IMMIGRATION, INCOME INEQUALITY, AND STOCHASTIC DOMINANCE

by

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ABSTRACT

Income inequality and immigration are two important issues with welfare and policy implications which have long been debated across the political spectrum. This dissertation ventures to shed light on some of the important questions related to income inequality and immigration, such as: What is the current level of inequality among immigrant cohorts; what are the determinants of income inequality of immigrants in the United States; how does the income inequality of immigrants change over time; and what is the impact of immigration on the income distribution of the United States? A cross-sectional regression analysis indicates that the variation in income inequality among immigrant cohorts can be explained by a wide range of variables such as median income, education, age, gender, deprivation, geographical dummies, and visa status. Moreover, the analysis demonstrates that immigrant cohorts exhibit substantial progression in their income inequality over time. The results suggest that the initial level of inequality of recent immigrants in comparison to the U.S. is the most important factor explaining the variation in inequality dynamics. More precisely, immigrant cohorts that have inequality that is remarkably different than the host country's inequality exhibit a faster improvement in equality and they follow a more rapid convergence path to the host country's inequality. Finally, the counterfactual effects of immigrants are investigated by decomposing the surveyed sample of more than three million respondents into natives and immigrants. Income inequality of the population is then calculated in the presence and in the absence of each immigrant cohort. The difference between these figures is presented as the distributional effects of immigrants on U.S. income inequality. The results are striking. Even after controlling for the size of the immigrant cohorts, several other factors are found to be significant for the counterfactual effects of immigrants. The immigrant cohorts that have very low and very high income compared to the U.S. average income have disequalizing effects. The findings of this dissertation provide essential information to policymakers. Based on these findings, immigrants can better be evaluated and immigration policy can be redesigned.

DEDICATION

This dissertation is dedicated to my beloved father, Recep Yaya, who passed away on February 9th, 2006. He inspired me deeply with his hard work and devotion to his children throughout his life.

LIST OF ABBREVIATIONS AND SYMBOLS

ACS	American Community Survey
ATK	Atkinson Index
BEA	Bureau of Economic Analysis
CPS	Current Population Survey
CV	Coefficient of Variation
EU	European Union
GINI	Gini Coefficient
INS	Immigration and Naturalization Service
LD	Lorenz Dominance
MPS	Mean Preserving Spread
OECD	Organization of Economic Development and Cooperation
OLS	Ordinary Least Squares
PT	Principle of Transfer
RMD	Relative Mean Deviation
SSD	Second Order Stochastic Dominance
SSI	Supplemental Security Income
STD	Standard Deviation of Logs
THEIL	Theil Index
TSD	Third Order Stochastic Dominance

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CHAPTER 1

INTRODUCTION

Champernowne and Cowell (1998) defined inequality as the economic attainment differences between individuals or groups in a population. Economic inequality is an important subject because it has been a persistent problem with the potential to generate resentment among individuals and alter the redistributive policies adopted by governments. Inequality of populations can be calculated based on several different variables, such as welfare, utility, or income. However, income is the most popular one in the literature because it is an important determinant of consumption and economic welfare. Moreover, it is easily observed by researchers.

Migration, on the other hand, is broadly defined as the movement of people from one location to another. Differences in the level of wages, economic opportunities, the standard of living across countries and political freedom encourage people to move. Stark (2006) argued that the relative deprivation of households induces migration as well. He stated that individuals care about their position in the society and feel deprived if they are not satisfied with their relative position. Migration reduces this deprivation through two channels. In the first channel, people move to different locations where they have a better chance of earning more income. Once they start earning more, their relative deprivation decreases. The second channel considers the change in the reference group after migration. In the new reference group, the relatively elevated position of the individual decreases the level of deprivation. Furthermore, Liebig and Sousa-Poza

(2004) argued that people living in countries that have unequally distributed incomes have more incentive to migrate. They found that the Gini coefficient, a widely used measure of income inequality, always has a positive and significant impact on the propensity to migrate.

The availability of information about the country of destination and ease of transportation allows more people to move from one country to another. On the other hand, visa requirements, language barriers, and job market uncertainties impede this movement. The number of immigrants, people who are living in a country other than their country of birth, has been steadily rising. In 2005, there were 203 million people living outside their country of birth, and 190 million were considered immigrants. The rest of these people were refugees and asylum seekers. Contrary to general perception, immigrants are not only living in developed countries but also in developing countries. In 2005, 115 million immigrants were living in developed countries and 75 million were living in developing countries (International Migration 2006).

Some regions and countries in the world, such as Western Europe and Japan, have been suffering from low fertility rates. In these areas, immigration plays a significant role in the dynamics of the demographic structure. For example, from 1995 to 2000, the population in Europe increased by only 600,000, but the number of immigrants increased by more than five million. Only seven countries (the United States, France, Canada, Australia, Côte d'Ivoire, Sweden, and Israel) had consistent positive immigration flows, while sixteen counties, including India, Indonesia, Bangladesh, and Mexico had consistent negative migration (emigration) for a lengthy period of time (World Economic and Social Survey 2004: International Migration 2005). In general, developing countries are a big source of immigration, while developed countries are the preferred destinations for immigrants. Furthermore, the survey argued that geographical proximity became more important for immigrants while colonial ties and cultural similarities became less important for the destination decisions of immigrants compared to a decade ago.

Illegal immigration is a controversial issue. In 2000, seven million unauthorized immigrants were believed to be residing in the U.S., and 70% of these illegal immigrants were estimated to be Mexican (World Economic and Social Survey 2004: International Migration 2005). There is difficulty in finding illegal immigration statistics which limits empirical studies on the issue. However, there are still some theoretical and empirical studies related to illegal immigration. Winegarden and Khor (1993) used the 1980 Census and the INS records to estimate that 2,100,000 illegal immigrants resided in the United States. In their cross-sectional regression analysis, they used the variance of the household's income as the measure of income inequality. Their results suggested a small disequalizing effect of illegal immigrants on income inequality among natives. Bandyopadhyay and Bandyopadhyay (1998) studied the supply of illegal immigrants and the wage effects of emigration on the source country's labor market. They concluded that the size of the host country's demand for illegal labor determines the effect of emigration on the source country wages. Hanson and McIntosh (2009) have examined the Mexican migrants in the United States. They argued that the sharp increase in the Mexico-U.S. relative labor supply and the economic slowdown in Mexico contributed to the Mexican emigration surge in the United States. However, their demographic projections suggested that the plummeting fertility rate in Mexico will decrease the Mexican emigration or even reverse the migration flow in the next few decades.[1]

1 A recent recession in the U.S. has affected both the number of immigrants applying for the H1B visa for skilled workers as well as illegal immigrants (The Economist 2008). Border patrols encounter less illegal immigration attempts, while the highly sought H1B visas have not reached the preset annual quota of 85,000 even months after its application start date in 2008.

One of the positive consequences of immigration is the fact that immigrants have the opportunity to obtain jobs which are not available in their countries of origin. Immigration also helps to alleviate the excess labor supply in the country of origin. Moreover, immigrant remittances assist the balance of payment accounts of the source country when immigrants settle in the country of destination and start sending portions of their income to the country of origin. Technology transfer and foreign investment should also be considered as positive results of immigration for the country of origin. Furthermore, immigration contributes to increased international trade between the countries of origin and destination. Finally, immigration stimulates domestic education and human capital investment in the country of origin (World Economic and Social Survey 2004). At the introduction of "Issues in the Economics of Immigration", Borjas (2000) states: "… the impact of immigrants on the national economy is not limited to the labor market, but immigration also changes the education system, financial well being of social security system, cost of preventing crime etc. and these factors yet to be incorporated to the cost-benefit analysis of immigration."

Some of the negative consequences of immigration in the country of origin are "brain drain," reduced growth and productivity slowdown. New growth theory argues that skilled workers are not only productive themselves, but also have a positive effect on the productivity of others. Brain drain is the most evident concern of immigration in the country of origin because it eliminates the productivity of skilled workers directly and indirectly, as suggested by the new growth theory. Moreover, immigration leads to lower returns from public investment in public education. Immigration also creates a loss on tax income from emigrating workers. Lastly, immigration may change the income inequality scheme in the countries of origin and destination.

One of the questions this study strives to answer is the distributional effects of legal immigrants in the country of destination.

Immigration is a special case of a change in labor market equilibrium. In a two-factor model, factors of production are labor and capital. An influx of immigrants increases the supply of labor, forcing native employees to accept lower wages. In a two-factor model, the skill level of labor is assumed to be the same and wages between the countries of origin and destination are expected to converge, assuming perfect mobility of labor. Indeed, these two-factor models held true in some instances in the past. For example, between 1870 and 1910, wages across the Great Atlantic economy and Europe had a persistent convergence during the European emigration to America. During this period, wages in Europe increased by 9% and dropped more than 8% in America, mostly due to immigration. Although wages were dropping in the country of destination, it enjoyed rapid growth after the influx of migrants due to the decreasing cost of labor.

However, skill differentiation became an important aspect of industrialization and the workers started to specialize in different jobs. To accommodate the need for skill differentials among workers, three-factor models have been proposed in the literature. In these models, the three factors of production are skilled labor, unskilled labor, and capital. Once two skill levels for labor are proposed, the effect of immigrants on the economy depends on the skill level of immigrants. Using their three-factor model, Winter-Ebmer and Zimmerman (1998) found that immigration had a negative effect on native employment and wages in Austria. Mishra (2007) and Islam and Fausten (2008) have examined the effect of emigration on the source country's labor market. Islam and Fausten found no significant impact of immigration on wages in the Australian labor market, while Mishra showed that emigration has a significant positive impact on wages of different skill level groups in Mexico. He concluded that emigration contributes to a faster increase in high skill worker wages; hence, it contributes to an increase in income inequality in Mexico.

There is also extensive research studying the types of workers who are more likely to migrate. Borjas (1987) has studied the "self-selection" of immigrants in his influential paper. He stated that immigrants are not a random sample of the country of origin's population. Chiswick (1978) concluded that the earnings of immigrants overtake natives after a short period of adaptation and assimilation. Chiswick argued that immigrants are more motivated than the remaining citizens of the source country such that they are a "self-selected" group. According to the author, the income of immigrants surpasses the native population because immigrants have stronger investment incentives than the native workers. Hatton (2004) empirically tested the positive selection hypothesis of Borjas with UK migration data. Hatton found an insignificant effect of income inequality, measured by the Gini coefficient, on immigration, suggesting that the UK income inequality level did not affect the decisions of immigrants migrating to the United Kingdom.

Borjas (1987) further questioned the theory of immigrants being selected from an upper tail of the income distribution of the country of origin. He concluded that if there were a strong correlation between the expected income of immigrants in the country of origin and in the country of destination, and the income in the country of destination was more unequally distributed than in the country of origin, a "positive selection" would be observed. However, in his theoretical framework, Borjas had some restrictive assumptions, such as the fixed costs of emigration for all immigrants, which may not be the case for immigrants coming from different distances and cultures.

Davies and Wooton (1992) used a three-factor model to explain the welfare impact of migration on the host and the source country's income inequality. Their analysis employed a simple two-country model wherein both countries produce two goods using their factor endowments of capital, skilled labor, and unskilled labor. The authors summarized the conventional wisdom about the effect of immigration on income equality as follows: "…unskilled migration reduces income inequality in source countries and increases in the host countries. Brain drain, on the other hand, is often viewed as doing the opposite, raising inequality in the source and lowering it in the host." More precisely, if unskilled labor leaves the source country, the supply of unskilled labor decreases. This situation will put an upward pressure on wages for unskilled labor. Ceteris paribus, higher wages for unskilled labor in the source country creates a more equal distribution of income and lowers income inequality. The opposite will be observed in the host country. However, Davies and Wooton showed that there are other possible outcomes. They presented a theoretical model in which a movement of unskilled labor has created ambiguous welfare effects on both source and host countries. The authors also showed that brain drain (skilled labor migration) could unambiguously reduce income inequality in the source country and increase it in the host country. Card (2009) has extended the number of skill groups into three using high school dropouts, 12-15 years of schooling, and college and more education as categories. He found that immigrants had only minor effects on wage inequality in the U.S. over the past few decades.

The purpose of this study is to examine the income distribution of U.S. citizens and immigrants living in the United States. The comparison of immigrants' and U.S. citizens' income distribution is believed to shed light on some of the important questions yet to be answered: What are the determinants of income inequality of immigrants in the U.S.; how does the income inequality of immigrants change over time; and how do immigrants affect the income inequality of the host country?

The parts of the study are organized as follows: part two ties stochastic dominance literature to the income distributions of immigrants. Several income inequality measures are also presented in this section. Part three reviews the literature on immigration and income inequality. Part four introduces the variables used in the study. Part five illustrates the characteristics of immigrants. The immigrants are divided into133 counties of origins, where each cohort exhibits different characteristics such as income, education, English ability, etc. The models and the variables for the empirical study on the immigrant cohorts are demonstrated in part six. The results are presented in part seven. Finally, part eight concludes.

CHAPTER 2

STOCHASTIC DOMINANCE AND INCOME INEQUALITY MEASURES

Measurement of inequality in precision has been a difficult task for researchers since the 1920s. There have been several studies that have been published on income inequality. Inequality is essentially a metric of dispersion, and it is possible to measure dispersion using different statistical metrics such as relative mean deviation, variance and coefficient of variance, the Gini coefficient, and the Atkinson or Theil indexes. Most of these inequality metrics have the shortcoming of not capturing all the aspects of actual inequality when average income levels differ significantly (Temkin 1993). Nonetheless, the assertion of a higher level of income inequality caused by immigration is even more controversial. Although the research on this topic is limited, it is still a popular debate among policy makers. People who hold immigration responsible for its adverse income inequality consequences argue that immigrants have a potential to increase the current income inequality scheme of the host country.

Dalton (1920) proposed the Population Principle, suggesting that income inequality is unchanged when equal amounts of immigrants are added to the existing groups of income receivers. However, it is impossible to find a single example in history where an equal amount of immigrants were added to the existing income groups of the host country; but, politicians who are against immigration use this feature of immigration to support their case. In his influential paper, Dalton stated that the Principle of Transfer (PT) can be defined as: "…if there are only two income receivers and a transfer of income takes place from richer to poorer then the income inequality diminishes." Dalton assumed that welfare is additive and each individual's marginal economic welfare diminishes as income increases. The foundation of this dissertation relies in part on Dalton's PT that proportionate additions to people at each income class have no effect on income inequality.

There are some empirical studies on the effect of immigration on income inequality. Moore and Pacey (2003) and Reed (2001) both found no or very limited and statistically insignificant evidence of an effect of immigration on income inequality. Both of these studies pointed out that the largest immigration move from one country to another does not exceed a small percentage of the host countries' population. Thus, the effect of immigration with such a small change on the host country's population may not be reflected in any conventional income inequality measure. However, there are some country-based exceptions in the world. For example, immigrants constitute 70% of Qatar's population; therefore, it is hard to argue that the effects of immigration are as insignificant as Reed suggested for this country. In our sample of almost 2.5 million households surveyed in United States, there are approximately three hundred fifteen thousand immigrants that constitute nearly 12% of the sample.

Sections 2.1-2.6 present the most widely recognized income inequality measures which will also be used for the remainder of the study (Temkin 1993). Readers should note that this study does not extend to the principal of transfer per se but merely investigates the determinants of income inequalities of immigrant cohorts, inequality dynamics, and counterfactual effects of immigrants on the host country's inequality.

2.1 Relative Mean Deviation (RMD)

RMD is an income inequality metric that measures the total sum of deviation from the mean. RMD can be calculated as follows:

$$RMD = \sum_{i=1}^{n} \frac{\left|\mu - y_i\right|}{n\mu} \,. \tag{1}$$

μ is mean income, n is the population size, and y_i is the income of the i^{th} individual in the population. RMD suggests that inequality in population A is worse than population B if the total deviation of the mean is greater for population A than population B. RMD violates the PT because it is insensitive to income transfers on the same side of the mean.

2.2 Coefficient of Variation (CV)

Coefficient of variation is the square root of variance divided by the mean income. It is calculated as follows:

$$CV = \sqrt{\sum_{i=1}^{n} \frac{(\mu - y_i)^2}{n}} \Bigg/ \mu \,. \tag{2}$$

μ is mean income, n is the population size, and y_i is income of the i^{th} individual in the population. CV attaches more weight to the differences in mean income than RMD and unlike RMD, CV is sensitive to income transfers on the same side of the mean.

2.3 Standard Deviation of Logs (St.Dev.)

Standard deviation of logs is calculated as follows:

$$St.Dev = \sqrt{\sum_{i=1}^{n} \frac{(\log \mu - \log y_i)^2}{n}} \,. \tag{3}$$

μ is mean income, n is the population size, and y_i is the i^{th} individual in the population. The logarithmic function is known to attach more weight to small numbers than large numbers;

therefore, the Standard Deviation of Logs is more sensitive to the income transfers at the bottom of the income distribution.

2.4 Gini Coefficient and Lorenz Curve

2.4.1 Gini Coefficient (GINI)

The measurement of income inequality has been an area of interest since the early 1900s. The American economist Max Otto Lorenz and Italian statistician Corrado Gini laid the foundations of inequality research with their influential works published in 1905 and 1912, respectively. The Gini coefficient is a measure of the inequality of a distribution that was first introduced in Gini's seminal paper called "Variability and Mutability." The coefficient lies between zero and one, and higher Gini coefficient corresponds to a higher level of inequality. A zero Gini coefficient indicates perfect equality of income; whereas a coefficient of one means perfect inequality of income (one person has all the income while the others have zero income). The Gini coefficient can be calculated as follows:

$$GINI = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|y_i - y_j\right|. \tag{4}$$

μ is mean income, n is the number of individuals in the society, y_i is income of the i^{th} individual, and y_j is income of the j^{th} individual.

There is a close relationship between the Gini coefficient and the Lorenz Curve.[2] The Lorenz curve is the graphical representation of the relationship between the percentage of the population (measured on the x-axis) and the percentage of income (measured in the y-axis). It

[2] Proof of the relationship between Gini Coefficient and Lorenz curve can be found in Appendix A.

measures what percent of income is received by the corresponding percent of the population. The income inequality measure based on the Lorenz Curve is always one half of the Gini coefficient.

2.4.2 Second Order Stochastic Dominance and Lorenz Dominance

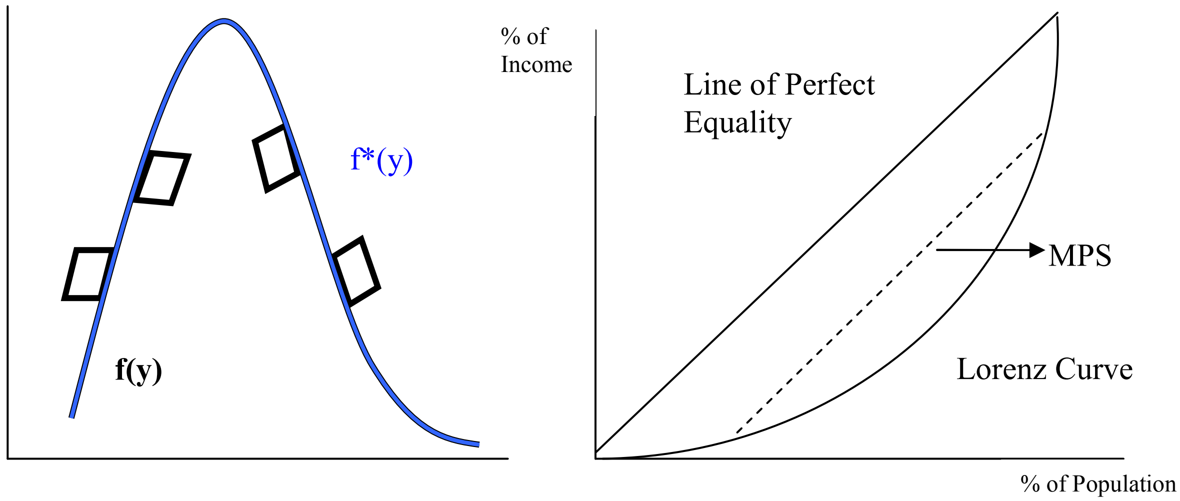
Rothschild and Stiglitz (1970), Hadar and Russell (1969), and Hanoch and Levy (1969) all showed that a distribution, *f(y)*, is preferred to another distribution, *f*(y)*, by Second Order Stochastic Dominance (SSD) if and only if:

$$\int_0^z [F(y) - F^*(y)]dy \leq 0 , \qquad \text{for all z, } 0 \leq z \leq \bar{y} . \tag{5}$$

Furthermore, Atkinson (1970) showed that when two distributions have the same mean and the SSD condition holds, *f(y)* always lies above *f*(y).* However, Atkinson suggested that any ranking of income distributions can be made if and only if these distributions do not intersect.

Atkinson (1970) stated that the PT is identical to the concept of Mean Preserving Spread (MPS) established by Rothschild and Stiglitz (1970). He suggested that a necessary and sufficient condition to rank two distributions (independent of the functional form of the utility) is that one of the distributions be obtained by redistributing income (taking money from the rich and giving it to the poor). PT and its effect on the Lorenz Curve are shown in Figure 1.

Figure 1: Principle of Transfer and the Lorenz Curve



Principle of Transfers (MPS) **Effect of MPS on Lorenz Curve**

The Lorenz Curve represents the aggregate income possessed by *p%* of the population. Moyes (1999) studied two distributions which can be called the distribution of *x* and the distribution of *y*. He argued that the *x* Lorenz dominates *y* if the Lorenz curve of *x* is nowhere below the Lorenz curve *y*. Moyes assumed that all the individuals in a society are identical in all aspects other than income. He also showed that if the mean of two distributions are the same, then Lorenz Dominance (LD) and SSD are equivalent. This statement also suggests the inequality index for *y* distribution is higher than the inequality index for *x* distribution. In conclusion, the direct consequence is the ordering of distributions suggested when Lorenz dominance and Second Order Stochastic Dominance are equivalent.

The ranking of two income distributions based on SSD is not possible if these distributions intersect. However, it is possible to rank these distributions under special circumstances by using a transfer-sensitive measure. When this class of measure is used, the variance of the distribution plays a crucial role. Shorrocks and Foster (1987) showed that if the Lorenz curve *x* intersects the Lorenz curve *y* from above, the variance of *x* must be no greater than the variance of *y* for *x* to rank above *y* according to Third Order Stochastic Dominance (TSD). When Lorenz curves intersect more than once, *x* ranks above *y* if and only if the number of intersections of the Lorenz curve of *x* above the Lorenz curve of *y* is odd, and *y* ranks above *x* if the number of intersections is even. Davies and Hoy (1994) proposed that if the variance of *y* is greater than the variance of *x,* the Lorenz curve of *x* intersecting the Lorenz curve of *y* first from above is a sufficient condition for *x* to rank above *y.* The literature is further extended to distributions with unequal means. In this case, a *relative transfer sensitive* inequality measure should be used.

2.5 Atkinson's Inequality Measure (ATK)

Atkinson's (1970) paper on the measurement of inequality addresses the importance of choosing the proper form of social welfare function. He found that the Gini coefficient assigns higher weights to transfers made to middle-income classes. Atkinson proposed a social welfare function where the inequality measure derived from a symmetric, additively separable and homothetic function would be:

$$Atkinson_e = 1 - \left[\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i}{\mu} \right)^{1-\varepsilon} \right]^{1/(1-\varepsilon)} . \tag{6}$$

Atkinson$_e$ is the inequality measure and ε is the degree of inequality aversion, μ is mean income, n is the number of individuals in the society, and y_i is income of the i^{th} individual. Atkinson showed that as the degree of inequality aversion (ε) increases, the model adds more weight to income transfers at the lower level of the income distribution. If there is no inequality aversion in society (i.e. ε = 0), then the measures rank the distributions based solely on total income. The Census Bureau uses the Atkinson index with inequality aversion levels of 0.25, 0.50, and 0.75.

2.6 Theil Index (THEIL)

The Theil Index is the difference between the log of the arithmetic and geometric means. It can be calculated as:

$$Theil = \ln(\mu_y) - \ln(\mu_{gm}) = \ln\left(\frac{\mu_y}{\mu_{gm}}\right). \tag{7}$$

μ_y is the arithmetic mean and μ_{gm} is the geometric mean. The Theil Index is one of the most commonly known income inequality measures (Theil 1967). The Theil Index has the advantage of summing income inequalities within subgroups based on the statistical information theory. The Theil Index always takes zero or positive values, but the contribution of each subgroup to total income inequality can be negative. A zero Theil Index indicates perfect equality, where the geometric mean is equal to the arithmetic mean, mode, and median. If the Theil Index is greater than zero, then the income distribution is skewed to the right; the higher the index, the more unequal the income distribution. Indeed, the income distribution of United States full sample and immigrants are all skewed to the right in ACS survey, as in Figures 2 and 3.[3]

[3] The description of the American Community Survey is presented in Chapter 4.

Figure 2: Right-skewed Income Distribution of Full Sample in United States

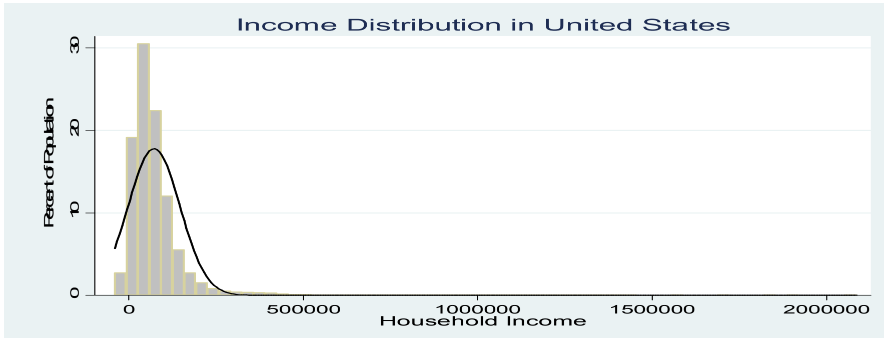
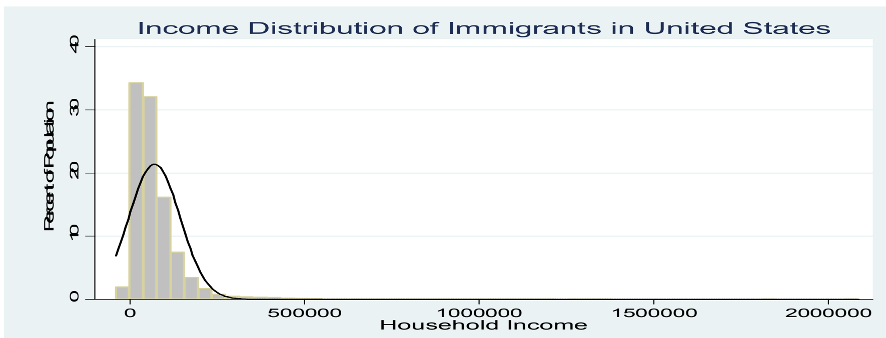


Figure 3: Right-skewed Income Distribution of Immigrants in United States



One drawback of the Theil Index however is that this index is not bound by one as is the Gini Coefficient. Thus, the Theil Index makes it hard for researchers to evaluate the skewness of income inequality of two distributions just by looking at the index.

CHAPTER 3

LITERATURE REVIEW

Rather than exploring how to choose an income inequality measure, this dissertation will derive results and suggest policy implications from these measures. It is certain that the literature on income inequality and immigration is extensive. Some authors studied the effect of immigration on employment and wages.[4] Others studied the effect of immigration on income inequality.[5] Yet others studied the determinants of income inequality.[6] In this study, these areas will be substantially tied to each other for the first time using a sample of the immigrant population in the United States. In other words, first, the determinants of immigrants' income inequality will be examined thoroughly. Then I examine how quickly income distributions of immigrant groups change over time in detail. Finally, the counterfactual effect of each immigrant subgroup on native income distribution will be inspected.

Determinants of income inequality have been studied broadly in the literature. Vanhoudt (2000) studied the macroeconomic determinants of income inequality and revisited the disagreement on the Kuznets' hypothesis. Kuznets (1955) proposed an inverted U-shaped relationship between income inequality and economic growth. He argued that as an economy grows, income inequality increases up to the threshold level of economic development. Only

[4] See Winter-Ebner and Zimmerman (1998), Mishra (2007), and Lerman (1999).
[5] See Davies and Wooton (1992), Hatton (2004), Moore and Pacey (2003), Reed (2001), Dolmas and Huffman (2004), Hoover et. al (2007).
[6] See Odedokun and Round (2004), Gray, Mills and Zandvakili (2003), Sylwester (2004), Vanhoudt (2000), Aigner and Heins (1967).

after this threshold is passed does income inequality start to decrease. Vanhoudt (2000) argued that the per capita GDP may not be a sufficient metric of development because the fundamentals affecting the per capita GDP may differ substantially across countries. With his empirical work, Vanhoudt found that easily observable economic fundamentals, such as average investment share in education and total government expenditure on education, may account for most of the variation and trends in income inequality. Odedokun and Round (2004) studied African countries to determine the factors affecting income inequality. They used the level of economic development, regional factors, share of government spending, inflation, unemployment, corruption, openness to trade, and education to explain income inequality in their cross-sectional study to test the Kuznets' hypothesis. In an earlier work, Aigner and Heins (1967) had also tested the Kuznets hypothesis. In their study, they have controlled median school years completed, percentage of unemployment, median age of population, and mean family income. They found that the median age of the population negatively affects income inequality because of the high degree of skill rigidity of the older population. The authors argued that these older people cause enforcement and proliferation of equality barriers. Their study also showed the positive effect of schooling and family income on income inequality. Unemployment, on the other hand, has mixed effects on income inequality.

There are also numerous works written by political economists related to the effect of immigration on income inequality. Dolmas and Huffman (2004) examined this effect by using simulation analysis. Their model was very restrictive and consisted of several assumptions about the host country's economy and the immigrants themselves. Nevertheless, the authors' simulation results showed there is only a small and ambiguous relationship between immigration and income inequality. The effect of immigration is rather small and the Gini coefficient slightly increases due to immigration. In some combination of parameters of the authors' model, the Gini coefficient increased as expected. However, in other cases, the Gini actually decreased as the number of immigrants increased. Reed (2001) has studied the effect of immigration on males' earnings inequality in the U.S. using Current Population Survey (CPS) data from 1960-1990. Reed used a six counterfactual scenario analysis to conclude that immigration accounted for a substantial portion of variation in inequality across U.S. regions. She found that over the last three decades immigration has had a significant effect on the variation in males' earnings inequality at national levels and across regions. CPS data revealed that male earnings inequality and its growth tended to be higher in those regions receiving large shares of immigrants. Reed also concluded that immigration tends to increase income inequality in the U.S. because immigrants increase the size of the low-wage workforce. Indeed, in 1997, only 28% of all immigrants had earnings above the median income of natives. Moore and Pacey (2003) used Canadian immigration data for the last two decades and identified a significant difference between the characteristics of immigration into the U.S. and Canada. The number of immigrants in the U.S. was approximately twice as much as in Canada, and the education level of immigrants in Canada was much higher than the education level of the native-born population. Even if this was the case, Moore and Pacey (2003) found immigration increased the pace of income inequality in Canada. Moreover, the convergence of the "visible" minorities' income to the natives was prolonged and tended to be slower than the case of older European immigrants. Moore and Pacey (2003) compared the change in income inequality and immigration levels by regions. They found a strong relationship between these two factors. The authors defined the contribution of immigrants to the growth of income inequality by subtracting non-immigrant's income inequality from the income inequality of immigrants. The difference of income inequalities between immigrants and natives gave the immigrants' contribution to income inequality growth. The authors compared the difference between the income inequality of immigrants and natives. Once immigrants arrive, the income inequality of the host country is expected to be altered by the new immigrants. However, it is hard to argue that the difference in inequality directly depends on the difference of the non-immigrants' and immigrants' income inequality. To one extreme, an immigrant who has no job in the sender country is placed at the bottom of the income distribution in the country of origin. However, if this individual moves to the host country, he/she should be expected to have a job; otherwise, there is no incentive for the individual to migrate. If the immigrant gets a job upon arrival, he/she is unlikely to be placed at the very bottom of the income distribution of the host country. Hoover et al. (2009) used long time series data of the U.S. to show the impact of immigration on income inequality. They used the Gini coefficient as a measure of inequality. Among many socioeconomic factors, Hoover et al. found that only unemployment and immigration were relevant to explaining income inequality. The authors showed that immigration does not Granger-cause unemployment but does indeed Granger-cause income inequality to rise. Granger causality is observed when the contemporaneous and lagged values of a variable can be used to predict the future values of another variable. Impulse response functions show that an immediate reduction in immigration reduces income inequality, but inequality goes back up to the initial values after some time passes.

Unlike the results of Dolmas and Huffman's (2004), Reed's (2001), and Moore and Pacey's (2003) studies, Lerman's (1999) cross-sectional study showed that the conventional belief of decreasing median wages, as well as increasing inequality due to immigration, was not quite precise. Lerman argued that most of the literature on wage inequality and immigration ignores the welfare gains of the immigrants. Lerman included immigrant welfare gains by using wage imputations. These welfare gains were then calculated by comparing the immigrants' current wage rate at the time of entry to the country. He found that the welfare gains of immigrants reduce the spread in the income inequality.

Gray, Mills, and Zandvakili (2003) studied income inequality of immigrants compared to natives in Canada. They found that there exists an inequality difference between natives and immigrants that is not important in magnitude. The authors used household income to calculate the decomposable Theil Index and concluded that inequality between native and immigrant groups does not contribute to total inequality. However, most of the observed inequality is due to income dispersion within each of the groups. Finally, they studied the assimilation of immigrants to the Canadian work force by splitting the immigrants into two groups. The group which has just entered Canada had higher income inequality than the group who have resided in Canada longer.

Lemieux (2006) and Domeij (2008) decomposed the rise in inequality into changes in market returns of observable characteristics, changes in the composition of the labor force across demographic groups, and changes in unobservables. Lemieux showed that changes in the composition of the labor force have become more important over time for the change in inequality in the United States. Domeij, on the other hand, showed that the rise in earnings inequality in Sweden is affected mostly by the changes in market returns of observable characteristics such as schooling and experience.

CHAPTER 4

DATA

For the empirical study on immigrant groups in the U.S., the American Community Survey (ACS) data was employed. The fundamental function of ACS is to provide information about the dynamics of the U.S. economy and demographics as well as "…filling the gaps between each 10 year census," according to the Census Bureau. The American Community Survey sends out questionnaires annually to approximately three million households who constitute 1% of the total population in the United States. Data is collected in all 3,141 U.S. counties, American Indian, and Alaska Native areas, as well as Native Hawaiian areas.

The surveyed respondents were split into two categories by the Census Bureau. The first category was composed of *U.S. citizens* and accounted for 88% of the sample. Most of these respondents were citizens of the U.S. by birth. However, a small percentage of the respondents who were born abroad but have American parents were also considered U.S. citizens. *Immigrants* who moved to the U.S. from a different country permanently or temporarily constituted the second category. These people were either citizens of other countries or they were U.S. citizens but had obtained their U.S. citizenship through naturalization. There were approximately 315,000 immigrants in the 2006 ACS survey who accounted for approximately 12% of the sample. Almost 50% of these immigrants were citizens of other countries, and the remaining 50% were U.S. citizens through naturalization. These naturalized individuals were considered immigrants because they were born outside of the U.S. and their parents are citizens of other countries. Although they are U.S. citizens, there are significant cultural differences between these individuals and native U.S. citizens.

The data included several important variables such as personal and household income, English ability, visa and employment status of immigrants, educational attainment, year that the immigrant entered the U.S., country of birth, age, gender, etc. If one of these variables were not available, those observations were excluded from the sample. Before the exclusion, the number of immigrants surveyed was 315,728. Approximately 9.5% of all immigrants were excluded due to omitted responses. Consequently, the number of immigrants used in this study is 297,454. The total number of respondents who were U.S. citizens was 2,654,013 before exclusion and 2,099,066 after exclusion. Approximately 21% of the U.S. citizens were excluded. Thus, the total number of respondents used for this study was 2,969,741 before and 2,396,520 after the exclusion.

Personal income (PINCP) is the sum of eight different sources of income in the ACS. These sources of income are wage or salary income; net self-employment income; interest, dividends, net rental, or royalty income; income from estates and trusts, social security, or railroad retirement income; Supplemental Security Income (SSI); public assistance or welfare payments; retirement, survivor, or disability pensions; and all other income. Average personal income for the sample is lower than the Bureau of Economic Analysis (BEA) estimates. The Census Bureau in 2006 published a note on the subject of definitions stating that:

> …The ACS data is obtained from a household survey, whereas the BEA income series is estimated largely on the basis of data from administrative records of business and governmental sources. Moreover, the definitions of income are different. The BEA income series includes some questions not included in the income data shown in ACS publications, such as income "in kind," income received by nonprofit institutions, the value of services of banks and other financial intermediaries rendered to people without the assessment of specific charges, and Medicare payments. On the other hand, the ACS

income data includes contributions for support received from people not residing in the same household if the income is received on a regular basis.[7]

Income inequality is often calculated by using household income (HINCP), not PINCP. This variable is equal to the sum of all incomes of a household. For example, if a family of three people is surveyed: two adults and a child with one adult employed and earning $40,000 per year, the other adult is unemployed and a child with a part time job earning $5,000 per year, ACS reports $45,000 household income. Inequality measures using household income are much closer to those reported by the Census Bureau.

Sixteen income inequality measures were calculated using *personal income* and *household income* of immigrant groups. These measures are relative mean deviation (RMD), coefficient variation (CV), standard deviation (St.Dev.), the Gini coefficient (GINI), the Theil Index (THEIL), and Atkinson's inequality measures (ATK) with three different inequality aversion levels (0.25, 0.50, and 0.75). These inequality measures evaluate the income dispersions of populations. In other words, they illustrate how tightly income is distributed among immigrants. The definition of each inequality measure can be found in the previous sections 2.1-2.6.

Educational attainment (SCHL) is a categorical variable. The responses of individuals do not correspond to actual years of schooling. A zero response corresponds to a missing variable rather than no education, while one corresponds to "no schooling completed". The maximum level of schooling is sixteen, which corresponds to a doctorate degree. Omitted responses were excluded from the study. For the ACS 2006 sample, the mean education of U.S. households ranges between ten years of schooling to an associate degree.

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[7] The BEA publication on the personal income can be found at the following link: http://www.bea.gov/newsreleases/regional/spi/2007/pdf/spi0307.pdf.

Age (AGE) and gender (per_male) variables are self-explanatory. Age and sex are commonly used to control for the variation in sub-groups. If an immigrant group has a higher average age than another group, this may imply that the mean and median income of the former group differs significantly from the latter. This can be attributed to differences in experience or assimilation of the former group. Gender is also an important demographic variable. Immigrant groups that have high percentages of men may have different earnings or income distributions than the ones with lower percentages of men.

Year of Entry (YOEB) indicates when the immigrant entered the U.S. for the first time. In Chiswick's (1978) article, he assumed that immigrants adapt to the U.S. economy and culture in a short period of time. How quickly the incomes and income distributions of immigrant groups converge to native households will be explored in this study. English Ability (ENG) measures how commonly English is being spoken in the household. Any immigrant who did not respond to this question was excluded from the study. However, there are sixty-four countries in the world where English is the official language or the language predominantly spoken (Table 1). Since most of the respondents from these countries omitted this question, they were not excluded from the study.

