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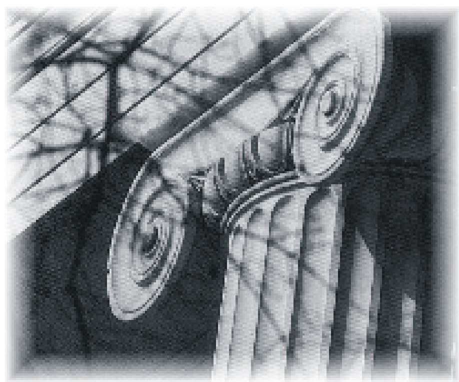

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Gender Differences in Income Inequality among Immigrant Populations to the United States

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Abstract:

This work examines the level of income inequality of immigrants to the United States. We separately examine income inequality of males and females using several different inequality measures for robustness. The work finds that males have the traditional inverted "U" relationship between inequality and growth but females have the opposite. These differences are caused by several key factors but mainly due to the level of work force participation of the two groups. Finally, we examine the differences in inequality between immigrants that have been in the country for a decade and newly arrived immigrants finding that income inequality is much greater for new immigrants.

1. INTRODUCTION

The US Census estimated that, as of 2006, there were 37.6 million legal immigrants living in the United States. 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."

There has been a great expenditure of resources to understanding the impacts of immigrants, both legal and illegal to the United States over the last thirty years. Most works in this regard have centered on wage inequality created when unskilled immigrant workers displace native workers. For an excellent overview of the issues surrounding this analysis see Card (2009).

In addition, there has been a considerable amount of attention paid to the impact that immigrants have on overall income inequality in the country of destination. See Davies and Wooton (1992) and Dolmas and Huffman (2004). Does income inequality for the entire population rise or fall when there is a sizable influx of immigrants? Do immigrants make up a larger portion of the lower tail of the income distribution?

What has not been fully explored in the literature, to this point, is the composition of the immigrant cohort itself. In essence, there has been little attention paid to the level of existing inequality of immigrant groups from various countries. Theoretically, US income inequality would be unaffected by entering cohorts with income characteristics that exactly matched the mean and distribution of current citizens. One of the major contributors to varying levels of income inequality is the gender ratio of the entering cohorts. It would seem critically important to know the gender mix of entering immigrant groups and how much inequality, if any, existed in the group.

If the ultimate goal of a successful immigration policy is to have immigrants assimilated into the culture as well as the economy of the host county, it is critical to know what the existing level of inequality is and how factors both demographic and economic impact that level. In this paper, we investigate the differences in income inequality of male and female immigrants to the United States. We then examine the differences in inequality for males and females using several different inequality measures and examine the differences in inequality when certain independent variables are introduced. Finally, we see what a decade of living in the United States does to income inequality of immigrants from various regions of the world.

2. LITERATURE REVIEW

The seminal work of Kuznets (1955) has led to a rich stream of research regarding the nature of the relationship between economic growth and income inequality. The Kuznets hypothesis stated that the functional relationship between inequality and economic development had an inverted "U" shape. Kuznets speculated that inequality would initially be positively correlated with economic development but that the relationship between income and inequality would become negative at higher levels of development. Results supporting this hypothesis typically come from the use of cross-sectional country-specific data. Later, researchers like Blinder and Esaki (1978) and Bruno et al. (1998), among many others, have found results that support the basic premise of the Kuznets hypothesis.

In addition, Nielsen and Alderson (1997) use a panel of U.S. counties and discover that the Kuznets hypothesis held for the period 1925 through 1970, where growth and income inequality had the expected inverted U-shape but that since 1970 there has been a “U-turn” in that relationship. Nielsen and Alderson (1997) partly attribute this change to racial and gender compositions. Here, the authors promote the idea that gender “dualism” may have contributed to this upswing in that males and females systematically find different employment opportunities and sources of income that leads to dual economies and persistent income inequality.

As mentioned earlier, to a large extent, gender differences in inequality have centered around wages. McCall (2001) examines the differences in wage inequality among racial/ethnic groups and gender in metropolitan areas. The authors’ findings for wage inequality, that the impacts of schooling on opportunities are important and consistent with our findings for income inequality.

If we believe that male and female immigrants are influenced differently about whether to participate in the labor force by cultures in their host countries than participation in the labor force is an important explanatory factor regarding income inequality. The work of Fernadez and Fogli (2009) adds to the literature and helps guide our work regarding interpretation of the results found later. The authors examine the labor force participation rates of second generation American women, along with fertility, as a proxy for cultural influences of the country of ancestry and find that these factors are significant. Our work of immigrants accounts for both the number of children and work force participation of male and female immigrants, finding that work force participation is highly significant regarding income inequality but not significant for the number of children.

