43	13.5	12.4%
Oakland, CA	7.45	95,520	39	13.2	17.2%
Orlando, FL	1.41	71,267	41	12.7	12.9%
Philadelphia, PA	0.45	69,727	39	12.9	22.1%
Phoenix, AZ	0.33	101,303	39	13.3	10.8%
Pittsburgh, PA	0.35	79,581	38	12.7	21.4%
Providence, RI	0.39	53,508	34	13.4	12.5%
Raliegh-Duhram, NC	0.85	92,420	40	13.5	14.3%
San Diego, CA	0.97	84,461	39	13.0	15.7%
San Francisco, CA	2.34	109,529	41	12.9	18.3%
San Jose, CA	5.56	129,582	40	13.8	12.7%
Seattle, WA	2.08	73,607	39	13.1	17.0%
St. Louis, MO	0.56	107,451	41	13.0	13.0%
Tampa, FL	0.51	55,412	40	12.5	5.4%
Washington, DC	3.47	98,585	40	13.2	13.5%

Egypt

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	0.90	78,139	44	13.0	9.4%
Atlantic City, NJ	6.98	37,304	45	10.8	29.0%
Austin, TX	0.16	53,217	38	13.0	11.1%
Baltimore, MD	0.78	75,469	46	13.5	2.3%
Boston, MA	2.02	84,464	45	12.6	9.9%
Charlotte, NC	0.30	41,322	46	12.1	21.4%
Chicago, IL	0.41	75,858	42	13.5	6.8%
Cleveland, OH	0.84	54,280	43	13.1	5.9%
Dallas, TX	0.32	78,962	45	12.9	0.0%
Daytona Beach, FL	2.57	75,257	36	12.9	0.0%
Detroit, MI	0.92	101,917	49	11.8	6.8%
Fort Lauderdale, FL	3.25	60,972	56	13.2	2.4%
Houston, TX	0.39	66,536	46	12.8	9.4%
Jersey City, NJ	14.32	55,874	42	11.8	17.4%
Las Vegas, NV	0.52	55,314	49	11.3	0.0%
Los Angeles, CA	1.96	75,645	49	12.0	12.5%
Melbourne, FL	1.98	47,322	49	13.0	0.0%
Miami, FL	1.14	69,224	46	12.6	5.7%
Minneapolis, MN	1.05	53,972	44	11.5	26.5%
Nassau Co, NY	1.11	85,813	52	12.7	7.1%
New York, NY	0.96	70,663	43	12.3	10.1%
Newark, NJ	3.49	76,494	44	12.7	11.1%
Oakland, CA	1.92	80,442	44	13.4	4.6%
Orlando, FL	2.60	63,383	49	13.1	12.2%
Philadelphia, PA	0.71	78,733	44	12.7	9.8%
Phoenix, AZ	0.38	53,854	46	13.1	13.9%
Pittsburgh, PA	0.39	56,127	49	13.5	0.0%
Providence, RI	1.49	71,324	50	12.2	32.0%
Raliegh-Duhram, NC	0.73	68,579	47	12.8	0.0%
San Diego, CA	0.42	68,367	48	13.6	4.5%
San Francisco, CA	0.59	98,959	52	12.8	7.6%

San Jose, CA	0.51	138,060	47	13.2	5.1%
Seattle, WA	0.69	104,091	41	12.4	15.0%
St. Louis, MO	0.27	132,858	55	12.1	0.0%
Tampa, FL	2.48	65,631	47	12.6	14.0%
Washington, DC	4.06	98,945	44	13.4	7.6%

Ethiopia

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	7.95	46,185	35	10.7	9.1%
Austin, TX	0.27	66,184	35	11.3	0.0%
Baltimore, MD	0.74	37,138	40	11.1	14.8%
Boston, MA	1.96	54,619	34	11.0	6.1%
Charlotte, NC	0.26	28,250	39	11.1	0.0%
Chicago, IL	0.23	64,243	33	11.6	10.8%
Dallas, TX	1.81	41,604	35	11.1	9.1%
Denver, CO	1.64	67,188	33	10.9	3.9%
Detroit, MI	0.17	81,489	44	12.4	0.0%
Houston, TX	0.23	43,526	37	11.6	4.0%
Jacksonville, FL	0.17	52,614	32	9.7	14.2%
Jersey City, NJ	1.41	54,049	40	11.9	5.2%
Las Vegas, NV	2.72	50,324	35	10.0	10.9%
Los Angeles, CA	0.91	55,822	37	11.1	4.7%
Miami, FL	0.15	30,006	40	11.7	0.0%
Minneapolis, MN	5.63	50,662	34	10.2	9.1%
Nassau Co, NY	0.16	76,683	42	10.8	0.0%
New York, NY	0.15	60,863	42	12.4	4.3%
Newark, NJ	0.78	44,680	38	10.8	8.3%
Oakland, CA	4.23	69,593	37	11.6	6.3%
Orlando, FL	0.96	49,620	32	10.5	0.0%
Philadelphia, PA	0.32	71,251	35	10.8	0.0%
Phoenix, AZ	0.19	39,641	33	11.1	14.3%
San Diego, CA	0.63	54,788	38	11.8	9.3%
San Francisco, CA	0.53	90,995	36	11.6	4.3%
San Jose, CA	1.31	67,911	35	11.3	10.6%
Seattle, WA	4.01	36,240	35	9.9	17.3%
St. Louis, MO	0.72	22,862	33	8.2	21.4%
Washington, DC	20.25	57,158	37	11.1	8.1%