Table 1: Predominantly English Speaking Countries		
Antigua and Barbuda	Ireland	Scotland
Australia	Israel	Sierra Leone
Bahamas	Jamaica	Singapore
Barbados	Kenya	South Africa
Belize	Liberia	Tanzania
Bermuda	Micronesia	Tonga
Cameroon	New Zealand	Trinidad and Tobago
Canada	Nigeria	Uganda
Dominica	Northern Ireland	United Kingdom
England	Pakistan	Zimbabwe
Ethiopia	Panama	
Fiji	Philippines	
Ghana	Saint Kitts and Nevis	
Grenada	Saint Lucia	
Guyana	Saint Vincent and the Grenadines	
India	Samoa	

Immigrants are clustered in two groups. Immigrants who are citizens of the U.S. through naturalization constitute the first group. These people have all the residency and employment rights of ordinary U.S. citizens. Immigrants who stay in the U.S. with a valid visa constitute the second group. Some of these people have limited employment rights (F-1B, H-1B, E-1, E-2, and E-3), and some of them have no legal right to work during their stay in the U.S. (F-2, H-2, and B-1). A variable (per_visa) is used to control for the percentage of people who are U.S. citizens through naturalization. Immigrants who obtain citizenship through naturalization have no restriction on earning income; therefore, immigrant groups that contain a high percentage of this type of immigrant have different income distribution characteristics.

Furthermore, some groups may have higher percentages of employed immigrants than other groups. A control variable (per_unemp) is used to prevent bias toward more employed immigrant groups. The percentage of people who actually worked during the last three months of their stay in the U.S. as an immigrant is measured with the (per_unemp) variable. It is also possible to control for the percentage of students (per_stud) in immigrant groups. Immigrant groups that have a higher percentage of students have different income distribution characteristics than immigrant groups with a lower percentage of students.

The data shows that the income inequality of immigrants from different countries varies greatly. The Political Freedom Index (POL) is believed to explain some of this variation of inequalities. Therefore, a political freedom index is incorporated with the explanatory variables to evaluate the effect of political freedom on the income inequality of immigrants. It is possible that immigrants from politically and economically suppressed countries are more willing to migrate from their country of origin to another country. Sylwester (2004) used political freedom measures to explain the cross-country variation of income inequality measured by the Gini coefficient. In his study, he concluded that income inequality is not affected by institutional development. Moreover, he found that income inequality is not affected by colonial ties, inflation, real exchange rate, or the number of years that the country had an open economy. The only factor Sylwester consistently found significant was being landlocked. If the country is landlocked, i.e. has no seashore, income inequality is lower than in countries with a sea border.

The Heritage Foundation publishes a political freedom index that is the average of several freedom indices. These indices are business, trade, fiscal, monetary, investment, financial, labor, and corruption freedom as well as government size and property rights.[8] The indices take values between zero and 100. One hundred indicates perfect freedom. The index is reported for 157 countries around the world since 1995. The Heritage Foundation defines economic freedom as:

> … (it) encompasses all liberties and rights of production, distribution, or consumption of goods and services. The highest form of economic freedom provides an absolute right of property ownership; fully realized freedoms of movement for labor, capital, and goods;

[8] The methodology of the indices can be found at the Heritage Foundation website.

> and an absolute absence of coercion or constraint of economic liberty beyond the extent necessary for citizens to protect and maintain liberty itself.

Based on the 2006 report, Hong Kong, Singapore, Ireland, New Zealand, and the U.S. are at the top of the rankings. North Korea, Cuba, Libya, Zimbabwe, and Burma, on the other hand, are at the bottom of the rankings. Generally, political freedom is high for the European region and low for the Sub-Saharan Africa. One interesting observation is the fact that European political freedom ranked fourth in 1995 but ranked first in 2006. This shows the importance of the European Union and its success in diffusion of political freedom in the region (See Figures 4-5).

Figure 4: Time Path of Economic Freedom among Different Regions

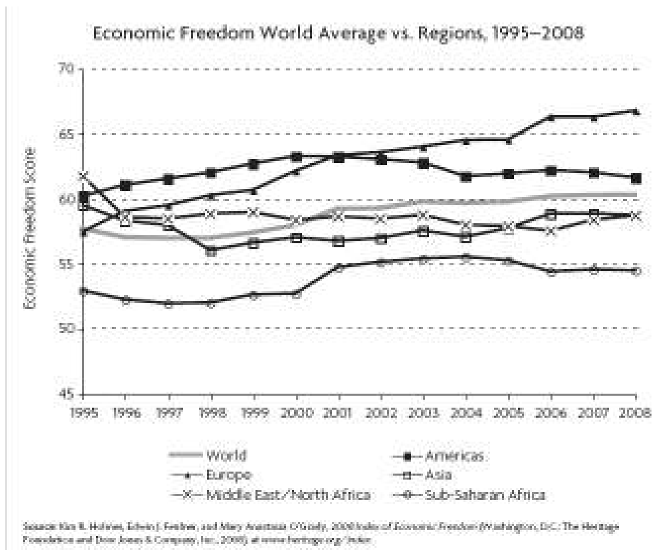
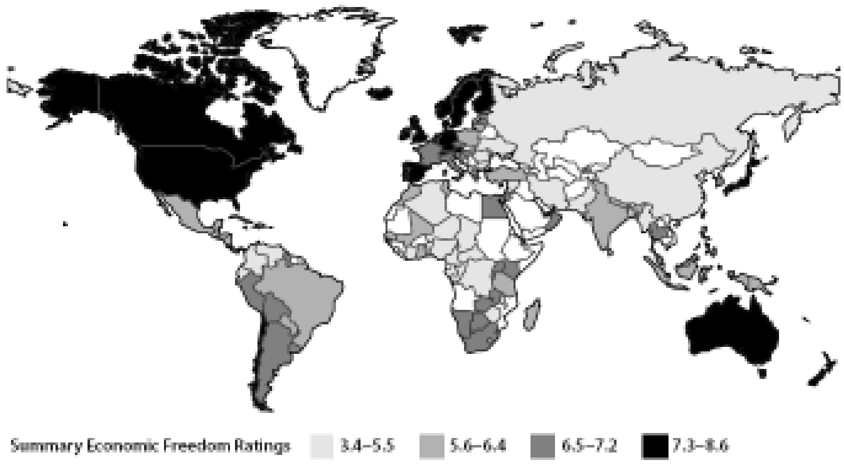


Figure 5: Economic Freedom in the World



Source: Economic Freedom of the World 2007 Annual Report

The political freedom index from the Heritage Foundation is then augmented with the data provided by the Fraser Institute. Gwartney and Lawson, the authors of the 1996 Annual Report of Economic Freedom, defined economic freedom as follows:

> Individuals have economic freedom when property they acquire without the use of force, fraud, or theft is protected from physical invasions by others and they are free to use, exchange, or give their property as long as their actions do not violate the identical rights of others. An index of economic freedom should measure the extent to which rightly acquired property is protected and individuals are engaged in voluntary transactions.

Unlike the Heritage Foundation’s indices, the Fraser Institute uses 42 distinct pieces of data to measure the degree of freedom over five broad areas in 142 countries. These areas are government size, legal structure and the security of property rights, access to sound money, freedom to trade internationally, and the regulation of credit, labor and business. The Fraser Institute’s most recent political freedom index (2005) is used in this study. The index is scaled from zero to ten, with ten corresponding to total economic freedom. According to this index, Hong Kong is the freest country in the world, followed by Singapore, New Zeeland, Switzerland, and Canada.

The two political and economic freedom indices mentioned above are fairly sensitive measures. Nonetheless, some critical countries of interest were not reported. Some of these countries were Afghanistan, Belarus, Cuba, Iraq, Lebanon, Saudi Arabia, Somalia, Sudan, Uzbekistan, and Yemen. Careful examination of these countries indicates that most of them are underdeveloped and have either political problems or economic limitations. A study excluding these countries would without doubt generate a bias towards steady governments and economies. A final index with the countries listed above has been incorporated into this work, provided by the Freedom House, Inc. (2005). The index takes values between one and seven, with one corresponding to complete freedom and seven to no freedom. The institute also reports two different measures of freedom: *political rights* and *civil liberties.* The Political Rights index is calculated based on the following sub-categories: electoral process, political pluralism and participation, and the functioning of government. Civil liberties are freedom of expression and belief, associational and organizational rights, rule of law, and personal autonomy and individual rights. However, the Freedom House's index is not as sensitive as the prior two indices. For example, Freedom House ranks England and Poland the same, based on their political freedom. However, the Heritage Foundation ranks England 10^{th} and Poland 71^{st}. Nevertheless, the Freedom House index is complete for all countries studied and eliminates the selection bias problem. In order to address the sensitivity issue, the scores for each sub-category were summed over all indices, and the final score was used as a political freedom index in this study. In the adjusted Freedom House index, England ranked 11th and Poland ranked 32nd, which is more in line with the rankings of the two previous indices.

Immigrants leave their country of origin for different reasons. The effects of relative deprivation and income inequality on migration are empirically tested by Stark (2006) and Liebig and Sousa-Poza (2004). Inflation (INF), unemployment rate (UNEMP), and income inequality (INEQU), measured as Gini, and openness to trade (OPEN) are selected as the relative deprivation proxies of immigrants at the country of origin.[9] These proxies are intended to control for the *positive selection* of immigrants. Borjas (1987) showed that if the income distribution of the country of destination is more unequally distributed than the country of origin, a "positive selection" is observed. If a group is positively selected, then the group's mean income and income distribution might be different than the group that is not positively selected.

Some geographical control variables are also considered. A land-border between two countries promotes the cross-border trade of goods and services, including the trade of labor. Hence, immigrants who are coming from countries neighboring the U.S. may have different income distribution characteristics. Therefore, a dummy variable (NEIG) is constructed for immigrant groups that are from neighbor countries.[10] A geographical proximity (GEO) variable captures the transportation cost of migration. It measures the mile distance from the country of origin to the closest major U.S. airport. For this purpose, three major airports are selected as the initial destinations for immigrants. These major airports are JFK International Airport in New York (JFK), Miami International Airport in Florida (MIA), and Los Angeles International Airport in California (LAX). Using the closest major airport approach also allows for controlling the cost of air flight for immigrants. For example, a European immigrant who wishes to go to Augusta, Maine, would initially arrive in the JFK Airport in New York. The airfare for JFK is

[9] Data for these proxies is compiled from various sources, including the CIA World Factbook, World Bank, and the Texas University Inequality Project. The CIA World Factbook was especially useful for inflation, unemployment, and openness to trade variables.
[10] Mexico and Canada are defined as the neighbors of the United States with physical land borders.

always lower than Augusta, Maine, although Augusta is closer to Europe. Other geographical differences that are not captured by the previous two variables are accounted for with dummies for each continent. These variables are South America (LATIN), Asia (ASIA), Europe (EUR), Africa (AFR), North America (NORTH)[11], and Oceania (OCEA).

Colonial ties (COL) and countries that predominantly speak English (LAN) are also controlled for in the study. Colonial ties exist between the U.S. and the countries that either colonized the U.S. or were colonized by the U.S. These countries are Canada, England, France, Mexico, and the Philippines. Immigrants from countries that have historical ties with the U.S. may have less difficulty adapting in the United States. English ability also affects the assimilation rate of immigrants. Therefore, immigrant groups that are from countries that predominantly speak English may have different income distribution characteristics. Table 1 shows the countries in which English is predominantly spoken or is one of the official languages. Furthermore, the economic development of countries that immigrants are coming from differs significantly. For this reason, dummies for countries that are members of the Organization of Economic Development and Cooperation (OECD) and the European Union (EU) are considered. Immigrants who are citizens of these countries have different characteristics than immigrants from Non-OECD or Non-EU member countries. The list of countries that are members of EU and OECD are given in Table 2.

[11] Bermuda and Canada are the only two countries in the North American group.

Table 2: EU and OECD Member Countries

EU Members		OECD Members	
Austria	Lithuania	Australia	Korea
Belgium	Luxembourg	Austria	Luxembourg
Bulgaria	Malta	Belgium	Mexico
Cyprus	Netherlands	Canada	Netherlands
Czech Republic	Poland	Czech Republic	New Zealand
Denmark	Portugal	Denmark	Norway
Estonia	Romania	Finland	Poland
Finland	Slovakia	France	Portugal
France	Slovenia	Germany	Slovak Republic
Germany	Spain	Greece	Spain
Greece	Sweden	Hungary	Sweden
Hungary	United Kingdom	Iceland	Switzerland
Ireland		Ireland	Turkey
Italy		Italy	United Kingdom
Latvia		Japan	United States

CHAPTER 5

CHARACTERISTICS OF IMMIGRANTS

Table 3 and Figure 6 show the descriptive sample statistics of the respondents in ACS. For the full sample, average *personal income* is \$32,493 and average *household income* is \$71,478. The mean income difference between immigrants and U.S. citizens is approximately 12%. The Bureau Economic Analysis (BEA) estimated personal per capita income for the U.S. in 2006 was \$36,276. As is mentioned before, the difference between personal income in this study and BEA estimates stems from the methodology and the items included in the calculation of *personal income*. The income inequality literature also uses *median income* because income distributions are commonly skewed to the right. Median personal income is \$20,200, and median household income is \$56,000 for the full sample. The statistics also shows that the immigrants have lower median personal and household income compared to the U.S. citizens. U.S. citizens constitute 87.6% of the respondents, and on average, they earn higher personal and household income than their immigrant counterparts. Moreover, immigrants obtain one year less education than U.S. citizens.

Table 3: Sample Statistics of U.S. Citizens and Immigrants in the U.S.

	Sample Size	Percentage	Education	Average Personal Income	Average Household Income	Median Personal Income	Median Household Income
Full Sample	2,396,520	1.0000	9.9299	\$ 32,493	\$ 71,478	\$ 20,200	\$ 56,000
US Citizens	2,099,066	0.8759	10.0419	\$ 32,931	\$ 71,557	\$ 21,000	\$ 56,100
Immigrants	297,454	0.1241	9.1400	\$ 29,402	\$ 70,928	\$ 17,200	\$ 53,200

Figure 6: Income Characteristics of U.S. Citizens and Immigrants

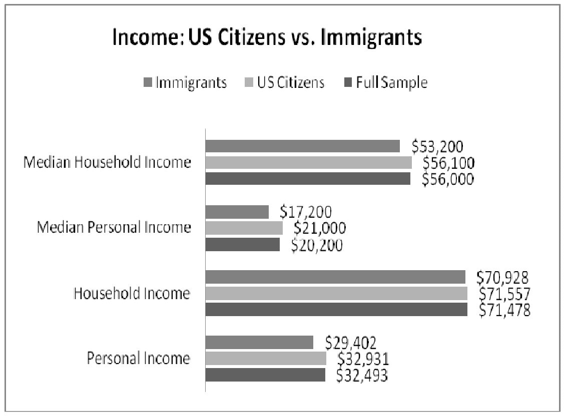
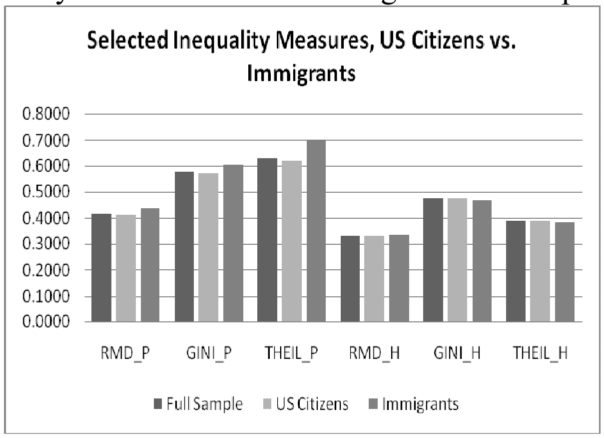


Table 4 and Figure 7 show sixteen different inequality metrics using personal income and household income. These measures are calculated for the full sample, for U.S. citizens, and for immigrants using *personal income* and *household income*. Table 4 is very comparable with the Census Bureau reports related to Gini, Theil, and Atkinson, with three inequality aversion levels (0.25, 0.50, and 0.75). Household income inequality metrics are lower than the personal income inequality for both U.S. citizens and immigrants. Interestingly, immigrants have higher personal income inequality but lower household income inequality. This can be due to differences in *family support networks* or differences in *family composition* among immigrants compared to natives.

Table 4: Income Inequality Metrics of U.S. Citizens and Immigrants

	RMD	CV	St.Dev.	GINI	Theil	Atkinson eps=0.25	Atkinson eps=0.5	Atkinson eps=0.75
Personal Income								
Full Sample	0.4154	1.4292	1.2892	0.5757	0.6283	0.1557	0.3205	0.5398
US Citizens	0.4119	1.4139	1.3009	0.5716	0.6184	0.1532	0.3151	0.5292
Immigrants	0.4386	1.5457	1.1973	0.6035	0.7005	0.1734	0.3584	0.6099
Household Income								
	RMD	**CV**	**St.Dev.**	**GINI**	**Theil**	**Atkinson eps=0.25**	**Atkinson eps=0.5**	**Atkinson eps=0.75**
Full Sample	0.3303	1.0357	0.9194	0.4738	0.3902	0.0783	0.1761	0.3046
US Citizens	0.3301	1.0354	0.9203	0.4745	0.3911	0.0776	0.1761	0.3064
Immigrants	0.3310	1.0377	0.9130	0.4682	0.3838	0.0829	0.1765	0.2916

Figure 7: Income Inequality Characteristics of Immigrants in Comparison with U.S. Citizens



Immigrants are then split into six different regions in the world: Latin America, Asia, Europe, Africa, North America, and Oceania. The Latin American region includes all immigrants from the South American countries and all the Caribbean island countries. Canada and Bermuda are the only two countries in the North American region. Australia, New Zealand, Fiji, Micronesia, Tonga, and Samoa are all in the Oceania region. The sample statistics suggest that 49% of immigrants in the U.S. are from Latin America. Table 5 and Figure 8 show that Latin American immigrants have, on average, the lowest level of education and income. Asian immigrants represent 28.7% of immigrants and have higher levels of education and income than other immigrant groups. Interestingly, African immigrants have the highest education level but the lowest mean and median income after Latin America. The highest mean personal and household incomes are earned by the North American immigrants, who also happen to have the highest education level.

Table 5: Sample Statistics of Immigrants from Different Regions							
	Sample Size	%	Education	Average Personal Income	Average Household Income	Median Personal Income	Median Household Income
Immigrants	297,454	1.0000	9.1400	$ 29,402	$ 70,928	$ 17,200	$ 53,200
Latin America	145,957	0.4907	7.5261	$ 20,767	$ 55,041	$ 15,000	$ 44,100
Asia	85,245	0.2866	10.8598	$ 36,656	$ 89,060	$ 20,500	$ 70,200
Europe	46,356	0.1558	10.3476	$ 38,857	$ 82,253	$ 22,000	$ 60,700
Africa	9,579	0.0322	10.8700	$ 34,486	$ 74,644	$ 20,500	$ 56,200
North America	8,637	0.0290	10.8019	$ 45,156	$ 91,772	$ 25,000	$ 67,000
Oceania	1,680	0.0056	10.3673	$ 40,586	$ 90,271	$ 22,000	$ 70,000

Figure 8: Income Characteristics of Immigrants by Region

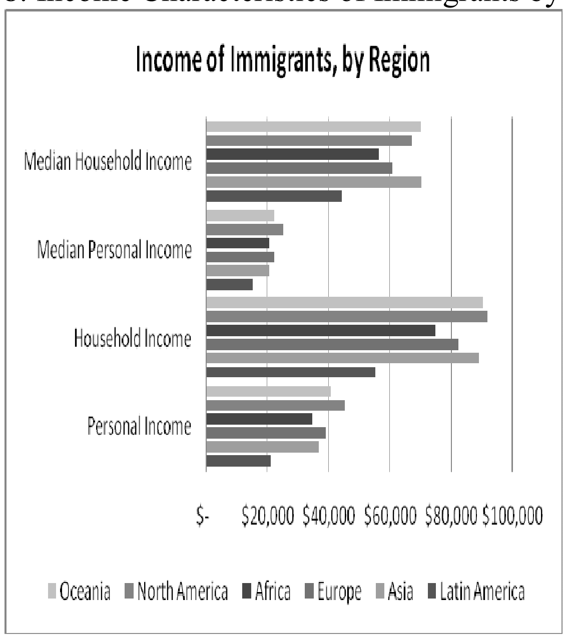
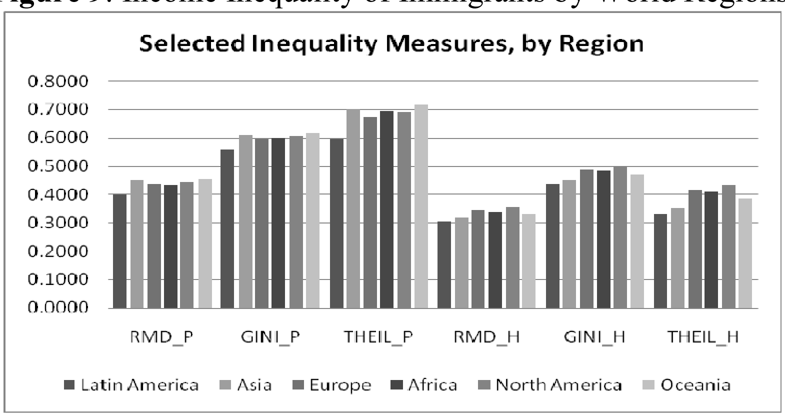


Table 6 and Figure 9 show the income inequality metrics for the six regions listed above. Although the immigrants from the Latin American region have the lowest income and education level, their income is the most equally distributed compared to any other region in terms of both personal and household income. However, the ranking of these distributions is impossible to show since the Lorenz curves of different regions cross each other at different points of the curve.

Table 6: Income Inequality Measures of Immigrant Groups by World Regions								
Personal Income								
Immigrants	**RMD**	**CV**	**St.Dev.**	**GINI**	**Theil**	**Atkinson eps=0.25**	**Atkinson eps=0.5**	**Atkinson eps=0.75**
Latin America	0.3972	1.3646	1.0785	0.5570	0.5957	0.1525	0.3299	0.5963
Asia	0.4490	1.4670	1.3008	0.6099	0.6994	0.1761	0.3685	0.6280
Europe	0.4346	1.4992	1.2059	0.5952	0.6711	0.1637	0.3296	0.5411
Africa	0.4329	1.5270	1.2873	0.5993	0.6939	0.1717	0.3540	0.5984
North America	0.4438	1.4746	1.3017	0.6064	0.6896	0.1697	0.3447	0.5678
Oceania	0.4527	1.5198	1.2879	0.6151	0.7165	0.1774	0.3638	0.6078
Household Income								
Immigrants	**RMD**	**CV**	**St.Dev.**	**GINI**	**Theil**	**Atkinson eps=0.25**	**Atkinson eps=0.5**	**Atkinson eps=0.75**
Latin America	0.3053	0.9429	0.8314	0.4355	0.3284	0.0660	0.1480	0.2538
Asia	0.3155	0.9547	0.9402	0.4478	0.3502	0.0799	0.1700	0.2839
Europe	0.3437	1.0817	0.9533	0.4862	0.4144	0.0911	0.1915	0.3120
Africa	0.3385	1.0689	0.9589	0.4827	0.4089	0.0867	0.1871	0.3126
North America	0.3531	1.0746	0.9913	0.4995	0.4326	0.0955	0.2054	0.3469
Oceania	0.3333	1.0298	0.9368	0.4714	0.3866	0.0851	0.1814	0.3007

Figure 9: Income Inequality of Immigrants by World Regions



Although the ACS is repeated every year, it is important to note that the survey is a single-year study. However, it is possible to create the means of the immigrant cohorts who enter the U.S. at different points of time with the use of a *year of entry (Yoep)* variable. Each of these cohorts represents a representative sample of immigrants who reside in the U.S. for varying lengths of times. For this purpose, six cohorts of immigrants who entered the U.S. in 2006, 2005, 2004, 2003, 2002, and 2001 were created using the year of entry variable. This methodology is a standard technique in the literature, and it essentially allows inspection of some important dynamics in immigrant characteristics.

Figure 10: Mean Personal Income Convergence of Immigrants over Time, 2001-2006

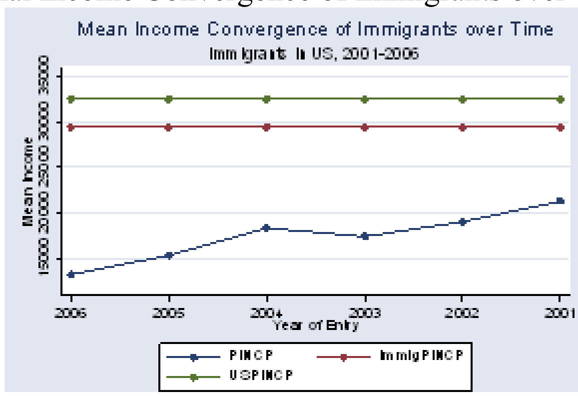
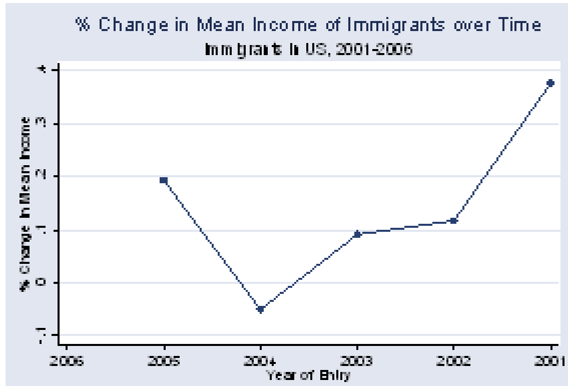


Figure 10 shows the evolution of the average personal income of immigrants in comparison to the U.S. citizens. Each of the points on the graph represents a different cohort that has resided in the U.S. for different periods of time. For example, the size of the sample for all immigrants who entered the U.S. in 2006 is 4,470 individuals, and these immigrants have an average income of approximately $13,346. On the other hand, the ones who have been residing in the U.S. for two years have an average income of $15,427, where the sample size is 8,307 households. Chiswick (1978) showed that the income of immigrants outpaces the natives' after a short period of assimilation. The results presented in this section confirm the fact that immigrants face some cultural and economic difficulties at the time of entry but quickly start to catch up with natives, but, contrary to Chiswick's findings, their income does not outpace natives' personal income for the first five years.

Figure 11: Percentage Change in Mean Income of Immigrants over Time, 2001-2006



In Figure 11, the percentage change in the mean income of immigrants is illustrated. The mean income growth rate of immigrants is positive for all the years except the second year, and the rate is growing with an increasing rate. This shows that assimilation plays an important role in the growth rate of income, and as immigrants adapt to the market conditions in the host country, their market performance increases at an increasing rate.

Figure 12: Income Inequality Convergence of Immigrants over Time, Based on Gini Coefficient, 2001-2006

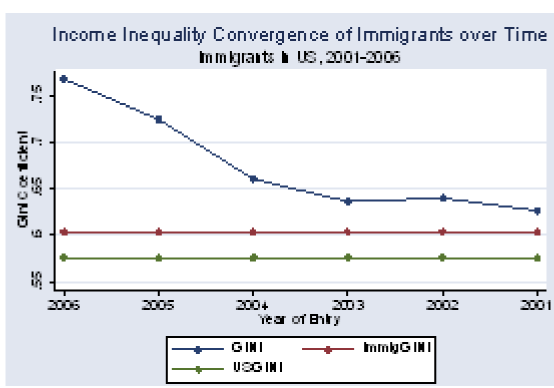


Figure 12 shows the evolution of personal income inequality of immigrants in comparison to U.S. citizens. Income inequality of immigrant cohorts that reside in the U.S. longer is lower than the recent immigrants. In other words, immigrants who entered the U.S. in

2006 have higher personal income inequality, measured by Gini coefficient, than immigrants who entered the U.S. in 2005, and so on. This implies that income inequality for immigrants converges to the income inequality of the host country over time. However, the income of immigrants is always less equally distributed than the United States citizens.

Figure 13: Percentage Change in Income Inequality of Immigrants over Time, Gini Coefficient, 2001-2006

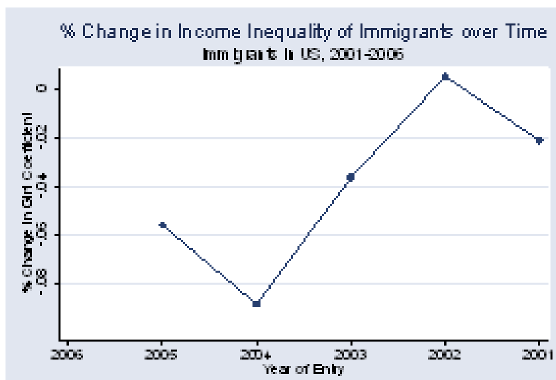


Figure 13 shows the percentage change in income inequality of immigrants over time. The percentage change of income inequality of immigrants who live in the U.S. is negative for all the years studied. Personal income inequality of immigrants converges to the inequality of U.S. natives, but the rate decreases as the number of years that the immigrants spent in the U.S. increases. This can be referred as the *hook-type* convergence of inequality. At the early years of arrival, income inequality decreases at a sluggish rate due to assimilation problems, but as the assimilation problems are resolved by immigrants, income inequality declines. However, each additional year they spend in the country, the improvement in equality decreases.

Table 7: Average Percentage Change in the Inequality and Income of Immigrants, 2001-2006

Region	Average % Change in Inequality Per Year During 2001-2006 period	Average % Increase in Income Per Year During 2001-2006 period	Total % Change in Income Inequality During 2001-2006 period	Total % Increase in Income During 2001-2006 period
Immigrants All	-3.932%	14.606%	-18.400%	59.954%
AFRICA	-6.175%	14.132%	-28.798%	83.342%
ASIA	-4.615%	13.735%	-21.175%	87.373%
EUROPE	-3.527%	10.163%	-16.562%	57.545%
LATIN AMERICA	-3.687%	11.958%	-18.185%	72.984%
NORTH AMERICA	-1.621%	12.522%	-8.629%	60.959%
OCEANIA	0.601%	16.677%	-0.896%	48.200%

Table 7 shows the average percentage changes in inequality and income per year and over 5 years. The decline in average per year income inequality is lowest for immigrants from Africa, then Asia. Total percentage decline in inequality is highest for Africa, followed by Asia, and is lowest for Oceanian and North American immigrants. When the average percentage increase in income per year is considered, the highest is observed among the Oceanian and the lowest among the European immigrants. Asian immigrants, on the other hand, have the highest total percent increase in income, followed by African immigrants.

Immigrants are then split into sub-groups based on their country of origin. Sample statistics of income and education of immigrants from 133 different countries are shown in Appendix C. These 133 counties are the ones that are recognized in the decoding process of the ACS, which left some countries out, such as Tunisia, newly established Kosovo, and Tajikistan. Three more countries (Guinea, Iceland, and the West Indies) are also excluded from the study because the sample sizes for these three countries were below thirty immigrants. The largest immigrant group is Mexicans, which constitute almost 29% of all immigrants in the United States. Immigrants from the Philippines, India, and China are the other large immigrant groups.

South African and British immigrants have the highest mean and median *personal* and *household* income, and immigrants from Somalia and Dominica have the lowest.

Mexican immigrants constitute approximately 56% of Latin American immigrants, and they are the least-educated households in the Latin America sample with a mean of 6.5, which corresponds to 10 to 11 years of schooling. This finding is comparable to Census 1980-2000 averages, which are presented in Card's (2009) paper. Cuba and El Salvador are two other large countries of origins for immigrants in the Latin American region. Immigrants from Colombia and Argentina perform exceptionally well with the highest mean educational attainment and the highest mean income, respectively.

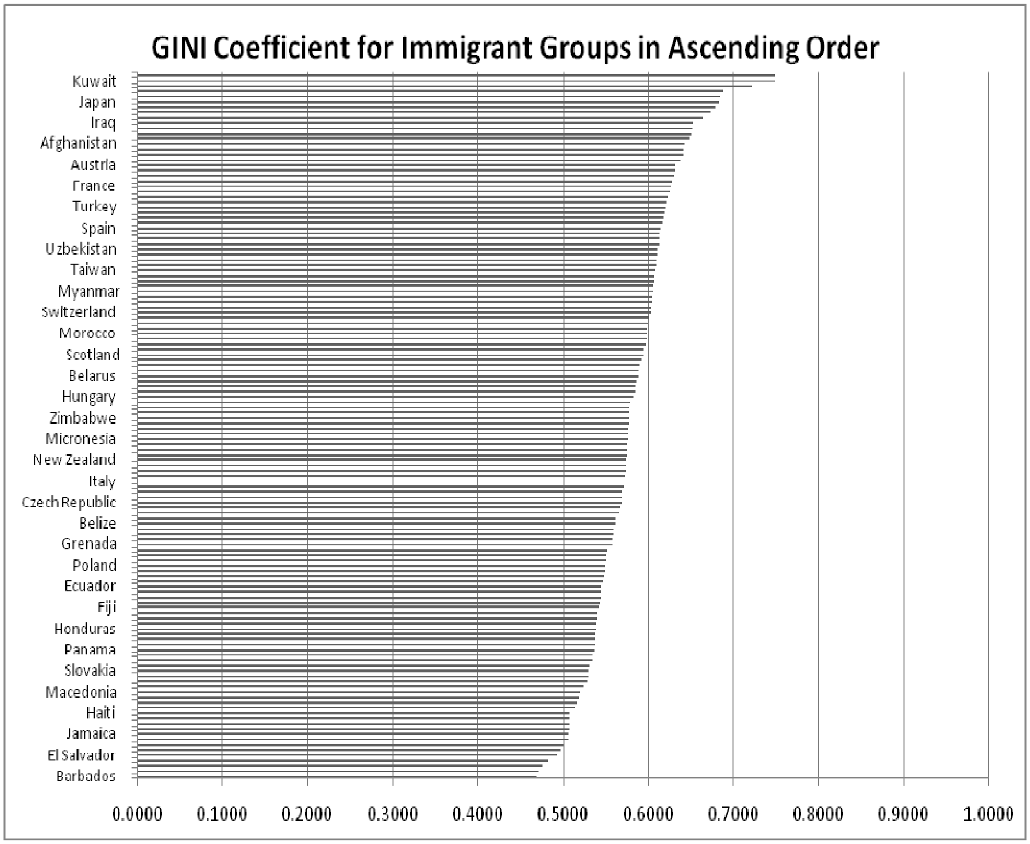
Five countries constitute more than two-thirds of all immigrants in the Asian region. These countries are the Philippines, India, China, Vietnam, and Korea. Immigrants from these countries are significantly more educated and have a higher mean income than those in the Latin America region. Cambodia and Laos are two extreme cases with the lowest mean education in the region, nearly 2.5 points less than the average educational attainment in the region. Furthermore, immigrants from Israel and Iran have the highest mean income and above average education in Asia. Interestingly, these countries have been under political stress for a sustained period of time. In Iran, political power shifted hands in 1979, leading to a continuous brain drain from the country to Western societies. Israel had political instability during the beginning of the same period. Therefore, these political problems will be controlled for. Indeed, Borjas (1987) indicated that assimilation rates are determined by political factors. Immigrants from politically repressed countries have higher assimilation rates compared to immigrants from freer countries. The reason is the high cost of return to the country of origin for these immigrants. Hence, these people have greater incentives to assimilate in the country of destination.

The European region is dominated by German immigrants, who constitute 25% of the immigrants from the region. Portuguese, Italian, and Greek immigrants have the lowest mean educational attainment in the region. The highest mean income belongs to immigrants from the UK and Switzerland. These findings are consistent with the notion that immigrants from developed countries generally have higher mean income in the country of destination as well.

The African region offers some interesting results regarding immigrants as well. Immigrants from Somalia and Cape Verde have the lowest mean education, whereas Ugandan and South African immigrants have the highest mean income in the region. The African region also has one of the highest (South Africa) and lowest (Somalia) mean incomes among all the immigrant cohorts. The North American region consists of only Canada and Bermuda. Mean education and income of Canadian immigrants are higher than U.S. natives. Oceania can be divided into two groups as well: Australia and New Zealand versus the other island countries. Immigrants from Australia and New Zealand have higher mean income and educational attainment than the latter.

Appendix C shows that median personal income is the lowest for Saudi Arabian immigrants. Saudi Arabia has rich natural resources; however, immigrants from this country to the U.S. are either students or are coming from families that do not have a share of these natural resources. Likewise, the mean and median personal and household incomes of Mexican immigrants are one of the lowest among the immigrant cohorts. Furthermore, Appendix D shows the sixteen income inequality measures for all of the 133 countries. As illustrated in Figure 14, the income inequality of Saudi Arabian immigrants is always higher than most other immigrant cohorts. In comparison to Saudi Arabian immigrants, the income inequality of immigrants from Mexico is ranked much lower. Both of these cohorts are now residing in the same host country and have the same set of opportunities available to every other immigrant cohort; hence, unless there is some sort of a nationwide discrimination against one of these cohorts, the unemployment rate, GDP per capita, or the business cycles in the host country should not explain the variation in their inequalities. All the possible explanatory variables should be specific to the particular immigrant cohort. This observation leads to an important question that this dissertation endeavors to answer: if immigrant cohorts live in the same host country and have similar mean and median incomes, why do they have such different income distributions? In other words, what are the determinants of income inequalities among different immigrant cohorts living in the United States? Moreover, are the inequality dynamics of immigrants similar, or do some of the immigrant cohorts follow a faster inequality convergence path over time? Finally, apart from the size of the immigrant cohorts, what other factors determine the magnitude of the counterfactual effects of these same cohorts?

Figure 14: Household Gini Coefficient of Immigrants in Descending Order



CHAPTER 6

AN EMPIRICAL STUDY ON IMMIGRANT GROUPS IN THE UNITED STATES

6.1 *Income Inequality Determinants of Immigrant Groups by Country of Origin*

The previous section showed that income inequality among immigrant cohorts varies significantly. In this section, a cross-sectional regression analysis will be employed to determine the factors that cause these income inequality differences among 133 immigrant cohorts. Consider the following regression model:

$$\begin{aligned} y_i = \alpha_0 &+ \sum_{j=1}^{n} \beta_j (Income\_Var)_i + \sum_{j=1}^{n} \delta_j (Immig\_Charac)_i + \sum_{j=1}^{n} \gamma_j (Selection\_Var)_i \\ &+ \sum_{j=1}^{n} \kappa_j (Geograpical)_i + \sum_{j=1}^{n} \nu_j (Econ\_Var)_i + \sum_{j=1}^{n} \phi_j (Interaction\_Var)_i + \alpha_1 Size_i + \varepsilon_i \end{aligned}, \qquad (8)$$

where y_i is one of the sixteen different income inequality measures, defined in Sections 2.1-2.6, for immigrant cohort *i*.

Table 8 shows the pairwise correlations between these sixteen income inequality measures. The correlation coefficient between these variables drops to 0.55 in some cases. Consequently, each income inequality metric depicts different characteristics of the income distribution of the underlying cohort. Therefore, as a robustness check for the explanatory variables, all the available income inequality measures will be used separately as dependent variables in sixteen successive regressions. The first eight estimations will use *personal* income inequality metrics, while the last eight regressions will use *household* income inequality metrics.

Table 8: Pairwise Correlations among the Inequality Measures

Personal Income								
	rmd_p	cv_p	std_p	gini_p	theil_p	atk_p1	atk_p2	atk_p3
rmd_p	1.0000							
cv_p	0.7995	1.0000						
std_p	0.7617	0.5574	1.0000					
gini_p	0.9882	0.8565	0.7567	1.0000				
theil_p	0.9452	0.9373	0.7055	0.9726	1.0000			
atk_p1	0.9588	0.8884	0.7327	0.9777	0.9903	1.0000		
atk_p2	0.9356	0.8055	0.7273	0.9470	0.9471	0.9818	1.0000	
atk_p3	0.8166	0.6355	0.6359	0.8227	0.8135	0.8812	0.9538	1.0000
Household Income								
	rmd_h	cv_h	std_h	gini_h	theil_h	atk_h1	atk_h2	atk_h3
rmd_h	1.0000							
cv_h	0.7658	1.0000						
std_h	0.6835	0.5709	1.0000					
gini_h	0.9878	0.7985	0.6872	1.0000				
theil_h	0.9373	0.8858	0.6781	0.9590	1.0000			
atk_h1	0.7520	0.7602	0.6694	0.7477	0.7947	1.0000		
atk_h2	0.9503	0.8196	0.7911	0.9606	0.9571	0.8356	1.0000	
atk_h3	0.9045	0.6913	0.7250	0.9354	0.8874	0.6564	0.9337	1.0000

The descriptive statistics of dependent variables are given in Table 9. The general finding of this study should be reiterated here again: There is substantive evidence that household income is more equally distributed than personal income. This result is robust to different immigrant cohorts and different inequality metrics tested in this study. For example, the average Gini coefficient based on personal income across these cohorts is 0.58, while household income inequality is only 0.47. The reason for this substantive difference in personal and household income stems from the fact that the personal income for males and females are significantly different. Hoover and Yaya (2009a) showed that female personal income inequality is much higher than males; hence, this is an important source of income dispersion within each immigrant cohort. On the other hand, household income is much more equally distributed because household income is the sum of all the incomes earned by the members of each household.