Osberg (2003) adds an interesting perspective to the differences in income inequality across countries. The author states that comparisons of international income inequality might be skewed without first accounting for workforce participation of older men and women. When comparing the United States to Germany over a twenty year period, beginning in 1980, the author states that greater equality of income among Germans "seems to come without much cost in decreased labor supply – among workers." Since females, historically earn less than males, the ever larger influx of women to the labor force has resulted in ever increasing measures of inequality in the United States. Part of our investigation here will be to find out if this relationship is true for immigrant males and females to the United States.

3. THE DATA

This empirical study on gender differences of immigrants to the U.S. used data from the American Community Survey (ACS) for the year 2006. These data are provided by the Census Bureau. The Census Bureau screens approximately three million households annually, who constitute one percent of the total population in the United States. Data is collected in all 3,141 U.S. counties. The questionnaire allows the Census Bureau to collect several important variables such as personal and household income, employment status, educational attainment, age, and gender etc.

The surveyed respondents are split into two categories by the Census Bureau. The first category was composed of U.S. citizens and accounted for approximately 88% of the sample in 2006. 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,* however, are defined as people who moved to the U.S. from a different country permanently or temporarily. These people are either citizens of other countries or they are U.S. citizens who obtained their U.S. citizenship through the naturalization process. There were approximately three hundred fifteen thousand 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 were citizens of other countries. Although they are U.S. citizens, there are significant cultural differences between these individuals and native U.S. citizens.

Male and female immigrants are then split into sub-groups based on their country of origin. These 133 counties are the ones that are recognized in the ACS. The ACS left some countries out, such as Tunisia, newly established Kosovo, and Tajikistan. Three more countries (Guinea, Iceland, and the West Indies) were excluded from the study because of the small sample sizes.

One of the most important variables in the survey is *personal income*, which was used to calculate the income inequality measures of the groups. Personal income 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, or net rental or royalty income or 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.

As shown in Figure 1.a-b, the distribution of personal income for both male and female immigrants carry the fundamental characteristic of most income distributions; namely, that they were positively skewed. However, the distribution for females has less positive skewness and has a maximum that is almost three times smaller than the maximum for males. In Figure 2, we present personal income broken down by region of the world for both males and females. In all cases, male average personal income is higher than that of females. Not surprisingly, the personal income of immigrant females was less than half of that of their male counterparts.

Table 1.a has descriptive statistics of all variables used in this analysis. As mentioned above, we calculated all of our income inequality measures using personal income. Not only was the average 2006 personal income of men twice that of women, there was a much higher standard deviation for women. For both men and women immigrant groups, there was very little difference in schooling, which is commonly included in the literature to control of certain human capital characteristics. The reader should note that schooling is a categorical variable. The responses of individuals do not correspond to actual years of schooling. A zero response corresponded to a missing variable rather than no education, while one corresponded to "no schooling completed". The maximum level of schooling was sixteen, which corresponded to a doctorate degree.[1]

Other demographic variables that differed little were the year of entry into the country. On average, immigrants had been in the country for approximately 10 years in 2006, regardless of gender. The number of children was slightly higher for women also. There also was a small difference in the size of the groups when separated by gender.

[1] The omitted responses for the variables are excluded from the sample.

The ability to earn income and subsequently the legal right to seek employment in the country is a significant contributor to income inequality among immigrants. Immigrants who stay in the U.S. with valid visas (F-1B, H-1B, E-1, E-2, and E-3) have limited employment rights and some of them have no rights to legally work during their stay in the United States (F-2, H-2, and B-1). In addition, some types of visas only allow immigrants into the country to attend school. Table 1.a shows that, on average, each gender cohort had approximately 47 percent holding work visas. The standard deviation was very similar for both men and women. We also accounted for the percentage of students by measuring the proportion of students in the sample for both males and females, finding that numbers were very similar.

Finally, as mentioned earlier, historically, there has been a tremendous difference in workforce participation between men and women. This held true for immigrant populations also where the average number of hours worked per week in the last 12 months was 33.9 for males but only 21.9 for females. The Bureau of Labor Statistics classifies full time work status as 35 hours per week so immigrant men in the sample were very close to full time status.

In this investigation, we used three different measures of income inequality. These measures were the Gini coefficient (GINI_P), the Theil measure of inequality (THEIL_P) and the Relative Mean Deviation (RMD_P), which are commonly used in the literature.

We formulated the Gini by calculating:

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

where μ is mean income, n is the number of individuals in the group, y_i is income of the i^{th} individual in the group, y_j is income of the j^{th} individual in the group. The coefficient lies between zero and one, with a higher Gini coefficient corresponding to a higher level of inequality. A zero Gini coefficient means perfect equality of incomes; whereas a coefficient of one means perfect inequality of incomes.