Nigeria

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	8.40	61,150	37	12.8	2.2%
Austin, TX	0.53	65,080	39	13.5	0.0%
Baltimore, MD	2.35	80,691	38	13.0	1.5%
Boston, MA	1.62	50,641	38	12.5	1.2%
Charlotte, NC	0.50	47,756	42	12.1	0.0%
Chicago, IL	0.89	52,718	39	12.6	2.6%
Cleveland, OH	0.47	117,795	38	14.2	0.0%
Dallas, TX	2.00	68,697	38	12.8	1.8%
Denver, CO	0.49	60,784	39	13.2	4.2%
Detroit, MI	0.98	53,201	40	12.9	2.4%
Fort Lauderdale, FL	1.92	52,186	38	12.1	3.8%

Houston, TX	2.20	54,008	40	12.6	0.7%
Jacksonville, FL	0.15	54,480	38	12.7	0.0%
Los Angeles, CA	0.68	69,237	39	12.4	3.2%
Miami, FL	1.55	47,444	38	11.7	14.0%
Minneapolis, MN	1.53	63,345	43	12.3	3.8%
Nassau Co, NY	0.40	78,162	42	13.9	0.0%
New Orleans, LA	0.35	43,592	40	13.1	6.7%
New York, NY	0.74	64,116	40	12.5	1.9%
Newark, NJ	7.48	64,118	40	12.5	1.1%
Oakland, CA	2.34	73,676	39	12.3	2.4%
Orlando, FL	1.15	66,753	40	13.3	0.0%
Philadelphia, PA	0.64	63,931	39	12.8	4.6%
Phoenix, AZ	0.28	66,588	38	13.2	0.0%
Providence, RI	2.72	39,390	39	11.8	4.7%
Raliegh-Duhram, NC	2.89	53,500	39	12.3	5.6%
San Diego, CA	0.22	53,463	38	12.9	0.0%
San Francisco, CA	0.28	112,375	43	11.6	5.2%
San Jose, CA	0.25	119,422	40	13.0	5.0%
Seattle, WA	0.40	75,345	41	13.4	0.0%
St. Louis, MO	0.68	57,657	41	13.2	4.7%
Tampa, FL	0.85	64,247	39	12.7	8.7%
Washington, DC	10.87	67,600	39	12.6	2.2%

South Africa

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	4.37	74,515	36	13.0	0.0%
Austin, TX	0.72	84,611	36	12.1	0.0%
Baltimore, MD	0.80	117,259	47	13.4	0.0%
Boston, MA	2.49	133,673	40	13.0	0.0%
Charleston, SC	2.45	83,170	38	13.0	0.0%
Charlotte, NC	0.61	77,285	34	11.4	0.0%
Chicago, IL	0.35	129,291	43	12.9	0.0%
Cleveland, OH	1.04	125,536	45	13.0	0.0%
Dallas, TX	1.47	123,189	42	12.5	0.0%
Denver, CO	1.75	104,512	44	12.5	0.0%
Detroit, MI	0.35	78,940	42	11.1	0.0%
Fort Lauderdale, FL	5.90	77,396	40	12.9	0.0%
Houston, TX	0.79	139,631	35	12.2	0.0%
Jacksonville, FL	0.32	79,457	38	12.7	0.0%
Jersey City, NJ	0.79	59,712	34	13.0	0.0%
Las Vegas, NV	0.69	68,771	42	12.1	0.0%
Los Angeles, CA	1.29	144,768	43	12.8	0.5%
Melbourne, FL	3.31	41,043	43	11.1	0.0%
Miami, FL	0.98	133,127	47	14.0	0.0%
Minneapolis, MN	0.80	150,377	43	13.5	0.0%
Nassau Co, NY	0.60	195,592	48	13.9	0.0%
New York, NY	0.31	151,927	40	13.6	0.9%
Newark, NJ	3.11	107,448	36	12.3	0.0%
Oakland, CA	2.61	80,459	40	12.6	0.0%
Orlando, FL	5.47	94,895	42	11.5	0.0%