Table 9: Descriptive Statistics for Dependent Variables (Income Inequality Metrics)

	Count	Mean	St. Dev	Min	Max
Relative Mean Deviation of Personal Income (RMD_P)	133	0.4256	0.0456	0.3363	0.5834
Relative Mean Deviation of Household Income (RMD_H)	133	0.3280	0.0374	0.2400	0.4938
Coefficient of Personal Income Variation (CV_P)	133	1.3902	0.2681	0.8902	2.8620
Coefficient of Household Income Variation (CV_H)	133	0.9852	0.1769	0.2791	1.9863
Standard Deviation of Logs of Personal Income (STD_P)	133	1.1988	0.1338	0.8735	1.6766
Standard Deviation of Logs of Household Income (STD_H)	133	0.9220	0.1016	0.7078	1.3250
Gini Coefficient of Personal Income (GINI_P)	133	0.5815	0.0531	0.4702	0.7494
Gini Coefficient of Household Income (GINI_H)	133	0.4632	0.0498	0.3435	0.6930
Theil Index of Personal Income (THEIL_P)	133	0.6455	0.1409	0.3821	1.2163
Theil Index of Household Income (THEIL_H)	133	0.3776	0.0852	0.2023	0.7488
Atkinson of Personal Income, eps=0.25 (ATK_P1)	133	0.1623	0.0315	0.1001	0.2812
Atkinson of Household Income, eps=0.25 (ATK_H1)	133	0.0808	0.0188	0.0434	0.1787
Atkinson of Personal Income, eps=0.50 (ATK_P2)	133	0.3398	0.0578	0.2166	0.5525
Atkinson of Household Income, eps=0.50 (ATK_H2)	133	0.1752	0.0333	0.1012	0.3078
Atkinson of Personal Income, eps=0.75 (ATK_P3)	133	0.5824	0.0815	0.3890	0.8375
Atkinson of Household Income, eps=0.75 (ATK_H3)	133	0.2957	0.0581	0.1772	0.5906

Table 10 shows the descriptive statistics of the independent variables that will be used to explain the variation in inequalities. The table excludes the geographical dummies. Average personal income across the 133 cohorts is approximately $33,000, while the average household income is more than $75,000. The median income is less than the average income, providing additional evidence of the positively skewed income distribution of immigrants. Average group size is around 4,600 individuals, with a maximum number of immigrants from Mexico (79,458) and only 62 immigrants from Estonia. Immigrant groups on average have an education level of 14 years of education, which corresponds to some college and/or an associate degree. They have also spent on average 19 years in the United States. The percentage of males and visa holders across the cohorts are approximately 47%. Moreover, 13% of immigrants in these cohorts, on average, are students and only 4.7% of them are unemployed.

Table 10: Descriptive Statistics of Independent Variables (Determinants of Income Inequality)

	Number of Cohorts	Mean	St. Dev	Min	Max
Average Personal Income (PINCP_mean)	133	$33,060	$10,408	$14,133	$65,597
Average Household Income (HINCP_mean)	133	$75,811	$17,229	$33,208	$138,737
Median Personal Income (PINCP_median)	133	$19,937	$5,539	$5,000	$35,000
Median Household Income (HINCP_median)	133	$58,071	$13,203	$24,400	$100,000
Average Education Level (SCHL)	133	10.2734	1.3080	6.3912	12.4656
Average Number of Years (YOEP)	133	19.5320	7.3161	7.0000	39.9620
Average English Proficiency (ENG)	133	1.5457	0.4454	1.0000	2.5772
Average Age (AGE)	133	45.6381	6.5610	26.7963	64.2240
Fraction of Males (Per_Male)	133	0.4746	0.0602	0.3293	0.6977
Fraction of non-permanent visa holders (Per_Visa)	133	0.4758	0.1493	0.1845	0.8448
Unemployment Rate (Per_Unemp)	133	0.0469	0.0274	0.0000	0.2316
Percentage students (Per_Stud)	133	0.1381	0.0789	0.0219	0.6577
Country of Origin Political Freedom Index (POL)	127	66.41	28.13	3.00	100.00
Country of Origin Income inequality (INEQU)	123	0.4300	0.0600	0.2400	0.5700
Country of Origin Inflation (INF)	129	20.58%	233.05%	-0.01%	2647.00%
Country of Origin Unemployment (UNEMP)	123	0.1200	0.1400	0.0200	0.8500
Country of Origin Openness to Trade (OPEN)	130	0.8500	1.1100	0.2200	11.3900
Country of Origin Geographical proximity (GEO)	133	4,651	2,320	0	9,373
Group Size (Size)	133	2,062	7,192	62	79,456
Household Head Size (hh_size)	133	939	3,037	30	33,285

These explanatory variables can be divided into six different groups. The first group includes income related variables, which are the mean and median incomes. For personal inequality metrics, *personal income* will be used, while *household income* is the explanatory variable for household inequality metrics. Earlier studies in income inequality used either mean or median income as an explanatory variable, and there is no consensus on the selection of the statistic. However, due to the skewness of the distribution, over the last 40 years median income is widely accepted and used in the literature.[12]

In his seminal papers, Kuznets (1955) showed that income inequality and economic development has an inverted U-shape relationship. Inequality is increasing at the early stages of

[12] See Gardner (1969), Betz (1974), Danziger (1976), Davies and Heather (1998), Lee and O'Leary (2008).

economic development but starts to decrease once a certain level of development is achieved. On the other hand, Nielsen and Alderson (1997) suggested a great U-turn in the relationship between economic development and inequality. The authors argued that, due to economic dynamics such as sectoral, gender, and racial dualism, the relationship between development and inequality has reversed in the United States since 1970. In this dissertation, a similar relationship will be tested for the economic development of immigrant cohorts and their respective inequality levels. In order to test this relationship, following Kuznets (1955) and Nielsen and Alderson's (1997) work, income and squared-income will be examined for sign and significance. Kuznets' hypothesis suggests a positive income and negative squared-income in the regression. On the other hand, Nielsen and Alderson suggest a reverse relation between these variables.

The second group of variables includes the ones that are directly related to the demographic characteristics of immigrant cohorts. These variables are the average level of educational attainment (Schl), average number of years spent in the U.S. (Yoep), English proficiency (Eng), average age (Age), percentage of visa holders (per_visa), percentage of students (per_stud), and percentage of unemployed (per_unemp) in a given immigrant group. The percentage of immigrants who were unemployed (per_unemp) during the last three months is used to control for the variation in employment among the immigrant cohorts. Additionally, some immigrants who hold student visas are able to work limited hours. Therefore, the percentage of immigrants who are studying in the U.S. (per_stud) becomes an important issue in this work.

There are several variables in the study that proxy the *relative deprivation* or *positive selection* of immigrants. These variables are all related to the characteristics of the countries of origins of these immigrant cohorts. Political freedom (Pol), economic freedom (Open), income inequality (Inequ), inflation (Inf), and unemployment (Unemp) are all included in this group. For example, if a country of origin of an immigrant cohort has low political freedom or high unemployment, then immigrants from these countries are relatively more deprived and have more incentives to migrate. Relative deprivation leads to a *positive selection* of immigrants who are shown to outperform other cohorts of immigrants in terms of assimilation and earnings. Therefore, the immigrant groups that are positively selected should have different income distributions.

The next set of variables control the geographical characteristics of immigrant groups. These variables are colonial ties (Col), geographical proximity (Geo), and neighbor (Neig) and continental dummies. Dummies for neighbors take the value of one for Mexico and Canada and zero otherwise. Continent dummies are created for South America (Lat), Asia (Asia), Europe (Eur), Africa (Afr), North America (North), and Oceania (Ocea).

The country of origin's economic development is also an important factor because it affects both the incentives and skill set of immigrants. Economic development dummies capture the economic strength of the country of origin. A dummy variable (EU) is created for the members of the European Union. Immigrants from members of these organizations have different distributional characteristics than other immigrant cohorts. Immigrants from these countries have more education and less difficulty adapting to the country of destination's economic atmosphere and culture. In addition to the European Union dummy, another dummy is created for immigrant cohorts from countries that are members of the Organisation for Economic Co-operation and Development (OECD).

Some interaction variables that are related to the fraction of visa holders, unemployed immigrants, and students are also considered. Visa status and unemployment (per_visa*per_unemp) of immigrant groups are used to capture the effect of unemployed visa holders in the United States. In addition, visa status and percentage of students in an immigrant group (per_visa*per_stud) are also used to capture the effect of immigrants who hold a valid visa but came to the U.S. to get an education. Finally, the percentage of unemployed immigrants is interacted with the percentage of students (per_unemp*per_stud) to control for the unemployed student differences across the immigrant cohorts.

6.2 Income Inequality Change of Immigrants by Country of Origin

The descriptive statistics derived from the ACS data strongly suggest that the immigrants in the survey have distinct income distribution characteristics compared to U.S. citizens due to the cultural, economic, and social differences between these samples. An interesting extension to the previous section is to explore the rate of assimilation among immigrants over time. Rather than examining assimilation in terms of demographical characteristics such as income, education, or language, the focus will be given to the assimilation of immigrants with respect to their distribution of income. In other words, this section will try to answer the following question: do all immigrant cohorts exhibit similar convergence paths or are there any differences in their convergences? Section 5 has already illustrated that the income inequality of immigrants converges to the income inequality of the U.S. over time. However, the inequality of immigrants from some of the regions converges to the U.S. inequality more rapidly than others. For example, over the 5-year period studied, the income inequality of all immigrants decreases by 18.4%; however, the income inequality of African immigrants decreases far more quickly, by approximately 29%.[13] If this is the case, what is the rationale behind varying speeds of convergences, and are there any regional differences in this convergence process?

In order to examine the rate of change in the income inequality of immigrant cohorts, the income distributions of immigrant cohorts are observed at two points in time: 1996 and 2005/6. The American Community Survey is not strictly panel data; hence, it does not show the evolution of the income of individuals over time. However, the income distribution of immigrant cohorts that have been living in the U.S. for different periods of time can be determined with the use of a year of entry (Yoep) variable. By using this variable, two sub-cohorts of immigrants from each country of origin are created. The first cohort of immigrants has resided in the U.S. for less than a year; in other words, these immigrants' year of entry was 2005/2006. The second cohort of immigrants is composed of those who have resided in the U.S. for approximately 10 years. Lopez and Lozano (1999) have employed a similar methodology in their recent study of immigrants in the United States, again using a ten-year lapse between the observation periods.

Now, consider the following two equations:

$$\hat{y}_i = y_{i,1996} - y_{i,2005/2006}, \tag{9}$$

where ($\hat{y}_i$) is the difference between the income inequality of immigrant cohort *i* who entered the U.S. at two different points in time. A negative number ($\hat{y}_i$) indicates that the income distribution of the 1996 cohort is more equally distributed than the 2005/2006 cohort. In other words, it suggests that an immigrant cohort who resided in the U.S. longer exhibits a more equally distributed income. While a positive number suggests that immigrants who have resided in the U.S. longer exhibit less equally distributed income compared to the recent immigrant cohort.

[13] See Table 7 in Section 5.

Consider:

$$dist(y_i) = y_{U.S.} - y_{i,2005/2006}, \tag{10}$$

where $dist(y_i)$ is equal to the difference between the income inequality of U.S. and the i^{th} immigrant cohort that entered the U.S. in 2005/2006. There are several reasons for using a distance measure [$dist(y_i)$] to explain the variation in inequality. It may well be the case that the inequality convergence of each immigrant cohort, if any, depends on how different the income inequality of the recent cohort from the host country's distribution. Moreover, immigrants face the same economic opportunities and constraints within the host country, no matter where their countries of origins are. Therefore, the income inequality of the host country becomes an *anchor* for the immigrants, and the distance variable captures the *initial point* issue of inequality convergence. Immigrant cohorts that start with significantly different income inequalities compared to the host country may improve much faster than the ones that start with low inequality differences.

In addition, the change in the demographic characteristics of immigrant cohorts varies greatly. Some groups come to the U.S. with a high level of education and a low level of cultural and language barriers, while some groups arrive with limited education and high cultural differences. Therefore, some immigrant groups improve their language abilities and education level and assimilate quicker than others due to cultural similarities and the high opportunity cost of going back to the country of origin. For such immigrants, the country of origin may have political or economic instability, or the immigrants may be refugees who cannot return to their country origins. Others, on the other hand, may preserve their national identities, i.e. by keeping their mother tongue as the primary means of communication at home. The assimilation rate is slow for these immigrant groups. Hence, the initial point, i.e. the distance variable, may not explain the entire variation in inequality convergence. Therefore, changes in these aforementioned demographic factors over the 10 years studied will also be used to distinguish the varying speeds of inequality convergence.

Now, consider the following regression model:

$$\begin{aligned}\hat{y}_i &= \alpha_0 + \sum_{j=1}^{n} \beta_j (\Delta Income\_Var)_i + \sum_{j=1}^{n} \delta_j (\Delta Immig\_Charac)_i + \sum_{j=1}^{n} \kappa_j (Geograpical)_i \\ &+ \alpha_1 dist(y_i) + \varepsilon_i\end{aligned} \quad . \quad (11)$$

Appendix E shows the differences in income inequalities among immigrant sub-groups that had entered the U.S. in 2005/2006 and 1996. Inequality differences for some immigrant groups are much higher than others. For example, the personal income inequality of Italian immigrants has decreased by 0.30 points over the last 10 years, while income inequality virtually stayed the same for British immigrants. If immigrants from the same continent have such variation in inequality convergence paths, then what are the determinants of the inequality convergence for immigrant cohorts in the United States? A regression analysis will be employed to examine this question by using the distance measure, differences in the explanatory variables between the sub-groups, and the geographical characteristics of the immigrant cohort's countries of origin.

Table 11: Change in Income Inequality of Immigrant Groups by World Regions between 1996 and 2005/6								
	Personal Income							
Regions	**ΔRMD**	**ΔCV**	**ΔSt.Dev.**	**ΔGINI**	**ΔTheil**	**ΔAtkinson eps=0.25**	**ΔAtkinson eps=0.5**	**ΔAtkinson eps=0.75**
Latin America	-0.0921	-0.3510	-0.1984	-0.0974	-0.2337	-0.0562	-0.0083	-0.1051
Asia	-0.1664	-0.8564	-0.2768	-0.1661	-0.5757	-0.1338	-0.0267	-0.2383
Europe	-0.1478	-0.5523	-0.2945	-0.1471	-0.4397	-0.1053	-0.0277	-0.1955
Africa	-0.1834	-0.6948	-0.4577	-0.1926	-0.5446	-0.1282	-0.0189	-0.2293
North America	-0.0542	-0.3408	0.0876	-0.0618	-0.1907	-0.0411	-0.0363	-0.0680
Oceania	-0.1282	-0.1982	-0.1357	-0.1187	-0.2897	-0.0783	0.0115	-0.1630
	Household Income							
Regions	**ΔRMD**	**ΔCV**	**ΔSt.Dev.**	**ΔGINI**	**ΔTheil**	**ΔAtkinson eps=0.25**	**ΔAtkinson eps=0.5**	**ΔAtkinson eps=0.75**
Latin America	-0.0436	-0.1360	-0.1893	-0.0662	-0.0922	-0.0083	-0.1051	-0.0367
Asia	-0.0931	-0.3194	-0.2463	-0.1418	-0.2280	-0.0267	-0.2383	-0.0950
Europe	-0.0875	-0.2402	-0.2144	-0.1196	-0.1955	-0.0277	-0.1955	-0.0865
Africa	-0.0793	-0.2221	-0.2558	-0.1076	-0.1658	-0.0189	-0.2293	-0.0635
North America	-0.1051	-0.3019	-0.3027	-0.1492	-0.2477	-0.0363	-0.0680	-0.1183
Oceania	-0.0985	-0.1725	0.0624	-0.1464	-0.1954	0.0115	-0.1630	-0.0547

Figure 15: Change in Income Inequality of Immigrant Groups between 1996 and 2005/6, by World Regions

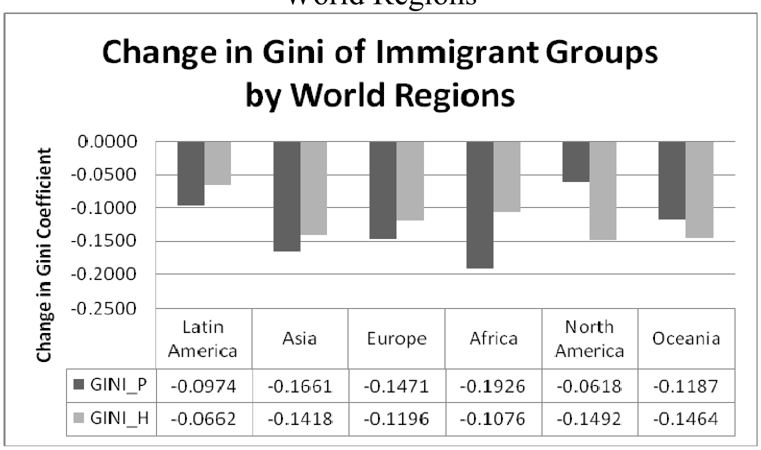


Table 11 and Figure 15 show some further statistics about the income inequality convergence of immigrant cohorts. One interesting finding that is worth mentioning is the fact that there is strong evidence that the income of immigrants becomes more equally distributed over the 10 years studied. This result is robust to different inequality metrics and regions that the immigrants are from. The fastest convergence is observed among the African and Asian immigrants, and the slowest is observed among the North and Latin American immigrants. However, it should be noted that Latin American immigrants as a group have the lowest inequality to begin with. This illustrates the close link between the inequality convergence and the initial level of inequality. Moreover, the results indicate that personal income inequality improves much faster than household income inequality. These results are consistent with the earlier evidence presented in Section 5, related to the change in income inequality of immigrant groups from different regions.

Table 12: Descriptive Statistics of Dependent Variables (Change in Income Inequality):

	Obs	Mean	Std. Dev.	Min	Max
Change in Relative Mean Deviation of Personal Income (ΔRMD_P)	45	-0.15945	0.086729	-0.3409	0.0442
Change in Relative Mean Deviation of Household Income (ΔRMD_H)	45	-0.08941	0.088683	-0.4399	0.0337
Change in Coefficient of Personal Income Variation (ΔCV_P)	45	-0.67314	0.551815	-1.9050	0.6964
Change in Coefficient of Household Income Variation (ΔCV_H)	45	-0.30784	0.279932	-1.1937	0.1872
Change in Standard Deviation of Logs of Personal Income (ΔSTD_P)	45	-0.22841	0.280555	-1.0096	0.6980
Change in Standard Deviation of Logs of Household Income (ΔSTD_H)	45	-0.17714	0.247495	-0.9726	0.2360
Change in Gini Coefficient of Personal Income (ΔGINI_P)	45	-0.17073	0.095907	-0.3810	0.0556
Change in Gini Coefficient of Household Income (ΔGINI_H)	45	-0.12838	0.118631	-0.5935	0.0272
Change in Theil Index of Personal Income (ΔTHEIL_P)	45	-0.49041	0.30088	-1.1319	0.1636
Change in Theil Index of Household Income (ΔTHEIL_H)	45	-0.21388	0.210713	-1.0732	0.0525
Change in Atkinson of Personal Income, eps=0.25 (ΔATK_P1)	45	-0.11569	0.065772	-0.2552	0.035
Change in Atkinson of Household Income, eps=0.25 (ΔATK_H1)	45	-0.02525	0.030781	-0.1025	0.0371
Change in Atkinson of Personal Income, eps=0.50 (ΔATK_P2)	45	-0.21177	0.115964	-0.4548	0.0735
Change in Atkinson of Household Income, eps=0.50 (ΔATK_H2)	45	-0.07999	0.070427	-0.2326	0.0435
Change in Atkinson of Personal Income, eps=0.75 (ΔATK_P3)	45	-0.24966	0.149552	-0.5779	0.1006
Change in Atkinson of Household Income, eps=0.75 (ΔATK_H3)	45	-0.15945	0.086729	-0.3409	0.0442

Regional comparisons give only limited information about the overall patterns in inequality convergence of immigrant cohorts. Table 12 shows descriptive statistics for the difference in the inequality of these 45 immigrant cohorts over the 10-year period. In order to obtain consistent statistical inference, each immigrant cohort is required to have at least 30 individuals at each point in time (1996 and 2005/6). The descriptive statistics indicate that the inequality difference between tenured and recent immigrants is consistently negative, suggesting that the income inequality of immigrants becomes more equally distributed as they reside longer in the host country. Furthermore, the convergence of personal income compared to household income is much faster for individual immigrant cohorts. This finding is consistent with the convergence rate of world regions.

Table 13: Descriptive Statistics of Independent Variables (Change in Immigrant Group Characteristics)

	Obs	Mean	Std. Dev.	Min	Max
Change in Mean Household Income (Δhincp_mean)	45	$ 16,759	$ 20,569	$ (16,639)	$ 81,963
Change in Mean Personal Income (Δpincp_mean)	45	$ 15,057	$ 8,008	$ 3,868	$ 38,683
Change in Median Household Income (Δhincp_median)	45	$ 19,101	$ 19,127	$ (11,450)	$ 79,050
Change in Median Personal Income (Δpincp_median)	45	$ 15,360	$ 6,715	$ 5,800	$ 30,800
Change in Educational Attainment (Δschl)	45	0.18682	0.793765	-1.8875	2.3185
Change in Average Age (Δage)	45	4.18006	3.686569	-4.0179	13.5444
Change in Percentage of Unemployed Immigrants (Δper_unemp)	45	-0.02842	0.033839	-0.1397	0.0427

Table 13 shows the descriptive statistics for the changes in the characteristics of immigrant cohorts. Based on the table, immigrant cohorts that have resided in the U.S. longer have higher income (in terms of both personal and household) and higher education. In addition, immigrant demographics indicate that, on average, immigrant cohorts are getting older and have less unemployed immigrants. One interesting finding is the fact that although immigrants are observed over a 10-year period, the average difference in age between these two cohorts is slightly higher than four years. This suggests that the composition of immigrants in the U.S. is also changing over time, and it has a dynamic nature. Moreover, these characteristics and demographic changes are different for each of the immigrant cohorts. Aigner and Heins (1967) empirically showed the negative effect of median age on income inequality. Immigrant groups cohorts that are getting older faster than other groups have higher income inequalities. If the age composition of immigrant groups changes over time, this may have a significant impact on the pace of inequality of immigrant groups.

This section explores the determinants of different paths of inequality convergence of immigrants over 10 years. If the speed of inequality convergence for some immigrant groups is different than others, what determines this speed? In other words, do the changes in demographics and group characteristics explain the variation in income inequality convergence of immigrant groups in the United States?

6.3 The Counterfactual Effects of Immigrant Cohorts on the U.S. Income Distribution

The distributional effects of immigration have been an area of controversy for the last few decades. One way to examine these effects of immigration on the income inequality of the host country is to decompose the inequality by population subgroups.[14] Shorrocks (1984), in his seminal paper, outlined the methodology to decompose inequality by population subgroup using a weak aggregation condition. Most of the generalized entropy measures, such as the Theil and Atkinson indices, satisfy this condition, while the Gini coefficient can be used for such decomposition under certain circumstances. Grabka, Schwarze and Wagner (1999) employed the same decomposition technique to investigate the effect of unification and immigration on German income distribution. However, unlike these methodologies that decompose the inequality, a methodology similar to Reed's will be uses in this section (Reed 2001). With this procedure, it is possible to observe an income distribution of a population in the absence of

[14] Semple (1975) has used a methodology called "standardized" inequality series, while Mookherjee and Shorrocks (1982) proposed a different technique that allows the distribution to be disaggregated by demographic factors such as age, gender, or household size.

certain population subgroups; hence, it is also possible to measure the counterfactual contribution of each cohort to the overall inequality.

Consider a population with a certain level of income inequality. Assume that the population is composed of the natives and *i* number of immigrant cohorts. It is possible to calculate the inequality of this population in the absence of a single cohort. This inequality metric illustrates the income distribution of the full sample, assuming that a cohort is not part of the sample. The difference between the initial level of inequality of the population and the counterfactual level of inequality reveals the effect of each cohort on the income inequality of the population. More formally, consider:

$$\tilde{y}_i = y_{US} - y_i , \qquad (12)$$

where ($\tilde{y}_i$) denotes the effect of immigrant cohort *i*, which is equal to the difference between the overall income inequality of the host country, the U.S. (y_{US}), and the income inequality of the U.S. in the absence of the immigrant cohort *i* (y_i). A positive $\tilde{y}_i$ indicates that the immigrant cohort *i* has a disequalizing effect on U.S. income inequality.

Appendix F shows the effect of each immigrant cohort ($\tilde{y}_i$) on U.S. personal and household income inequality. The counterfactual effects are very small due to the fact that most of the immigrant cohorts constitute only a very small fraction of the surveyed sample. However, there are a few exceptions. For example, refer back to Section 5 (Table 4), which illustrates that the Gini coefficient for the U.S. based on household income was 0.473787 in 2006. If Mexican immigrants are excluded from the full sample and then counterfactual Gini coefficient in the absence of Mexican immigrants would be 0.473815. The difference between 0.473787 and 0.473815 is the counterfactual inequality effect of Mexican immigrants on U.S. income inequality. Interestingly, although Mexicans constitute the largest immigrant cohort, they don't have the largest impact on the U.S. income distribution. The absence of Philippine immigrants, another large immigrant cohort, has a larger impact on the U.S. distribution. Therefore, it is natural to assume that the size of the immigrant group determines the counterfactual effect of immigrants, but there are some other factors that contribute to the counterfactual effects of the immigrant cohorts. Now, consider the following equation:

$$\begin{aligned} \widetilde{y}_i &= \alpha_0 + \sum_{j=1}^{n} \beta_j (Income\_Var)_i + \sum_{j=1}^{n} \delta_j (immig\_charac)_i + \sum_{j=1}^{n} \gamma_j (Selection\_Var)_i \\ &+ \sum_{j=1}^{n} \kappa_j (Geograpical)_i + \sum_{j=1}^{n} \nu_j (Econ\_Var)_i + \sum_{j=1}^{n} \phi_j (Interaction\_Var)_i + \alpha_1 Size + \varepsilon_i \end{aligned} \quad . \tag{13}$$

The regression analysis (13) has the exact same specification as Equation 8 in section 6.1; however, it attempts to answer a different question: what are the determinants of the counterfactual effects of different immigrant cohorts? The size of each immigrant cohort is expected to be the most important and significant factor. However, the important question is, once the size of the immigrant groups is controlled for, are there any other factors that contribute to the effects of these groups?

Table 14 shows the descriptive statistics for the counterfactual effects of each immigrant cohort on the U.S. income distribution. The average effects on each of the inequality metrics are very small. Therefore, these counterfactual effects are multiplied by a thousand for reporting purposes. On average, the counterfactual effects are mostly positive for personal income, and the pattern is mixed for household income. Consequently, immigrant cohorts have disequalizing counterfactual effects on U.S. inequality based on personal income, but mixed effects based on household income. In other words, if immigrants were removed from the U.S., the initial impact would be a more equally distributed personal income among the remaining population.

Hoover and Yaya (2009b) employed a similar approach to investigate the distributional effects of racial and ethnic groups in the United States. They acknowledged an essential weakness of this approach: as the immigrant cohorts were removed from the population, the remaining cohorts would reestablish the income distribution instantaneously. However, this approach is an important first step towards understanding immigrants and their contribution to the U.S. income distribution. It is also relevant to current immigration policies in developed countries, since the implementation of such policies were widely discussed in the U.S. during the 2008 presidential elections and more recently in Italy.[15]

Table 14: Descriptive Statistics of the Counterfactual Effects of Immigrant Groups in U.S. Income Inequality:

Personal Income Measures	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Effect in Relative Mean Deviation of Personal Income (e[RMD_P])	133	0.0247	0.1222	-0.2647	1.2231
Effect in Coefficient of Personal Income Variation (e[CV_P])	133	0.1036	0.6599	-1.9838	6.9400
Effect in Standard Deviation of Logs of Personal Income (e[STD_P])	133	-0.0721	0.5255	-5.7685	0.7817
Effect in Gini Coefficient of Personal Income (e[GINI_P])	133	0.0284	0.1422	-0.3535	1.4181
Effect in Theil Index of Personal Income (e[THEIL_P])	133	0.0682	0.3683	-0.9471	3.8029
Effect in Atkinson of Personal Income, eps=0.25 (e[ATK_P1])	133	0.0171	0.0922	-0.1928	0.9708
Effect in Atkinson of Personal Income, eps=0.50 (e[ATK_P2])	133	0.0373	0.2073	-0.2977	2.2448
Effect in Atkinson of Personal Income, eps=0.75 (e[ATK_P3])	133	0.0722	0.4251	-0.2786	4.7466
Household Income Measures					
Effect in Relative Mean Deviation of Household Income (e[RMD_H])	133	0.0005	0.0482	-0.3905	0.1766
Effect in Coefficient of Household Income Variation (e[CV_H])	133	0.0005	0.2632	-2.2208	1.4448
Effect in Standard Deviation of Logs of Household Income (e[STD_H])	133	-0.0062	0.2247	-2.2555	0.4924
Effect in Gini Coefficient of Household Income (e[GINI_H])	133	-0.0053	0.0665	-0.6070	0.1887
Effect in Theil Index of Household Income (e[THEIL_H])	133	-0.0067	0.1164	-1.0829	0.3408
Effect in Atkinson of Household Income, eps=0.25 (e[ATK_H1])	133	0.0042	0.0243	-0.1449	0.1108
Effect in Atkinson of Household Income, eps=0.50 (e[ATK_H2])	133	0.0002	0.0515	-0.3435	0.1812
Effect in Atkinson of Household Income, eps=0.75 (e[ATK_H3])	133	-0.0127	0.1089	-0.9518	0.2426

[15] President Obama, during his campaign, pledged to "bring the people out of shadow," was referring to the illegal immigration issue. During the first few months of his presidency, Mr. Obama has been actively working on a bill to give amnesty to and legalize the illegal immigrants. According to Euronews, Italy passes legislation in May 2009 to fine illegal immigrants up to 10,000 Euros and punish their accommodating sources with jail time up to three years.

CHAPTER 7

RESULTS

7.1 Determinants of Income Inequality of Immigrants by Country of Origin

A high degree of correlation among independent variables produces a *multicollinearity problem* in ordinary least square regressions. Perfect multicollinearity means that two or more regressors have a linear relationship. Less than perfect multicollinearity is the case when two or more regressors are inter-correlated but not perfectly so. Gujarati (2003) stated that if there exists a perfect multicollinearity, the coefficients of the explanatory variables are undetermined and their standard errors are infinite. However, if the multicollinearity is less than perfect, then the coefficients of the regressors have large standard errors; thus, they cannot be estimated with accuracy.

Appendix G shows the pairwise correlation matrix for the independent variables used in Equation 8. This matrix is inspected to determine the degree of correlation between explanatory variables. High correlation coefficients are observed among the mean and median income; year of entry and age; the English proficiency and language dummies; the interaction variables; the neighbor dummy and European Union continental dummy; and finally, size and household size. In addition to these high correlations, variance-inflation factor (VIF) and tolerance (TOL)[16] suggest that size, percentage of students, interaction variables, and the neighbor dummy are all highly correlated with the constant variable if a regression with all the explanatory variables is

[16] Variance-inflation factor (VIF) = $[1 / (1-r^2_{ij})]$, where r^2_{ij} is the correlation coefficient between two explanatory variables. Tolerance_i (TOL) = $1 / \text{VIF}_i$. A VIF in excess of 10 suggests a high degree of multicollinearity.

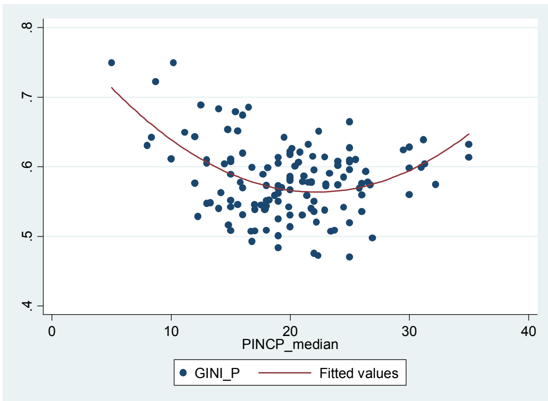
considered. One multicollinearity remedy offered by Gujarati is simply dropping the highly correlated variables. Therefore, mean income, age, language dummy, size, European Union dummy, and all the interaction variables, except Visa*Employment, are dropped from the study due to their high correlation with one or more explanatory variables.

Heteroscedasticity is another important issue in regression analysis. Greene (2003) defined homoscedasticity as the constant variance of the disturbance term. In other words, homoscedasticity refers to the variance of an explanatory variable around a regression line that does not change as the explanatory variable changes. On the other hand, heteroscedasticity refers to unequal variance of the disturbance term. Heteroscedasticity is observed when the conditional variance of the dependent variable varies with one or more explanatory variables. OLS assumes homoscedasticity and the failure of this assumption leads to inaccurate standard error estimations. White's Test is generally used to detect heteroscedasticity. The null hypothesis of White's Test is homoscedasticity of the disturbance term. This test for homoscedasticity uses a three-step procedure. In the first step, one estimates the model of interest and obtains the residual. Second, the squared residual is regressed on the explanatory variables of the initial model, their higher powers and cross products. In the third step, the R-square of the auxiliary regression is obtained. Under the null hypothesis of no heteroscedasticity, sample size (N) times the R-square follows a Chi-square (X^2) distribution with degrees of freedom of one less than the number of coefficients of the auxiliary regression. If the Chi-square value exceeds the critical value, then heteroscedasticity exists in the data. White's Test for heteroscedasticity indicates that Models 2-4 in Table 15 are not nullified because of unequal variance of the error terms. In other words, Model 1 has a heteroscedastic error term while the errors in Model 2-4 are homoscedastic. The Chi-square values and their respective p-values are given for the Models 1-4 at the bottom of Table 15 and 16.[17]

The ordinary least squares (OLS) method is also susceptible to outliers, which leads to biased estimation of coefficients of interest. For example, Figures 16-17 show that some of the immigrant cohorts are outlier candidates. Robust regression is generally used to eliminate the effect of outliers in the data. (Jousseeuw and Leroy 1987) Robust regression runs the OLS regression and then calculates Cook's D values for each variable.[18] Then, the procedure drops the variables that have a Cook's D value of 1 and above.

Figure 16 and 17 show the scatter diagram of the inequality of immigrant cohorts and their respective income level. For both personal and household income, there is a visible U-shape link between income and inequality as suggested by Nielsen and Alderson (1997). The figures suggest that immigrant cohorts that have very low and high income generally have higher income inequality.

Figure 16: Scatter Diagram of Gini Coefficient of Immigrant Cohorts, Based on Median Personal Income



[17] The Ramsey Test for specification error (RESET) is also examined. Based on Ramsey Tests, Models 1-3 are misspecified, but Model 4 shows no indication of misspecification.
[18] Cook's D value is an overall measure of influence. It has a bound of zero, which implies no influence of the explanatory variable on the dependent. The higher the value is, the more influential it is. For outlier detection, the threshold for Cook's D value is 4/n.

Figure 17: Scatter Diagram of Gini Coefficient of Immigrant Cohorts, Based on Median Household Income

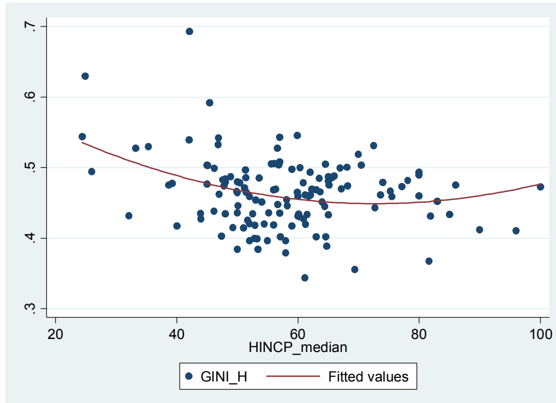


Table 15 shows the regression results for the empirical study of immigrants in the United States. Models 1-4 use the OLS method with White's robust errors. The Gini coefficient, based on personal income, is selected as the dependent variable. The number of observations and R^2 range from 113 to 133 and 58% to 72%, respectively. In Model 1, geographical controls and positive selection variables are excluded. The results suggest that personal income is an important and statistically significant factor determining the Gini coefficient of immigrant cohorts. The relationship shows a similar path to the one described by Nielsen and Alderson (1997). Immigrant groups that have exceptionally high and low personal income generally have higher inequality. Nielsen and Alderson defined this phenomenon as the "Great U-turn" between the relationship between economic development and inequality; results in Table 15 support Nielsen and Alderson's Great U-Turn hypothesis. Moreover, educational attainment (Schl), percentage of males (per_male), OECD membership, Asia dummy, and the constant are statistically significant. Immigrant cohorts that have higher levels of education or a higher percentage of males have higher personal income inequality. Furthermore, immigrant cohorts that are from OECD member countries or Asia have higher inequality compared to other groups.

The positive effect of OECD membership on inequality can be explained with the fact that immigrants from developed countries are more prepared for market conditions in the U.S., which are very similar to their countries of origin. Immigrants from these countries may come to the U.S. to start a high paying skilled job or as a student to increase his/her education. Since these two types constitute the two ends of a distribution, a less equally distributed income among these groups is not a surprise.

Geographical control variables are added into Model 2. None of the geographical variables is statistically significant except the Asian dummy. An F-test with the null hypothesis showed that all the geographical variables equal to zero cannot be rejected.[19] Educational attainment, OECD membership, Asian Dummy, and the constant variable remain significant as in Model 1. These variables also have the same directional relationship as the dependent variable. Model 3 introduces the positive selection-related variables and drops the geographical variables. Again, none of the positive selection variables seem to explain the personal income inequality of immigrants.

Finally, all the available variables are inserted into the regression in Model 4. The geographical and positive selection-related variables are all controlled for, and the results are very similar to Model 3. The coefficient of the Asian dummy indicates that, compared to immigrants from Oceania, Asian immigrants have a higher income inequality. However, the F-test of joint significance suggests that the null hypothesis cannot be rejected. The same hypothesis cannot be rejected for the positive selection-related variables as well. Therefore, the positive selection hypothesis of Borjas (1987) and Chiswick (1978) cannot be confirmed, at least for the immigrant cohorts surveyed in 2006.