In addition, we calculated the Theil measure using:

$$THEIL = \ln(\mu_y) - \ln(\mu_{gm}) = \ln\left(\frac{\mu_y}{\mu_{gm}}\right) \tag{2}$$

where μ_y is the arithmetic mean and μ_{gm} is the geometric mean of the distribution of income. The Theil measure has the advantage of summing income inequalities within subgroups based on statistical information theory. This measure always takes positive values but the contribution of each subgroup to total income inequality can be negative. A zero Theil measure would indicate perfect equality where the geometric mean is equal to the arithmetic mean, mode, and median. However, when the Theil measure is greater than zero, the distribution of income is skewed to the right. The higher the index, the more unequal income is distributed.

Finally, we calculated RMD as:

$$RMD = \sum_{i=1}^{n} \frac{|\mu - y_i|}{n\mu} \tag{3}$$

Where μ is mean income, n is the population size and y_i is income of the i^{th} individual in the population. RMD is an income inequality metric that measures the total sum of deviation from the mean; therefore RMD suggests that inequality of population A is larger than population *B* if the total deviation of the mean is greater for population *A* than population *B*.

From Figure 3 it is shown that, regardless of measure, females have greater income inequality than males. The greatest divergence among measures was between the Theil Measure and the RMD. Table 1.b confirms what was presented in Figure 3, in that, income inequality is greater among female immigrants than males. In addition, the results show robustness in that these findings hold over all measures.

There was something fundamentally different between males and females as demonstrated in Figure 4. A fitted line of income inequality (the Gini) and personal income shows the traditional U-shaped Kuznets curve, however this relationship is inverted for females. As mentioned earlier, the literature is split on the true nature of the relationship between growth and inequality. This work helps in showing that part of the ambiguity is due to gender differences, although it should be noted that we only addressed immigrant populations in this study.

The gender differences in incomes are significant as demonstrated in Tables 2.a-b, where we presented two-sample t-tests and variance ratio tests for our male and female cohorts. Finally, Tables 3.a-b has pairwise correlations of all of the variables used in this analysis. Not surprisingly, there is a strong correlation between schooling and income, although the correlation was higher for males. In addition, the number of children was negatively correlated with income and the negative correlation was higher for females who tended to have more children on average also, implying that females were limited in opportunities to earn income by child care responsibilities.

4. RESULTS

Modeling

Consider the following regression model:

$$\begin{aligned} Inequality_i &= \alpha_o + \alpha_1 Pincp_i + \alpha_2 Pincp_i^2 + \alpha_3 Schl_i + \alpha_4 YOEP_i + \alpha_5 NOC_i \\ &+ \alpha_6 WHPW_i + \alpha_7 Per\_Visa_i + \alpha_8 Per\_Stud_i + \alpha_9 Size_i + \varepsilon_i \end{aligned} \tag{4}$$

where $Inequality_i$ is the Gini coefficient, Theil measure, or RMD as defined in Equations 1 - 3 for immigrant group *i*. *Pincp* and $Pincp^2$ are income and income-squared to capture the non-linearity of the effect proposed by Kuznets; *Schl* is the educational attainment of each cohort, *YOEP* reflects the number of years that the immigrant had been in the United States, *NOC* accounts for the number of children that the immigrant cohorts had, and *WHPW* is the average number of hours worked per week for the last year which reflects labor participation rate.

The model presented used robust regressions. The Ordinary Least Squares (OLS) method is susceptible to outliers which can lead to biased estimation of coefficients of interest. "Robust regression" is generally used to eliminate the effect of outliers in the data. Robust regression runs the OLS regression, and then calculates the Cook's D values of each variable.[2] The procedure then drops the variables that have a Cook's D value of 1 and above. The models estimated with robust regressions have higher R-squared values and are more precisely estimated compared to OLS results. However, the general findings of OLS still hold because the comparable models of OLS and Robust Regression yield the same explanatory variables in most of the cases.

Impact of Independent Variables

[2] Cook's D value is an overall measure of influence. It has a bound of zero which implies no influence of explanatory variable on dependent. The higher the value is, the more influential it is. For outlier detection, the threshold for Cook's D value is 4/n.

We begin our analysis by simply trying to answer the following question. Were there significant differences to income inequality of immigrants when the sample was separated by gender?

Consistently and regardless of measure, we found that males and female immigrant income inequality was increased when the year of entry was higher. In other words, newly arrived immigrants added to increases in income inequality, regardless of gender. This result was supported by simple assimilation analysis that was performed and presented later in the paper. Interestingly, the effect was larger for females, where newly arriving female immigrants added more to the already higher income inequality of females than newly arriving males did to their group.

In addition, the same type of consistency, regardless of measure was found for workforce participation. Here, the estimated coefficient was negative for both male and female immigrants implying that increases in hours worked per week decreased inequality, regardless of gender. However, as shown in Table 3.a, workforce participation and income had correlation coefficients less then 0.5. The results are not surprising given that many immigrants are not in the work force initially causing an increase in inequality measures. As these immigrants acclimate to their new environment and find employment, income inequality falls.