Philadelphia, PA	0.65	114,601	39	12.2	0.0%
Phoenix, AZ	0.73	98,709	43	12.0	2.4%
Pittsburgh, PA	0.71	123,212	42	13.8	0.0%
Raliegh-Duhram, NC	2.74	116,166	39	12.7	0.0%
San Diego, CA	2.44	132,829	45	12.7	0.0%
San Francisco, CA	1.61	152,483	39	13.9	0.0%
San Jose, CA	0.90	182,866	42	13.7	0.0%
Seattle, WA	2.23	114,625	38	13.1	0.0%
St. Louis, MO	0.88	58,917	33	13.8	0.0%
Tampa, FL	3.43	65,927	41	11.7	2.2%
Washington, DC	3.31	131,819	41	12.8	0.0%

Greece

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	0.84	90,353	50	12.0	6.5%
Atlantic City, NJ	7.30	55,631	56	8.4	17.9%
Baltimore, MD	1.37	63,216	53	9.3	23.0%
Boston, MA	5.01	80,059	51	9.7	19.0%
Charlotte, NC	0.56	67,527	52	8.6	20.0%
Chicago, IL	2.03	84,723	56	9.1	21.0%
Cleveland, OH	1.32	59,419	60	8.9	22.9%
Dallas, TX	0.17	82,402	43	11.7	0.0%
Daytona Beach, FL	2.60	47,928	60	7.5	18.0%
Denver, CO	0.62	99,372	53	9.5	4.4%
Detroit, MI	1.29	78,749	57	8.8	20.4%
Fort Lauderdale, FL	3.68	49,439	59	10.3	9.5%
Houston, TX	0.21	83,679	54	10.6	11.3%
Jacksonville, FL	0.19	87,890	50	11.1	16.7%
Jersey City, NJ	1.55	69,182	49	9.3	18.4%
Las Vegas, NV	0.73	73,287	56	9.9	6.5%
Los Angeles, CA	0.62	57,985	60	8.8	42.5%
Miami, FL	0.84	57,651	49	11.1	10.0%
Nassau Co, NY	2.13	97,446	54	9.6	17.1%
New Haven, CT	0.67	83,236	48	10.6	9.1%
New Orleans, LA	0.36	34,853	53	10.3	13.0%
New York, NY	1.23	68,759	54	8.8	25.0%
Newark, NJ	3.13	82,894	53	9.3	16.8%
Oakland, CA	1.10	118,500	52	11.4	3.4%
Orlando, FL	1.02	100,196	47	11.2	4.0%
Philadelphia, PA	1.04	65,114	53	9.1	18.2%
Phoenix, AZ	0.27	92,096	49	11.1	2.0%
Pittsburgh, PA	1.11	60,102	57	10.2	20.0%
Providence, RI	2.31	76,295	57	8.5	13.2%
San Diego, CA	0.35	89,833	56	9.7	10.5%
San Francisco, CA	0.72	81,610	55	10.1	8.1%
San Jose, CA	0.47	105,099	50	10.9	10.9%
Seattle, WA	0.52	69,863	51	11.8	0.0%
St. Louis, MO	0.61	62,025	55	9.8	29.0%
Tampa, FL	5.30	53,950	57	8.6	12.2%
Washington, DC	2.58	114,450	52	11.0	9.7%