[19] H_0: All geographical variables are equal to zero. $F(7, 116) = 0.70$, Prob > F = 0.6690

Table 15: Model Selection for the Determinants of Income Inequality of Immigrants

	Ordinary Least Squares				Robust Regression			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Income								
pincp_median	-0.0242	-0.0215	-0.0239	-0.0211	-0.0221	-0.0192	-0.0196	-0.0168
	(7.63)**	(6.72)**	(5.92)**	(5.28)**	(6.93)**	(6.03)**	(5.60)**	(5.18)*
pincp_squared	0.0005	0.0004	0.0004	0.0004	0.0004	0.0003	0.0003	0.0003
	(6.25)**	(5.41)**	(4.99)**	(4.34)**	(5.33)**	(4.59)**	(4.28)**	(3.73)*
Immigrant								
Schl	0.0248	0.0223	0.0253	0.0235	0.0262	0.0220	0.0284	0.0249
	(8.00)**	(6.24)**	(6.80)**	(5.45)**	(8.10)**	(6.34)**	(7.27)**	(6.41)*
Yoep	0.0009	0.0019	0.0021	0.0024	0.0012	0.0012	0.0015	0.0015
	(0.88)	(2.15)**	(2.16)**	(2.41)**	(1.53)	(1.52)	(1.52)	(1.67)*
Eng	-0.0049	-0.0115	-0.0079	-0.0095	-0.0061	-0.0176	-0.0017	-0.0132
	(0.56)	(1.10)	(0.73)	(0.74)	(0.63)	(1.74)*	(0.13)	(1.09)
per_male	0.1898	0.1955	0.1969	0.2068	0.2075	0.1737	0.1347	0.1724
	(2.33)**	(2.70)**	(2.22)**	(2.38)**	(3.58)**	(3.02)**	(1.97)*	(2.69)*
per_visa	-0.0795	-0.0501	-0.0472	-0.0502	-0.0576	-0.0442	-0.0722	-0.0232
	(1.70)*	(0.97)	(0.94)	(0.87)	(1.33)	(0.98)	(1.39)	(0.46)
per_unemp	-0.2479	-0.2569	-0.2537	-0.3372	-0.1926	-0.2030	-0.3658	-0.1345
	(1.00)	(0.98)	(0.92)	(1.18)	(0.55)	(0.60)	(0.95)	(0.39)
Economic Development								
Oecd	0.0263	0.0270	0.0176	0.0193	0.0220	0.0271	0.0217	0.0218
	(2.09)**	(1.94)*	(1.30)	(1.22)	(2.08)**	(2.33)**	(1.77)*	(1.78)*
Geographical								
Afr		0.0078		0.0029		0.0160		0.0250
		(0.57)		(0.15)		(0.93)		(1.22)
Asia		0.0321		0.0295		0.0448		0.0469
		(2.39)**		(1.97)*		(2.71)**		(2.59)*
Eur		0.0087		0.0064		0.0119		0.0131
		(0.66)		(0.43)		(0.71)		(0.72)
Latin		0.0206		0.0143		0.0246		0.0238
		(1.16)		(0.59)		(1.24)		(1.04)
North		-0.0311		0.0344		-0.0385		0.0161
		(0.64)		(1.32)		(1.21)		(0.41)
Ocea		Dropped		Dropped		Dropped		Droppe
Col		0.0105		-0.0040		0.0303		0.0201
		(0.43)		(0.17)		(1.80)*		(1.19)
Geo		0.0031		0.0023		0.0022		0.0018
		(1.06)		(0.60)		(0.75)		(0.56)
Positive Selection								
Inequ			0.0182	0.0094			0.0774	0.0574
			(0.29)	(0.14)			(1.07)	(0.86)
Inf			0.0000	0.0000			-0.0997	-0.0779
			(1.24)	(1.26)			(1.00)	(0.87)
Open			0.0022	0.0006			0.0024	-0.0009
			(1.02)	(0.29)			(0.72)	(0.31)
Pol			-0.0002	0.0000			-0.0002	0.0000
			(0.81)	(0.07)			(0.84)	(0.19)
Unemp			-0.0461	-0.0308			-0.0553	-0.0067
			(1.52)	(0.96)			(1.70)*	(0.23)

Interaction								
visa_emp	0.3721	0.5663	0.3925	0.7957	0.2715	0.2506	0.7234	-0.0138
	(0.63)	(0.89)	(0.49)	(0.95)	(0.36)	(0.33)	(0.82)	(0.02)
Constant	**0.5515**	**0.4854**	**0.5185**	**0.4596**	**0.4957**	**0.5028**	**0.4602**	**0.4144**
	(6.03)**	**(5.69)****	**(5.16)****	**(4.54)****	**(6.13)****	**(6.42)****	**(4.52)****	**(4.48)***
Observations	133	133	113	113	133	133	112	112
R-squared	0.58	0.63	0.63	0.67	0.58	0.67	0.62	0.72
White's Test (P-Value)	77.97	123.88	113.00	113.00	-	-	-	-
	0.0830	0.3856	0.4557	0.4823				

Dependent variable: Gini Coefficient based on personal income. Robust t-statistics in parentheses for OLS estimates.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

The results that are related to household income inequality are illustrated in Table 16. A U-shaped relationship is confirmed with significant negative median income and positive income squared terms. Similar to the determinants of personal income inequality, household income inequality is determined by income, educational attainment, OECD membership, Asian dummy, and the constant. However, the percentage of males in immigrant cohorts does not explain the variation in household income inequality. Instead, the number of years spent in the U.S. (Yoep) becomes significant. This finding is expected, since the household income is composed of all the members of the household and inequality is determined by assimilation to the culture and the economy of the host country. Hence, recent immigrants have higher inequality compared to veteran immigrant cohorts.

Robust regression results are shown in Models 5-8 in Tables 15 and 16. The models estimated with robust regression have higher R-squared values and are more precisely estimated compared to OLS estimates. The general findings of OLS still hold because the comparable models of OLS and robust regression yield the same significant explanatory variables in most of the cases.

Table 16: Model Selection for the Determinants of Income Inequality of Immigrants

	Ordinary Least Squares				Robust Regression			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Income								
hincp_median	**-0.0068**	**-0.0065**	-0.0046	-0.0046	**-0.0091**	**-0.0080**	**-0.0088**	**-0.0088**
	(2.28)**	**(2.13)****	(1.43)	(1.33)	**(6.77)****	**(5.79)****	**(5.44)****	**(5.37)****
hincp_squared	**3.73e-05**	**3.39e-05**	2.30e-05	2.29e-05	**5.40e-05**	**4.66e-05**	**5.19e-05**	**5.22e-05**
	(1.77)*	(1.56)	(0.98)	(0.92)	**(5.05)****	**(4.22)****	**(4.12)****	**(4.04)****
Immigrant								
Schl	**0.0188**	**0.0187**	**0.0216**	**0.0198**	**0.0186**	**0.0175**	**0.0211**	**0.0187**
	(4.86)**	**(5.00)****	**(5.70)****	**(5.02)****	**(5.79)****	**(4.75)****	**(5.79)****	**(4.49)****
Yoep	0.0010	**0.0017**	**0.0026**	**0.0027**	0.0012	**0.0019**	**0.0021**	**0.0022**
	(1.05)	**(1.80)***	**(2.81)****	**(2.81)****	(1.61)	**(2.32)****	**(2.35)****	**(2.32)****
Eng	**-0.0185**	-0.0227	-0.0101	-0.0161	**-0.0186**	**-0.0233**	-0.0105	-0.0168
	(1.69)*	(1.64)	(0.85)	(1.17)	**(2.13)****	**(2.31)****	(0.94)	(1.37)
per_male	0.0943	0.1075	**0.1663**	**0.1672**	0.0374	0.0420	0.0705	0.0614
	(1.19)	(1.24)	**(2.03)****	**(1.82)***	(0.68)	(0.71)	(1.13)	(0.91)
per_visa	-0.0862	-0.0760	-0.0484	-0.0348	**-0.0753**	-0.0656	-0.0369	-0.0182
	(1.65)	(1.39)	(1.02)	(0.72)	**(1.81)***	(1.39)	(0.76)	(0.33)
per_unemp	-0.4717	-0.5407	-0.3854	-0.4093	-0.3597	-0.4317	-0.2194	-0.2077
	(1.55)	(1.65)	(1.05)	(1.12)	(1.04)	(1.20)	(0.61)	(0.55)
Economic Development								
Oecd	**0.0237**	0.0227	**0.0273**	0.0244	**0.0260**	**0.0235**	**0.0241**	**0.0227**
	(2.07)**	(1.64)	**(2.17)****	(1.76)*	**(2.60)****	**(1.97)***	**(2.17)****	**(1.75)***
Geographical								
Afr		-0.0200		0.0094		0.0199		0.0245
		(0.85)		(0.39)		(1.14)		(1.14)
Asia		0.0046		**0.0317**		**0.0344**		**0.0343**
		(0.20)		**(1.72)***		**(1.96)***		**(1.77)***
Eur		-0.0143		0.0153		0.0158		0.0155
		(0.65)		(0.76)		(0.90)		(0.79)
Latin		-0.0138		0.0068		0.0190		0.0104
		(0.53)		(0.31)		(0.94)		(0.43)
North		-0.0423		0.0283		-0.0250		0.0285
		(0.95)		(1.05)		(0.76)		(0.68)
Ocea		Dropped		Dropped		Dropped		Dropped
Col		-0.0066		-0.0121		0.0221		-0.0096
		(0.25)		(0.47)		(1.25)		(0.54)
Geo		-0.0001		-0.0021		0.0007		-0.0020
		(0.03)		(0.66)		(0.22)		(0.58)
Positive Selection								
Inequ			-0.0162	-0.0123			-0.0089	-0.0204
			(0.24)	(0.16)			(0.13)	(0.29)
Inf			0.0000	0.0000			-0.0374	-0.0039
			(0.57)	(0.64)			(0.40)	(0.04)
Open			0.0010	0.0004			0.0025	0.0018
			(0.41)	(0.15)			(0.79)	(0.57)
Pol			**-0.0004**	-0.0004			-0.0002	-0.0001
			(2.00)**	1.47)			(1.21)	(0.60)
Unemp			-0.0479	-0.0415			-0.0328	-0.0360
			(1.35)	(1.19)			(1.09)	(1.13)

Interaction								
visa_emp	1.0125	1.3223	1.2710	1.3031	0.4830	0.7729	0.2419	0.1175
	(1.06)	(1.29)	(1.13)	(1.08)	(0.65)	(0.97)	(0.29)	(0.13)
Constant	**0.5333**	**0.5145**	**0.3588**	**0.3623**	**0.6306**	**0.5613**	**0.5504**	**0.5708**
	(3.69)**	**(3.57)****	**(2.47)****	**(2.45)****	**(8.01)****	**(6.75)****	**(5.43)****	**(5.44)****
Observations	133	133	113	113	133	133	112	112
R-squared	0.43	0.46	0.49	0.52	0.56	0.56	0.60	0.62
White's Test (P-Value)	92.01	131.48			-	-	-	-
	0.0080	0.2233						

Dependent variable: Gini Coefficient based on household income. Robust t-statistics in parentheses for OLS estimates.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Tables 17-18 show the regression results from sixteen different income inequality measures based on the Robust Regression method. Table 17 uses personal income inequality as the dependent variable, while Table 18 uses household income to gauge inequality. R^2's for the robust regressions range from 0.41 to 0.78. There are several robust factors determining the income inequality of immigrants in the U.S, no matter how income inequality is measured. These factors are median income, educational attainment, and OECD membership, which are statistically significant for all the inequality measures examined.

Table 17: Robust Regression Results: Determinants of Income Inequality of Immigrant Groups in the U.S., Personal Median Income

	rmd_p	cv_p	std_p	gini_p	theil_p	atk_p1	atk_p2	atk_p3
Income								
pincp_median	**-0.0165**	**-0.0698**	**-0.0380**	**-0.0170**	**-0.0457**	**-0.0107**	**-0.0187**	**-0.0213**
	(5.94)***	**(3.28)*****	**(4.21)*****	**(4.95)*****	**(4.77)*****	**(5.44)*****	**(5.60)*****	**(4.78)*****
pincp-squared	**0.0003**	**0.0011**	**0.0008**	**0.0003**	**0.0008**	**0.0002**	**0.0003**	**0.0003**
	(4.38)***	**(2.34)****	**(3.67)*****	**(3.65)*****	**(3.49)*****	**(3.98)*****	**(3.97)*****	**(3.13)*****
Immigrant Characteristics								
Schl	**0.0238**	**0.0956**	**0.0588**	**0.0266**	**0.0597**	**0.0131**	**0.0228**	**0.0264**
	(7.22)***	**(3.79)*****	**(5.49)*****	**(6.53)*****	**(5.25)*****	**(5.64)*****	**(5.73)*****	**(4.98)*****
Yoep	**0.0020**	0.0094	0.0019	**0.0017**	0.0039	0.0005	0.0001	**-0.0028**
	(2.69)***	(1.64)	(0.80)	**(1.85)***	(1.50)	(1.03)	(0.09)	**(2.30)****
Eng	-0.0038	-0.0312	-0.0176	-0.0065	-0.0232	-0.0069	-0.0131	-0.0166
	(0.37)	(0.40)	(0.53)	(0.51)	(0.65)	(0.95)	(1.06)	(1.01)
per_male	**0.1336**	**0.8318**	0.2273	**0.1341**	**0.4295**	**0.0795**	**0.1271**	**0.1511**
	(2.42)**	**(1.97)***	(1.27)	**(1.97)***	**(2.26)****	**(2.04)****	**(1.91)***	**(1.71)***
per_visa	0.0357	-0.1319	0.1332	0.0097	0.0089	0.0060	0.0267	0.0347
	(1.02)	(0.49)	(1.18)	(0.23)	(0.07)	(0.25)	(0.63)	(0.62)
per_unemp	-0.0831	0.2360	0.3136	-0.1037	-0.0717	-0.0486	-0.1331	-0.2482
	(0.64)	(0.24)	(0.75)	(0.65)	(0.16)	(0.53)	(0.86)	(1.20)
Economic Development								
Oecd	0.0156	0.1119	0.0450	0.0204	**0.0668**	**0.0130**	**0.0221**	**0.0353**
	(1.50)	(1.40)	(1.33)	(1.59)	**(1.86)***	**(1.76)***	**(1.76)***	**(2.11)****
Geographical								
Afr	0.0081	0.0430	-0.0060	0.0176	0.0342	0.0102	0.0193	0.0435
	(0.48)	(0.34)	(0.11)	(0.86)	(0.60)	(0.87)	(0.97)	(1.63)
Asia	**0.0262**	0.0994	0.0141	**0.0381**	**0.0901**	**0.0256**	**0.0530**	**0.0930**
	(1.73)*	(0.86)	(0.29)	**(2.04)****	**(1.73)***	**(2.40)****	**(2.91)*****	**(3.83)*****
Eur	0.0049	0.0636	0.0080	0.0090	0.0211	0.0054	0.0043	0.0039
	(0.32)	(0.55)	(0.16)	(0.49)	(0.41)	(0.51)	(0.24)	(0.16)
Latin	0.0018	0.1392	0.0001	0.0126	0.0446	0.0108	0.0176	0.0472
	(0.09)	(0.94)	(0.00)	(0.53)	(0.67)	(0.79)	(0.75)	(1.52)
North	0.0124	0.1272	0.1495	0.0081	0.0508	0.0062	0.0055	0.0117
	(0.37)	(0.50)	(1.38)	(0.20)	(0.44)	(0.26)	(0.14)	(0.22)
Ocea	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
Col	0.0013	0.0031	-0.0184	0.0191	0.0114	0.0107	0.0219	0.0330
	(0.09)	(0.03)	(0.40)	(1.09)	(0.23)	(1.07)	(1.28)	(1.45)
Geo	0.0003	0.0053	0.0093	0.0005	0.0012	0.0005	0.0008	0.0014
	(1.10)	(0.26)	(1.07)	(0.16)	(0.13)	(0.26)	(0.24)	(0.32)
Positive Selection								
Inequ	0.0580	0.6174	**0.4152**	0.1067	0.2957	**0.0739**	**0.1298**	0.1209
	(1.02)	(1.42)	**(2.25)****	(1.52)	(1.51)	**(1.85)***	**(1.90)***	(1.33)
Inf	-0.0686	**-0.9648**	**-0.7179**	-0.0946	-0.3550	-0.0827	**-0.1582**	**-0.2707**
	(0.90)	**(1.66)***	**(2.90)*****	(1.01)	(1.35)	(1.54)	**(1.73)***	**(2.22)****
Open	0.0043	0.0146	**0.0146**	0.0039	0.0100	0.0025	**0.0059**	**0.0113**
	(1.63)	(0.73)	**(1.72)***	(1.22)	(1.11)	(1.37)	**(1.87)***	**(2.69)*****
Pol	-0.0001	-0.0006	**-0.0010**	-0.0001	-0.0002	0.0000	0.0001	**0.0005**
	(0.67)	(0.49)	**(1.89)***	(0.32)	(0.31)	(0.02)	(0.55)	**(1.80)***
Unemp	**0.1779**	0.6170	0.3867	0.1712	0.4448	**0.1055**	**0.2205**	**0.3644**
	(2.03)**	(0.92)	(1.36)	(1.58)	(1.48)	**(1.71)***	**(2.09)****	**(2.60)****

Interaction								
visa_emp	**-0.3929**	-1.4337	-0.7549	**-0.3961**	**-0.9895**	**-0.2323**	**-0.4792**	**-0.7622**
	(2.55)**	(1.22)	(1.51)	**(2.09)****	**(1.87)***	**(2.14)****	**(2.59)****	**(3.09)*****
Constant	**0.2512**	0.5101	**0.6925**	**0.3765**	0.2015	0.0791	**0.2139**	**0.4715**
	(2.94)***	(0.78)	**(2.50)****	**(3.57)*****	(0.69)	(1.31)	**(2.08)****	**(3.45)*****
Observations	112	112	112	112	112	112	112	112
R-squared	0.75	0.43	0.66	0.71	0.64	0.71	0.76	0.78

Z-statistics in parentheses. * significant at 10%;** significant at 5% level; *** significant at 1% level

The regression estimates for the income inequality measures that were calculated based on personal income are shown in Table 17. Personal median income, educational attainment, percentage of males, OECD membership, and the Asia dummy are all significant for almost all of the inequality measures. Income and income squared have alternating signs, indicating high inequality at very low and high levels of income for immigrant cohorts. The other variables have positive coefficients, suggesting that an increase in educational attainment or percentage of males leads to higher income inequality within each immigrant group. The visa*employment interaction variable (visa_emp) is significant with a negative coefficient for most of the inequality metrics. The OECD dummy is significant for some of the measures and has a positive sign, indicating that immigrant cohorts from OECD member countries have higher inequality. Geographical control variables are all insignificant. The only exception is the Asian continental dummy. The positive coefficient of the Asian dummy variable implies that immigrants from Asia have higher inequality compared to other groups. Positive selection variables are also insignificant for most of the cases.

Table 18: Robust Regression Results: Determinants of Income Inequality of Immigrant Groups in the U.S., Household Median Income

	rmd_h	cv_h	std_h	gini_h	theil_h	atk_h1	atk_h2	atk_h3
Income								
hincp_median	**-0.0067**	-0.0042	-0.0004	**-0.0088**	**-0.0081**	-0.0004	**-0.0021**	**-0.0057**
	(5.59)***	(0.68)	(0.11)	**(5.37)*****	**(3.12)*****	(0.65)	**(1.82)***	**(2.64)*****
hincp-squared	**3.98e-05**	1.45e-07	-1.94e-06	**5.22e-05**	**3.53e-05**	5.96e-07	9.87e-06	**2.99e-05**
	(4.19)***	(0.00)	(0.06)	**(4.04)*****	**(1.73)***	(0.12)	(1.08)	**(1.78)***
Immigrant Characteristics								
Schl	**0.014**	**0.064**	**0.042**	**0.0187**	**0.0344**	**0.0085**	**0.0147**	**0.0191**
	(4.56)***	**(4.13)*****	**(4.12)*****	**(4.49)*****	**(5.22)*****	**(5.22)*****	**(4.97)*****	**(3.51)*****
Yoep	**0.0018**	**0.007**	0.0023	**0.0022**	**0.0033**	**0.0008**	**0.0013**	0.0016
	(2.66)***	**(2.04)****	(1.01)	**(2.32)****	**(2.25)****	**(2.30)****	**(2.02)****	(1.31)
Eng	-0.0115	0.0004	0.0168	-0.0168	-0.0164	0.0027	-0.0017	-0.0221
	(1.27)	(0.01)	(0.56)	(1.37)	(0.84)	(0.56)	(0.19)	(1.38)
per_male	0.0271	**0.5659**	0.0111	0.0614	0.1724	**0.0457**	0.0233	0.0117
	(0.55)	**(2.26)****	(0.07)	(0.91)	(1.62)	**(1.74)***	(0.49)	(0.13)
per_visa	-0.0017	-0.2194	-0.0727	-0.0182	-0.0515	-0.0174	-0.0136	0.0234
	(0.04)	(1.09)	(0.55)	(0.33)	(0.60)	(0.82)	(0.36)	(0.33)
per_unemp	-0.1122	-1.4503	0.3759	-0.2077	-0.4905	-0.0644	-0.0993	-0.0839
	(0.40)	(1.03)	(0.41)	(0.55)	(0.82)	(0.44)	(0.37)	(0.17)
Economical Development								
Oecd	**0.0166**	0.074	0.0491	**0.0227**	**0.0402**	**0.0108**	**0.0168**	0.0234
	(1.75)*	(1.54)	(1.55)	**(1.75)***	**(1.96)***	**(2.13)****	**(1.84)***	(1.39)
Geographical								
Afr	0.0143	0.0414	0.0142	0.0245	0.0158	0.0049	0.0193	0.04
	(0.91)	(0.52)	(0.27)	(1.14)	(0.46)	(0.58)	(1.27)	(1.43)
Asia	0.019	0.0628	0.0782	**0.0343**	0.0463	0.0081	0.0226	**0.0541**
	(1.34)	(0.87)	(1.66)	**(1.77)***	(1.52)	(1.07)	(1.66)	**(2.15)****
Eur	0.009	0.0166	0.0061	0.0155	0.0076	0.0012	0.0071	0.0216
	(0.63)	(0.23)	(0.13)	(0.79)	(0.24)	(0.15)	(0.51)	(0.85)
Latin	0.0014	0.0353	-0.016	0.0104	-0.0011	0.001	0.0096	0.0352
	(0.08)	(0.40)	(0.27)	(0.43)	(0.03)	(0.11)	(0.57)	(1.12)
North	0.018	0.0291	0.0249	0.0285	0.0237	0.0075	0.018	0.0501
	(0.58)	(0.19)	(0.24)	(0.68)	(0.36)	(0.46)	(0.61)	(0.92)
Ocea	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
Col	-0.0091	-0.0127	-0.0043	-0.0096	-0.0226	-0.0039	-0.0034	-0.0085
	(0.69)	(0.19)	(0.10)	(0.54)	(0.80)	(0.55)	(0.27)	(0.36)
Geo	-0.0011	-0.0037	-0.0063	-0.002	-0.0055	-0.0004	-0.0012	-0.0014
	(0.43)	(0.29)	(0.76)	(0.58)	(1.02)	(0.32)	(0.48)	(0.31)
Positive Selection								
Inequ	-0.0128	-0.0566	0.112	-0.0204	-0.0546	-0.0087	-0.02	-0.058
	(0.25)	(0.22)	(0.65)	(0.29)	(0.49)	(0.32)	(0.40)	(0.63)
Inf	0.0254	-0.0076	-0.2628	-0.0039	-0.045	0.0093	-0.0168	-0.12
	(0.35)	(0.02)	(1.10)	(0.04)	(0.29)	(0.24)	(0.24)	(0.94)
Open	0.0011	-0.004	0.0091	0.0018	0.0038	0.0002	0.002	0.0069
	(0.48)	(0.33)	(1.15)	(0.57)	(0.75)	(0.13)	(0.88)	(1.64)
Pol	-0.0001	-0.0001	-0.0005	-0.0001	0.0000	-0.0001	-0.0001	-0.0001
	(1.00)	(0.08)	(1.11)	(0.60)	(0.14)	(0.71)	(0.61)	(0.38)
Unemp	-0.025	-0.1289	-0.0429	-0.036	-0.0785	-0.0157	-0.0229	-0.0257
	(1.07)	(1.09)	(0.55)	(1.13)	(1.56)	(1.27)	(1.02)	(0.62)

Interaction								
visa_emp	-0.0848	3.9361	-0.7976	0.1175	0.7943	0.1536	-0.0322	-0.4558
	(0.13)	(1.18)	(0.36)	(0.13)	(0.56)	(0.44)	(0.05)	(0.39)
Constant	**0.4183**	0.2433	**0.4651**	**0.5708**	0.3008	-0.0156	0.0908	**0.3173**
	(5.43)***	(0.62)	**(1.82)***	**(5.44)*****	(1.84)	(0.38)	(1.23)	**(2.32)****
Observations	112	112	112	112	112	112	112	112
R-squared	0.65	0.41	0.48	0.62	0.62	0.55	0.55	0.47

Z-statistics in parentheses. * significant at 10%;** significant at 5% level; *** significant at 1% level

Table 18 illustrates the robust regression estimates for inequality measures based on household income. Median household income of immigrant cohorts is a significant factor in explaining the variation in inequality. In addition, the number of years spent (Yoep) and educational attainment have positive and significant coefficients, suggesting that the income distribution of immigrant groups became more equal as they spent more time in the United States or obtained more formal education. One other robust explanatory variable for inequality is the Asian dummy. The coefficient for this variable is significant with a positive sign, implying that immigrants from Asia have more unequally distributed income.

Consequently, the determinants of income inequality among immigrant cohorts in the U.S. are somewhat similar to the determinants of income inequality in the host country. However, the unique characteristics of immigrants require additional exploration for distinct variables related not only to the national characteristics of immigrants but also to the relative performance of immigrants in terms of adaptation, assimilation, language barriers, etc. General results obtained from the regression analysis are as follows: first, median income and educational attainment are the significant factors determining income inequality of immigrant cohorts in the United States. Second, the percentage of males is an important factor of inequality, but only for personal income inequality metrics. Third, the number of years spent in the U.S. is an important factor only for household income inequality measures. Fourth, English proficiency, percentage of visa holders, percentage of unemployed immigrants, economic development, and geographical control variables, selection variables are not significant factors determining the income inequality of immigrants. Lastly, the models investigated generally explain a large portion of the variation in inequality among immigrant groups, with R^2 values ranging from 0.41 to 0.78.

7.2 Determinants of Income Inequality Change of Immigrants by Country of Origin

Appendix E shows the income inequality changes of immigrant cohorts over ten years. In order to maintain the statistical validity, countries with at least thirty immigrants in each of the sub-groups were selected. There are forty-five immigrant cohorts that satisfy this condition, and the scatter diagram of the income inequality changes is illustrated in Figures 18-19.

Figure 18: Change in Gini Coefficient of Immigrant Groups between 1996 and 2005/6, Personal Income

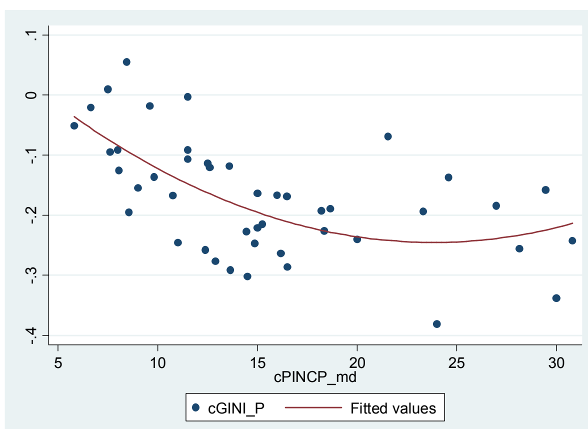
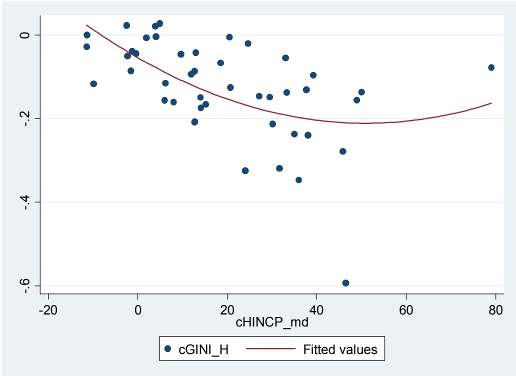


Figure 19: Change in Gini Coefficient of Immigrant Groups between 1996 and 2005/6, Household Income



Almost all of the differences in inequalities of immigrant cohorts are negative, suggesting that most of immigrant groups had an improvement in income inequality over the period of ten years.[20] This result is also robust to the type of income used, i.e. personal and household income. However, the change in personal inequality is higher than household income. The change in Gini coefficients based on personal and household income ranges between 0.0272 and -0.5935 and 0.0556 and -0.3810, respectively. The immigrant cohorts that have very low and very high changes in their income exhibit a smaller improvement in their income inequality. In contrast, immigrant cohorts that are clustered around the mean demonstrate a faster improvement. This relationship is displayed with convex lines in both figures. Figures 18-19 also indicate substantial variation in the inequality change among the immigrant groups.

[20] With an exception of few countries: For example, the Dominican Republic, Guatemala, and Israel experienced an increase in their Gini coefficient over the 10-year period studied. Table 19 shows the number of positive and negative changes in all 16 inequality measures.

Table 19: Direction of Changes in Income Inequality of Immigrant Cohorts between 1996 and 2005/6[*]								
	ΔRMD_P	ΔCV_P	ΔSTD_P	ΔGINI_P	ΔTHEIL_P	ΔATK_P1	ΔATK_P2	ΔATK_P3
+	1	4	7	2	3	2	2	2
-	44	41	38	43	42	43	43	43
	ΔRMD_H	ΔCV_H	ΔSTD_H	ΔGINI_H	ΔTHEIL_H	ΔATK_H1	ΔATK_H2	ΔATK_H3
+	5	6	11	3	6	8	5	5
-	40	39	34	42	39	37	40	40

[*]Positive change represents a worsening of income inequality, while negative change represents improvement in income distribution of immigrant groups. The number of immigrant groups studied is 45.

Table 19 shows the direction of change in inequality for the 45 immigrant cohorts. The results strongly suggest that a large fraction of cohorts exhibit improvements in equality in terms of both personal and household income. However, the number of cohorts with more equal distribution varies significantly. For example, 96% of immigrant cohorts have more equal distribution based on the Gini coefficient (GINI_P). But this percentage drops to 84% based on standard deviation (STD_P). The pairwise correlations between the sixteen dependent inequality measures are shown in Table 20. The correlation coefficient between the changes in inequality metrics varies greatly as well. For example, the standard deviation of logs based on household income (Δstd_h) and the Atkinson measure based on personal income, with an epsilon value of 0.75 (Δatk_p3), is only 0.002. Consequently, the factors determining the variance of one measure may not be the same for others.

Table 20: Pairwise Correlations between the Dependent Variables of Change in Inequality

	Personal Income							
	Δrmd_p	**Δcv_p**	**Δstd_p**	**Δgini_p**	**Δtheil_p**	**Δatk_p1**	**Δatk_p2**	**Δatk_p3**
Δrmd_p	1							
Δcv_p	0.7330	1						
Δstd_p	0.6149	0.3451	1					
Δgini_p	0.9641	0.8075	0.6225	1				
Δtheil_p	0.8901	0.9453	0.4773	0.9081	1			
Δatk_p1	0.9389	0.8943	0.5335	0.9440	0.9879	1		
Δatk_p2	0.9607	0.8061	0.5786	0.9640	0.9344	0.9769	1	
Δatk_p3	0.8728	0.6273	0.5708	0.9085	0.7621	0.8376	0.9280	1
	Household Income							
	Δrmd_h	**Δcv_h**	**Δstd_h**	**Δgini_h**	**Δtheil_h**	**Δatk_h1**	**Δatk_h2**	**Δatk_h3**
Δrmd_h	1							
Δcv_h	0.8827	1						
Δstd_h	0.6841	0.5465	1					
Δgini_h	0.9911	0.9058	0.6721	1				
Δtheil_h	0.9772	0.9414	0.6399	0.9873	1			
Δatk_h1	0.3990	0.586	0.5096	0.4024	0.4362	1		
Δatk_h2	0.8992	0.8957	0.7356	0.9109	0.9146	0.7192	1	
Δatk_h3	0.7528	0.7048	0.5592	0.7789	0.7723	0.4248	0.7996	1

Pairwise correlations between the explanatory and control variables are given in Appendix H. There is no evidence of a serious multicollinearity problem among the explanatory variables. Table 21 shows the model selection process for the determinants of income inequality change of immigrants in the United States. Model specifications for the first and last four regressions are exactly the same; however, the Gini coefficient based on personal income is the dependent variable for the first four regressions, while the last four use the Gini coefficient based on household income. In these regressions, the robust regression method is employed where heteroscedasticity in dependent and independent variables are jointly controlled for.

Table 21: Model Selection for the Determinants of Rate of Inequality Change of Immigrants

	Personal Income				Household Income			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Distance								
distance(gini)	**0.6762**	**0.4427**	**0.4764**	**0.8307**	**0.9123**	**0.8763**	**0.9449**	**0.9419**
	(4.31)***	**(2.94)*****	**(3.62)*****	**(6.23)*****	**(22.60)*****	**(17.72)*****	**(14.66)*****	**(13.13)*****
Income								
ΔMedian Income		**-0.0219**	**-0.0206**	**-0.0150**		-0.0008	-0.0004	-0.0018
		(2.62)**	**(2.33)****	**(1.86)***		(0.95)	(0.47)	(1.56)
ΔMedian Income-squared		**0.0004**	**0.0004**	0.0002		0.0000	0.0000	0.0000
		(1.91)*	**(1.71)***	(1.02)		(0.90)	(0.61)	(1.34)
Immigrant Characteristics								
Δschl			-0.0055	-0.0054			0.0020	0.0065
			(0.32)	(0.29)			(0.23)	(0.72)
Δage			-0.0013	0.0015			**0.0057**	**0.0056**
			(0.44)	(0.67)			**(2.34)****	**(1.91)***
Δper_unemp			**0.5730**	0.3522			-0.0945	0.0338
			(1.80)*	(1.34)			(0.35)	(0.12)
Geographical Dummies								
Latin				**-0.1852**				**-0.0912**
				(6.29)***				**(3.81)*****
Asia				**-0.0833**				**-0.0431**
				(2.57)**				**(2.18)****
Eur				**-0.1315**				-0.0431
				(4.28)***				(1.48)
Afr				**-0.1143**				**-0.0458**
				(3.23)***				**(2.44)****
North				Dropped				Dropped
Ocea				0.0049				**-0.0826**
				(0.18)				**(10.14)*****
Constant	**-0.0719**	**0.1068**	**0.1220**	**0.2508**	**0.0676**	**0.0684**	**0.0506**	**0.1322**
	(2.68)**	**(1.79)***	**(1.83)***	**(3.62)*****	**(5.63)*****	**(5.63)*****	**(2.76)*****	**(5.38)*****
Observations	45	45	45	45	45	45	45	45
R-squared	0.28	0.47	0.52	0.70	0.85	0.86	0.88	0.91

Robust t-statistics in parentheses for OLS regression results. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Model 1 in Table 21 uses a single explanatory variable, the *distance variable* defined in Section 6.2, while it excludes all the income, demographic characteristics, and geographical controls of the immigrant cohorts. The distance variable is statistically significant and explains 28% of the variation in the change in personal income inequality of immigrants in the U.S. The positive coefficient of the distance variable suggests that as the distance between the initial inequality of immigrants and the U.S. income inequality increases, a faster convergence is observed. This is consistent with the earlier analysis presented in Section 6.2, that the inequality of immigrant cohorts begin to resemble the income inequality of natives as time passes, and the pace of change depends on the difference between the initial distribution and the host country's distribution. Model 2 includes the change in income and squared income to the specification. Both of these variables are significant with alternating signs, suggesting a U-type relationship between the change in income and inequality convergence. In other words, immigrant cohorts that have mediocre improvement in their income experience slower convergence to U.S. inequality. On the other hand, cohorts that assimilate faster in terms of income exhibit faster inequality convergence. This finding is consistent with the scatter diagrams illustrated in Figures 18-19.

Changes in immigrant characteristics are added to change income and distance variables in Model 3. The results indicate that none of the immigrant characteristics are helpful in explaining the variation in personal income inequality convergence, except the *change in unemployment rate*. A positive and statistically significant *change in the unemployment rate* coefficient suggests that immigrant cohorts that have a lower unemployment rate over time exhibit faster convergence of personal income inequality. Finally, Model 4 includes additional geographical controls that considerably increase the explanatory power of the regression. Most of these geographical controls are significant and suggest that personal income inequality convergence among Latin American, African, and Asian immigrant cohorts is faster than North American immigrants, while immigrants from Oceania have a convergence that is virtually the same as North American immigrants.

Models 5-8 employ the same methodology and specifications as in Models 1-4, but this time household income inequality is used as the dependent variable. In Model 5, the distance variable is still significant, and the magnitude is far higher than with personal income, suggesting the initial point is more important for household income inequality than personal income inequality. In Model 6, changes in income and its squared are added to the model specification; however, income variables are not significant in explaining the variation which is mostly due the presence of the distance variable absorbing much of the variation.

The immigrant characteristics are added in Model 7. Only the *change in age* is a significant factor in determining the inequality convergence of immigrants in the United States. A positive coefficient of the variable suggests that immigrant cohorts that have a higher increase in the average age exhibit faster convergence in their household income inequality. In other words, immigrant cohorts that have fewer new incoming immigrants exhibit a faster convergence. Finally, Model 8 adds geographical controls to the estimation, and the results are similar to the ones presented in Model 4. The R-square of the Models 5-8 is between 0.85 and 0.91, and they are much higher than those calculated with personal income.

The same specification used in Model 4 and Model 8, with a robust regression method, was applied to the remaining inequality measures, and the estimates are shown in Tables 22-23. The results from these other inequality metrics will be used as a robustness check of the findings in Table 21. The estimates for the personal income inequality measures are given in Table 22, while Table 23 shows the estimation results for the change in household income inequality metrics.

Table 22: Regression Results: Determinants of Rate of Inequality Change of Immigrant Groups in the U.S., Personal Income

	Δrmd_p	Δcv_p	Δstd_p	Δgini_p	Δtheil_p	Δatk_p1	Δatk_p2	Δatk_p3
Distance								
distance(y_i)	**0.6931**	**1.0171**	**-0.0268**	**0.8307**	**0.9260**	**0.8688**	**0.8024**	**0.7665**
	(5.46)* **	**(10.87)*** **	**(0.12)**	**(6.23)*** **	**(11.17)*** **	**(9.16)*** **	**(6.67)*** **	**(4.02)*** **
Income								
Δpincp	**-0.0160**	**-0.0710**	-0.0389	**-0.0150**	**-0.0457**	**-0.0113**	**-0.0227**	**-0.0308**
	(2.44) **	**(2.13)** **	(1.06)	**(1.86)***	**(2.27)** **	**(2.42)** **	**(2.49)** **	**(2.09)** **
Δpincp-squared	0.0003	0.0013	0.0002	0.0002	0.0008	**0.0002**	**0.0004**	0.0006
	(1.46)	(1.61)	(0.20)	(1.02)	(1.65)	**(1.72)***	**(1.73)***	(1.43)
Immigrant Characteristics								
Δschl	-0.0001	-0.0074	-0.0300	-0.0054	0.0021	0.0005	0.0004	-0.0045
	(0.01)	(0.11)	(0.53)	(0.29)	(0.05)	(0.05)	(0.02)	(0.11)
Δage	0.0006	0.0137	-0.0077	0.0015	0.0027	0.0001	-0.0010	-0.0031
	(0.33)	(1.23)	(0.82)	(0.67)	(0.49)	(0.11)	(0.43)	(0.80)
Δper_unemp	0.3663	-0.7416	-2.5414	0.3522	0.2361	0.1509	**0.5268**	**1.1567**
	(1.56)	(0.62)	(1.62)	(1.34)	(0.34)	(0.96)	**(1.79)***	**(2.58)** **
Geographical								
Latin	**-0.1685**	**-0.5480**	**-0.5882**	**-0.1852**	**-0.3793**	**-0.0900**	**-0.1650**	**-0.1900**
	(7.02)* **	**(4.54)*** **	**(6.57)*** **	**(6.29)*** **	**(5.40)*** **	**(5.54)*** **	**(5.21)*** **	**(3.81)*** **
Asia	**-0.0832**	**-0.2606**	**-0.4568**	**-0.0833**	**-0.1550**	**-0.0390**	**-0.0751**	-0.0797
	(2.78)* **	**(2.57)** **	**(3.95)*** **	**(2.57)** **	**(2.18)** **	**(2.06)** **	**(1.78)***	(1.18)
Eur	**-0.1026**	**-0.4558**	**-0.3822**	**-0.1315**	**-0.2694**	**-0.0644**	**-0.1226**	**-0.1681**
	(4.38)* **	**(4.11)*** **	**(3.03)*** **	**(4.28)*** **	**(4.13)*** **	**(3.96)*** **	**(3.43)*** **	**(2.52)** **
Afr	**-0.0971**	**-0.5268**	**-0.6776**	**-0.1143**	**-0.2831**	**-0.0622**	**-0.1021**	-0.1017
	(3.18)* **	**(3.90)*** **	**(4.60)*** **	**(3.23)*** **	**(3.21)*** **	**(3.00)*** **	**(2.45)** **	(1.58)
North	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
Ocea	-0.0132	0.0330	-0.0041	0.0049	-0.0017	-0.0037	-0.0073	0.0088
	(0.59)	(0.37)	(0.05)	(0.18)	(0.03)	(0.25)	(0.25)	(0.20)
Constant	**0.2438**	**0.8300**	**0.7692**	**0.2508**	**0.6441**	**-0.5014**	**0.2709**	**0.7337**
	(4.12)* **	**(2.50)** **	**(2.43)** **	**(3.62)*** **	**(3.40)*** **	**(5.36)*** **	**(3.42)*** **	**(5.90)*** **
Observations	45	45	45	45	45	45	45	45
R-squared	0.75	0.84	0.55	0.7	0.83	0.8	0.74	0.59

Absolute value of T-statistics in parentheses. * significant at 1% level; ** significant at 5% level; *** significant at 1% level

In Table 22, the dependent variable is one of the eight personal income inequality metrics, and the explanatory variables are the distance variable, changes in income, income squared, immigrant group characteristics, and geographical controls. The estimation results indicate that the distance variable and income are the two robust factors explaining the variation in the inequality change of immigrant cohorts. The distance variable has a significant and positive coefficient, suggesting that if the initial inequality of an immigrant cohort is very different than U.S. inequality, then the change in inequality is faster. The second robust factor is the change in median income. Any increase in the change in median income speeds up the convergence in income inequality of immigrant cohorts. Although, weak support of the U-shape relationship is observed in Table 22 with a significant positive income-squared term, this U-shape relationship is not robust to different inequality metrics. Moreover, the evidence for unemployment is not robust to different personal inequality metrics. However, geographical controls for the immigrant cohorts are statistically significant.