For a few variables, there were significant estimated coefficients for males but for only one of the three measures for females. The number of children, the percentage of visa holders, and the percentage of students were all statistically significant for males. Not surprisingly, increases in the percentage of visa holders were significantly correlated with decreases in income inequality. In essence, the lack of a legal right to enter into the labor force would decrease income earning opportunities, therefore leading to increases in inequality. However, the variable had no significance, regardless of model, for females.

The percentage of students had a positive and significant estimated coefficient for males. As the number of students rises, there is less short-run income earnings opportunities, leading to increases in inequality. This result was not consistently found across measures for females. Only the Gini measure, for females, had an estimated coefficient that was positive and significant.

Finally, for income and the square of income, we tested the non-linear relationship between growth and inequality posited by Kuznets and others. As mentioned previously and shown in Figures 4.a-b, male immigrants had a U-shaped relationship while female immigrants had inverted U-shaped curves. In our regression analysis, we found that for male immigrants the data did show this traditional inverted U-shaped relationship with income and the square of income being positive and negatively significant, respectively. The U-shape of female immigrants was also borne out by the data but was not as strong since the negative estimated coefficient on income for females, regardless of measure, was not significant at standard levels. Only in the Gini and RMD models did we find the square of income with the significant estimated coefficient, although all models had the expected sign.

Time and Inequality

In a recent paper by Manning and Swaffield (2008), the authors find that in the entry level job market, there is no gender difference in wages initially. However, the authors find that ten years later, there is a substantial gap in the wages of men and women. Figure 5 shows the difference in inequality, measured using RMD, the Gini Coefficient, and the Theil Measure between immigrants who had been in the country for 10 years and those that were newly arrived. The Gini measure is extremely close for both males and females, showing that newly arriving immigrants had more income inequality than those that had been in the country for a while. The other two measures, RMD and Theil, showed that newly arriving immigrants had more income inequality than their 10 year counter-parts but that the effect was exaggerated for females.

Figure 6 is a graphical presentation of the data contained in Table 6.a which breaks down the differences in inequality between 10 year immigrants and newly arrived immigrants by region of the world. The results are rather interesting in that consistently, male and female inequality shrinks over time. The greatest gap between time-cohorts using the standard Gini measure was for female immigrants from Africa.

The smallest gap, meaning that ten year immigrants had inequality closest to newly arriving immigrants belonged to Canadian women. This would seem to be a troubling statistic as it relates to assimilating immigrants if after ten years the level of inequality of given groups had changed little. However, the move is significant when compared to the overall level of inequality among US females in 2006 which was 0.5730, showing that this group was trending toward the norm.

The same parallels can be seen in the male cohort where, for all groups, the level of inequality among 10 year immigrants is substantially lower than newly arriving immigrants. This difference was most pronounced among Africans.

It is also interesting to note that among immigrants from Latin America, which includes Mexico, the level of inequality of among newly arriving immigrants is quite similar to that of US males as a whole and that the level of 10 year immigrants from this region is actually lower than that of US males as a whole. Of course, these measures of inequality are only among legal immigrants to the country.

5. CONCLUSIONS and POLICY IMPLICATIONS

Our investigation of the gender differences in income inequality have yielded some compelling results that should be of interest to policy makers concerned with gender inequities and immigration policy.

Given the on-going debate about the true nature of the interaction between inequality and development, our results confirm that some of the uncertainty, at least as it relates immigrants, is gender related. With female immigrants having a “U” shaped fit of income and inequality and males having the more traditional inverted “U” shape, it is no surprise that there is some amount of ambiguity about the overall relationship.

In addition, we found that workforce participation among immigrant groups, regardless of gender is significant in reducing inequality. This is important to note, given that getting immigrants assimilated to the host population will require that they occupy all levels in the income distribution.

Finally, we found that, after a decade of being in the United States, the amount of income inequality among immigrants was greatly diminished for cohorts from some regions of the world from their newly arrived counterparts. This result held for both males and females. However, for immigrants from some regions, a decade was not long enough for them to have inequality that mirrored that of the host nation. This could be an area of increased scrutiny for policy makers, given the ever increasing portion of the population that is made up from different immigrant groups.