Hungary

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	0.71	126,627	50	12.7	0.0%
Baltimore, MD	0.41	89,941	67	10.9	5.6%
Boston, MA	1.13	99,805	48	13.3	6.7%
Chicago, IL	0.80	70,552	62	10.7	8.9%
Cleveland, OH	5.35	51,606	65	10.3	11.0%
Dallas, TX	0.29	50,945	49	11.4	17.0%
Daytona Beach, FL	3.46	38,556	71	8.4	6.7%
Denver, CO	0.93	59,530	60	11.3	0.0%
Detroit, MI	1.07	79,019	63	10.4	4.3%
Fort Lauderdale, FL	9.41	55,674	67	9.5	8.2%
Houston, TX	0.18	91,795	51	13.0	4.2%
Jacksonville, FL	0.38	81,322	56	11.2	5.3%
Las Vegas, NV	0.80	54,400	51	10.5	3.8%
Los Angeles, CA	1.31	76,371	59	11.2	8.7%
Miami, FL	2.28	81,261	63	11.7	7.1%
Minneapolis, MN	0.46	145,625	63	13.8	0.0%
Nassau Co, NY	0.97	109,707	57	11.8	3.4%
New York, NY	0.98	61,825	61	10.1	12.9%
Newark, NJ	3.89	75,170	62	10.3	4.2%
Oakland, CA	2.52	106,518	57	12.1	8.8%
Orlando, FL	2.15	68,968	50	11.2	11.0%
Philadelphia, PA	0.80	70,387	61	10.5	4.8%
Phoenix, AZ	0.46	73,050	58	10.5	4.9%
Pittsburgh, PA	0.66	41,587	71	10.9	6.7%
Providence, RI	1.02	48,616	57	13.1	0.0%
San Diego, CA	0.60	56,539	60	11.4	4.0%
San Francisco, CA	0.76	78,601	51	12.4	7.5%
San Jose, CA	0.69	99,881	51	12.4	2.3%
Seattle, WA	1.18	98,402	52	11.5	8.9%
St. Louis, MO	0.47	55,267	55	10.7	0.0%
Tampa, FL	2.92	50,629	56	10.4	11.7%
Washington, DC	2.61	103,650	55	13.1	4.0%

Poland

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	0.48	81,821	52	11.8	9.3%
Atlantic City, NJ	1.99	48,207	58	9.8	11.5%
Baltimore, MD	0.45	55,013	65	9.8	9.6%
Boston, MA	1.30	73,578	51	11.2	8.9%
Charlotte, NC	0.13	99,182	43	11.8	4.5%
Chicago, IL	5.47	67,543	46	10.1	31.2%
Cleveland, OH	1.39	48,414	57	9.8	17.2%
Dallas, TX	0.14	90,959	47	12.1	7.7%
Daytona Beach, FL	1.21	36,623	62	9.3	24.0%
Denver, CO	0.69	69,010	53	11.2	17.7%
Detroit, MI	1.54	66,773	56	9.8	16.3%
Fort Lauderdale, FL	6.41	48,334	68	10.0	7.3%
Houston, TX	0.12	73,670	52	11.8	4.1%

Jacksonville, FL	0.13	65,215	54	10.5	25.0%
Jersey City, NJ	2.85	63,132	49	10.3	27.6%
Las Vegas, NV	0.44	61,242	52	11.0	7.4%
Los Angeles, CA	0.37	81,237	61	10.8	6.7%
Melbourne, FL	1.04	50,788	58	11.6	4.0%
Miami, FL	1.39	58,246	69	9.3	8.6%
Minneapolis, MN	0.41	64,764	59	10.7	14.0%
Nassau Co, NY	1.20	84,165	52	10.9	14.6%
New Haven, CT	1.86	72,753	47	10.5	17.6%
New York, NY	1.12	56,661	52	10.2	28.0%
Newark, NJ	6.56	74,980	47	10.4	20.4%
Oakland, CA	0.85	92,097	51	12.0	7.3%
Orlando, FL	0.80	52,798	49	10.8	16.7%
Philadelphia, PA	0.64	63,455	54	10.2	17.8%
Phoenix, AZ	0.29	57,186	55	11.1	8.9%
Pittsburgh, PA	0.59	64,728	61	10.4	16.0%
Providence, RI	0.96	73,376	53	9.8	27.8%
Raliegh-Duhram, NC	0.36	93,354	47	12.5	15.6%
San Diego, CA	0.28	68,234	54	10.9	2.7%
San Francisco, CA	0.29	101,776	55	12.1	5.5%
San Jose, CA	0.33	115,088	49	12.9	11.7%
Seattle, WA	0.59	67,067	44	11.9	8.3%
St. Louis, MO	0.34	74,015	54	11.1	10.5%
Tampa, FL	1.91	53,393	55	10.8	10.6%
Washington, DC	1.00	95,719	52	12.6	4.3%