Table 23: Regression Results: Determinants of Rate of Inequality Change of Immigrant Groups in the U.S., Household Income

	Δrmd_h	Δcv_h	Δstd_h	Δgini_h	Δtheil_h	Δatk_h1	Δatk_h2	Δatk_h3
Distance								
distance(y_i)	**0.9976**	**0.8797**	**0.9785**	**0.9419**	**0.9541**	**0.8698**	**0.9135**	**0.8956**
	(12.11)*	**(9.89)***	**(7.11)***	**(13.13)***	**(15.47)***	**(8.02)***	**(9.17)***	**(6.93)***
Income								
Δhincp	-0.0011	-0.0056	**-0.0054**	-0.0018	-0.0024	-0.0003	-0.0008	-0.0006
	(1.35)	(1.63)	**(1.97)***	(1.56)	(1.43)	(1.05)	(1.08)	(0.25)
Δhincp-squared	0.0000	0.0001	**0.0001**	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.55)	(1.23)	**(2.17)****	(1.34)	(1.16)	(1.43)	(1.06)	(0.57)
Immigrant Characteristics								
Δschl	0.0007	0.0244	-0.0057	0.0065	0.0079	0.0014	0.0031	-0.0053
	(0.10)	(0.98)	(0.10)	(0.72)	(0.56)	(0.33)	(0.39)	(0.28)
Δage	**0.0045**	0.0109	**0.0176**	**0.0056**	**0.0084**	0.0015	**0.0037**	0.0036
	(2.04)**	(1.45)	**(3.06)***	**(1.91)***	**(1.85)***	(1.56)	**(1.73)***	(0.62)
Δper_unemp	0.0176	-0.6517	1.0928	0.0338	-0.1265	-0.0212	0.0426	1.4124
	(0.08)	(0.75)	(1.81)*	(0.12)	(0.30)	(0.23)	(0.22)	(1.59)
Geographical								
Latin	**-0.0576**	**-0.1766**	**-0.3688**	**-0.0912**	**-0.1289**	**-0.0236**	**-0.0610**	**-0.1008**
	(3.18)*	**(2.18)****	**(3.97)***	**(3.81)***	**(3.25)***	**(2.24)****	**(3.09)***	**(2.16)****
Asia	-0.0250	-0.0812	**-0.2060**	**-0.0431**	**-0.0621**	-0.0082	-0.0265	-0.0545
	(1.64)	(1.32)	**(3.10)***	**(2.18)****	**(2.00)****	(0.96)	(1.64)	(1.34)
Eur	-0.0271	-0.0372	-0.1515	-0.0431	-0.0527	-0.0123	-0.0304	-0.0685
	(1.26)	(0.55)	(1.34)	(1.48)	(1.23)	(1.18)	(1.34)	(1.29)
Afr	**-0.0231**	-0.1155	**-0.2378**	**-0.0458**	**-0.0719**	**-0.0137**	**-0.0321**	0.1333
	(1.67)*	(1.39)	**(4.22)***	**(2.44)****	**(2.30)****	**(1.71)***	**(2.29)****	(1.10)
North	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
Ocea	**-0.0419**	**-0.1447**	**-0.2740**	**-0.0826**	**-0.1127**	**-0.0190**	**-0.0587**	**-0.1479**
	(5.99)*	**(3.70)***	**(8.28)***	**(10.14)***	**(7.71)***	**(3.98)***	**(7.54)***	**(6.48)***
Constant	**0.1683**	**0.5413**	**0.5871**	**0.1322**	**-0.6339**	**-0.3485**	**0.0892**	**0.0543**
	(8.28)*	**(5.56)***	**(4.72)***	**(5.38)***	**(11.33)***	**(8.43)***	**(4.25)***	**(1.12)**
Observations	45	45	45	45	45	45	45	45
R-squared	0.90	0.85	0.72	0.91	0.93	0.80	0.86	0.76

Absolute value of T-statistics in parentheses. * significant at 1% level; ** significant at 5% level; *** significant at 1% level

In Table 23, the dependent variable is change in one of the eight household income inequality metrics. The most visible difference between these estimates and earlier ones is the fact that these explanatory variables explain a much higher percentage of the variation in inequality changes compared to the estimates based on personal income. The distance variable is the most important factor that is consistently significant. This variable also explains a large percentage of the variation in the inequality convergences of immigrant cohorts. The change in the median income variable, on the other hand, is not significant in any of the metrics tested except the standard deviation of logs. This finding is also consistent with the results illustrated in Models 5-8 in Table 21. Finally, change in age for the immigrant cohorts is significant for most of the metrics tested. The variable has a positive coefficient suggesting that immigrant cohorts that are getting older faster have a faster convergence to the U.S. distribution. Although this finding seems counterintuitive at first, it underlines an important aspect of immigration flows.

The ACS survey indicated that the immigrant groups become older on average over the 10 year period. The aging dynamics can be explained with stricter immigration policies implemented by the U.S. Immigrant groups that get older faster over time are found to have a faster convergence to the distribution of the host country. A crucial question is if time is passing at the same rate for all groups, how is it possible for some groups to have different paces of aging? The answer comes from the fact that immigrant groups exhibit different demographic dynamics over time. Some immigrants come to the U.S. for a short period of time, i.e. temporary employment, education, while others abandon the ties with the source country and start a new life in the host country. The ones that abandon their country of origins exhibit faster assimilation, i.e. convergence to the U.S. income distribution, while the cohorts that have rapid turnaround among the immigrants show a slower pace of convergence.

Geographical dummies also play a significant role in the inequality change of immigrant groups. Changes in most of the inequality measures have several significant coefficients for the geographical dummies. The coefficients of the geographical variables also suggest the pace of inequality convergence among the world regions. For example, Latin American immigrants have the fastest rate of inequality convergence compared to other groups.

7.3 The Counterfactual Effects of Immigrants on the Income Distribution of United States

Appendix F shows the distributional effects of each immigrant group on income inequality in the United States. If the difference between U.S. income inequality with immigrants and without immigrants is positive, then this corresponds to the disequalizing effect of an immigrant cohort from country *i*. In contrast, if the difference is negative, then immigrants play an equalizing role in United States. For example, income is more equally distributed in the absence of Afghan immigrants. This can be easily observed from the difference between the actual U.S. Gini coefficient and the U.S. Gini coefficient in the absence of Afghan immigrants, which is equal to 0.0000074.

There are three possible types of effects of immigrant cohorts on income distribution. The first is the unambiguous equalizing role of immigrant groups in the U.S. income distribution. This unambiguous role stems from the fact that the inequality difference is negative for almost all of the metrics employed. Azerbaijan, Barbados, and Bosnia-Herzegovina are the immigrant cohorts for this type. The second group of immigrants are those that have an ambiguous effect on the income distribution in the U.S. For these immigrant groups, for some inequality measures, the difference is positive, and for others, the difference is negative. Most of the countries fall into this classification, including but not limited to Afghanistan, Cuba, Greece, Mexico, and Vietnam.

The last group of countries includes those that have an unambiguous disequalizing effect on the U.S. income distribution. For these countries, the difference is always positive no matter what inequality metric is used. Some of these countries are Australia, Belgium, Canada, Taiwan, and Zimbabwe.

Figure 20: Size Weighted Effects of Immigrant Groups in the U.S., Personal Income

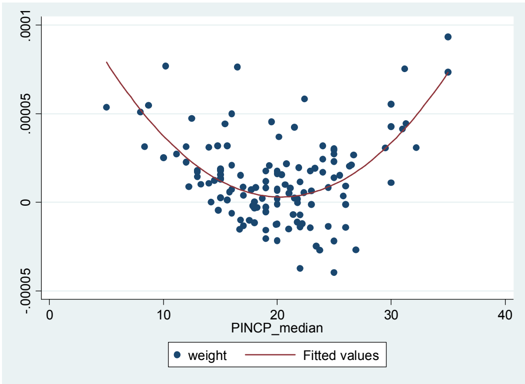
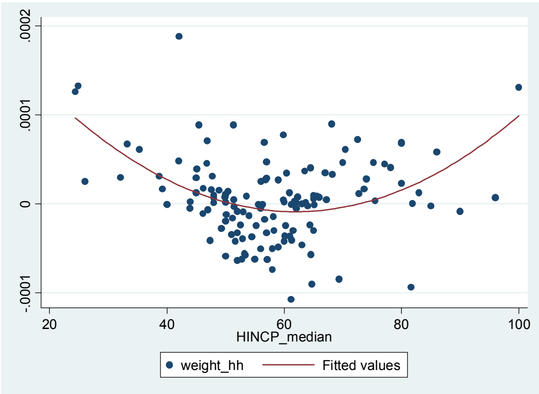


Figure 21: Size Weighted Effects of Immigrant Groups in the U.S., Household Income



Figures 20-21 show the effect of each immigrant group on the U.S. income distribution using both personal and household Gini coefficients. The counterfactual effects of each of these cohorts are size adjusted. The figures suggest that some cohorts have an equalizing effect (i.e. counterfactual effect is below zero mark), while some have a disequalizing effect (i.e.

counterfactual effect is above zero mark), and finally some have no effect on income inequality (i.e. counterfactual effect is zero) in the United States. If immigrant cohorts have such distinct patterns of counterfactual effects, then what determines the direction of their effects? Namely, why do some countries have equalizing distributional effects while others have disequalizing effects?

Table 24: Model Selection for the Determinants of the Counterfactual Effects of Immigrant Cohorts on the U.S. Inequality, Personal Income

	Ordinary Least Squares				Robust Regression			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Income								
pincp_median	**-0.01492**	**-0.01093**	**-0.01474**	**-0.00948**	**-0.00363**	**-0.00307**	**-0.00624**	**-0.00565**
	(2.84)* **	**(2.27)** **	**(2.51)** **	**(1.80)**	**(3.56)** **	**(2.61)** **	**(3.26)** **	**(2.68)** **
pincp_squared	**0.00034**	**0.00026**	**0.00033**	**0.00024**	**0.00008**	**0.00006**	**0.00015**	**0.00013**
	(2.60) **	**(2.12)** **	**(2.21)** **	**(1.70)***	**(3.25)** **	**(2.33)** **	**(3.29)** **	**(2.75)** **
Immigrant Characteristics								
Schl	**0.01683**	**0.01951**	**0.02160**	**0.02376**	**0.00237**	**0.00277**	**0.00810**	**0.00987**
	(3.71)* **	**(2.87)** **	**(3.41)** **	**(3.30)** **	**(2.24)** **	**(2.11)** **	**(3.70)** **	**(3.80)** **
Yoep	0.00082	0.00107	0.00070	0.00082	-0.00007	0.00004	0.00017	0.00017
	(0.55)	(0.92)	(0.38)	(0.63)	(0.29)	(0.13)	(0.31)	(0.31)
Eng	0.00824	0.01098	0.01971	0.03191	-0.00214	0.00115	0.00431	0.01218
	(0.31)	(0.43)	(0.60)	(1.14)	(0.67)	(0.29)	(0.60)	(1.49)
Per_male	0.21902	0.14223	0.35622	0.16414	0.00168	-0.00195	0.00616	0.01073
	(1.48)	(1.49)	(1.66)	(1.41)	(0.09)	(0.09)	(0.16)	(0.25)
per_visa	0.05487	0.00875	0.07307	-0.02959	-0.02099	-0.01972	-0.02189	-0.04017
	(0.61)	(0.15)	(0.63)	(0.39)	(1.52)	(1.19)	(0.77)	(1.22)
per_unemp	0.32599	-0.03631	0.50637	-0.18313	**-0.20942**	-0.18338	-0.18106	-0.23651
	(0.61)	(0.11)	(0.76)	(0.48)	**(1.86)***	(1.46)	(0.86)	(1.04)
Economic Development								
Oecd	0.01737	0.01993	0.01534	0.01635	**0.00845**	**0.00894**	0.00060	-0.00447
	(0.77)	(0.76)	(0.57)	(0.49)	**(2.44)** **	**(2.06)***	(0.09)	(0.56)
Geographical								
Afr		-0.03550		-0.03916		0.00031		-0.00531
		(0.90)		(0.71)		(0.05)		(0.39)
Asia		-0.02812		-0.02144		-0.00028		-0.00426
		(0.59)		(0.39)		(0.04)		(0.35)
Eur		-0.04498		-0.06176		-0.00386		-0.01543
		(0.88)		(0.96)		(0.62)		(1.28)
Latin		-0.04258		-0.04852		-0.00496		-0.01456
		(1.15)		(0.93)		(0.84)		(1.17)
North		-0.09258		-0.57805		Dropped		**-0.66129**
		(1.06)		(1.05)				**(9.39)** **
Ocea		Dropped		Dropped		Dropped		Dropped
Col		-0.21248		-0.18732		**0.02914**		0.02339
		(1.27)		(1.22)		**(3.14)** **		(1.50)
Neig		**0.38369**		0.82686		Dropped		**0.77341**

		(1.69)*		(1.35)				**(10.50)***
Positive Selection								
Inequ			-0.13354	-0.10273			0.03325	0.01931
			(0.86)	(0.73)			(0.83)	(0.44)
Inf			0.00001	0.00000			-0.06322	-0.09527
			(0.40)	(0.04)			(1.14)	(1.62)
Open			0.00275	-0.00250			-0.00053	-0.00015
			(0.86)	(0.75)			(0.28)	(0.08)
Pol			0.00023	0.00041			0.00002	0.00019
			(0.80)	(1.14)			(0.15)	(1.50)
Unemp			-0.01309	0.02324			**0.03169**	0.02285
			(0.30)	(0.59)			**(1.76)***	(1.17)
Interaction								
visa_emp	-0.62713	0.18303	-0.81326	0.49968	0.30248	0.26249	0.08040	0.28449
	(0.78)	(0.22)	(0.79)	(0.44)	(1.26)	(0.95)	(0.17)	(0.53)
Size	**0.00002**	**0.00002**	**0.00002**	0.00001	**0.00001**	**0.00001**	**0.00001**	**0.00001**
	(7.63)**	**(6.04)****	**(7.73)****	(1.25)	**(19.70)***	**(13.77)***	**(11.55)***	**(8.95)****
Constant	-0.19238	-0.17617	-0.29891	-0.23350	0.03121	0.01825	-0.03137	-0.05479
	(1.02)	(1.37)	(1.34)	(1.49)	(1.20)	(0.63)	(0.56)	(0.91)
Observations	133	133	113	113	132	129	111	111
R-squared	0.76	0.82	0.77	0.84	0.80	0.74	0.68	0.98
White's Test	127.88	132.73	113	113	-	-	-	-
(P-Value)	0.01	0.20	0.48	0.48				

Dependent variable: The counterfactual effect of immigrant cohorts on Gini Coefficient based on personal income (e[gini_p]). Robust t-statistics in parentheses for OLS estimates. * significant at 10% level; ** significant at 5% level; *** significant at 1%

As shown in Table 24, Models 1-4 utilize OLS estimation while Models 5-8 use robust regression analysis. The dependent variable is the personal and household Gini coefficient in respective sections of the table. Robust regression explains a higher percentage of variation in the dependent variable. The results indicate that the *size* of the immigrant groups is the most important factor determining the distributional effects. However, *personal income* and *schooling* are also critical factors for the counterfactual effects of immigrant cohorts. The coefficient of personal income suggests a U-shape relationship with the counterfactual effects. The results in Figures 20-21 and Table 24 suggest that immigrant cohorts with a very low and high income generally have a disequalizing impact on the distribution, while the cohorts at the center of the income distribution have mixed effects on the U.S. distribution. Finally, immigrant cohorts that have higher education have a greater impact on the U.S. income distribution.

Table 25: Model Selection for the Determinants of the Counterfactual Effects of Immigrant Cohorts on the U.S. Inequality, Household Income

	Ordinary Least Squares				Robust Regression			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Income								
hincp_median	-0.00287	-0.00225	-0.00307	-0.00274	-0.00113	-0.00144	-0.00340	-0.00351
	(1.41)	(1.06)	(0.99)	(0.96)	(2.90)**	(3.56)***	(4.34)***	(4.82)***
hincp_squared	0.00001	0.00001	0.00001	0.00002	0.00001	0.00001	0.00003	0.00003
	(0.68)	(0.56)	(0.50)	(0.71)	(2.16)**	(3.03)***	(4.49)***	(5.02)***
Immigrant								
Schl	0.01591	0.02137	0.01716	0.02240	0.00209	0.00334	0.00816	0.00808
	(3.35)**	(3.02)***	(3.15)**	(3.37)**	(2.19)**	(3.03)***	(4.56)***	(4.31)***
Yoep	0.00157	0.00172	0.00220	0.00185	0.00000	0.00030	-0.00006	-0.00005
	(1.27)	(1.58)	(1.43)	(1.36)	(0.01)	(1.22)	(0.13)	(0.11)
Eng	0.01746	0.03375	0.01640	0.03570	-0.00217	-0.00494	-0.00506	-0.00144
	(0.77)	(1.57)	(0.66)	(1.61)	(0.83)	(1.58)	(0.93)	(0.26)
per_male	0.14885	0.07414	0.22186	0.07394	0.01044	0.02114	0.04708	0.04175
	(1.12)	(0.95)	(1.14)	(0.78)	(0.64)	(1.19)	(1.51)	(1.38)
per_visa	0.02758	-0.05464	0.07102	-0.08834	-0.03540	-0.04072	-0.07057	-0.07540
	(1.31)	(1.14)	(0.58)	(1.42)	(2.91)**	(2.93)***	(3.00)***	(3.15)***
per_unemp	0.30514	-0.13196	0.41563	-0.40132	-0.23651	-0.19610	-0.29236	-0.30565
	-0.53	-0.49	-0.59	-1.23	(2.34)**	(1.86)*	(1.68)*	(1.83)*
Economic Development								
Oecd	0.03508	0.03987	0.03015	0.04088	0.01422	0.01259	0.00279	0.00376
	(1.70)*	(1.89)*	(1.41)	(1.68)*	(4.77)**	(3.56)***	(0.50)	(0.66)
Geographical								
Afr		-0.03665		-0.03946		0.00007		-0.21934
		(1.05)		(0.90)		(0.01)		(11.33)**
Asia		-0.05602		-0.05399		0.00425		-0.21083
		(1.31)		(1.16)		(0.82)		(11.15)**
Eur		-0.06479		-0.07251		-0.00306		-0.22149
		(1.40)		(1.32)		(0.59)		(11.76)**
Latin		-0.04551		-0.03247		-0.00252		-0.22244
		(1.33)		(1.73)		(0.52)		(11.88)**
North		-0.09973		-0.51432		Dropped		Dropped
		(1.37)		(1.44)				
Ocea		Dropped		Dropped		Dropped		-0.20906
								(11.33)**
Col		-0.17470		-0.15043		0.06461		0.04858
		(1.17)		(1.14)		(8.40)***		(4.32)***
Neig		0.46497		0.84854		Dropped		Dropped
		(2.40)**		(2.00)**				
Positive Selection								
Inequ			-0.20845	-0.20797			0.00230	0.01533
			(1.49)1	(1.67)			(0.07)	(0.49)
Inf			0.00001	0.00000			-0.00389	-0.02219
			(0.39)	(0.21)			(0.09)	(0.52)
Open			0.00058	-0.00264			-0.00011	-0.00052
			(0.15)	(0.99)			(0.07)	(0.37)
Pol			-0.00014	-0.00013			0.00008	0.00022
			(0.55)	(0.35)			(0.98)	(2.56)***
Unemp			0.00409	0.03438			0.00786	0.01315
			(0.09)	(0.96)			(0.54)	(0.93)
Interaction								
visa_emp	-0.34396	0.46717	-0.37927	1.08204	0.42234	0.44121	0.51468	0.64057
	(0.36)	(0.72)	(0.32)	(1.16)	(1.94)*	(1.90)*	(1.27)	(1.63)
Size	0.00000	0.00000	0.00000	-0.00001	0.00000	-0.00001	-0.00001	-0.00001
	(0.86)	(2.66)***	(0.78)	(1.81)*	(7.01)**	(32.21)**	(15.74)**	(14.16)**
Constant	-0.20228	-0.17932	-0.18107	-0.07427	0.03592	0.02880	0.03406	0.23747
	(0.98)	(1.23)	(0.84)	(0.55)	(1.56)	(1.20)	(0.69)	(4.74)***

Observations	133	133	113	113	132	129	111	110
R-squared	0.15	0.44	0.19	0.50	0.53	0.93	0.82	0.89
White's Test	124.02	132.64	113.00	113	-	-	-	-
(P-Value)	0.00	0.20	0.46	0.48				

Dependent variable: The counterfactual effect of immigrant cohorts on Gini Coefficient based on household income (e[gini_h]). Robust t-statistics in parentheses for OLS estimates. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

The results are mostly the same based on the household income shown in Table 25. However, OLS seems to perform poorly in picking up the effect of size and income sufficiently, mostly due to outliers in the data. Robust regression captures the effects of size and income in all the model specifications, as illustrated in Models 5-8. Similar to the personal income, the counterfactual effects of immigrant cohorts depends on household income level, and the relationship is U-shaped. Once the size is controlled for, immigrant cohorts with very high and low household incomes generally have a higher impact on U.S. inequality, and this impact is generally disequalizing. In contrast, the ones in the middle of the income distribution have mixed effects on the distribution. In other words, some of these cohorts have equalizing and some of them have a disequalizing effect on U.S. income distribution, and a conclusive inference cannot be made. Finally, the effects of immigrant cohorts on U.S. household income inequality also depend on the percentage of visa holders and the unemployment rate within the cohort. Immigrant cohorts that have a high level of visa holders and a high unemployment rate have a smaller impact on the U.S. income distribution.

Table 26: Robust Regression Results: Determinants of the Counterfactual Effects of Immigrant Groups on the U.S. Inequality, Personal Income

	e[rmd_p]	e[cv_p]	e[std_p]	e[gini_p]	e[theil_p]	e[atk_p1]	e[atk_p2]	e[atk_p3]
Income								
Pincp	**-0.00486**	-0.01381	**-0.00945**	**-0.00565**	-0.00562	-0.00140	**-0.00572**	**-0.00533**
	(3.02)***	(1.55)	**(1.97)****	**(2.68)*****	(1.27)	(1.38)	**(2.80)*****	**(1.92)***
Pincp-squared	**0.00011**	0.00020	**0.00019**	**0.00013**	0.00008	0.00002	**0.00013**	**0.00014**
	(2.97)***	(0.97)	**(1.72)***	**(2.75)*****	(0.79)	(0.80)	**(2.82)*****	**(2.21)****
Immigrant Characteristics								
Schl	**0.00818**	0.01474	**0.02493**	**0.00987**	**0.01588**	**0.00223**	**0.00425**	**0.00654**
	(4.13)***	(1.35)	**(4.24)*****	**(3.80)*****	**(2.92)*****	**(1.79)***	**(1.69)***	**(1.91)***
Yoep	0.00036	0.00357	-0.00043	0.00017	0.00049	0.00009	-0.00009	-0.00039
	(0.83)	(1.49)	(0.34)	(0.31)	(0.42)	(0.32)	(0.16)	(0.52)
Eng	0.00998	0.04073	-0.02526	0.01218	0.02809	0.00342	0.00615	0.01166
	(1.60)	(1.18)	(1.36)	(1.49)	(1.64)	(0.87)	(0.78)	(1.08)
per_male	0.00349	0.17087	0.02157	0.01073	0.06029	-0.00033	-0.01854	0.01502
	(0.11)	(0.94)	(0.22)	(0.25)	(0.67)	(0.02)	(0.44)	(0.26)
per_visa	-0.01574	0.01532	0.01353	-0.04017	-0.06157	0.00515	0.00872	0.01538
	(0.63)	(0.11)	(0.18)	(1.22)	(0.89)	(0.33)	(0.27)	(0.35)
per_unemp	-0.13424	-0.51389	0.27538	-0.23651	-0.47263	-0.03491	-0.04369	0.00972
	(0.77)	(0.53)	(0.53)	(1.04)	(0.99)	(0.32)	(0.20)	(0.03)
Economic Development								
Oecd	-0.00167	0.04071	-0.00928	-0.00447	0.01481	0.00385	-0.00539	-0.01251
	(0.27)	(1.21)	(0.51)	(0.56)	(0.88)	(1.00)	(0.69)	(1.18)
Geographical								
Afr	-0.00510	-0.03381	0.00188	-0.00531	-0.02752	-0.00322	0.00712	0.01203
	(0.49)	(0.59)	(0.06)	(0.39)	(0.97)	(0.50)	(0.54)	(0.67)
Asia	-0.00727	-0.05140	0.00147	-0.00426	-0.01989	-0.00295	0.00568	0.01501
	(0.79)	(1.02)	(0.05)	(0.35)	(0.79)	(0.51)	(0.49)	(0.95)
Eur	-0.01003	-0.03994	-0.00655	-0.01543	-0.03644	-0.00284	0.00007	0.00170
	(1.09)	(0.79)	(0.24)	(1.28)	(1.45)	(0.49)	(0.01)	(0.11)
Latin	-0.00809	-0.06096	-0.02106	-0.01456	**-0.04553**	-0.00702	-0.00433	0.01453
	(0.85)	(1.16)	(0.75)	(1.17)	**(1.75)***	(1.18)	(0.36)	(0.89)
Ocea	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
North	**-0.61261**	**-4.22978**	**5.92153**	**-0.66129**	**-2.06413**	**-0.68643**	**-1.73044**	**-3.97164**
	(11.40)***	**(14.24)*****	**(37.08)*****	**(9.39)*****	**(13.99)*****	**(20.30)*****	**(25.36)*****	**(42.76)*****
Col	0.01782	**0.18906**	-0.02634	0.02339	**0.06587**	**0.01679**	0.02358	0.00832
	(1.50)	**(2.87)*****	(0.74)	(1.50)	**(2.02)****	**(2.24)****	(1.56)	(0.40)
Neig	**0.69974**	**4.57162**	**-5.70348**	**0.77341**	**2.32847**	**0.75235**	**1.83768**	**4.07812**
	(12.45)***	**(14.72)*****	**(34.15)*****	**(10.50)*****	**(15.09)*****	**(21.28)*****	**(25.75)*****	**(41.99)*****
Positive Selection								
Inequ	0.02278	0.14391	-0.05444	0.01931	0.05713	0.02282	0.05735	0.04262
	(0.68)	(0.78)	(0.55)	(0.44)	(0.62)	(1.08)	(1.35)	(0.74)
Inf	-0.07100	-0.22819	-0.15849	-0.09527	-0.17242	-0.02070	-0.04963	-0.11287
	(1.58)	(0.92)	(1.19)	(1.62)	(1.40)	(0.73)	(0.87)	(1.45)
Open	-0.00026	0.00277	-0.00035	-0.00015	0.00100	0.00030	0.00075	0.00240
	(0.17)	(0.33)	(0.08)	(0.08)	(0.24)	(0.32)	(0.39)	(0.92)
Pol	0.00003	-0.00007	0.00001	0.00019	0.00038	0.00005	0.00014	-0.00007
	(0.30)	(0.13)	(0.05)	(1.50)	(1.46)	(0.79)	(1.16)	(0.43)
Unemp	0.02371	-0.02948	**0.07749**	0.02285	0.00900	-0.00173	-0.00279	-0.00556
	(1.59)	(0.36)	**(1.75)***	(1.17)	(0.22)	(0.18)	(0.15)	(0.22)
Interaction								
visa_emp	0.06525	0.96362	-1.11966	0.28449	0.87039	0.01085	-0.21595	-0.58334
	(0.16)	(0.43)	(0.93)	(0.53)	(0.78)	(0.04)	(0.42)	(0.83)

Size	**0.00001**	**0.00003**	0.00000	**0.00001**	**0.00002**	**0.00000**	**0.00001**	**0.00001**
	(9.46)* **	**(6.84)*** **	(0.76)	**(8.95)*** **	**(9.28)*** **	**(5.67)*** **	**(5.57)*** **	**(6.99)*** **
Constant	-0.04725	-0.19097	-0.09296	-0.05479	-0.14968	-0.01908	-0.01048	-0.04156
	(1.03)	(0.76)	(0.68)	(0.91)	(1.19)	(0.66)	(0.18)	(0.53)
Observations	111	111	111	111	111	111	111	111
R-squared	0.98	0.99	0.99	0.98	0.99	0.99	0.99	0.99

Absolute value of T-statistics in parentheses. * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table 26 shows the regression results for the equation given in section 6.3. There is a great similarity in the determinants of the distributional effects of immigrant groups based on different personal income inequality metrics. The first conclusion of the regression analysis is the fact that the size of the immigrant group is the main determinant of distributional effects. Significant coefficients for most of these inequality metrics point out the intuitive fact that the magnitude of the counterfactual effect is dependent on the size of the immigrant group. Moreover, as the size of the immigrant group increases, the disequalizing effect of the immigrant cohort increases. Alternating and statistically significant coefficients for the level and the square of *personal income* are the second important finding of the regression analysis. All regression estimates show that the counterfactual effects have a U-shape relationship with income. The *educational attainment* of immigrant cohorts is also a significant variable determining the effects of immigrant cohorts. Results suggest that more educated immigrant cohorts have higher counterfactual effects on the U.S. distribution. Finally, some of the geographical variables are significant, such as the *neighbor* dummy. These findings suggest immigrant cohorts from neighbor countries have higher counterfactual effects than other cohorts. This result is not surprising due to the fact that immigrants from one of the neighbor countries, Mexico, have the lowest median income while the other neighbor cohort, Canada, has one of the highest median incomes. Therefore, the impact of these immigrants combined results in a high counterfactual impact on U.S. distribution.

Table 27: Robust Regression Results: Determinants of the Counterfactual Effects of Immigrant Groups on U.S. Inequality, Household Income

	e[rmd_h]	e[cv_h]	e[std_h]	e[gini_h]	e[theil_h]	e[atk_h1]	e[atk_h2]	e[atk_h3]
Income								
hincp	**-0.00217**	**-0.01286**	-0.00209	**-0.00351**	**-0.00222**	**-0.00108**	**-0.00267**	**-0.00306**
	(3.43)* **	**(5.00)*** **	(1.45)	**(4.82)*** **	**(1.73)* **	**(3.55)*** **	**(4.92)*** **	**(3.85)*** **
hincp-squared	**0.00002**	**0.00011**	**0.00002**	**0.00003**	0.00001	**0.00001**	**0.00002**	**0.00002**
	(3.17)* **	**(5.45)*** **	**(1.66)* **	**(5.02)*** **	(1.18)	**(3.88)*** **	**(5.27)*** **	**(3.87)*** **
Immigrant Characteristics								
Schl	**0.00726**	**0.02160**	**0.01052**	**0.00808**	**0.01466**	**0.00417**	**0.00764**	**0.00588**
	(4.44)* **	**(3.26)*** **	**(2.85)*** **	**(4.31)*** **	**(4.44)*** **	**(5.32)*** **	**(5.46)*** **	**(2.88)*** **
Yoep	-0.00005	-0.00041	0.00020	-0.00005	-0.00005	-0.00017	-0.00026	0.00006
	(0.13)	(0.29)	(0.25)	(0.11)	(0.07)	(0.97)	(0.85)	(0.13)
Eng	-0.00056	0.01360	-0.01062	-0.00144	-0.00005	-0.00036	**0.00703**	-0.00812
	(0.12)	(0.69)	(0.97)	(0.26)	(0.00)	(0.16)	**(1.70)* **	(1.34)
per_male	0.00507	0.17330	0.02638	0.04175	0.03796	0.01854	0.02255	0.01682
	(0.19)	(1.62)	(0.44)	(1.38)	(0.71)	(1.46)	(1.00)	(0.51)
per_visa	**-0.05568**	**-0.23480**	**-0.09795**	**-0.07540**	**-0.10669**	**-0.03757**	**-0.06638**	**-0.05107**
	(2.67)* **	**(2.78)*** **	**(2.08)** **	**(3.15)*** **	**(2.53)** **	**(3.76)*** **	**(3.72)*** **	**(1.96)** **
per_unemp	**-0.24364**	**-1.05189**	-0.04501	**-0.30565**	**-0.52229**	**-0.12831**	**-0.24128**	-0.26855
	**(1.67)* **	**(1.78)* **	(0.14)	**(1.83)* **	**(1.77)* **	**(1.84)* **	**(1.94)* **	(1.48)
Economic Development								
Oecd	0.00102	0.01999	0.01646	0.00376	0.01133	0.00202	0.00510	0.00072
	(0.21)	(0.99)	(1.46)	(0.66)	(1.12)	(0.85)	(1.19)	(0.12)
Geographical								
Afr	**-0.13207**	**-0.51332**	**-0.37928**	**-0.21934**	**-0.29266**	**-0.05279**	**-0.13451**	**-0.26510**
	(7.82)* **	**(7.50)*** **	**(9.93)*** **	**(11.33)*** **	**(8.57)*** **	**(6.53)*** **	**(9.30)*** **	**(12.56)*** **
Asia	**-0.12702**	**-0.49469**	**-0.36006**	**-0.21083**	**-0.28060**	**-0.05126**	**-0.12694**	**-0.25674**
	(7.70)* **	**(7.40)*** **	**(9.65)*** **	**(11.15)*** **	**(8.41)*** **	**(6.49)*** **	**(8.99)*** **	**(12.45)*** **
Eur	**-0.13708**	**-0.52810**	**-0.39155**	**-0.22149**	**-0.29602**	**-0.05431**	**-0.13600**	**-0.26543**
	(8.34)* **	**(7.92)*** **	**(10.53)*** **	**(11.76)*** **	**(8.90)*** **	**(6.90)*** **	**(9.66)*** **	**(12.92)*** **
Latin	**-0.13953**	**-0.52826**	**-0.39574**	**-0.22244**	**-0.30011**	**-0.05223**	**-0.13297**	**-0.27070**
	(8.53)* **	**(7.97)*** **	**(10.71)*** **	**(11.88)*** **	**(9.08)*** **	**(6.67)*** **	**(9.50)*** **	**(13.26)*** **
Ocea	**-0.12950**	**-0.45647**	**-0.38824**	**-0.20906**	**-0.27600**	**-0.05284**	**-0.12539**	**-0.26679**
	(8.04)* **	**(6.99)*** **	**(10.66)*** **	**(11.33)*** **	**(8.47)*** **	**(6.85)*** **	**(9.09)*** **	**(13.26)*** **
North	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
Col	**0.02317**	**0.18375**	**0.07700**	**0.04858**	**0.05377**	0.00764	**0.01845**	**0.05772**
	(2.36) **	**(4.62)*** **	**(3.47)*** **	**(4.32)*** **	**(2.71)*** **	(1.62)	**(2.19)** **	**(4.71)*** **
Neig	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped	Dropped
Positive Selection								
Inequ	-0.00542	0.10281	0.02235	0.01533	-0.01942	-0.01624	0.01662	0.03251
	(0.20)	(0.94)	(0.36)	(0.49)	(0.35)	(1.25)	(0.72)	(0.96)
Inf	-0.04063	0.02481	-0.02386	-0.02219	-0.10158	-0.02112	**-0.07139**	-0.01127
	(1.09)	(0.16)	(0.28)	(0.52)	(1.34)	(1.18)	**(2.23)** **	(0.24)
Open	-0.00033	-0.00406	-0.00226	-0.00052	-0.00039	-0.00075	-0.00080	0.00045
	(0.27)	(0.81)	(0.81)	(0.37)	(0.16)	(1.26)	(0.76)	(0.29)
Pol	**0.00021**	**0.00090**	0.00016	**0.00022**	**0.00033**	0.00005	**0.00020**	**0.00017**
	(2.75)* **	**(2.92)*** **	(0.94)	**(2.56)** **	**(2.12)** **	(1.48)	**(3.09)*** **	**(1.81)* **
Unemp	0.01343	0.02903	**0.04888**	0.01315	0.03149	**0.01694**	**0.02844**	0.00240
	(1.09)	(0.58)	**(1.76)* **	(0.93)	(1.27)	**(2.88)*** **	**(2.70)*** **	(0.16)
Interaction								
visa_emp	0.43556	**2.34450**	0.14332	0.64057	1.01564	0.23681	**0.50637**	0.47716

	(1.27)	(1.69)*	(0.19)	(1.63)	(1.47)	(1.44)	(1.73)*	(1.12)
Size	0.00000	-0.00002	-0.00001	-0.00001	0.00000	0.00001	0.00000	-0.00001
	(3.01)***	(7.72)***	(11.33)***	(14.16)***	(1.70)*	(19.27)***	(6.06)***	(13.75)***
Constant	0.14630	0.56216	0.35859	0.23747	0.24691	0.05485	0.12399	0.30310
	(3.35)***	(3.17)***	(3.63)***	(4.74)***	(2.79)***	(2.62)***	(3.31)***	(5.55)***
Observations	110	110	110	110	110	110	110	110
R-squared	0.77	0.81	0.85	0.89	0.78	0.92	0.85	0.89

Absolute value of T-statistics in parentheses. * significant at 10% level; ** significant at 5% level; *** significant at 1% level

Table 27 shows the regression analysis for the distributional effects of immigrant groups based on household income. Similar to the findings in Table 26, regression estimation indicates that *household size* is the most important determinant of the counterfactual effects. However, unlike personal income estimations, the sign of the coefficient is not consistent over different inequality metrics. Some of the findings suggest that as the size of the immigrant group increases, the magnitude of the effect lessens. This result may stem from the fact that as the immigrant group size increases; the immigrants' income distribution may start to resemble the distribution of the host country due to increased networking ability, ease of job search and housing, etc. Thus, the size of the cohort may have a diminishing effect on the income inequality of the host country. For example, immigrants from China may have relatively lower costs of finding a suitable job that reflects their abilities and lower costs of finding affordable housing compared to Estonian immigrants. Therefore, the income inequality of Chinese immigrants may look more similar to U.S. than the Estonian cohort; hence, the counterfactual effects of sizeable cohorts are lower compared to cohorts with a small number of immigrants. *Household income* still has a U-shape relationship with the counterfactual effects of immigrant cohorts, while education increases the magnitude of the effect. The *colonial ties* variable is also a common factor determining the distributional effects of immigrant groups. Immigrants from countries that have colonial ties have larger effects on U.S. income distribution. *Continental dummies* are all significant and have a negative sign, suggesting that compared to the North American cohort all other immigrant groups have smaller effects on U.S. income distribution, ceteris paribus.