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FIGURES

Figure 1.a-b

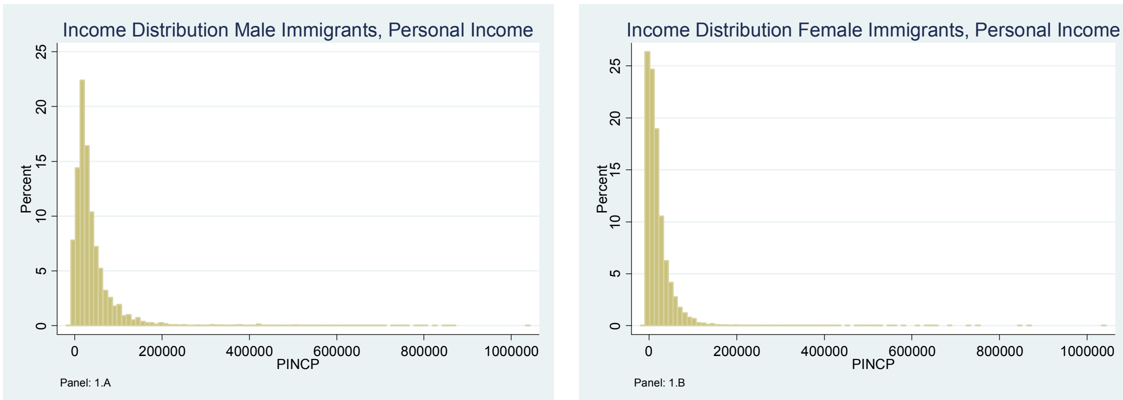


Figure 2

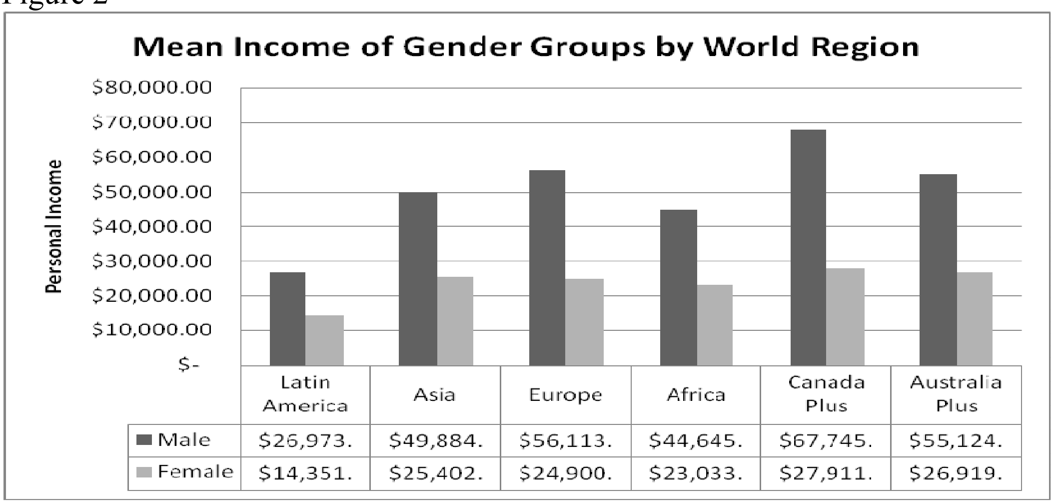


Figure 3

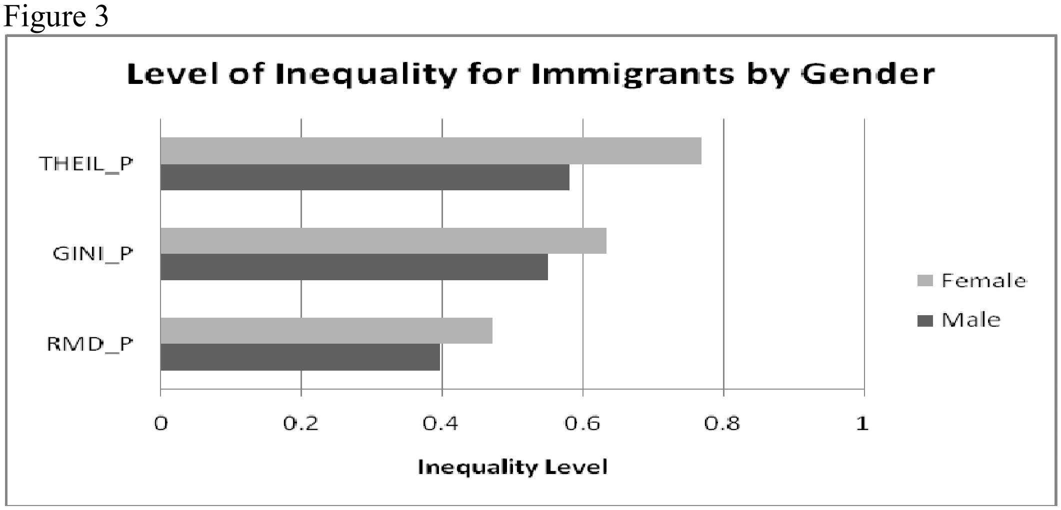
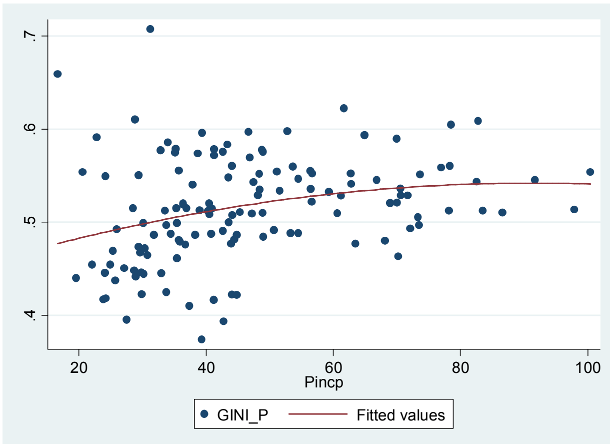
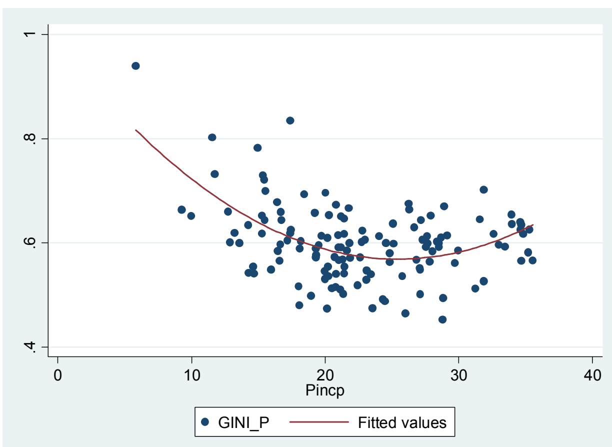