Romania

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	2.20	68,308	39	10.7	23.0%
Baltimore, MD	0.37	73,386	53	12.5	20.0%
Boston, MA	1.14	88,834	50	13.5	11.5%
Chicago, IL	1.38	70,019	45	10.7	15.3%
Cleveland, OH	3.55	54,445	50	10.4	24.0%
Dallas, TX	0.25	49,837	41	12.3	19.0%
Daytona Beach, FL	5.17	66,762	48	11.2	2.9%
Detroit, MI	2.71	72,682	45	10.7	25.0%
Fort Lauderdale, FL	10.69	58,488	52	10.4	10.8%
Houston, TX	0.21	79,911	48	12.4	4.7%
Jersey City, NJ	0.77	84,754	54	10.9	31.5%
Las Vegas, NV	0.65	61,606	46	10.7	6.3%
Los Angeles, CA	1.00	79,316	53	11.4	13.2%
Miami, FL	1.48	69,880	62	11.4	15.0%
Minneapolis, MN	0.51	52,467	42	12.4	10.0%
Nassau Co, NY	0.64	109,972	52	12.3	3.4%
New York, NY	1.10	65,889	54	10.7	15.4%
Newark, NJ	2.46	97,047	53	11.4	8.7%
Oakland, CA	2.00	94,321	43	12.4	8.5%
Orlando, FL	0.94	52,567	53	10.7	11.0%
Philadelphia, PA	0.63	70,863	52	11.2	11.2%
Phoenix, AZ	0.95	70,718	43	10.9	10.0%

Providence, RI	0.62	114,463	35	12.5	9.1%
Raliegh-Duhram, NC	0.35	71,864	35	14.7	0.0%
San Diego, CA	0.32	82,461	58	12.2	7.5%
San Francisco, CA	0.41	93,484	57	12.0	15.2%
San Jose, CA	0.47	97,111	44	13.7	2.3%
Seattle, WA	2.09	80,544	37	11.6	11.0%
St. Louis, MO	0.62	41,666	52	10.7	9.1%
Tampa, FL	1.00	49,067	57	11.3	22.5%
Washington, DC	1.36	85,626	47	12.6	10.0%

India

City	*Agglomeration Index*	*Avg. Income*	*Avg, Age*	*Education*	*% Non-English*
Atlanta, GA	3.23	85,414	39	12.8	10.4%
Atlantic City, NJ	4.53	81,245	43	11.3	12.5%
Austin, TX	0.61	83,722	36	13.6	8.6%
Baltimore, MD	1.00	100,000	41	13.2	8.2%
Boston, MA	2.23	100,713	38	13.8	5.9%
Champaign, IL	1.12	52,302	33	14.8	2.2%
Charleston, SC	0.51	137,756	43	13.1	6.7%
Chicago, IL	1.53	95,187	41	12.6	12.2%
Cleveland, OH	1.03	110,612	40	13.7	7.7%
Dallas, TX	1.31	89,982	38	12.9	8.3%
Daytona Beach, FL	1.12	98,270	46	11.5	11.4%
Denver, CO	0.60	86,246	34	13.8	2.0%
Detroit, MI	1.49	106,118	40	13.6	6.3%
Fort Lauderdale, FL	2.09	85,427	41	12.4	9.2%
Honolulu, HI	0.17	90,333	45	13.0	10.3%
Houston, TX	0.93	88,562	43	12.8	8.5%
Jacksonville, FL	0.22	105,487	40	13.7	8.0%
Jersey City, NJ	4.58	70,518	39	11.7	19.2%
Las Vegas, NV	0.17	76,087	40	12.9	0.0%
Los Angeles, CA	0.70	97,591	43	12.6	8.5%
Melbourne, FL	1.49	79,060	42	13.2	7.6%
Miami, FL	0.72	88,010	39	12.9	7.5%
Minneapolis, MN	1.02	98,769	36	13.8	5.0%
Nassau Co, NY	1.14	129,862	44	12.8	7.7%
New Haven, CT	0.76	68,895	42	12.2	7.0%
New Orleans, LA	0.28	96,225	43	13.5	7.3%
New York, NY	0.65	81,776	41	11.8	11.9%
Newark, NJ	4.91	113,418	41	12.9	13.0%
Oakland, CA	6.72	109,310	39	12.8	9.0%
Orlando, FL	1.97	104,728	42	12.8	8.5%
Philadelphia, PA	1.10	88,592	41	12.7	10.0%
Phoenix, AZ	0.36	93,688	39	13.6	4.5%
Pittsburgh, PA	1.20	113,410	39	14.3	2.0%
Providence, RI	0.65	91,165	42	13.4	5.8%
Raliegh-Duhram, NC	1.91	88,582	38	13.8	5.9%
San Diego, CA	0.35	103,632	41	13.9	7.3%
San Francisco, CA	1.04	107,681	37	13.5	3.2%
San Jose, CA	3.95	118,139	36	13.6	6.1%

Seattle, WA	1.23	93,987	37	12.8	9.0%
St. Louis, MO	0.93	110,489	40	14.0	4.6%
Tampa, FL	1.47	104,740	42	13.3	4.0%
Washington, DC	5.58	105,960	41	13.3	6.6%