CHAPTER 8

CONCLUSION

The number of immigrants has been steadily rising in the United States. Immigrants now account for more than 11% of the population, and they constitute a large portion of population growth. Consequently, immigrants are at the center of political disputes related not only to their demographic impacts but also to their labor market performance, especially in terms of culture and inequality. Although inequality has an important area of research in the literature since the 1920s, interest in the causes and consequences has mounted after the rapid increase in inequality in the U.S. over the last few decades. The causes and consequences of increasing inequality are still controversial, and changes in immigration policies add more grounds for further research associated to immigration and income inequality. This dissertation examines the income inequality of immigrants using information from more three hundred thousand immigrants surveyed by the Census Bureau in the American Community Survey 2006, and it provides extensive results for four broad issues related to immigrants and their income inequality characteristics.

First, it presents a snapshot of the current state of immigrant characteristics while examining the income inequality differences between U.S. citizens and immigrants. There is strong evidence that income is more unequally distributed among immigrants compared to U.S. citizens based on personal income and more equally distributed based on household income. The most evident justification for this finding is the differences in characteristics of U.S. citizens and immigrants. Specifically, U.S. citizens have higher education levels than immigrants, earn more personal and household income, and most importantly, do not experience market frictions such as language barriers, cultural adaptation periods, etc., that immigrants face.

Second, the study examines the determinants of income inequality among immigrant cohorts. Since immigrants have unique characteristics compared to natives, the analysis requires additional attention and further control variables to account for these diverse characteristics. In addition to the usual explanatory variables such as income, age, gender, educational attainment, and unemployment rate, this study introduced immigrant group characteristics such as the number of years spent in the U.S., English ability, visa status, geographical controls, and positive selection variables to explain the variation in income inequality among immigrant cohorts. The ordinary least squares with robust errors and robust regression techniques were employed due to the existence of outliers in the study. The results suggest that the type of income (i.e. personal vs. household) that is being used to calculate inequality plays a crucial role in the determination of inequality. Inequality metrics based on personal income can best be explained by median income, educational attainment, and the percentage of males in the immigrant cohorts. On the other hand, the variation in household income inequality among immigrant cohorts can be explained by median income, educational attainment, and the number of years spent in the United States.

Next, the study examined to the income inequality dynamics of immigrant cohorts. For this purpose, the immigrant cohorts were divided into two sub-groups. The first group consisted of the immigrants who just entered the U.S. in 2006, while the second group consisted of the ones who have been residing in the U.S. for approximately 10 years. Comparing these groups allows one to study some of the fundamental questions regarding the inequality dynamics of immigrants. First of all, immigrant cohorts were found to exhibit a substantial amount of improvement in their income inequality over the time period studied. Moreover, the improvement in equality is higher for personal income than household income. Secondly, the determinants of the inequality dynamics were investigated using 45 suitable immigrant cohorts. The results suggest that the initial level of inequality among recent immigrant cohorts in comparison to the U.S. is the prevalent factor explaining the variation in inequality dynamics. More precisely, if a recent immigrant cohort has inequality remarkably different than the host country's inequality, then it exhibits a faster improvement in equality and faster convergence to the host country's distribution. In addition, the change in median income is another important variable for inequality convergence. Geographical controls are also very crucial for the determination of the inequality dynamics of immigrant cohorts.

Finally, the counterfactual effects of immigrant cohorts were investigated by decomposing the surveyed sample into natives and immigrants. The income inequality of the sample was calculated in the presence and absence of each immigrant cohort. The difference between these figures is presented as the distributional effects of immigrant cohorts on U.S. income inequality. The results show that the immigrant cohorts have two distinct effects on the distribution: unambiguous disequalizing effects and mixed effects. The size of immigrant cohorts has the foremost importance in the study. However, even after controlling for size, several significant factors were found for immigrants. Immigrant groups with very low and very high incomes compared to the U.S. average income have a disequalizing effect, while others clustered around the mean income have mixed counterfactual effects on the U.S. income distribution. Moreover, the immigrant cohorts that have a higher educational attainment have a larger counterfactual impact on the distribution of income. Geographical controls also play an important role for the distributional effects. Most of these controls are statistically significant, and they explain a large portion of the variation of the counterfactual effects.

This research is one of the first to examine the determinants and dynamics of income inequality of immigrants in the United States. It proposes notable methodologies to demonstrate the inequality dynamics of immigrants and their counterfactual effects. The results provide valuable information to researchers and policymakers, since they illustrate the current state of inequality of each immigrant cohort. Moreover, the work offers useful information about the inequality dynamics which can be used as a proxy of assimilation to the host country. Finally, the counterfactual estimates for the effects of immigrants can be useful in altering current immigration policies towards desired goals the government may wish to achieve.

One valuable extension of this work would be incorporating the earlier surveys provided by the ACS and producing a time dimension to the existing methodology. Using an appropriate panel data technique would not only introduce time dynamics, but also would allow for controlling the unobserved heterogeneity across the immigrant cohorts. However, one shortcoming of incorporating the earlier surveys is the fact that the ACS has only been published for a short period of time.[21] Since income inequality is a very persistent variable, a time dimension of a couple of years may have only a limited benefit. Nevertheless, the American Community Survey offers insightful, extensive, and valuable information about the immigrants on a yearly basis; this research will hopefully lead to significant future works on the inequality of immigrants.

[21]The full implementation of ACS has began in 2005 with a sample of about three million addresses throughout the United States.

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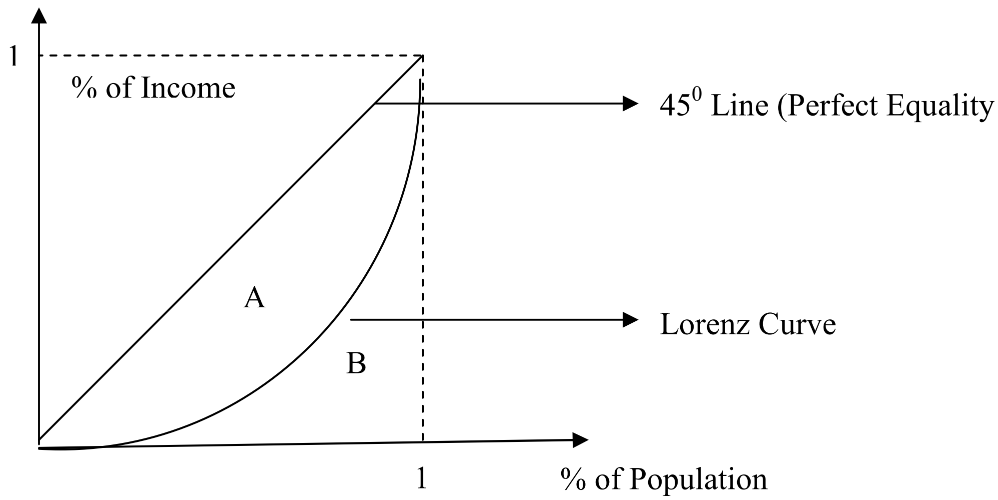
APPENDIX A

THE RELATIONSHIP BETWEEN THE GINI COEFFICIENT AND LORENZE CURVE



The Gini coefficient is measured as the area of A divided by the total area of A + B. As the area of A gets larger, the income inequality rises, as shown below:

Sum of the areas A + B = ½

Gini Coefficient = A / A+ B

= A / 0.5 = 2A or

= 1 – 2B since A + B = ½

$$= 1 - 2\int_0^1 L(x)dx$$

APPENDIX B

MEASURES AND DETERMINANTS OF INCOME INEQUALITY

1. Relative Mean Deviation of Personal Income (RMD_P)
2. Relative Mean Deviation of Household Income (RMD_H)
3. Coefficient of Personal Income Variation (CV_P)
4. Coefficient of Household Income Variation (CV_H)
5. Standard Deviation of Logs of Personal Income (STD_P)
6. Standard Deviation of Logs of Household Income (STD_H)
7. Gini Coefficient of Personal Income (GINI_P)
8. Gini Coefficient of Household Income (GINI_H)
9. Theil of Personal Income (THEIL_P)
10. Theil of Household Income (THEIL_H)
11. Atkinson of Personal Income, eps=0.25 (ATK_P1)
12. Atkinson of Household Income, eps=0.25 (ATK_H1)
13. Atkinson of Personal Income, eps=0.50 (ATK_P2)
14. Atkinson of Household Income, eps=0.50 (ATK_H2)
15. Atkinson of Personal Income, eps=0.75 (ATK_P3)
16. Atkinson of Household Income, eps=0.75 (ATK_H3)

1. Average Personal Income of Immigrants from county i, (PINCP_mean)
2. Average Household Income of Immigrants from county i, (HINCP_mean)
3. Median Personal Income of Immigrants from county i, (PINCP_median)
4. Median Household Income of Immigrants from county i, (HINCP_median)
5. Average Education Level of Immigrants from country i, (SCHL)
6. Average Number of Years that immigrants from country i spent in the U.S., (YOEP)
7. Average English Proficiency of Immigrants from country i, (ENG)
8. Average Age of Immigrants from country i, (AGE)
9. Fraction of Male Immigrants from country i, (PER_MALE)
10. Fraction of immigrants from country i who are holding a non-permanent visa (PER_VISA)
11. Fraction of immigrants from country i who are unemployed (PER_UNEMP)
12. Percentage of immigrants from country i who are student (PER_STUD)
13. Political Freedom Index of Immigrants' county i, (POL)
14. Income inequality for country i, (INEQU)
15. Inflation in country i, (INF)
16. Unemployment in country i, (UNEMP)
17. Openness to Trade in country i, (OPEN)

18. Geographical proximity measured as the distance from the nearest shore, (GEO)
19. Dummy for neighbor countries of US, (NEIG)
20. Dummy for colonial ties between the U.S. and country i, (COL)
21. Dummy for countries that predominantly speaks English (LAN)
22. Dummy for a Latin region of the world (LAT)
23. Dummy for a Asia region of the world (ASIA)
24. Dummy for a Europe region of the world (EUR)
25. Dummy for a Africa region of the world (AFR)
26. Dummy for a North America region of the world (NORTH)
27. Dummy for a Oceania of the world (OCEA)
28. Dummy for country i, if it is a member of EU, (EU)
29. Dummy for country i, if it is a member of OECD, (OECD)
30. Dummy for country i, if it is landlocked, (LAND)
31. Interaction Dummy of Employment and Student (EMPLOY*STUD)
32. Interaction Dummy for Visa and Student (VISA*STUD)
33. Interaction Dummy for Visa and Employment (VISA*EMPLOY)
34. Immigrant group size (SIZE)
35. Immigrant Group Size, Household heads only (HH_SIZE

APPENDIX C

SAMPLE STATISTICS OF IMMIGRANT COHORTS

Country No	Country	Sample Size	% Immig.	Education	Personal Income	Household Income	Median Personal Income	Median Household Income
1	Afghanistan	356	0.1298%	10.0337	$ 27,547.33	$ 66,547.33	$ 12,000.00	$ 45,110.00
2	Albania	353	0.1287%	9.8102	$ 21,904.82	$ 65,810.34	$ 17,850.00	$ 52,800.00
3	Algeria	93	0.0339%	11.0215	$ 38,360.32	$ 76,578.54	$ 20,000.00	$ 51,200.00
4	Antigua & Barbuda	111	0.0405%	10.2072	$ 30,448.23	$ 68,829.92	$ 22,000.00	$ 50,000.00
5	Argentina	1,197	0.4363%	10.6458	$ 35,400.38	$ 77,159.80	$ 23,000.00	$ 56,000.00
6	Armenia	571	0.2081%	10.3765	$ 24,611.78	$ 63,929.30	$ 13,000.00	$ 50,400.00
7	Australia	658	0.2399%	11.6687	$ 55,585.67	$ 108,993.40	$ 30,000.00	$ 78,150.00
8	Austria	352	0.1283%	10.7841	$ 46,765.33	$ 98,538.91	$ 21,500.00	$ 59,900.00
9	Azerbaijan	158	0.0576%	11.4747	$ 23,609.75	$ 61,766.68	$ 14,800.00	$ 51,700.00
10	Bahamas	238	0.0868%	10.0168	$ 27,280.25	$ 58,413.12	$ 17,700.00	$ 42,000.00
11	Bangladesh	953	0.3474%	10.7282	$ 25,607.68	$ 67,643.60	$ 12,500.00	$ 45,000.00
12	Barbados	441	0.1608%	9.6576	$ 30,297.57	$ 66,310.43	$ 25,000.00	$ 58,140.00
13	Belarus	401	0.1462%	11.4015	$ 26,692.83	$ 60,212.57	$ 15,000.00	$ 47,600.00
14	Belgium	198	0.0722%	11.4293	$ 44,894.46	$ 86,221.58	$ 26,700.00	$ 64,550.00
15	Belize	361	0.1316%	9.5512	$ 27,211.50	$ 63,005.37	$ 19,000.00	$ 48,000.00
16	Bermuda	70	0.0255%	10.6429	$ 28,774.71	$ 60,815.64	$ 22,350.00	$ 48,000.00
17	Bolivia	485	0.1768%	10.4804	$ 30,515.75	$ 76,758.61	$ 20,000.00	$ 63,000.00
18	Bosnia-Herzegovina	814	0.2967%	9.4287	$ 25,154.76	$ 68,285.84	$ 20,000.00	$ 61,150.00
19	Brazil	2,241	0.8169%	10.1508	$ 30,507.29	$ 79,523.37	$ 20,000.00	$ 61,300.00
20	Bulgaria	398	0.1451%	11.6357	$ 35,467.40	$ 81,037.98	$ 21,025.00	$ 62,045.00
21	Cambodia	1,088	0.3966%	7.5386	$ 22,699.41	$ 67,658.52	$ 17,050.00	$ 57,100.00
22	Cameroon	164	0.0598%	11.6463	$ 33,910.12	$ 70,569.80	$ 21,800.00	$ 54,000.00
23	Canada	8,563	3.1213%	10.8043	$ 45,306.84	$ 92,053.88	$ 25,000.00	$ 67,000.00
24	Cape Verde	207	0.0755%	7.7150	$ 24,083.14	$ 64,873.49	$ 19,000.00	$ 53,400.00
25	Chile	626	0.2282%	10.6582	$ 34,154.15	$ 75,587.10	$ 21,800.00	$ 61,500.00
26	China	10,830	3.9477%	10.3133	$ 32,297.26	$ 82,580.33	$ 16,000.00	$ 62,300.00
27	Colombia	4,447	1.6210%	10.2584	$ 26,015.03	$ 65,729.44	$ 18,200.00	$ 52,900.00
28	Costa Rica	572	0.2085%	9.3234	$ 24,065.33	$ 68,271.89	$ 18,000.00	$ 56,000.00
29	Croatia	330	0.1203%	9.0000	$ 37,118.72	$ 84,857.27	$ 21,150.00	$ 61,200.00
30	Cuba	7,538	2.7477%	9.1727	$ 27,850.25	$ 62,319.22	$ 15,800.00	$ 45,000.00
31	Czech Republic	234	0.0853%	11.1624	$ 38,952.82	$ 88,144.03	$ 25,800.00	$ 63,500.00
32	Czechoslovakia	183	0.0667%	10.4863	$ 35,058.91	$ 69,684.66	$ 19,300.00	$ 46,900.00
33	Denmark	191	0.0696%	11.3508	$ 47,641.58	$ 99,143.96	$ 24,000.00	$ 73,600.00
34	Dominica	244	0.0889%	8.4344	$ 17,241.52	$ 41,261.11	$ 12,250.00	$ 32,100.00
35	Dominican Republic	5,079	1.8514%	8.3507	$ 19,200.24	$ 48,584.85	$ 13,300.00	$ 38,700.00
36	Ecuador	2,456	0.8952%	8.8188	$ 21,421.84	$ 62,212.42	$ 15,600.00	$ 53,240.00
37	Egypt	928	0.3383%	11.9127	$ 40,255.96	$ 83,448.29	$ 20,152.00	$ 64,000.00
38	El Salvador	7,049	2.5695%	6.8790	$ 20,898.16	$ 58,826.34	$ 16,800.00	$ 50,000.00
39	England	3,806	1.3873%	10.9430	$ 44,488.20	$ 88,990.50	$ 25,000.00	$ 65,000.00
40	Eritrea	125	0.0456%	9.0880	$ 31,359.84	$ 67,815.54	$ 26,900.00	$ 58,000.00
41	Estonia	62	0.0226%	11.8065	$ 45,469.84	$ 114,733.80	$ 25,000.00	$ 72,500.00

42	**Ethiopia**	828	0.3018%	10.4698	$ 27,554.16	$ 65,677.82	$ 19,000.00	$ 53,010.00
43	**Fiji**	316	0.1152%	8.7911	$ 27,290.32	$ 76,872.55	$ 19,900.00	$ 64,750.00
44	**Finland**	126	0.0459%	11.6111	$ 41,871.06	$ 100,230.30	$ 24,000.00	$ 77,110.00
45	**France**	1,093	0.3984%	11.7072	$ 47,432.26	$ 99,501.39	$ 25,000.00	$ 70,000.00
46	**Georgia**	90	0.0328%	11.2889	$ 23,100.89	$ 52,562.56	$ 11,150.00	$ 44,000.00
47	**Germany**	3,899	1.4212%	10.5191	$ 36,242.57	$ 79,287.78	$ 19,000.00	$ 55,600.00
48	**Ghana**	670	0.2442%	10.6015	$ 29,218.60	$ 62,310.59	$ 22,000.00	$ 52,000.00
49	**Greece**	1,302	0.4746%	8.4401	$ 38,333.83	$ 81,279.80	$ 20,400.00	$ 59,902.00
50	**Grenada**	255	0.0930%	9.4510	$ 29,694.33	$ 74,397.39	$ 21,400.00	$ 57,000.00
51	**Guatemala**	4,767	1.7376%	6.6459	$ 18,879.42	$ 57,321.26	$ 15,000.00	$ 47,400.00
52	**Guyana**	2,006	0.7312%	9.2966	$ 28,015.11	$ 70,392.66	$ 21,000.00	$ 59,000.00
53	**Haiti**	3,241	1.1814%	9.1311	$ 22,536.68	$ 57,883.43	$ 18,000.00	$ 49,300.00
54	**Honduras**	2,485	0.9058%	7.1911	$ 18,300.18	$ 52,740.53	$ 14,000.00	$ 43,900.00
55	**Hong Kong**	1,928	0.7028%	10.9487	$ 44,252.34	$ 98,462.61	$ 30,000.00	$ 81,890.00
56	**Hungary**	581	0.2118%	10.5060	$ 34,497.65	$ 69,310.19	$ 20,000.00	$ 46,800.00
57	**India**	12,251	4.4657%	12.2817	$ 50,922.37	$ 112,899.80	$ 31,000.00	$ 90,000.00
58	**Indonesia**	664	0.2420%	11.4578	$ 29,024.41	$ 72,721.11	$ 18,100.00	$ 60,950.00
59	**Iran**	2,509	0.9146%	11.3850	$ 47,650.65	$ 102,998.70	$ 22,400.00	$ 70,450.00
60	**Iraq**	692	0.2522%	9.4798	$ 28,091.19	$ 69,929.91	$ 14,750.00	$ 51,450.00
61	**Ireland**	1,355	0.4939%	10.2103	$ 43,310.29	$ 87,732.77	$ 26,000.00	$ 26,000.00
62	**Israel**	1,159	0.4225%	11.2364	$ 52,011.12	$ 106,375.10	$ 30,000.00	$ 80,000.00
63	**Italy**	3,056	1.1140%	7.6531	$ 34,267.54	$ 74,038.39	$ 19,000.00	$ 53,600.00
64	**Jamaica**	5,021	1.8302%	9.7064	$ 29,721.01	$ 64,726.90	$ 23,400.00	$ 55,200.00
65	**Japan**	2,653	0.9671%	11.1749	$ 34,715.79	$ 83,849.70	$ 14,000.00	$ 62,030.00
66	**Jordan**	414	0.1509%	10.3720	$ 35,369.88	$ 70,725.84	$ 15,400.00	$ 51,400.00
67	**Kazakhstan**	102	0.0372%	10.9706	$ 16,607.06	$ 52,090.71	$ 8,350.00	$ 39,235.00
68	**Kenya**	488	0.1779%	11.3648	$ 35,481.75	$ 76,719.98	$ 20,000.00	$ 56,800.00
69	**Korea**	6,975	2.5425%	11.0505	$ 31,351.22	$ 76,612.98	$ 15,600.00	$ 59,000.00
70	**Kuwait**	155	0.0565%	11.3936	$ 37,209.19	$ 74,020.45	$ 10,200.00	$ 57,000.00
71	**Laos**	1,378	0.5023%	7.5399	$ 23,759.65	$ 64,714.07	$ 19,000.00	$ 58,000.00
72	**Latvia**	196	0.0714%	11.0000	$ 36,293.95	$ 70,968.61	$ 20,000.00	$ 46,200.00
73	**Lebanon**	898	0.3273%	10.2339	$ 40,792.29	$ 79,538.05	$ 19,500.00	$ 60,000.00
74	**Liberia**	418	0.1524%	9.7129	$ 22,153.39	$ 57,151.37	$ 17,900.00	$ 50,000.00
75	**Lithuania**	253	0.0922%	10.7708	$ 29,697.72	$ 63,361.97	$ 18,700.00	$ 47,800.00
76	**Macedonia**	161	0.0587%	9.1491	$ 28,424.98	$ 78,868.00	$ 22,200.00	$ 69,400.00
77	**Malaysia**	425	0.1549%	11.2165	$ 38,552.55	$ 86,813.49	$ 24,500.00	$ 75,500.00
78	**Mexico**	79,456	28.9629%	6.3912	$ 17,169.39	$ 48,486.34	$ 13,000.00	$ 40,000.00
79	**Micronesia**	84	0.0306%	8.8214	$ 14,890.48	$ 43,014.92	$ 12,000.00	$ 24,900.00
80	**Moldova**	213	0.0776%	10.8357	$ 29,131.08	$ 64,136.83	$ 13,000.00	$ 56,340.00
81	**Morocco**	388	0.1414%	10.3196	$ 26,719.46	$ 68,439.44	$ 16,800.00	$ 48,000.00
82	**Myanmar**	336	0.1225%	10.6310	$ 35,477.95	$ 87,919.23	$ 20,700.00	$ 68,200.00
83	**Nepal**	176	0.0642%	11.4148	$ 23,071.52	$ 60,194.64	$ 17,000.00	$ 46,150.00
84	**Netherlands**	618	0.2253%	11.2605	$ 47,308.23	$ 91,674.84	$ 22,900.00	$ 65,600.00
85	**New Zealand**	249	0.0908%	11.3414	$ 53,933.88	$ 109,462.90	$ 32,200.00	$ 96,000.00
86	**Nicaragua**	1,824	0.6649%	8.9841	$ 22,583.18	$ 63,001.65	$ 16,000.00	$ 52,000.00
87	**Nigeria**	1,429	0.5209%	11.9636	$ 35,506.88	$ 76,373.36	$ 26,000.00	$ 65,000.00
88	**Northern Ireland**	144	0.0525%	10.6458	$ 50,022.74	$ 91,367.71	$ 26,345.00	$ 60,900.00
89	**Norway**	141	0.0514%	11.0284	$ 43,736.35	$ 81,180.96	$ 23,300.00	$ 74,000.00
90	**Pakistan**	1,985	0.7236%	11.1542	$ 35,653.11	$ 89,248.87	$ 16,000.00	$ 63,700.00
91	**Panama**	885	0.3226%	10.4780	$ 32,262.75	$ 73,631.66	$ 22,900.00	$ 60,100.00
92	**Paraguay**	81	0.0295%	9.9383	$ 21,299.26	$ 60,840.02	$ 15,000.00	$ 47,000.00
93	**Peru**	2,758	1.0053%	10.4068	$ 25,664.66	$ 66,622.14	$ 18,000.00	$ 55,000.00
94	**Philippines**	15,250	5.5589%	11.1738	$ 34,642.27	$ 93,580.62	$ 25,000.00	$ 81,650.00
95	**Poland**	3,485	1.2703%	10.2121	$ 31,578.76	$ 75,181.97	$ 22,000.00	$ 60,200.00
96	**Portugal**	1,435	0.5231%	6.9833	$ 32,321.37	$ 76,430.94	$ 23,700.00	$ 64,600.00

97	**Romania**	1,159	0.4225%	10.7860	$ 36,058.26	$ 79,663.69	$ 23,000.00	$ 61,800.00
98	**Russia**	2,514	0.9164%	11.6846	$ 31,139.20	$ 77,107.82	$ 15,000.00	$ 60,400.00
99	**Samoa**	111	0.0405%	8.8559	$ 23,082.25	$ 73,910.83	$ 14,200.00	$ 63,000.00
100	**Saudi Arabia**	111	0.0405%	10.6577	$ 21,038.77	$ 74,914.25	$ 5,000.00	$ 42,100.00
101	**Scotland**	845	0.3080%	10.6556	$ 42,262.20	$ 85,126.70	$ 22,000.00	$ 65,000.00
102	**Senegal**	86	0.0313%	9.7791	$ 21,827.91	$ 53,588.41	$ 16,700.00	$ 49,900.00
103	**Sierra Leone**	154	0.0561%	10.2727	$ 30,609.35	$ 60,199.53	$ 24,500.00	$ 52,000.00
104	**Singapore**	228	0.0831%	11.9693	$ 41,493.46	$ 93,228.71	$ 24,000.00	$ 83,020.00
105	**Slovakia**	130	0.0474%	10.9385	$ 28,634.89	$ 82,226.85	$ 20,000.00	$ 64,400.00
106	**Somalia**	313	0.1141%	7.8690	$ 14,132.83	$ 33,207.50	$ 8,000.00	$ 24,400.00
107	**South Africa**	781	0.2847%	12.0013	$ 65,596.76	$ 138,736.90	$ 35,000.00	$ 100,000.00
108	**Spain**	698	0.2544%	10.3209	$ 40,070.53	$ 87,262.20	$ 21,900.00	$ 66,000.00
109	**Sri Lanka**	268	0.0977%	11.7388	$ 42,341.51	$ 92,183.16	$ 25,500.00	$ 65,150.50
110	**St. Kitts & Nevis**	80	0.0292%	9.7875	$ 34,895.18	$ 76,659.31	$ 20,000.00	$ 45,450.00
111	**St. Lucia**	126	0.0459%	9.6349	$ 25,312.14	$ 68,755.42	$ 19,000.00	$ 51,350.00
112	**St. Vincent & Grenadines**	146	0.0532%	9.2123	$ 27,743.97	$ 55,997.92	$ 17,550.00	$ 50,000.00
113	**Sudan**	195	0.0711%	9.8000	$ 19,254.63	$ 49,235.63	$ 15,000.00	$ 35,301.00
114	**Sweden**	316	0.1152%	11.7437	$ 50,278.31	$ 108,295.20	$ 29,500.00	$ 80,000.00
115	**Switzerland**	302	0.1101%	11.8742	$ 58,527.02	$ 108,058.50	$ 31,300.00	$ 75,250.00
116	**Syria**	425	0.1549%	9.8659	$ 42,639.52	$ 88,301.31	$ 16,500.00	$ 56,600.00
117	**Taiwan**	3,206	1.1686%	12.2374	$ 43,275.75	$ 99,560.54	$ 25,000.00	$ 80,000.00
118	**Tanzania**	108	0.0394%	11.7593	$ 37,885.46	$ 83,788.27	$ 21,505.00	$ 67,200.00
119	**Thailand**	1,402	0.5111%	9.9750	$ 23,830.36	$ 72,810.23	$ 15,000.00	$ 58,245.00
120	**Tonga**	128	0.0467%	9.1484	$ 21,609.09	$ 64,664.61	$ 17,050.00	$ 54,500.00
121	**Trinidad & Tobago**	1,884	0.6867%	9.9713	$ 29,841.15	$ 67,912.42	$ 21,750.00	$ 56,640.00
122	**Turkey**	691	0.2519%	10.9262	$ 38,544.08	$ 81,037.99	$ 20,800.00	$ 56,050.00
123	**Uganda**	123	0.0448%	11.5285	$ 56,354.02	$ 107,302.80	$ 31,200.00	$ 68,100.00
124	**Ukraine**	2,356	0.8588%	11.0794	$ 28,127.47	$ 67,376.09	$ 14,465.00	$ 48,900.00
125	**United Kingdom**	2,398	0.8741%	11.8924	$ 64,348.08	$ 120,350.00	$ 35,000.00	$ 86,000.00
126	**Uruguay**	333	0.1214%	9.4384	$ 25,206.22	$ 65,537.21	$ 16,000.00	$ 51,000.00
127	**USSR**	305	0.1112%	12.4656	$ 44,546.65	$ 93,753.60	$ 26,000.00	$ 85,000.00
128	**Uzbekistan**	277	0.1010%	10.9567	$ 21,990.61	$ 62,424.57	$ 10,000.00	$ 50,100.00
129	**Venezuela**	1,166	0.4250%	11.2590	$ 29,199.87	$ 71,969.28	$ 19,000.00	$ 57,000.00
130	**Vietnam**	8,790	3.2041%	9.1090	$ 28,214.30	$ 75,933.35	$ 18,000.00	$ 60,000.00
131	**Yemen**	155	0.0565%	7.3677	$ 21,061.64	$ 49,573.92	$ 8,700.00	$ 33,200.00
132	**Yugoslavia**	888	0.3237%	9.2376	$ 29,526.72	$ 67,290.49	$ 19,000.00	$ 52,600.00
133	**Zimbabwe**	118	0.0430%	11.81356	$ 44,804.44	$ 85,375.04	$ 26,502.00	$ 72,750.00

APPENDIX D

INCOME INEQUALITY OF IMMIGRANT COHORTS

		Personal Income							
Country No	**Country**	**RMD**	**CV**	**St.Dev.**	**GINI**	**Theil**	**Atkinson eps=0.25**	**Atkinson eps=0.5**	**Atkinson eps=0.75**
1	**Afghanistan**	0.4860	1.5780	1.2580	0.6430	0.7830	0.1960	0.4040	0.6710
2	**Albania**	0.3940	1.0810	1.1620	0.5390	0.5300	0.1430	0.3220	0.5990
3	**Algeria**	0.4660	1.4680	1.1240	0.6220	0.7130	0.1750	0.3640	0.6140
4	**Antigua**	0.3500	0.8900	1.0080	0.4760	0.3900	0.1040	0.2300	0.4240
5	**Argentina**	0.4150	1.4140	1.1340	0.5750	0.6270	0.1560	0.3230	0.5530
6	**Armenia**	0.4500	1.4050	1.1880	0.6050	0.6730	0.1680	0.3570	0.6170
7	**Australia**	0.4400	1.4190	1.3720	0.5980	0.6640	0.1650	0.3370	0.5550
8	**Austria**	0.4760	1.5980	1.2180	0.6320	0.7610	0.1820	0.3560	0.5560
9	**Azerbaijan**	0.3880	1.0250	1.0830	0.5160	0.4660	0.1220	0.2650	0.4730
10	**Bahamas**	0.4170	1.7040	1.1330	0.5890	0.7190	0.1730	0.3470	0.5780
11	**Bangladesh**	0.5090	1.9240	1.3930	0.6880	0.9590	0.2370	0.4840	0.7830
12	**Barbados**	0.3360	1.0030	1.0750	0.4700	0.4030	0.1050	0.2280	0.4120
13	**Belarus**	0.4370	1.3770	1.2040	0.5890	0.6340	0.1580	0.3250	0.5420
14	**Belgium**	0.4240	1.2180	1.1550	0.5740	0.5880	0.1510	0.3220	0.5600
15	**Belize**	0.4010	1.6130	1.1950	0.5620	0.6430	0.1590	0.3340	0.5880
16	**Bermuda**	0.3410	0.9100	1.0050	0.4720	0.3820	0.1000	0.2170	0.3890
17	**Bolivia**	0.4030	1.4370	1.1160	0.5670	0.6230	0.1540	0.3260	0.5750
18	**Bosnia-Herzegovina**	0.3620	1.1470	1.1690	0.5140	0.4900	0.1260	0.2720	0.4870
19	**Brazil**	0.4200	1.5250	1.2510	0.5860	0.6690	0.1660	0.3450	0.5940
20	**Bulgaria**	0.4220	1.4000	1.2890	0.5780	0.6320	0.1590	0.3310	0.5640
21	**Cambodia**	0.3690	1.0240	1.0800	0.5080	0.4570	0.1200	0.2640	0.4880
22	**Cameroon**	0.4210	1.3300	1.4040	0.5780	0.6240	0.1590	0.3350	0.5700
23	**Canada**	0.4440	1.4750	1.3040	0.6070	0.6900	0.1700	0.3450	0.5690
24	**Cape Verde**	0.3520	1.0400	0.9610	0.5010	0.4620	0.1230	0.2750	0.5250
25	**Chile**	0.4220	1.2690	1.1310	0.5770	0.6090	0.1570	0.3370	0.5960
26	**China**	0.4690	1.4250	1.3380	0.6190	0.7050	0.1790	0.3740	0.6320
27	**Colombia**	0.3930	1.3400	1.0980	0.5520	0.5810	0.1480	0.3160	0.5670
28	**Costa Rica**	0.3940	1.1270	1.1340	0.5440	0.5360	0.1410	0.3130	0.5750
29	**Croatia**	0.4210	1.5540	1.2200	0.5870	0.6760	0.1620	0.3230	0.5280

30	**Cuba**	0.4220	1.5150	1.0860	0.5770	0.6400	0.1540	0.3080	0.5040
31	**Czech Republic**	0.4060	1.4580	1.1600	0.5690	0.6310	0.1550	0.3150	0.5290
32	**Czechoslovakia**	0.4170	1.3420	1.1250	0.5700	0.5990	0.1470	0.2990	0.4930
33	**Denmark**	0.4560	1.3050	1.1970	0.6020	0.6500	0.1650	0.3460	0.5910
34	**Dominica**	0.3960	0.9820	0.9810	0.5280	0.4950	0.1360	0.3110	0.5920
35	**Dominican Republic**	0.3960	1.3310	1.0770	0.5480	0.5680	0.1450	0.3130	0.5640
36	**Ecuador**	0.3910	1.2250	1.0840	0.5450	0.5550	0.1450	0.3180	0.5840
37	**Egypt**	0.4630	1.5250	1.3590	0.6260	0.7370	0.1830	0.3730	0.6150
38	**El Salvador**	0.3470	1.1350	0.9780	0.4930	0.4600	0.1200	0.2670	0.5050
39	**England**	0.4370	1.4770	1.2100	0.5960	0.6650	0.1620	0.3260	0.5290
40	**Eritrea**	0.3450	1.2920	0.9660	0.4980	0.4980	0.1240	0.2610	0.4630
41	**Estonia**	0.4860	2.1020	1.1610	0.6650	0.9450	0.2190	0.4190	0.6560
42	**Ethiopia**	0.3970	1.2870	1.2670	0.5500	0.5650	0.1430	0.3030	0.5300
43	**Fiji**	0.3880	1.2350	1.0320	0.5420	0.5460	0.1390	0.3000	0.5430
44	**Finland**	0.4370	1.1420	1.2580	0.5740	0.5780	0.1520	0.3280	0.5750
45	**France**	0.4600	1.5610	1.2840	0.6270	0.7500	0.1850	0.3760	0.6190
46	**Georgia**	0.4900	1.4260	1.3500	0.6490	0.7830	0.2040	0.4400	0.7510
47	**Germany**	0.4530	1.6250	1.2160	0.6130	0.7270	0.1740	0.3450	0.5560
48	**Ghana**	0.3800	1.2010	1.1260	0.5350	0.5350	0.1380	0.3000	0.5420
49	**Greece**	0.4410	1.5490	1.1810	0.6010	0.6860	0.1660	0.3290	0.5310
50	**Grenada**	0.4010	1.5020	1.0590	0.5590	0.6250	0.1560	0.3310	0.5880
51	**Guatemala**	0.3560	1.1770	1.0380	0.5080	0.4940	0.1290	0.2840	0.5320
52	**Guyana**	0.3800	1.1760	1.1070	0.5310	0.5220	0.1360	0.2970	0.5410
53	**Haiti**	0.3630	1.1280	1.0030	0.5090	0.4790	0.1250	0.2780	0.5210
54	**Honduras**	0.3840	1.2280	1.0690	0.5400	0.5520	0.1440	0.3190	0.5900
55	**Hong Kong**	0.4090	1.2340	1.4000	0.5600	0.5780	0.1490	0.3210	0.5660
56	**Hungary**	0.4260	1.4640	1.1580	0.5830	0.6480	0.1570	0.3140	0.5140
57	**India**	0.4380	1.3920	1.3420	0.5990	0.6770	0.1730	0.3690	0.6390
58	**Indonesia**	0.4450	1.2350	1.2780	0.5990	0.6470	0.1700	0.3740	0.6650
59	**Iran**	0.4840	1.6200	1.3400	0.6510	0.8030	0.1970	0.3970	0.6410
60	**Iraq**	0.4830	1.6440	1.2860	0.6530	0.8210	0.2040	0.4210	0.7020
61	**Ireland**	0.4070	1.3790	1.0790	0.5590	0.5860	0.1430	0.2880	0.4720
62	**Israel**	0.4600	1.5360	1.3610	0.6280	0.7480	0.1850	0.3800	0.6300
63	**Italy**	0.4200	1.4560	1.0750	0.5730	0.6220	0.1500	0.2960	0.4760
64	**Jamaica**	0.3610	1.1250	1.1430	0.5070	0.4740	0.1220	0.2650	0.4790
65	**Japan**	0.5130	1.6790	1.4190	0.6840	0.8970	0.2250	0.4640	0.7570
66	**Jordan**	0.5080	1.7470	1.3120	0.6790	0.8960	0.2200	0.4470	0.7250
67	**Kazakhstan**	0.4920	1.3670	1.2490	0.6420	0.7550	0.1980	0.4260	0.7280
68	**Kenya**	0.4480	1.6290	1.2710	0.6170	0.7470	0.1810	0.3610	0.5890