Figure 4: Scatter diagrams

a. Male, Personal income vs. Gini_P



b. Female, Personal income vs. Gini_P



c. Household Income vs. Gini_P

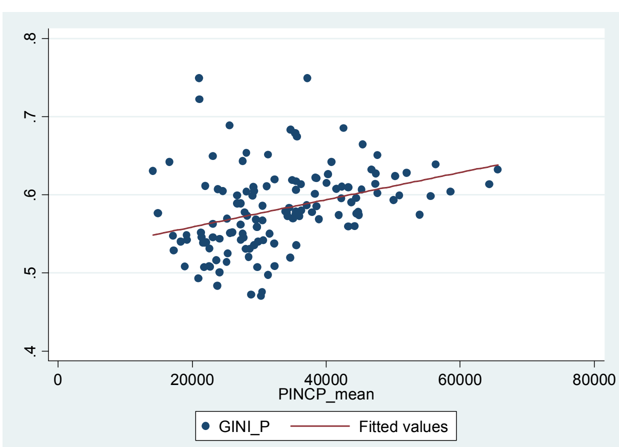


Figure 5:

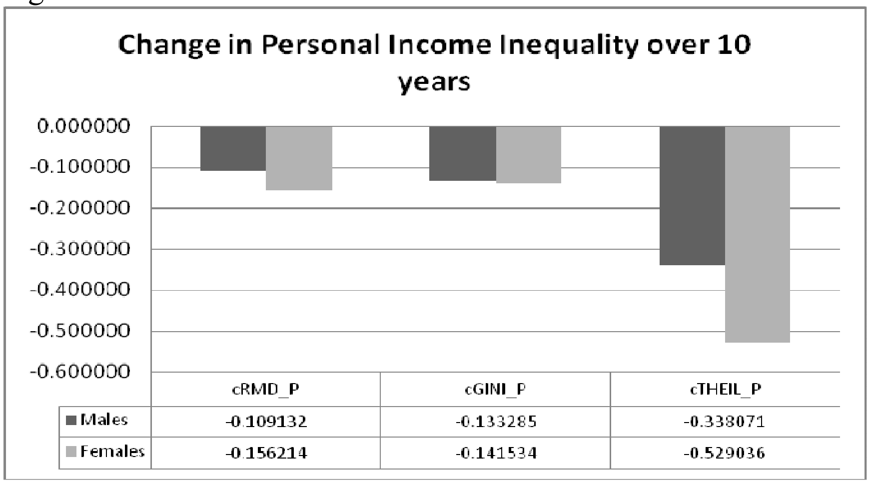
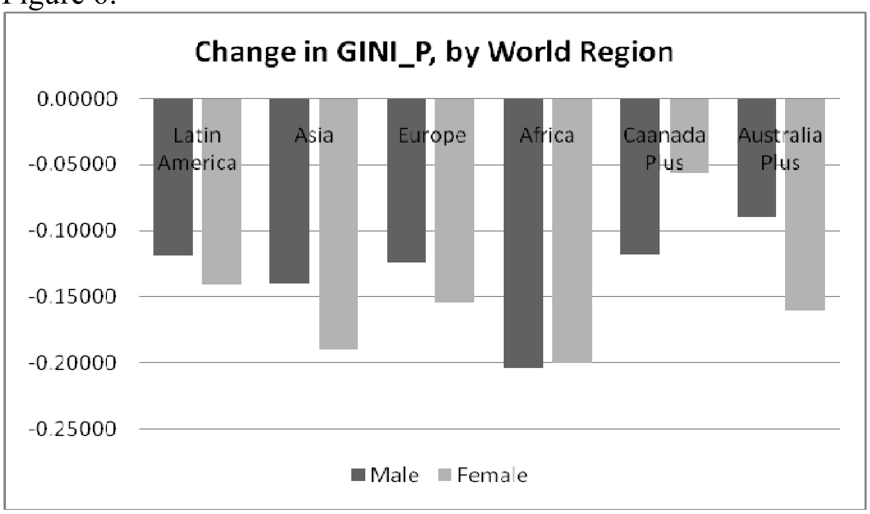