69	**Korea**	0.4830	1.6360	1.3500	0.6510	0.8170	0.2050	0.4290	0.7200
70	**Kuwait**	0.5700	2.2950	1.5800	0.7490	1.1910	0.2810	0.5430	0.8190
71	**Laos**	0.3450	1.0760	0.9690	0.4840	0.4340	0.1120	0.2440	0.4500
72	**Latvia**	0.4220	1.4910	1.1710	0.5800	0.6450	0.1540	0.2990	0.4640
73	**Lebanon**	0.4790	1.5300	1.3260	0.6420	0.7710	0.1930	0.3980	0.6620
74	**Liberia**	0.3900	1.1780	1.2310	0.5390	0.5440	0.1450	0.3220	0.5910
75	**Lithuania**	0.4060	1.3690	1.0090	0.5590	0.5860	0.1450	0.2960	0.5030
76	**Macedonia**	0.3760	1.1230	1.1830	0.5210	0.4940	0.1280	0.2760	0.4940
77	**Malaysia**	0.4340	1.3790	1.3080	0.5850	0.6430	0.1660	0.3580	0.6300
78	**Mexico**	0.3900	1.2760	1.0430	0.5470	0.5740	0.1510	0.3370	0.6250
79	**Micronesia**	0.4130	1.2420	0.9850	0.5770	0.6200	0.1640	0.3620	0.6560
80	**Moldova**	0.4620	1.3530	1.2180	0.6100	0.6730	0.1700	0.3530	0.5900
81	**Morocco**	0.4360	1.5250	1.2820	0.5990	0.6940	0.1760	0.3710	0.6450
82	**Myanmar**	0.4410	1.4620	1.2890	0.6060	0.6900	0.1720	0.3550	0.5990
83	**Nepal**	0.3920	1.0810	1.1160	0.5450	0.5280	0.1400	0.3090	0.5620
84	**Netherlands**	0.4600	1.3960	1.2740	0.6140	0.6830	0.1690	0.3460	0.5680
85	**New Zealand**	0.4180	1.2700	1.2720	0.5740	0.6030	0.1540	0.3260	0.5630
86	**Nicaragua**	0.3800	1.1660	1.0380	0.5310	0.5170	0.1340	0.2900	0.5290
87	**Nigeria**	0.3860	1.1380	1.2240	0.5350	0.5270	0.1390	0.3060	0.5590
88	**Northern Ireland**	0.4340	1.5820	1.0830	0.5930	0.6880	0.1600	0.3060	0.4670
89	**Norway**	0.4430	1.2440	1.1710	0.5910	0.6160	0.1570	0.3270	0.5530
90	**Pakistan**	0.5040	1.6940	1.3360	0.6740	0.8800	0.2200	0.4560	0.7490
91	**Panama**	0.3830	1.3450	1.1990	0.5380	0.5570	0.1390	0.2920	0.5110
92	**Paraguay**	0.4070	1.1660	1.2910	0.5520	0.5680	0.1510	0.3350	0.6130
93	**Peru**	0.3940	1.3790	1.1310	0.5510	0.5830	0.1470	0.3130	0.5550
94	**Philippines**	0.3740	1.1320	1.1270	0.5200	0.4920	0.1270	0.2750	0.4950
95	**Poland**	0.3950	1.2920	1.1170	0.5500	0.5680	0.1440	0.3060	0.5410
96	**Portugal**	0.3630	1.2170	0.9970	0.5090	0.4840	0.1210	0.2540	0.4440
97	**Romania**	0.4140	1.3560	1.1370	0.5720	0.6130	0.1540	0.3230	0.5600
98	**Russia**	0.4580	1.4430	1.2900	0.6110	0.6910	0.1740	0.3610	0.6070
99	**Samoa**	0.4120	1.2020	1.1230	0.5630	0.5830	0.1540	0.3380	0.6140
100	**Saudi Arabia**	0.5830	2.1270	1.6770	0.7490	1.1500	0.2800	0.5530	0.8370
101	**Scotland**	0.4410	1.4390	1.2220	0.5950	0.6570	0.1600	0.3180	0.5100
102	**Senegal**	0.3690	0.9740	0.8740	0.5070	0.4610	0.1250	0.2860	0.5520
103	**Sierra Leone**	0.3840	1.2680	1.2350	0.5410	0.5540	0.1410	0.2990	0.5190
104	**Singapore**	0.4550	1.2850	1.3380	0.6080	0.6720	0.1760	0.3810	0.6610
105	**Slovakia**	0.4000	0.9750	1.0830	0.5310	0.5000	0.1370	0.3140	0.5920
106	**Somalia**	0.4580	1.7350	1.2770	0.6310	0.7960	0.1990	0.4150	0.7040
107	**South Africa**	0.4650	1.4750	1.3660	0.6320	0.7450	0.1860	0.3820	0.6320

108	**Spain**	0.4460	1.6290	1.2300	0.6150	0.7410	0.1790	0.3560	0.5760
109	**Sri Lanka**	0.4430	1.5120	1.2470	0.6100	0.7180	0.1810	0.3790	0.6490
110	**St. Kitts & Nevis**	0.4400	1.6800	1.2790	0.6190	0.7720	0.1850	0.3650	0.5890
111	**St. Lucia**	0.3730	1.1460	0.9880	0.5250	0.5130	0.1340	0.2960	0.5480
112	**St. Vincent & Grenadines**	0.3960	1.3720	1.0500	0.5450	0.5680	0.1410	0.2920	0.5030
113	**Sudan**	0.3850	1.2120	1.3120	0.5420	0.5580	0.1460	0.3180	0.5720
114	**Sweden**	0.4560	1.5300	1.3480	0.6240	0.7390	0.1830	0.3750	0.6260
115	**Switzerland**	0.4480	1.4010	1.3360	0.6040	0.6740	0.1690	0.3480	0.5820
116	**Syria**	0.5180	1.7680	1.4090	0.6850	0.9110	0.2230	0.4450	0.7100
117	**Taiwan**	0.4540	1.3480	1.4840	0.6090	0.6870	0.1780	0.3830	0.6590
118	**Tanzania**	0.4220	1.3820	1.1020	0.5780	0.6280	0.1570	0.3280	0.5640
119	**Thailand**	0.4400	1.5020	1.2730	0.6070	0.7060	0.1790	0.3800	0.6580
120	**Tonga**	0.3990	1.0210	1.1960	0.5390	0.5210	0.1430	0.3260	0.6120
121	**Trinidad & Tobago**	0.3890	1.1940	1.1480	0.5400	0.5390	0.1400	0.3040	0.5500
122	**Turkey**	0.4580	1.5170	1.2520	0.6210	0.7280	0.1810	0.3710	0.6200
123	**Uganda**	0.4690	1.7240	1.2850	0.6390	0.8200	0.1940	0.3820	0.6130
124	**Ukraine**	0.4470	1.6040	1.2330	0.6040	0.6990	0.1700	0.3410	0.5580
125	**United Kingdom**	0.4530	1.4550	1.3460	0.6130	0.6980	0.1730	0.3520	0.5790
126	**Uruguay**	0.4100	1.2970	0.9740	0.5690	0.6070	0.1570	0.3410	0.6160
127	**USSR**	0.4280	1.3950	1.4020	0.5760	0.6190	0.1550	0.3220	0.5410
128	**Uzbekistan**	0.4700	1.2700	1.2420	0.6120	0.6710	0.1750	0.3770	0.6520
129	**Venezuela**	0.4400	1.4610	1.2130	0.6050	0.7000	0.1790	0.3860	0.6780
130	**Vietnam**	0.4190	1.3190	1.1770	0.5730	0.6060	0.1540	0.3260	0.5710
131	**Yemen**	0.5370	2.8620	1.2550	0.7220	1.2160	0.2790	0.5380	0.8290
132	**Yugoslavia**	0.4140	1.2850	1.1130	0.5690	0.5900	0.1490	0.3140	0.5430
133	**Zimbabwe**	0.4160	1.5320	1.3130	0.5780	0.6550	0.1580	0.3140	0.5030

		Household Income							
Country No	**Country**	**RMD**	**CV**	**St.Dev.**	**GINI**	**Theil**	**Atkinson eps=0.25**	**Atkinson eps=0.5**	**Atkinson eps=0.75**
1	**Afghanistan**	0.3660	1.0610	1.0080	0.5030	0.4330	0.1020	0.2080	0.3260
2	**Albania**	0.2800	0.8140	0.7730	0.3990	0.2730	0.0580	0.1280	0.2160
3	**Algeria**	0.3400	1.0520	0.8910	0.4710	0.3970	0.0930	0.1860	0.2910
4	**Antigua**	0.3490	0.9100	0.9460	0.4800	0.3730	0.0690	0.1710	0.3130
5	**Argentina**	0.3330	1.0270	0.8790	0.4680	0.3830	0.0870	0.1780	0.2840
6	**Armenia**	0.3420	0.9500	0.9380	0.4780	0.3800	0.0830	0.1820	0.3050
7	**Australia**	0.3440	1.0760	0.9610	0.4820	0.4060	0.0910	0.1880	0.2960
8	**Austria**	0.4000	1.1420	1.0730	0.5460	0.5030	0.1120	0.2350	0.3780
9	**Azerbaijan**	0.3070	0.8030	0.9150	0.4250	0.3000	0.0640	0.1450	0.2470
10	**Bahamas**	0.3710	1.2430	0.8710	0.5390	0.5090	0.0890	0.2100	0.3740
11	**Bangladesh**	0.3420	1.1590	0.8750	0.4770	0.4200	0.0940	0.1830	0.2730
12	**Barbados**	0.3110	0.9900	0.9560	0.4550	0.3700	0.0780	0.1770	0.3130
13	**Belarus**	0.3490	1.0180	0.9850	0.4830	0.3990	0.0900	0.1900	0.3070
14	**Belgium**	0.3680	1.0160	1.0180	0.5050	0.4250	0.0940	0.2060	0.3470
15	**Belize**	0.3370	1.0110	0.8080	0.4840	0.3930	0.0640	0.1690	0.3290
16	**Bermuda**	0.3060	0.8080	0.9540	0.4340	0.3050	0.0500	0.1370	0.2690
17	**Bolivia**	0.2800	0.8390	0.7760	0.4020	0.2840	0.0610	0.1370	0.2430
18	**Bosnia-Herzegovina**	0.2400	0.6590	0.7110	0.3440	0.2020	0.0430	0.1010	0.1850
19	**Brazil**	0.2940	0.9740	0.8160	0.4200	0.3220	0.0730	0.1490	0.2400
20	**Bulgaria**	0.3200	1.0170	0.9430	0.4610	0.3780	0.0750	0.1730	0.3060
21	**Cambodia**	0.2840	0.7730	0.8580	0.4020	0.2720	0.0590	0.1360	0.2470
22	**Cameroon**	0.3220	0.8920	0.9060	0.4510	0.3380	0.0680	0.1580	0.2810
23	**Canada**	0.3530	1.0740	0.9910	0.5000	0.4330	0.0960	0.2060	0.3470
24	**Cape Verde**	0.2760	0.7310	0.7080	0.3840	0.2400	0.0530	0.1150	0.1900
25	**Chile**	0.3020	0.9470	0.8750	0.4330	0.3320	0.0740	0.1560	0.2560
26	**China**	0.3390	0.9700	0.9870	0.4690	0.3750	0.0860	0.1830	0.3030
27	**Colombia**	0.2920	0.9060	0.8120	0.4180	0.3080	0.0650	0.1430	0.2450
28	**Costa Rica**	0.2950	0.8510	0.8220	0.4180	0.2980	0.0650	0.1430	0.2450
29	**Croatia**	0.3280	1.0790	0.9330	0.4610	0.3860	0.0860	0.1730	0.2680
30	**Cuba**	0.3570	1.1180	0.9410	0.5030	0.4370	0.0890	0.1930	0.3180
31	**Czech Republic**	0.3450	1.0990	1.0320	0.4850	0.4220	0.0940	0.1920	0.3030
32	**Czechoslovakia**	0.3870	1.1370	0.9010	0.5420	0.4790	0.0800	0.1990	0.3590
33	**Denmark**	0.3380	0.9250	0.9450	0.4610	0.3560	0.0880	0.1760	0.2650
34	**Dominica**	0.3110	0.8050	0.9120	0.4320	0.3060	0.0700	0.1580	0.2810
35	**Dominican Republic**	0.3330	0.9800	0.9330	0.4750	0.3760	0.0690	0.1660	0.2960
36	**Ecuador**	0.2780	0.8380	0.7950	0.3990	0.2770	0.0610	0.1310	0.2200

37	**Egypt**	0.3190	1.0320	0.9300	0.4510	0.3670	0.0830	0.1690	0.2630
38	**El Salvador**	0.2700	0.8380	0.7450	0.3840	0.2590	0.0550	0.1200	0.2020
39	**England**	0.3440	1.1070	0.9350	0.4870	0.4190	0.0910	0.1920	0.3150
40	**Eritrea**	0.2740	0.7970	0.8890	0.3960	0.2710	0.0630	0.1330	0.2130
41	**Estonia**	0.3770	1.2180	0.9860	0.5310	0.5010	0.1080	0.2220	0.3510
42	**Ethiopia**	0.3150	0.9800	0.9230	0.4540	0.3610	0.0770	0.1670	0.2790
43	**Fiji**	0.2750	0.7880	0.7260	0.3880	0.2580	0.0600	0.1270	0.2110
44	**Finland**	0.3440	0.8880	1.3250	0.4730	0.3780	0.0950	0.2050	0.3430
45	**France**	0.3680	1.1210	1.0320	0.5190	0.4660	0.1030	0.2200	0.3670
46	**Georgia**	0.3050	0.8680	0.8330	0.4270	0.4270	0.0790	0.1600	0.2590
47	**Germany**	0.3600	1.1360	0.9670	0.5050	0.4460	0.0960	0.2010	0.3270
48	**Ghana**	0.3170	0.9420	0.8460	0.4590	0.3550	0.0620	0.1570	0.2980
49	**Greece**	0.3340	1.0170	0.9440	0.4650	0.3790	0.0890	0.1820	0.2880
50	**Grenada**	0.3560	1.1840	1.0110	0.5080	0.4660	0.0980	0.2110	0.3530
51	**Guatemala**	0.2840	0.8720	0.7920	0.4030	0.2820	0.0590	0.1290	0.2160
52	**Guyana**	0.2920	0.8650	0.8770	0.4170	0.3010	0.0650	0.1430	0.2440
53	**Haiti**	0.2910	0.8280	0.7930	0.4150	0.2890	0.0580	0.1340	0.2380
54	**Honduras**	0.3050	0.8670	0.8040	0.4350	0.3130	0.0570	0.1390	0.2540
55	**Hong Kong**	0.3010	0.9070	0.9480	0.4310	0.3260	0.0760	0.1620	0.2730
56	**Hungary**	0.3800	1.2310	0.9660	0.5330	0.4960	0.0990	0.2160	0.3640
57	**India**	0.2890	0.8910	0.8440	0.4120	0.3010	0.0700	0.1440	0.2320
58	**Indonesia**	0.3070	0.7900	0.9990	0.4270	0.3050	0.0690	0.1620	0.3010
59	**Iran**	0.3610	1.1710	1.0430	0.5030	0.4550	0.1070	0.2140	0.3300
60	**Iraq**	0.3320	0.9670	0.9550	0.4650	0.3690	0.0820	0.1740	0.2830
61	**Ireland**	0.3450	1.1050	0.9270	0.4940	0.4290	0.0890	0.1950	0.3280
62	**Israel**	0.3490	1.0340	1.0720	0.4890	0.4150	0.0980	0.2040	0.3300
63	**Italy**	0.3460	1.0720	0.9140	0.4850	0.4090	0.0900	0.1870	0.3020
64	**Jamaica**	0.3040	0.8670	0.8790	0.4360	0.3210	0.0640	0.1510	0.2750
65	**Japan**	0.3450	1.0690	1.0230	0.4930	0.4290	0.0960	0.2090	0.3660
66	**Jordan**	0.3480	1.0210	1.1290	0.4860	0.4070	0.0960	0.2000	0.3240
67	**Kazakhstan**	0.3380	0.9950	0.9040	0.4780	0.3860	0.0800	0.1760	0.2930
68	**Kenya**	0.3520	1.1180	1.0310	0.5040	0.4460	0.0940	0.2020	0.3360
69	**Korea**	0.3480	1.0920	1.0500	0.4980	0.4390	0.0970	0.2120	0.3690
70	**Kuwait**	0.3760	1.3030	1.1560	0.5430	0.5430	0.1070	0.2480	0.4520
71	**Laos**	0.2630	0.7520	0.7530	0.3790	0.2460	0.0520	0.1190	0.2080
72	**Latvia**	0.3670	1.0840	0.9280	0.4990	0.4270	0.0980	0.1950	0.2910
73	**Lebanon**	0.3280	0.9650	0.9620	0.4590	0.3630	0.0850	0.1770	0.2880
74	**Liberia**	0.3100	0.8610	0.8510	0.4360	0.3220	0.0650	0.1560	0.2880
75	**Lithuania**	0.3340	1.0540	0.8410	0.4740	0.3940	0.0800	0.1740	0.2890

76	**Macedonia**	0.2500	0.7250	0.8270	0.3560	0.2210	0.0520	0.1100	0.1770
77	**Malaysia**	0.3130	1.0320	1.0330	0.4590	0.3850	0.0770	0.1800	0.3310
78	**Mexico**	0.2920	0.8800	0.7900	0.4170	0.2980	0.0570	0.1330	0.2330
79	**Micronesia**	0.4620	1.3790	1.0570	0.6300	0.6470	0.1070	0.2610	0.4570
80	**Moldova**	0.3350	0.9030	0.9900	0.4690	0.3670	0.0800	0.1790	0.3030
81	**Morocco**	0.3410	1.0980	0.9550	0.4790	0.4130	0.0940	0.1880	0.2930
82	**Myanmar**	0.3350	0.9840	0.9280	0.4740	0.3880	0.0910	0.1920	0.3230
83	**Nepal**	0.3130	0.8880	0.8610	0.4380	0.3280	0.0640	0.1550	0.2880
84	**Netherlands**	0.3520	0.9800	0.9480	0.4860	0.3940	0.0900	0.1910	0.3160
85	**New Zealand**	0.2820	0.8240	0.8790	0.4100	0.2910	0.0660	0.1440	0.2460
86	**Nicaragua**	0.2800	0.7880	0.7610	0.3960	0.2630	0.0560	0.1240	0.2100
87	**Nigeria**	0.3030	0.8520	0.8780	0.4330	0.3150	0.0630	0.1500	0.2720
88	**Northern Ireland**	0.3500	1.2450	0.8200	0.4780	0.4490	0.1010	0.1890	0.2710
89	**Norway**	0.3260	0.9460	0.9090	0.4790	0.3900	0.0730	0.1870	0.3660
90	**Pakistan**	0.3330	1.0290	0.9280	0.4650	0.3810	0.0880	0.1780	0.2800
91	**Panama**	0.3040	0.9170	0.9620	0.4340	0.3290	0.0750	0.1600	0.2660
92	**Paraguay**	0.3360	0.8900	0.8210	0.4620	0.3580	0.0780	0.1840	0.3520
93	**Peru**	0.2790	0.8320	0.8280	0.3960	0.2730	0.0630	0.1320	0.2110
94	**Philippines**	0.2570	0.7410	0.7490	0.3670	0.2330	0.0520	0.1140	0.1950
95	**Poland**	0.3020	0.9420	0.8670	0.4310	0.3280	0.0730	0.1550	0.2550
96	**Portugal**	0.2790	0.2790	0.8390	0.4020	0.2880	0.0660	0.1380	0.2250
97	**Romania**	0.3230	0.9890	0.9240	0.4590	0.3680	0.0820	0.1720	0.2810
98	**Russia**	0.3520	1.0820	1.0200	0.5000	0.4310	0.0910	0.2010	0.3400
99	**Samoa**	0.3290	0.8680	0.9270	0.4680	0.3600	0.0680	0.1790	0.3590
100	**Saudi Arabia**	0.4940	1.3970	1.0570	0.6930	0.7490	0.1080	0.3080	0.5910
101	**Scotland**	0.3420	1.0150	0.9500	0.4810	0.3950	0.0870	0.1840	0.3010
102	**Senegal**	0.3150	1.0660	0.8780	0.4660	0.3880	0.0730	0.1670	0.2890
103	**Sierra Leone**	0.2970	0.8430	0.8280	0.4210	0.3010	0.0540	0.1350	0.2470
104	**Singapore**	0.3130	0.8610	1.0380	0.4520	0.3500	0.0780	0.1850	0.3430
105	**Slovakia**	0.3130	1.0450	0.9720	0.4450	0.3700	0.0890	0.1760	0.2660
106	**Somalia**	0.3770	1.2980	1.0160	0.5440	0.5120	0.0810	0.2020	0.3640
107	**South Africa**	0.3380	0.9840	0.9240	0.4730	0.4730	0.0900	0.1840	0.2950
108	**Spain**	0.3430	1.0870	0.9170	0.4880	0.4180	0.1790	0.1900	0.3150
109	**Sri Lanka**	0.3380	1.1870	0.9140	0.4750	0.4240	0.0970	0.1890	0.2830
110	**St. Kitts & Nevis**	0.4310	1.2540	1.1450	0.5920	0.5840	0.1170	0.2610	0.4390
111	**St. Lucia**	0.3460	1.1470	0.8570	0.4970	0.4370	0.0840	0.1860	0.3140
112	**St. Vincent & Grenadines**	0.3230	0.9090	0.8740	0.4640	0.3620	0.0640	0.1700	0.3360
113	**Sudan**	0.3790	1.0260	1.0990	0.5300	0.4520	0.0840	0.2080	0.3790
114	**Sweden**	0.3490	1.0430	0.8940	0.4930	0.4190	0.0920	0.1980	0.3380

115	**Switzerland**	0.3370	0.9820	0.9150	0.4670	0.3760	0.0900	0.1840	0.2970
116	**Syria**	0.3830	1.1970	0.9860	0.9860	0.4900	0.1120	0.2240	0.3440
117	**Taiwan**	0.3240	0.9270	1.0670	0.4600	0.3660	0.0870	0.1900	0.3310
118	**Tanzania**	0.3250	1.0120	0.9040	0.4700	0.3890	0.0830	0.1840	0.3210
119	**Thailand**	0.3120	0.9250	0.9180	0.4460	0.3430	0.0760	0.1660	0.2850
120	**Tonga**	0.3160	0.7580	0.8670	0.4200	0.2830	0.0610	0.1400	0.2420
121	**Trinidad & Tobago**	0.3130	0.9170	0.8960	0.4480	0.3420	0.0710	0.1630	0.2930
122	**Turkey**	0.3610	1.1350	1.0930	0.5060	0.4530	0.1020	0.2110	0.3380
123	**Uganda**	0.3640	1.0960	0.9280	0.5010	0.4370	0.1000	0.2020	0.3170
124	**Ukraine**	0.3510	1.0630	0.9830	0.4870	0.4120	0.0950	0.1940	0.3030
125	**United Kingdom**	0.3390	1.0700	0.9570	0.4750	0.4000	0.0930	0.1880	0.2970
126	**Uruguay**	0.2930	0.8940	0.7220	0.4140	0.3000	0.0680	0.1410	0.2290
127	**USSR**	0.3010	0.8570	0.9400	0.4330	0.3250	0.0740	0.1680	0.3030
128	**Uzbekistan**	0.3200	0.8490	0.9680	0.4460	0.3270	0.0760	0.1630	0.2640
129	**Venezuela**	0.3050	0.9700	0.8040	0.4350	0.3380	0.0740	0.1580	0.2650
130	**Vietnam**	0.3060	0.8970	0.8910	0.4310	0.3190	0.0720	0.1540	0.2520
131	**Yemen**	0.3640	1.9860	1.2040	0.5270	0.6740	0.1400	0.2540	0.3660
132	**Yugoslavia**	0.3090	0.8720	0.8640	0.4350	0.3170	0.0680	0.1500	0.2550
133	**Zimbabwe**	0.3020	0.9640	0.8830	0.4430	0.3470	0.0670	0.1550	0.2730

APPENDIX E

CHANGE IN INCOME INEQUALITY OVER 10 YEARS, BY COUNTRY OF ORIGIN

		Personal Income							
Country No	**Country**	**ΔRMD**	**ΔCV**	**ΔST.DEV.**	**ΔGINI**	**ΔTHEIL**	**ΔAtkinson eps=0.25**	**ΔAtkinson eps=0.50**	**ΔAtkinson eps=0.75**
1	**Bangladesh**	-0.1225	-0.6928	-0.1496	-0.1255	-0.4905	-0.1069	-0.1670	-0.1205
2	**Brazil**	-0.0247	0.4723	-0.1258	-0.0185	0.0483	-0.0027	-0.0276	-0.0599
3	**Canada**	-0.0587	-0.3628	0.0371	-0.0685	-0.2049	-0.0445	-0.0753	-0.0868
4	**China**	-0.1583	-0.6608	-0.3193	-0.1685	-0.5329	-0.1292	-0.2453	-0.2684
5	**Colombia**	-0.1327	-0.2223	-0.2083	-0.1208	-0.2643	-0.0726	-0.1565	-0.2256
6	**Cuba**	-0.2221	-0.9958	-0.3330	-0.2636	-0.6423	-0.1522	-0.2841	-0.3605
7	**Dominican Republic**	-0.1531	-0.3871	-0.1083	-0.1551	-0.3843	-0.1019	-0.2129	-0.2900
8	**Ecuador**	-0.2593	-1.4149	-0.2093	-0.2771	-0.8072	-0.1809	-0.3145	-0.3341
9	**Egypt**	-0.0632	-0.4589	-0.3132	-0.0950	-0.2532	-0.0510	-0.0706	-0.0421
10	**El Salvador**	-0.1632	-0.3637	-0.3918	-0.1672	-0.3281	-0.0870	-0.1823	-0.2550
11	**England**	-0.1792	-1.1440	-0.1303	-0.1840	-0.7040	-0.1455	-0.2187	-0.1851
12	**Ethiopia**	-0.0856	-0.2840	-0.1831	-0.1136	-0.2589	-0.0685	-0.1483	-0.2343
13	**France**	-0.0392	-1.0374	0.1544	-0.1068	-0.4015	-0.0726	-0.0985	-0.0906
14	**Germany**	-0.1755	-0.9184	-0.0863	-0.2147	-0.6661	-0.1575	-0.2900	-0.3530
15	**Ghana**	-0.3409	-1.7628	-0.4018	-0.3810	-1.1319	-0.2552	-0.4548	-0.5715
16	**Guatemala**	-0.0179	0.6964	0.2347	0.0099	0.1636	0.0284	0.0406	0.0430
17	**Guyana**	-0.1866	-0.7113	-0.2029	-0.2273	-0.4769	-0.1160	-0.2241	-0.2927
18	**Haiti**	-0.2755	-1.1141	-0.2375	-0.3019	-0.8071	-0.1942	-0.3579	-0.3843
19	**Honduras**	-0.1037	-0.1655	-0.1542	-0.0916	-0.1896	-0.0522	-0.1132	-0.1628
20	**Hong Kong**	-0.2692	-1.4637	-0.5244	-0.2864	-1.0310	-0.2275	-0.3708	-0.3547
21	**India**	-0.1611	-0.5312	-0.3194	-0.1576	-0.4402	-0.1111	-0.2156	-0.2491
22	**Iran**	-0.1449	-1.0150	-0.0425	-0.1364	-0.6721	-0.1434	-0.2290	-0.2077
23	**Israel**	-0.0021	-0.3490	0.6980	-0.0207	-0.1196	-0.0256	-0.0469	-0.0519
24	**Italy**	-0.2641	-0.9851	-1.0096	-0.3380	-0.7130	-0.1804	-0.3710	-0.5673
25	**Jamaica**	-0.1835	-1.1544	-0.2530	-0.2214	-0.6506	-0.1402	-0.2378	-0.2679
26	**Japan**	-0.1461	-0.6037	-0.2732	-0.1371	-0.4414	-0.1020	-0.1751	-0.1605
27	**Korea**	-0.2394	-1.0278	-0.5753	-0.2261	-0.7822	-0.1794	-0.2993	-0.2482
28	**Mexico**	-0.0554	0.0204	-0.1797	-0.0510	-0.0846	-0.0235	-0.0467	-0.0533

29	**Nicaragua**	-0.2654	-0.6122	-0.4317	-0.2916	-0.5658	-0.1565	-0.3508	-0.5779
30	**Nigeria**	-0.2510	-0.7069	-0.6928	-0.2558	-0.6273	-0.1582	-0.3057	-0.3700
31	**Pakistan**	-0.1292	-0.2997	0.0759	-0.0916	-0.3605	-0.0947	-0.1794	-0.1578
32	**Peru**	-0.1542	-0.1985	-0.3051	-0.1665	-0.3296	-0.0942	-0.2131	-0.3308
33	**Philippines**	-0.1468	-0.5778	-0.1010	-0.1636	-0.4247	-0.1055	-0.2084	-0.2857
34	**Poland**	-0.2309	-0.8645	-0.3568	-0.2402	-0.6297	-0.1448	-0.2540	-0.2743
35	**Romania**	-0.2141	-0.8390	-0.5869	-0.2429	-0.5701	-0.1329	-0.2369	-0.2552
36	**Russia**	-0.1132	-0.0920	-0.1100	-0.1181	-0.2863	-0.0832	-0.1900	-0.3065
37	**South Africa**	0.0442	0.2087	-0.0925	0.0556	0.1518	0.0350	0.0735	0.1006
38	**Taiwan**	-0.2071	-1.0425	-0.4349	-0.1924	-0.7658	-0.1673	-0.2604	-0.1954
39	**Thailand**	-0.2637	-1.2171	0.3244	-0.2469	-0.8351	-0.1870	-0.3229	-0.3658
40	**Trinidad & Tobago**	-0.2300	-1.6382	-0.3893	-0.2576	-0.9022	-0.1875	-0.2974	-0.2929
41	**Turkey**	-0.1765	-1.9050	-0.4045	-0.2455	-0.9583	-0.2033	-0.3513	-0.4341
42	**Ukraine**	-0.1721	-0.6086	-0.2894	-0.1893	-0.5080	-0.1258	-0.2484	-0.3506
43	**United Kingdom**	-0.0110	-0.0067	0.0463	-0.0026	-0.0169	-0.0090	-0.0201	-0.0437
44	**Venezuela**	-0.2430	-0.3759	-0.5398	-0.1937	-0.5488	-0.1486	-0.2985	-0.3363
45	**Vietnam**	-0.1835	-0.8778	-0.3828	-0.1947	-0.6247	-0.1472	-0.2727	-0.3237

		Household Income							
Country No	Country	ΔRMD	ΔCV	ΔST.DEV.	ΔGINI	ΔTHEIL	ΔAtkinson eps=0.25	ΔAtkinson eps=0.50	ΔAtkinson eps=0.75
1	**Bangladesh**	-0.0647	-0.4518	-0.1220	-0.0940	-0.2052	-0.0230	-0.0609	-0.1187
2	**Brazil**	-0.0516	-0.4377	0.0341	-0.0861	-0.1722	-0.0253	-0.0586	-0.1091
3	**Canada**	-0.1105	-0.3430	-0.1742	-0.1554	-0.2576	-0.0364	-0.1167	-0.2484
4	**China**	-0.0930	-0.4358	-0.1657	-0.1381	-0.2363	-0.0210	-0.0780	-0.1645
5	**Colombia**	-0.0960	-0.4605	-0.3882	-0.1498	-0.2382	-0.0404	-0.0995	-0.1850
6	**Cuba**	-0.1215	-0.4046	-0.4849	-0.1613	-0.2496	-0.0680	-0.1215	-0.1536
7	**Dominican Republic**	0.0252	0.0653	0.2360	0.0204	0.0388	0.0366	0.0435	0.0235
8	**Ecuador**	-0.0686	-0.3863	-0.0259	-0.1169	-0.1829	-0.0317	-0.0718	-0.1304
9	**Egypt**	-0.1124	-0.3106	-0.2344	-0.1487	-0.2205	-0.0242	-0.0826	0.4080
10	**El Salvador**	-0.0298	-0.0460	-0.1539	-0.0385	-0.0456	-0.0048	-0.0232	-0.0611
11	**England**	-0.2133	-0.7599	-0.3356	-0.3192	-0.5635	-0.0757	-0.2304	-0.4559
12	**Ethiopia**	-0.0039	0.0010	-0.0411	-0.0054	0.0008	-0.0009	0.0046	0.0283
13	**France**	-0.1613	-0.6621	-0.3256	-0.2400	-0.4375	-0.0631	-0.1682	-0.3095
14	**Germany**	-0.0894	-0.3825	0.2349	-0.1259	-0.2244	-0.0474	-0.0964	-0.1535
15	**Ghana**	-0.1238	-0.2648	0.0714	-0.1661	-0.1951	0.0108	-0.0499	-0.1769
16	**Guatemala**	0.0032	0.1872	-0.0845	0.0232	0.0525	-0.0034	0.0012	0.0124
17	**Guyana**	-0.0040	-0.1647	-0.0781	-0.0284	-0.0946	-0.0229	-0.0400	-0.0586
18	**Haiti**	-0.0399	-0.0984	0.0293	-0.0464	-0.0478	0.0092	0.0055	0.0059
19	**Honduras**	-0.0095	0.1794	0.2210	-0.0002	0.0313	0.0371	0.0262	-0.0302
20	**Hong Kong**	-0.4399	-1.1937	-0.4345	-0.5935	-1.0732	0.0294	-0.2196	-0.4961
21	**India**	-0.0569	-0.2115	-0.0729	-0.0964	-0.1385	-0.0160	-0.0593	-0.1402
22	**Iran**	-0.0239	-0.2951	-0.0065	-0.0550	-0.1276	-0.0126	-0.0283	-0.0426
23	**Israel**	0.0337	-0.0040	-0.0132	0.0272	0.0060	-0.0134	-0.0251	-0.0653
24	**Italy**	-0.0965	-0.3233	-0.2338	-0.1366	-0.2193	-0.0404	-0.1066	-0.2243
25	**Jamaica**	-0.0766	-0.1003	-0.1405	-0.1154	-0.1374	0.0143	-0.0365	-0.1419
26	**Japan**	-0.1589	-0.3939	-0.5690	-0.2376	-0.3738	-0.0355	-0.1587	-0.3664
27	**Korea**	-0.2566	-0.8345	-0.4685	-0.3469	-0.6279	-0.0691	-0.2326	-0.4320
28	**Mexico**	-0.0343	0.0151	-0.1731	-0.0507	-0.0491	0.0018	-0.0201	-0.0630
29	**Nicaragua**	0.0080	-0.0339	0.1175	-0.0071	-0.0187	-0.0032	-0.0105	-0.0352
30	**Nigeria**	-0.1033	-0.3653	-0.5776	-0.1567	-0.2596	-0.0285	-0.0931	-0.1595
31	**Pakistan**	-0.1542	-0.4441	-0.3114	-0.2078	-0.3223	-0.0556	-0.1396	-0.2630
32	**Peru**	-0.0460	-0.2449	-0.3339	-0.0869	-0.1325	-0.0339	-0.0723	-0.1278
33	**Philippines**	-0.0341	-0.1220	-0.1078	-0.0426	-0.0596	-0.0181	-0.0287	-0.0272
34	**Poland**	-0.1250	-0.3303	-0.3066	-0.1471	-0.2202	-0.0652	-0.1243	-0.1953
35	**Romania**	-0.1469	-0.7901	-0.1363	-0.1748	-0.4068	-0.1025	-0.1548	-0.1540

36	**Russia**	0.0005	0.0231	0.0833	-0.0040	0.0018	0.0110	-0.0019	-0.0530
37	**South Africa**	-0.0379	-0.1959	0.0399	-0.0785	-0.1137	-0.0021	-0.0360	-0.1146
38	**Taiwan**	-0.2254	-0.4926	-0.9726	-0.2791	-0.4712	-0.0497	-0.1727	-0.2858
39	**Thailand**	-0.2481	-0.5714	-0.6712	-0.3250	-0.5170	-0.0693	-0.2242	-0.4533
40	**Trinidad & Tobago**	-0.1389	-0.5258	-0.3403	-0.2091	-0.3297	-0.0258	-0.1025	-0.2051
41	**Turkey**	-0.0713	-0.5089	0.0222	-0.1306	-0.2461	-0.0632	-0.0992	-0.1141
42	**Ukraine**	-0.0385	-0.1311	-0.1515	-0.0673	-0.1148	-0.0272	-0.0504	-0.0689
43	**United Kingdom**	-0.0240	-0.0357	0.0186	-0.0209	-0.0238	-0.0083	-0.0116	-0.0107
44	**Venezuela**	-0.1273	-0.4555	-0.2652	-0.2130	-0.3384	-0.0362	-0.1413	-0.3104
45	**Vietnam**	-0.0362	-0.1115	-0.1788	-0.0448	-0.0637	-0.0225	-0.0330	-0.0242

APPENDIX F

THE COUNTERFACTUAL EFFECTS OF IMMIGRANT COHORTS

		Personal Income							
Country No	Country	RMD	CV	St.Dev.	GINI	Theil	Atkinson eps=0.25	Atkinson eps=0.5	Atkinson eps=0.75
1	Afghanistan	0.000009	0.000009	-0.000007	0.000009	0.000017	0.000005	0.000011	0.000021
2	Albania	-0.000001	-0.000004	-0.000016	-0.000001	0.000000	0.000001	0.000004	0.000013
3	Algeria	0.000002	-0.000002	-0.000006	0.000002	0.000002	0.000001	0.000002	0.000003
4	Antigua	-0.000003	-0.000018	-0.000013	-0.000004	-0.000011	-0.000002	-0.000004	-0.000005
5	Argentina	-0.000001	-0.000034	-0.000065	-0.000002	-0.000008	-0.000002	-0.000002	0.000002
6	Armenia	0.000009	0.000010	-0.000019	0.000009	0.000015	0.000004	0.000011	0.000021
7	Australia	0.000025	0.000154	0.000054	0.000033	0.000083	0.000017	0.000027	0.000027
8	Austria	0.000022	0.000232	-0.000018	0.000030	0.000093	0.000017	0.000021	0.000011
9	Azerbaijan	-0.000001	-0.000005	-0.000012	-0.000001	-0.000002	0.000000	0.000000	0.000000
10	Bahamas	0.000001	0.000022	-0.000017	0.000002	0.000008	0.000002	0.000003	0.000004
11	Bangladesh	0.000038	0.000168	0.000036	0.000047	0.000117	0.000030	0.000067	0.000125
12	Barbados	-0.000015	-0.000061	-0.000039	-0.000018	-0.000041	-0.000009	-0.000017	-0.000022
13	Belarus	0.000006	0.000005	-0.000007	0.000006	0.000008	0.000002	0.000004	0.000006
14	Belgium	0.000009	0.000016	0.000033	0.000011	0.000023	0.000005	0.000008	0.000008
15	Belize	-0.000002	0.000024	-0.000014	-0.000001	0.000004	0.000001	0.000003	0.000008
16	Bermuda	0.000001	0.000006	0.000000	0.000001	0.000003	0.000001	0.000001	0.000002
17	Bolivia	-0.000001	0.000001	-0.000031	-0.000001	0.000001	0.000000	0.000002	0.000010
18	Bosnia Herzegovina	-0.000010	-0.000031	-0.000033	-0.000011	-0.000023	-0.000005	-0.000008	-0.000007
19	Brazil	0.000012	0.000151	-0.000019	0.000019	0.000062	0.000015	0.000033	0.000068
20	Bulgaria	0.000002	-0.000007	0.000003	0.000002	0.000004	0.000001	0.000004	0.000007
21	Cambodia	-0.000013	-0.000046	-0.000094	-0.000016	-0.000037	-0.000008	-0.000013	-0.000010
22	Cameroon	0.000000	-0.000010	0.000012	0.000000	-0.000002	0.000000	0.000001	0.000002
23	Canada	0.000176	0.000844	0.000205	0.000226	0.000538	0.000113	0.000178	0.000180
24	Cape Verde	-0.000003	-0.000011	-0.000019	-0.000004	-0.000008	-0.000002	-0.000002	0.000000
25	Chile	0.000002	-0.000045	-0.000025	0.000001	-0.000004	0.000001	0.000005	0.000016
26	China	0.000257	0.000009	0.000229	0.000240	0.000375	0.000111	0.000260	0.000471
27	Colombia	-0.000020	-0.000004	-0.000307	-0.000015	-0.000015	0.000000	0.000016	0.000079
28	Costa Rica	-0.000001	-0.000023	-0.000035	-0.000002	-0.000007	-0.000001	0.000002	0.000013