Figure 6:



TABLES

Table 1.a: Descriptive Statistics of Independent Variables, Male and Female Immigrant Groups

Variable	Obs	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
		Males				Females			
Income ($1000)	133	46.76124	17.95601	19.5942	100.4093	22.63097	6.401868	5.8343	35.5432
Schooling	133	10.64352	1.404034	6.3569	12.7895	10.0927	1.387447	5.6923	12.5034
Year of Entry	133	1986.869	6.773901	1968.777	1999.057	1986.249	7.890739	1965.266	1999.141
Number of Children	133	0.7834233	0.3077113	0.2400	2.0435	0.8280744	0.384021	0.2010	2.4897
Work Hour per Week	133	33.29527	4.482053	18.3333	42.463	21.95588	4.967519	2.7308	31.8727
% of Visa Holders	133	0.4884804	0.1623137	0.1538	0.8617	0.4606647	0.14522	0.1768	0.831
% of Students	133	0.1272481	0.0800944	0.0000	0.6545	0.1360226	0.07867	0.0099	0.6061
Size	133	929.203	3542.272	27	39662	1010.481	3246.542	23	35189

Table 1.b: Descriptive Statistics of Dependent Variables, Male and Female Immigrant Groups

Variable	Obs	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
		Males				Females			
RMD_P	133	0.371135	0.047295	0.2700	0.5364	0.446587	0.068452	0.3245	0.8624
GINI_P	133	0.514917	0.056535	0.3742	0.7069	0.599811	0.072243	0.4523	0.9393
THEIL_P	133	0.500737	0.122728	0.2283	0.9879	0.701505	0.253769	0.3606	2.5364

Table 2.a: Two-sample t-test with unequal variances, Personal Income Gini Coefficient

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Males	133	0.5149165	0.0049022	0.0565346	0.5052196	0.5246135
Females	133	0.5998113	0.0062642	0.0722425	0.5874200	0.6122025
combined	266	0.5573639	0.0047495	0.0774614	0.5480124	0.5667154
diff		-0.0848947	0.0079544		-0.1005568	-0.0692327
diff = mean(0) - mean(1)					t = -10.6727	df = 264

Ho: diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000

Table 2.b: Variance ratio test, Personal Income Gini Coefficient

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Males	133	0.5149165	0.0049022	0.0565346	0.5052196	0.5246135
Females	133	0.5998113	0.0062642	0.0722425	0.5874200	0.6122025
combined	266	0.5573639	0.0047495	0.0774614	0.5480124	0.5667154
ratio = sd(0) / sd(1)					f = 0.6124	df = 132, 132

Ho: ratio = 1

Ha: ratio < 1	Ha: ratio != 1	Ha:ratio > 1
Pr(F < f) = 0.0026	2*Pr(F< f) = 0.0051	Pr(F >f) = 0.9974

Table 3.a: Pairwise Correlations between the Immigrant Characteristics, Males

	pincp	schl	yoep	noc	whpw	per_visa	per_stud	Size
pincp	1.0000							
schl	0.6256	1.0000						
yoep	-0.3839	0.0630	1.0000					
noc	-0.3501	-0.2822	0.5138	1.0000				
whpw	0.1105	0.0661	0.5522	0.3665	1.0000			
per_visa	-0.0523	0.0121	0.4864	0.1717	0.3599	1.0000		
per_stud	-0.2490	0.2810	0.6102	0.1531	0.0782	0.2903	1.0000	
size	-0.1008	-0.2835	0.0139	0.1090	0.0894	0.1174	-0.1140	1.0000

Table 3.b: Pairwise Correlations between the Immigrant Characteristics, Females

	pincp	schl	yoep	noc	whpw	per_visa	per_stud	Size
pincp	1.0000							
schl	0.6072	1.0000						
yoep	-0.3342	0.0390	1.0000					
noc	-0.5379	-0.4304	0.5726	1.0000				
whpw	0.3106	0.1179	0.4275	0.0329	1.0000			
per_visa	-0.2395	0.0375	0.4743	0.3103	0.2245	1.0000		
per_stud	-0.1444	0.1911	0.6296	0.3609	0.2898	0.3397	1.0000	
size	-0.1255	-0.2201	-0.0061	0.0720	-0.0102	0.1122	-0.1241	1.0000

Table 4: Robust Regression Analysis for the Determinants of Income Inequality of Immigrant Groups, by Gender						
	Gini_p		**Rmd_p**		**Theil_p**	
	Male	Female	Male	Female	Male	Female
Personal Income	**0.0064*** **	-0.0063	**0.0052*** **	-0.0048	**0.0141*** **	-0.0008
	(4.80)	(1.34)	**(4.68)**	(1.15)	**(4.87)**	(0.06)
Personal Income^2	**-3.56e-05*** **	**0.0002** **	**-2.85e-05*** **	**0.0001* **	**-0.0001*** **	0.0002
	(3.36)	**(2.29)**	**(3.24)**	**(1.91)**	**(3.48)**	(1.01)
Schooling	-0.0064	0.0025	-0.0048	0.005	**-0.0243** **	-0.0071
	(1.43)	(0.61)	(1.30)	(1.38)	**(2.50)**	(0.62)
Year of Entry	**0.0036*** **	**0.0064*** **	**0.0030*** **	**0.0052*** **	**0.0069*** **	**0.0148*** **
	(3.18)	**(7.63)**	**(3.20)**	**(7.07)**	**(2.83)**	**(6.43)**
Number of Children	**0.0325** **	0.013	**0.0239** **	**0.0219* **	**0.0664** **	0.0297
	(2.36)	(0.97)	**(2.09)**	**(1.87)**	**(2.23)**	(0.82)
Work Hours Per Week	**-0.0064*** **	**-0.014*** **	**-0.0058*** **	**-0.0117*** **	**-0.0126*** **	**-0.0341*** **
	(5.56)	**(12.56)**	**(6.08)**	**(12.00)**	**(5.09)**	**(10.69)**
% of Visa Holders	**-0.0667*** **	0.0078	**-0.0511** **	-0.0007	**-0.1252** **	0.04
	(2.65)	(0.28)	**(2.44)**	(0.03)	**(2.30)**	(0.54)
% of Students	**0.3207*** **	**-0.1022** **	**0.2591*** **	-0.0732	**0.8411*** **	-0.1527
	(5.25)	**(1.86)**	**(5.09)**	(1.51)	**(6.36)**	(1.03)
Size	-7.07e-08	5.05e-07	-3.85e-08	3.16e-06	2.64e-07	2.59e-06
	(0.07)	(0.48)	-0.05	-1.39	(0.12)	-0.91
Constant	**-6.5635*** **	**-11.7377*** **	**-5.5319*** **	**-9.6336*** **	**-13.086*** **	**-27.9894*** **
	(2.99)	**(7.13)**	**(3.03)**	**(6.66)**	**(2.75)**	**(6.19)**
Observations	133	133	133	132	133	132
R-squared	0.57	0.76	0.58	0.76	0.54	0.63

Absolute value of t statistics in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Income Inequality of Immigrants by World Regions

	Male			Female		
	RMD	**GINI**	**Theil**	**RMD**	**GINI**	**Theil**
USA	0.390636	0.548553	0.568824	0.419095	0.573062	0.610056
New Immigrants Yoep: 2005/6	**Male**			**Female**		
Regions	**RMD**	**GINI**	**Theil**	**RMD**	**GINI**	**Theil**
Latin America	0.396996	0.556607	0.588102	0.632779	0.787437	1.351446
Asia	0.552838	0.713842	1.004257	0.675902	0.814989	1.404485
Europe	0.505903	0.669401	0.844168	0.617674	0.775729	1.230511
Africa	0.530624	0.688997	0.894397	0.650127	0.804306	1.367454
Canada Plus	0.487340	0.649708	0.786004	0.535466	0.696089	0.921913
Australia Plus	0.487340	0.649708	0.786004	0.597364	0.748987	1.093932
Veteran Immigrants Yoep: 1995/6	**Male**			**Female**		
Regions	**RMD**	**GINI**	**Theil**	**RMD**	**GINI**	**Theil**
Latin America	0.304664	0.445705	0.396281	0.493063	0.655144	0.841053
Asia	0.423219	0.571496	0.589231	0.477463	0.635432	0.746963
Europe	0.392382	0.545319	0.546885	0.462083	0.632585	0.781858
Africa	0.348693	0.496957	0.449979	0.450646	0.607189	0.693969
Canada Plus	0.380749	0.530816	0.498122	0.499167	0.652494	0.810401
Australia Plus	0.380749	0.530816	0.498122	0.429190	0.595156	0.686484
Change in Income Inequality	**Male**			**Female**		
Regions	**ΔRMD**	**ΔGINI**	**ΔTheil**	**ΔRMD**	**ΔGINI**	**ΔTheil**
Latin America	-0.092332	-0.110902	-0.191821	-0.139717	-0.132293	-0.510393
Asia	-0.129619	-0.142347	-0.415026	-0.198438	-0.179556	-0.657522
Europe	-0.113520	-0.124081	-0.297283	-0.155592	-0.143144	-0.448653
Africa	-0.181930	-0.192040	-0.444418	-0.199481	-0.197117	-0.673485
Canada Plus	-0.106592	-0.118893	-0.287882	-0.036299	-0.043595	-0.111512
Australia Plus	-0.106592	-0.118893	-0.287882	-0.168174	-0.153831	-0.407448