29	**Croatia**	0.000001	0.000049	-0.000013	0.000003	0.000015	0.000002	0.000002	-0.000002
30	**Cuba**	0.000058	0.000345	-0.000580	0.000048	0.000107	0.000011	-0.000015	-0.000091
31	**Czech Republic**	-0.000001	0.000017	-0.000014	0.000001	0.000007	0.000001	0.000000	-0.000003
32	**Czechoslovakia**	0.000006	0.000032	-0.000013	0.000006	0.000016	0.000003	0.000002	-0.000004
33	**Denmark**	0.000007	-0.000004	0.000005	0.000008	0.000013	0.000003	0.000006	0.000006
34	**Dominica**	0.000002	0.000013	-0.000015	0.000002	0.000006	0.000002	0.000004	0.000010
35	**Dominican Republic**	0.000050	0.000324	-0.000318	0.000055	0.000146	0.000034	0.000073	0.000143
36	**Ecuador**	0.000003	0.000030	-0.000168	0.000004	0.000015	0.000006	0.000024	0.000073
37	**Egypt**	0.000033	0.000166	0.000058	0.000041	0.000100	0.000022	0.000038	0.000047
38	**El Salvador**	-0.000067	0.000066	-0.000770	-0.000074	-0.000110	-0.000029	-0.000046	-0.000004
39	**England**	0.000053	0.000353	-0.000049	0.000066	0.000161	0.000029	0.000034	0.000000
40	**Eritrea**	-0.000004	-0.000007	-0.000015	-0.000004	-0.000007	-0.000002	-0.000003	-0.000004
41	**Estonia**	0.000002	0.000041	-0.000007	0.000002	0.298048	0.000002	0.000003	0.000003
42	**Ethiopia**	-0.000002	0.000003	-0.000002	-0.000003	-0.000003	-0.000001	-0.000001	0.000002
43	**Fiji**	-0.000003	-0.000016	-0.000032	-0.000004	-0.000010	-0.000002	-0.000003	0.000000
44	**Finland**	0.000003	-0.000008	0.000000	0.000003	0.000004	0.000001	0.000003	0.000004
45	**France**	0.000045	0.000276	0.000028	0.000059	0.000150	0.000032	0.000052	0.000058
46	**Georgia**	0.000003	0.000002	0.000000	0.000003	0.000006	0.000002	0.000005	0.000011
47	**Germany**	0.000080	0.000357	0.000064	0.000096	0.000221	0.000045	0.000067	0.000057
48	**Ghana**	-0.000009	-0.000046	-0.000039	-0.000010	-0.000022	-0.000004	-0.000005	0.000001
49	**Greece**	0.000022	0.000180	-0.000057	0.000026	0.000069	0.000012	0.000012	-0.000003
50	**Grenada**	-0.000002	0.000006	-0.000021	-0.000002	-0.000001	0.000000	0.000001	0.000005
51	**Guatemala**	0.000013	0.000226	-0.000386	0.000013	0.000060	0.000012	0.000027	0.000077
52	**Guyana**	-0.000027	-0.000130	-0.000135	-0.000031	-0.000070	-0.000013	-0.000016	0.000004
53	**Haiti**	-0.000037	-0.000059	-0.000351	-0.000041	-0.000076	-0.000017	-0.000022	0.000008
54	**Honduras**	0.000025	0.000155	-0.000171	0.000029	0.000078	0.000020	0.000047	0.000105
55	**Hong Kong**	0.000029	-0.000085	0.000151	0.000025	0.000025	0.000010	0.000028	0.000054
56	**Hungary**	0.000001	0.000020	-0.000051	0.000002	0.000006	0.000000	-0.000006	-0.000017
57	**India**	0.000454	0.001296	0.000782	0.000512	0.001099	0.000272	0.000544	0.000848
58	**Indonesia**	0.000007	-0.000048	-0.000003	0.000007	0.000004	0.000004	0.000014	0.000037
59	**Iran**	0.000133	0.000864	0.000108	0.000171	0.000441	0.000093	0.000152	0.000174
60	**Iraq**	0.000021	0.000048	0.000010	0.000025	0.000052	0.000014	0.000030	0.000055
61	**Ireland**	0.000001	0.000011	-0.000094	-0.000002	-0.000005	-0.000003	-0.000013	-0.000030
62	**Israel**	0.000052	0.000354	0.000084	0.000071	0.000185	0.000040	0.000068	0.000086
63	**Italy**	-0.000011	-0.000110	-0.000355	-0.000026	-0.000081	-0.000026	-0.000068	-0.000139
64	**Jamaica**	-0.000109	-0.000469	-0.000277	-0.000126	-0.000290	-0.000064	-0.000106	-0.000114
65	**Japan**	0.000119	0.000243	0.000212	0.000145	0.000308	0.000082	0.000180	0.000317
66	**Jordan**	0.000017	0.000064	0.000007	0.000021	0.000049	0.000012	0.000025	0.000041
67	**Kazakhstan**	0.000003	0.000008	0.000001	0.000004	0.000008	0.000002	0.000006	0.000011

68	**Kenya**	0.000006	0.000050	-0.000004	0.000009	0.000026	0.000005	0.000009	0.000011
69	**Korea**	0.000226	0.000719	0.000329	0.000273	0.000626	0.000166	0.000377	0.000705
70	**Kuwait**	0.000011	0.000090	0.000023	0.000015	0.000043	0.000010	0.000018	0.000027
71	**Laos**	-0.000028	-0.000058	-0.000159	-0.000030	-0.000061	-0.000015	-0.000029	-0.000036
72	**Latvia**	0.000001	0.000014	-0.000014	0.000002	0.000005	0.000000	-0.000002	-0.000007
73	**Lebanon**	0.000040	0.000129	0.000038	0.000049	0.000107	0.000025	0.000047	0.000067
74	**Liberia**	-0.000002	-0.000001	-0.000006	-0.000001	0.000000	0.000001	0.000004	0.000013
75	**Lithuania**	0.000001	0.000041	-0.000033	0.000001	0.000006	0.000000	-0.000001	-0.000005
76	**Macedonia**	-0.000002	-0.000010	-0.000006	-0.000002	-0.000005	-0.000001	-0.000002	-0.000002
77	**Malaysia**	0.000006	-0.000029	0.000009	0.000004	0.000000	0.000002	0.000007	0.000018
78	**Mexico**	0.001223	0.006940	-0.005769	0.001418	0.003803	0.000971	0.002245	0.004747
79	**Micronesia**	0.000003	0.000007	-0.000002	0.000003	0.000006	0.000002	0.000004	0.000007
80	**Moldova**	0.000005	-0.000002	0.000008	0.000004	0.000006	0.000002	0.000004	0.000007
81	**Morocco**	0.000007	0.000023	0.000007	0.000008	0.000018	0.000005	0.000011	0.363707
82	**Myanmar**	0.000003	-0.000003	-0.000002	0.000004	0.000006	0.000002	0.000004	0.000007
83	**Nepal**	0.000002	0.000003	-0.000005	0.000002	0.000004	0.000001	0.000002	0.000004
84	**Netherlands**	0.000018	0.000013	-0.000003	0.000019	0.000034	0.000007	0.000008	0.000000
85	**New Zealand**	0.000007	0.000005	0.000011	0.000009	0.000016	0.000004	0.000007	0.000008
86	**Nicaragua**	-0.000009	-0.000030	-0.000169	-0.000012	-0.000027	-0.000006	-0.000007	0.000006
87	**Nigeria**	-0.000014	-0.000187	-0.000014	-0.000021	-0.000065	-0.000010	-0.000008	0.000014
88	**Northern Ireland**	0.000002	0.000038	-0.000009	0.000003	0.000012	0.000002	0.000001	-0.000002
89	**Norway**	0.000006	-0.000012	0.000004	0.000006	0.000008	0.000002	0.000004	0.000004
90	**Pakistan**	0.000081	0.000309	0.000046	0.000101	0.000239	0.000060	0.000128	0.000226
91	**Panama**	-0.000016	-0.000077	-0.000040	-0.000019	-0.000043	-0.000009	-0.000016	-0.000017
92	**Paraguay**	0.000002	0.000006	0.000018	0.000002	0.000005	0.000002	0.000004	0.000007
93	**Peru**	-0.000009	0.000023	-0.000150	-0.000009	-0.000007	-0.000001	0.000006	0.000033
94	**Philippines**	-0.000265	-0.001984	-0.000845	-0.000354	-0.000947	-0.000193	-0.000298	-0.000279
95	**Poland**	-0.000025	-0.000155	-0.000228	-0.000030	-0.000073	-0.000015	-0.000023	-0.000012
96	**Portugal**	-0.000038	-0.000160	-0.000171	-0.000047	-0.000108	-0.000025	-0.000048	-0.000065
97	**Romania**	0.000009	-0.000007	-0.000046	0.000009	0.000014	0.000005	0.000012	0.000026
98	**Russia**	0.000053	0.000025	0.000039	0.000051	0.000085	0.000025	0.000057	0.000101
99	**Samoa**	0.000000	-0.000003	-0.000007	0.000000	0.000000	0.000000	0.000001	0.000004
100	**Saudi Arabia**	0.000009	0.000024	0.000037	0.000010	0.000023	0.000006	0.000014	0.000023
101	**Scotland**	0.000010	0.000022	-0.000010	0.000011	0.000021	0.000003	0.000001	-0.000010
102	**Senegal**	-0.000001	-0.000004	-0.000014	-0.000002	-0.000003	-0.000001	-0.000001	0.000001
103	**Sierra Leone**	-0.000002	-0.000009	-0.000004	-0.000002	-0.000005	-0.000001	-0.000002	-0.000002
104	**Singapore**	0.000008	-0.000011	0.000010	0.000008	0.000012	0.000004	0.000010	0.000018
105	**Slovakia**	0.000015	0.000057	0.000028	0.000017	0.000040	0.000010	0.000021	0.000036
106	**Somalia**	0.000054	0.000432	0.000081	0.000077	0.000214	0.000044	0.000071	0.000079

107	**South Africa**	0.000016	0.000117	0.000033	0.000021	0.000059	0.000012	0.000019	0.000019
108	**Spain**	0.000005	0.000009	0.000008	0.000005	0.000011	0.000003	0.000006	0.000011
109	**Sri Lanka**	0.000001	0.000009	-0.000001	0.000001	0.000005	0.000001	0.000001	0.000001
110	**St. Kitts & Nevis**	0.000001	0.000009	-0.000001	0.000001	0.000005	0.000001	0.000001	0.000001
111	**St. Lucia**	-0.000001	-0.000002	-0.000014	-0.000002	-0.000003	-0.000001	-0.000002	-0.000002
112	**St. Vincent & Grenadines**	0.000002	0.000022	0.000012	0.000004	0.000011	0.000002	0.000005	0.000007
113	**Sudan**	0.000012	0.000073	0.000017	0.000016	0.000042	0.000009	0.000014	0.000016
114	**Sweden**	0.000018	0.000090	0.000038	0.000023	0.000055	0.000012	0.000018	0.000018
115	**Switzerland**	0.000027	0.000207	0.000029	0.000036	0.000099	0.000021	0.000036	0.000046
116	**Syria**	0.000101	-0.000069	0.000352	0.000106	0.000173	0.000053	0.000126	0.000228
117	**Taiwan**	0.000000	-0.000004	-0.000007	0.000000	0.000000	0.000000	0.000000	0.000001
118	**Tanzania**	0.000018	0.000051	-0.000005	0.000023	0.000054	0.000016	0.000042	0.000091
119	**Thailand**	0.000000	0.000001	-0.000002	0.000001	0.000002	0.000001	0.000003	0.000007
120	**Tonga**	-0.000018	-0.000119	-0.000094	-0.000022	-0.000052	-0.000009	0.242239	0.000011
121	**Trinidad & Tobago**	0.000017	0.000066	0.000004	0.000020	0.000048	0.000011	0.000020	0.000028
122	**Turkey**	0.000005	0.000091	0.000008	0.000010	0.000034	0.000006	0.000009	0.000009
123	**Uganda**	0.000033	0.000145	-0.000028	0.000032	0.000069	0.000014	0.000023	0.000022
124	**Ukraine**	0.000142	0.001115	0.000229	0.000193	0.000519	0.000106	0.000165	0.000168
125	**United Kingdom**	0.000001	0.000040	-0.000036	0.000003	0.000012	0.000003	0.000006	0.000013
126	**Uruguay**	0.000005	-0.000001	0.000021	0.000003	0.000002	0.000001	0.000002	0.000002
127	**USSR**	0.000007	0.000013	0.000002	0.000007	0.000015	0.000004	0.000011	0.000020
128	**Uzbekistan**	0.000013	0.000014	-0.000012	0.000017	0.000039	0.000013	0.000035	0.000079
129	**Venezuela**	0.000019	-0.000256	-0.000378	0.000003	-0.000044	0.000001	0.000033	0.000130
130	**Vietnam**	0.000008	0.000068	-0.000004	0.000010	0.000030	0.000007	0.000014	0.000025
131	**Yemen**	-0.000003	-0.000060	-0.000076	-0.000006	-0.000022	-0.000004	-0.000007	-0.000005
132	**Yugoslavia**	0.000002	0.000029	0.000006	0.000003	0.000010	0.000002	0.000002	0.000000
133	**Zimbabwe**	0.000009	0.000009	-0.000007	0.000009	0.000017	0.000005	0.000011	0.000021

		Household Income							
Country No	**Country**	**RMD**	**CV**	**St.Dev.**	**GINI**	**Theil**	**Atkinson eps=0.25**	**Atkinson eps=0.5**	**Atkinson eps=0.75**
1	**Afghanistan**	0.000007	0.000015	0.000020	0.000007	0.000012	0.000005	0.000007	0.000005
2	**Albania**	-0.000007	-0.000027	-0.000021	-0.000010	-0.000016	-0.000003	-0.000006	-0.000012
3	**Algeria**	-0.000001	-0.000002	-0.000003	-0.000001	-0.000001	0.000000	0.000000	-0.000002
4	**Antigua**	0.000001	-0.000005	0.000000	0.000001	0.000000	-0.000001	0.000000	0.000001
5	**Argentina**	0.000001	-0.000009	-0.000011	-0.000004	-0.000005	0.000005	0.000001	-0.000012
6	**Armenia**	0.000003	-0.000011	0.000015	0.000004	0.000002	0.000002	0.000003	0.000004
7	**Australia**	0.000014	0.000095	0.000033	0.000016	0.000035	0.000012	0.000016	0.000010
8	**Austria**	0.000025	0.000121	0.000046	0.000033	0.000061	0.000018	0.000027	0.000027
9	**Azerbaijan**	-0.000002	-0.000011	-0.000001	-0.000003	-0.000005	-0.000001	-0.000002	-0.000004
10	**Bahamas**	0.000005	0.000017	-0.000004	0.000007	0.000011	0.000001	0.000004	0.000009
11	**Bangladesh**	0.000007	0.000048	-0.000014	0.000005	0.000013	0.000006	0.000004	-0.000009
12	**Barbados**	-0.000004	-0.000007	0.000005	-0.000004	-0.000004	0.000000	0.000000	0.000001
13	**Belarus**	0.000004	0.000001	0.000020	0.000003	0.000004	0.000002	0.000003	0.000002
14	**Belgium**	0.000007	0.000012	0.000011	0.000009	0.000012	0.000003	0.000007	0.000010
15	**Belize**	0.000001	-0.000003	-0.000016	0.000002	0.000001	-0.000002	-0.000001	0.000004
16	**Bermuda**	0.000001	-0.000002	0.000003	0.000001	0.000000	0.000001	0.000001	0.000000
17	**Bolivia**	-0.000009	-0.000039	-0.000023	-0.000012	-0.000020	-0.000004	-0.000007	-0.000008
18	**Bosnia Herzegovina**	-0.000029	-0.000091	-0.000065	-0.000038	-0.000058	-0.000011	-0.000023	-0.000036
19	**Brazil**	-0.000032	0.000004	-0.000075	-0.000046	-0.000048	0.000001	-0.000017	-0.000051
20	**Bulgaria**	-0.000001	-0.000003	0.000005	-0.000001	-0.000001	0.000000	0.000001	0.000001
21	**Cambodia**	-0.000022	-0.000101	-0.000031	-0.000032	-0.000054	-0.000009	-0.000019	-0.000028
22	**Cameroon**	0.000000	-0.000009	-0.000002	-0.000001	-0.000003	-0.000001	-0.000001	-0.000002
23	**Canada**	0.000147	0.000552	0.000354	0.000189	0.000341	0.000111	0.000181	0.000240
24	**Cape Verde**	-0.000004	-0.000017	-0.000015	-0.000006	-0.000011	-0.000002	-0.000004	-0.000009
25	**Chile**	-0.000008	-0.000006	-0.000010	-0.000010	-0.000012	0.000001	-0.000004	-0.000012
26	**China**	0.000090	-0.000253	0.000352	0.000038	-0.000013	0.000055	0.000068	0.000045
27	**Colombia**	-0.000057	-0.000169	-0.000172	-0.000085	-0.000125	-0.000019	-0.000051	-0.000093
28	**Costa Rica**	-0.000011	-0.000049	-0.000027	-0.000015	-0.000027	-0.000004	-0.000010	-0.000016
29	**Croatia**	0.000000	0.000028	0.000004	0.000000	0.000006	0.000003	0.000002	-0.000004
30	**Cuba**	0.000107	0.000327	0.000176	0.000125	0.000190	0.000045	0.000075	0.000072
31	**Czech Republic**	0.000004	0.000028	0.000015	0.000006	0.000014	0.000005	0.000006	0.000005
32	**Czechoslovakia**	0.000009	0.000044	0.000007	0.000013	0.000022	0.000004	0.000008	0.000011
33	**Denmark**	0.000005	-0.000008	0.000014	0.000003	0.000002	0.000004	0.000004	0.000000
34	**Dominica**	0.000004	0.000011	0.000014	0.000004	0.000006	0.000002	0.000003	0.000004
35	**Dominican Republic**	0.000066	0.000183	0.000202	0.000082	0.000116	0.000015	0.000041	0.000069

36	**Ecuador**	-0.000047	-0.000109	-0.000114	-0.000062	-0.000090	-0.000014	-0.000039	-0.000077
37	**Egypt**	-0.000001	0.000039	0.000028	-0.000002	0.000008	0.000008	0.000006	-0.000007
38	**El Salvador**	-0.000132	-0.000278	-0.000453	-0.000185	-0.000270	-0.000049	-0.000128	-0.000246
39	**England**	0.000021	0.000209	0.000039	0.000023	0.000063	0.000029	0.000035	0.000022
40	**Eritrea**	-0.000003	-0.000010	-0.000002	-0.000004	-0.000006	-0.000001	-0.000002	-0.000005
41	**Estonia**	-0.705370	0.116223	0.445656	0.083552	0.000008	0.000002	0.000003	0.000003
42	**Ethiopia**	-0.000003	-0.000010	0.000004	-0.000004	-0.000006	0.000000	-0.000002	-0.000007
43	**Fiji**	-0.000008	-0.000034	-0.000022	-0.000012	-0.000019	-0.000003	-0.000007	-0.000013
44	**Finland**	0.000004	0.000020	0.000030	0.000005	0.000010	0.000004	0.000006	0.000005
45	**France**	0.000039	0.000165	0.000084	0.000049	0.000092	0.000029	0.000045	0.000051
46	**Georgia**	0.000001	-0.000001	0.000002	0.000000	0.000000	0.000001	0.000000	-0.000001
47	**Germany**	0.000002	0.000046	-0.000002	-0.000006	0.000009	0.000023	0.000017	-0.000013
48	**Ghana**	-0.000003	-0.000016	-0.000020	-0.000003	-0.000007	-0.000004	-0.000004	-0.000001
49	**Greece**	0.000009	0.000025	0.000026	0.000004	0.000010	0.000012	0.000011	-0.000004
50	**Grenada**	0.000003	0.000016	0.000011	0.000004	0.000008	0.000002	0.000004	0.000005
51	**Guatemala**	-0.000054	-0.000101	-0.000215	-0.000083	-0.000120	-0.000021	-0.000062	-0.000131
52	**Guyana**	-0.000032	-0.000128	-0.000038	-0.000046	-0.000074	-0.000012	-0.000027	-0.000049
53	**Haiti**	-0.000031	-0.000124	-0.000156	-0.000047	-0.000082	-0.000019	-0.000039	-0.000063
54	**Honduras**	-0.000001	-0.000012	-0.000080	-0.000006	-0.000016	-0.000008	-0.000014	-0.000021
55	**Hong Kong**	0.000009	-0.000012	0.000083	0.000000	0.000003	0.000017	0.000018	0.000011
56	**Hungary**	0.000018	0.000058	0.000017	0.000023	0.000036	0.000007	0.000015	0.000025
57	**India**	0.000003	0.000005	0.000276	-0.000048	-0.000018	0.000105	0.000079	-0.000058
58	**Indonesia**	-0.000007	-0.000066	0.000023	-0.000013	-0.000026	-0.000002	-0.000004	-0.000003
59	**Iran**	0.000072	0.000577	0.000199	0.000093	0.000210	0.000071	0.000097	0.000086
60	**Iraq**	0.000001	-0.000020	0.000038	-0.000001	-0.000005	0.000002	0.000001	-0.000005
61	**Ireland**	0.000016	0.000086	0.000016	0.000020	0.000039	0.000011	0.000017	0.000020
62	**Israel**	0.000035	0.000153	0.000112	0.000042	0.000079	0.000027	0.000041	0.000043
63	**Italy**	0.000028	0.000049	0.000009	0.000021	0.000031	0.000019	0.000019	-0.000003
64	**Jamaica**	-0.000051	-0.000250	-0.000078	-0.000068	-0.000122	-0.000027	-0.000045	-0.000053
65	**Japan**	0.000006	-0.000020	0.000113	0.000003	0.000015	0.000023	-0.144177	0.000051
66	**Jordan**	0.000002	-0.000008	0.000055	0.000001	0.000001	0.000003	0.000004	0.000002
67	**Kazakhstan**	0.000001	-0.000001	0.000001	0.000001	0.000000	0.000000	0.000000	0.000000
68	**Kenya**	0.000004	0.000018	0.000022	0.000007	0.000012	0.000003	0.000005	0.000007
69	**Korea**	0.000073	0.000250	0.000492	0.000105	0.000199	0.000068	0.000134	0.000243
70	**Kuwait**	0.000003	0.000013	0.000019	0.000004	0.000008	0.000002	0.000004	0.000010
71	**Laos**	-0.000037	-0.000118	-0.000090	-0.000049	-0.000076	-0.000013	-0.000031	-0.000052
72	**Latvia**	0.000003	0.000001	0.000002	0.000003	0.000003	0.000002	0.000002	-0.000002
73	**Lebanon**	0.000004	0.000000	0.000026	0.000001	0.000003	0.000007	0.000007	-0.000001
74	**Liberia**	-0.000003	-0.000013	-0.000010	-0.000004	-0.000007	-0.000001	-0.000002	-0.000001

75	**Lithuania**	0.000005	0.000021	-0.000005	0.000005	0.000009	0.000002	0.000003	0.000004
76	**Macedonia**	-0.000005	-0.000020	-0.000005	-0.000007	-0.000011	-0.000002	-0.000004	-0.000007
77	**Malaysia**	0.000000	0.000011	0.000030	0.000001	0.000005	0.000002	0.000004	0.000007
78	**Mexico**	0.000177	0.001445	-0.002256	-0.000028	-0.000017	-0.000038	-0.000291	-0.000952
79	**Micronesia**	0.000005	0.000009	0.000012	0.000006	0.000008	0.000001	0.000004	0.000007
80	**Moldova**	0.000000	-0.000009	0.000009	0.000000	-0.000002	0.000000	0.000000	0.000000
81	**Morocco**	0.000002	0.000004	0.000007	0.000000	0.000001	0.000003	0.000002	-0.000004
82	**Myanmar**	0.000005	0.000002	0.000007	0.000006	0.000008	0.000004	0.000006	0.000007
83	**Nepal**	-0.000001	-0.000005	0.000000	-0.000001	-0.000002	-0.000001	-0.000001	0.000000
84	**Netherlands**	0.000008	-0.000019	0.000017	0.000006	0.000004	0.000007	0.000007	0.000000
85	**New Zealand**	0.000001	-0.000012	0.000008	0.000001	0.000000	0.000001	0.000002	0.000002
86	**Nicaragua**	-0.000034	-0.000131	-0.000114	-0.000052	-0.000086	-0.000015	-0.000037	-0.000066
87	**Nigeria**	-0.000016	-0.000115	-0.000020	-0.000023	-0.000048	-0.000009	-0.000016	-0.000019
88	**Northern Ireland**	0.000000	0.000027	-0.116194	0.000001	0.000007	0.000002	0.000002	0.000000
89	**Norway**	0.000004	-0.000007	0.000004	0.000005	0.000004	0.000000	0.000003	0.000010
90	**Pakistan**	0.000005	0.000054	0.000023	0.000001	0.000015	0.000016	0.000012	-0.000009
91	**Panama**	-0.000017	-0.000081	0.000009	-0.000025	-0.000041	-0.000004	-0.000012	-0.000024
92	**Paraguay**	0.000000	-0.000006	-0.000003	0.000000	-0.000001	-0.000001	0.000000	0.000003
93	**Peru**	-0.000053	-0.000163	-0.000078	-0.000079	-0.000119	-0.000014	-0.000045	-0.000098
94	**Philippines**	-0.000391	-0.002221	-0.000554	-0.000607	-0.001083	-0.000145	-0.000344	-0.000583
95	**Poland**	-0.000032	-0.000127	-0.000035	-0.000052	-0.000080	-0.000003	-0.000023	-0.000061
96	**Portugal**	-0.000036	-0.000124	-0.000045	-0.000050	-0.000076	-0.000008	-0.000026	-0.000054
97	**Romania**	0.000003	0.000018	0.000017	0.000002	0.000007	0.000007	0.000006	-0.000003
98	**Russia**	0.000036	0.000082	0.000134	0.000046	0.000067	0.000018	0.000037	0.000059
99	**Samoa**	0.000000	-0.000008	0.000000	0.000000	-0.000002	-0.000001	0.000000	0.000003
100	**Saudi Arabia**	0.000011	0.000029	0.000010	0.000017	0.000025	0.000002	0.000009	0.000022
101	**Scotland**	0.000004	-0.000007	0.000009	0.000003	0.000002	0.000004	0.000004	-0.000002
102	**Senegal**	0.000000	0.000002	0.000016	0.000000	0.000001	0.000000	0.000000	0.000000
103	**Sierra Leone**	-0.000002	-0.000007	-0.000006	-0.000003	-0.000004	-0.000001	-0.000002	-0.000003
104	**Singapore**	0.000002	-0.000020	0.000018	0.000001	-0.000001	0.000001	0.000003	0.000006
105	**Slovakia**	0.000016	0.000048	0.000070	0.000021	0.000032	0.000007	0.000014	0.000023
106	**Somalia**	0.000038	0.000226	0.000075	0.000052	0.000107	0.000031	0.000046	0.000047
107	**South Africa**	0.000002	0.000034	0.000011	0.000004	0.000012	0.000005	0.000007	0.000004
108	**Spain**	0.000001	0.000027	0.000004	0.000000	0.000004	0.000003	0.000003	-0.000003
109	**Sri Lanka**	0.000004	0.000009	0.000008	0.000005	0.000007	0.000001	0.000003	0.000005
110	**St. Kitts & Nevis**	0.000004	0.000009	0.000008	0.000005	0.000007	0.000001	0.000003	0.000005
111	**St. Lucia**	0.000000	-0.000002	-0.000002	0.000000	0.000000	0.000000	0.000000	0.000002
112	**St. Vincent & Grenadines**	0.000005	0.000008	0.000023	0.000006	0.000009	0.000001	0.000004	0.000009
113	**Sudan**	0.000014	0.000059	0.000030	0.000019	0.000035	0.000010	0.000016	0.000022

114	**Sweden**	0.000011	0.000063	0.000017	0.000014	0.000029	0.000010	0.000014	0.000013
115	**Switzerland**	0.000012	0.000077	0.000021	0.000016	0.000033	0.000010	0.000015	0.000013
116	**Syria**	0.000044	-0.000067	0.000287	0.000039	0.000046	0.000039	0.000064	0.000094
117	**Taiwan**	0.000000	-0.000001	-0.000001	0.000000	0.000001	0.000000	0.000001	0.000001
118	**Tanzania**	-0.000013	-0.000078	-0.000004	-0.000019	-0.000033	-0.000002	-0.000007	-0.000012
119	**Thailand**	-0.000001	-0.000010	0.000001	-0.000002	-0.000005	-0.000001	-0.000001	-0.000002
120	**Tonga**	-0.000012	-0.000075	-0.000017	-0.000017	-0.000032	-0.000005	-0.000008	-0.000006
121	**Trinidad & Tobago**	0.000010	0.000051	0.000062	0.000012	0.000026	0.000010	0.000014	0.000013
122	**Turkey**	0.000005	0.000039	0.000005	0.000007	0.000015	0.000004	0.000006	0.000005
123	**Uganda**	0.000022	0.000031	0.000090	0.000019	0.000027	0.000018	0.000021	0.000003
124	**Ukraine**	0.000065	0.000550	0.000146	0.000086	0.000197	0.000064	0.000088	0.000077
125	**United Kingdom**	-0.000004	-0.000001	-0.000023	-0.000006	-0.000007	0.000000	-0.000003	-0.000009
126	**Uruguay**	0.000001	-0.000023	0.000018	-0.000001	-0.000004	0.000002	0.000002	0.000004
127	**USSR**	0.000000	-0.000012	0.000011	-0.000002	-0.000004	0.000001	0.000000	-0.000004
128	**Uzbekistan**	-0.000013	-0.000038	-0.000032	-0.000020	-0.000028	-0.000001	-0.000008	-0.000020
129	**Venezuela**	-0.000094	-0.000551	-0.000100	-0.000166	-0.000288	-0.000021	-0.000084	-0.000192
130	**Vietnam**	0.000004	0.000047	0.000031	0.000006	0.000015	0.000004	0.000005	0.000004
131	**Yemen**	-0.000007	-0.000055	-0.000024	-0.000013	-0.000026	-0.000004	-0.000009	-0.000018
132	**Yugoslavia**	0.000000	0.000003	0.000001	0.000001	0.000002	0.000000	0.000000	0.000001
133	**Zimbabwe**	0.000007	0.000015	0.000020	0.000007	0.000012	0.000005	0.000007	0.000005

APPENDIX G

PAIRWISE CORRELATIONS BETWEEN IMMIGRANT CHARACTERISTICS

	pincp mean	hincp mean	pincp median	hincp median	Schl	Yoep	Eng	Age	per_male	per_visa
pincp_mean	1									
hincp_mean	0.9269	1								
pincp_median	0.8244	0.7779	1							
hincp_median	0.7702	0.8680	0.7617	1						
Schl	0.6300	0.6071	0.4402	0.5305	1					
Yoep	0.3975	0.3162	0.3583	0.154	-0.0622	1				
Eng	-0.5585	-0.4792	-0.5895	-0.3933	-0.4928	-0.2795	1			
Age	0.4466	0.3585	0.3806	0.2125	0.1026	0.9184	-0.2183	1		
per_male	-0.0420	-0.0855	-0.0790	-0.0804	-0.1342	-0.3402	0.1075	-0.3856	1	
per_visa	-0.1632	-0.1561	-0.1060	-0.0788	0.0412	-0.4974	0.0483	-0.5543	0.1683	1
per_unemp	-0.4598	-0.438	-0.3401	-0.3491	-0.2365	-0.3996	0.1013	-0.4488	-0.001	0.0843
per_stud	-0.2570	-0.2002	-0.3035	-0.1694	0.2542	-0.6599	-0.058	-0.6913	0.2517	0.3801
Pol	0.3495	0.3126	0.4507	0.2619	0.0715	0.5633	-0.3321	0.5024	-0.3254	0.0280
Inequ	-0.2785	-0.2897	-0.1713	-0.2266	-0.1264	-0.431	-0.1031	-0.5041	0.3234	0.2478
Inf	0.0998	0.0483	0.105	0.1004	0.1051	-0.0742	-0.1067	-0.0983	0.012	0.1214
Unemp	-0.2216	-0.2536	-0.1244	-0.1762	-0.1135	-0.3228	0.0214	-0.3516	0.2287	0.2255
Open	-0.0517	-0.0275	0.0179	0.0529	0.0118	-0.0534	-0.0137	-0.0845	-0.0832	0.0129
Geo	0.2212	0.2954	0.0501	0.2984	0.3662	-0.3203	-0.0349	-0.2342	0.2211	-0.016
Neig	-0.0217	-0.0399	-0.021	-0.0429	-0.1589	0.0789	0.0676	0.0129	0.0219	0.1305
Col	0.0905	0.1003	0.0954	0.1001	-0.0105	0.1378	-0.0763	0.0974	-0.0963	0.0506
Lan	0.2030	0.1405	0.3636	0.1407	0.1153	0.0514	-0.7304	-0.0297	-0.1079	0.0513
Latin	-0.3683	-0.3651	-0.1547	-0.2849	-0.3944	-0.0348	0.1597	-0.1282	-0.1612	0.1334
Asia	-0.0231	0.0815	-0.2515	0.0833	0.1586	-0.2845	0.2117	-0.2731	0.1106	-0.1253
Eur	0.3320	0.2879	0.2486	0.1752	0.1675	0.5033	-0.0486	0.5951	-0.2165	-0.2523
Afr	0.0143	-0.0739	0.1135	-0.0462	0.0898	-0.3296	-0.1943	-0.3114	0.3403	0.2033
North	0.0474	0.0045	0.0837	-0.0054	0.0427	0.1843	-0.152	0.1373	-0.0028	0.0575
Ocea	0.0307	0.0691	0.0658	0.1019	-0.0606	0.0255	-0.2374	-0.0068	-0.0032	0.1523
Eu	0.3820	0.3413	0.3061	0.1568	0.1434	0.5993	-0.1844	0.5951	-0.2529	-0.1459
Oecd	0.4729	0.4043	0.3482	0.2648	0.1246	0.5527	-0.1945	0.5291	-0.2047	0.0453
Land	-0.0514	-0.0543	-0.0924	-0.0703	0.1328	-0.0491	0.0966	0.0011	-0.1154	-0.0417
Size	-0.1187	-0.0928	-0.0827	-0.056	-0.2679	-0.0062	0.2475	-0.0631	0.0446	0.1192
hh_size	-0.1063	-0.0843	-0.0723	-0.0512	-0.2636	0.0097	0.2423	-0.0462	0.0373	0.1106

	per_unemp	per_stud	Pol	Inequ	Inf	Unemp	Open	Geo	Neig	Col
per_unemp	1									
per_stud	0.4014	1								
Pol	-0.2960	-0.4518	1							
Inequ	0.3746	0.3853	-0.1948	1						
Inf	-0.1015	0.1013	-0.175	0.0658	1					
Unemp	0.2276	0.3264	-0.2411	0.2379	0.4424	1				
Open	0.1556	0.1427	0.0003	-0.0426	-0.0489	0.3202	1			
Geo	-0.0989	0.2992	-0.4388	-0.0221	0.1260	0.0627	0.0646	1		
Neig	-0.0236	-0.0985	0.0952	-0.0201	-0.0111	-0.0676	-0.0281	-0.2487	1	
Col	-0.1049	-0.1363	0.1502	-0.0653	-0.0178	-0.0896	-0.055	-0.1441	0.6252	1
Lan	0.1247	0.0576	0.2003	0.3111	0.1272	0.116	0.0995	-0.114	0.049	0.1208
Latin	0.2744	-0.1183	0.1857	0.2906	-0.0508	-0.0194	-0.0631	-0.7228	0.075	-0.0188
Asia	-0.0115	0.2396	-0.4605	-0.0337	-0.0539	-0.0818	0.0596	0.6113	-0.0738	-0.0283
Eur	-0.3612	-0.3251	0.4301	-0.5027	-0.0540	-0.1754	-0.0201	-0.0862	-0.0781	-0.0375
Afr	0.2498	0.3717	-0.2969	0.3587	0.2195	0.4679	0.0781	0.2415	-0.0504	-0.0807
North	-0.0853	-0.0450	0.1036	-0.061	-0.0111	-0.075	-0.0388	-0.2268	0.4924	0.3004
Ocea	-0.1169	-0.1463	0.1135	-0.003	-0.0212	-0.0455	-0.0583	0.0978	-0.0291	0.1304
Eu	-0.3568	-0.3465	0.508	-0.4669	-0.0445	-0.2122	-0.0166	-0.1038	-0.0609	0.1019
Oecd	-0.4295	-0.3604	0.5484	-0.4426	-0.0487	-0.2494	-0.0763	-0.1182	0.2289	0.2716
Land	-0.0765	0.0863	-0.2270	-0.1813	0.2064	0.1287	-0.0267	0.1729	-0.0535	-0.0856
Size	-0.0085	-0.1266	0.0165	0.0141	-0.0243	-0.1015	-0.0415	-0.1906	0.7234	0.5398
hh_size	-0.0165	-0.1365	0.0235	0.0051	-0.0258	-0.1068	-0.0453	-0.2028	0.7370	0.5489
emp_stud	0.7283	0.8590	-0.4203	0.4039	-0.0405	0.3076	0.1909	0.1424	-0.0678	-0.1192
visa_stud	0.3371	0.9380	-0.3518	0.3836	0.1344	0.3682	0.1245	0.2454	-0.0497	-0.0978
visa_emp	0.8469	0.5626	-0.2908	0.4408	-0.0689	0.3285	0.1845	-0.0741	0.0432	-0.0632

	Lan	Latin	Asia	Eur	Afr	North	Ocea	Eu	Oecd	Land	Size	hh_size
Lan	1											
Latin	0.1095	1										
Asia	-0.2223	-0.3364	1									
Eur	-0.2864	-0.356	-0.3780	1								
Afr	0.2311	-0.2298	-0.2440	-0.2582	1							
North	0.1819	-0.0695	-0.0738	-0.0781	-0.0504	1						
Ocea	0.3469	-0.1327	-0.1409	-0.1491	-0.0962	-0.0291	1					
Eu	-0.1309	-0.2775	-0.2946	0.7374	-0.2012	-0.0609	-0.0313	1				
Oecd	-0.0570	-0.2617	-0.2000	0.5347	-0.2203	0.0811	0.1145	0.6866	1			
Land	-0.1611	-0.1473	0.0690	0.1369	0.0000	-0.0535	-0.1021	-0.0055	0.0130	1		
Size	-0.0450	0.1807	0.0176	-0.1042	-0.0946	0.0389	-0.0427	-0.0669	0.1609	-0.1039	1	
hh_size	-0.0380	0.1818	0.0124	-0.1018	-0.0996	0.0580	-0.0420	-0.0594	0.1737	-0.1106	0.9987	1
emp_stud	0.0915	0.0019	0.1129	-0.3064	0.3538	-0.0685	-0.1236	-0.3045	-0.3531	0.0008	-0.0909	-0.0991
visa_stud	0.0564	-0.0796	0.1430	-0.3027	0.3751	-0.0212	-0.0933	-0.2771	-0.2447	0.0809	-0.0833	-0.0931
visa_emp	0.0804	0.2642	-0.0616	-0.3969	0.3404	-0.0594	-0.0823	-0.353	-0.3607	-0.0700	0.0610	0.0500

	emp_stud	visa_stud	visa_emp
emp_stud	1		
visa_stud	0.8066	1	
visa_emp	0.8026	0.6255	1

APPENDIX H

PAIRWISE CORRELATIONS BETWEEN THE CHANGES IN IMMIGRANT CHARACTERISTICS

	Δpincp_ median	**Δschl**	**Δage**	**Δper_unemp**	**latin**	**asia**	**eur**	**afr**	**north**	**ocea**
Δpincp_median	1									
Δschl	0.0223	1								
Δage	0.0320	0.0562	1							
Δper_unemp	-0.0693	-0.1412	0.2331	1						
latin	-0.3084	0.2414	-0.0103	-0.0648	1					
asia	-0.0437	-0.4409	0.0844	0.0920	-0.4992	1				
eur	0.2488	-0.0712	0.2548	0.2234	-0.3454	-0.3125	1			
afr	0.0415	0.2936	-0.255	-0.3913	-0.2626	-0.2376	-0.1644	1		
north	0.1405	0.0959	-0.2231	0.0907	-0.1120	-0.1013	-0.0701	-0.0533	1	
ocea	0.2643	0.0636	-0.1255	0.0857	-0.1120	-0.1013	-0.0701	-0.0533	-0.0227	1