Refugees and Economic Migrants: Assimilation of Russian Immigrants in the United States

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Abstract

Effective immigration and refugee policy for host countries requires that we understand the assimilation paths of refugees and economic immigrants and note important ways in which these two groups' assimilation path may be different. This paper explores the differences between refugees and economic immigrants using the case of Russians migrating to the US. Building on earlier work (Cortes (2004) and Chiswick (1998)), the paper tests for differences between refugees and economic immigrants. Using micro-data from the United States censuses, the paper identifies synthetic cohorts of the two groups and estimates a model of their economic assimilation, to explore the hypothesis that refugees and economic immigrants will have different assimilation paths, with refugees experiencing slower assimilation in their earlier years living in the host country. The paper concludes that refugees are statistically significantly different in earlier durations, but become indistinguishable after they have been at least twenty years in the host-country.

1. Introduction

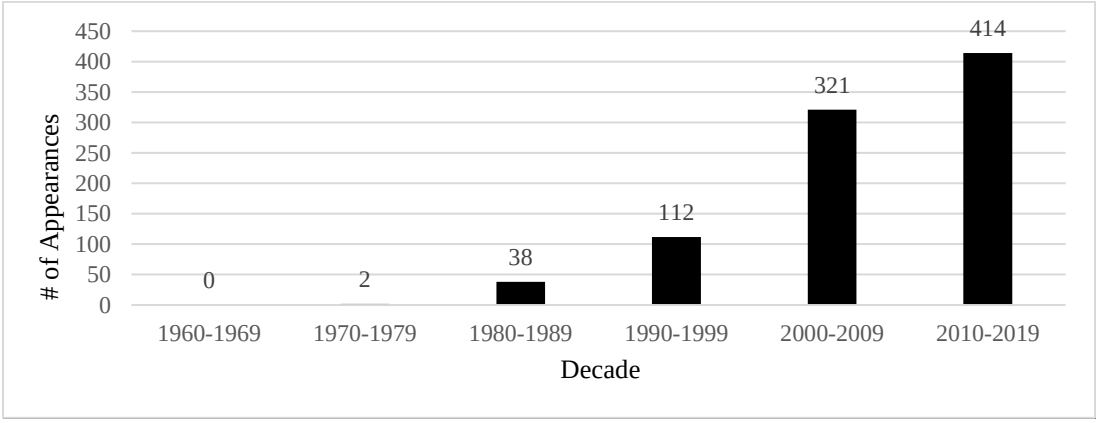
The topic of refugees is a pressing political issue. According to the UN High Commission on Refugees (UNHCR), there are currently more than 22.5 million refugees in the world and the number continues to rise (UNHCR 2017). Political, moral, and economic questions arise in the context of both refugee and economic migration. In an increasingly global and interconnected world, the effects of mass waves of migration are an important factor in public policy for host countries (Nijenhuis and Leung 2017). There is relatively little relevant, economic research; "migration studies have only recently become an area of serious research and study, dating back just to the 1980s" and refugee studies have come to the fore even more recently (Martin 2017). Jasso et al (2005) assert that in "no other area of social science and public policy research has there been as large a gap between information needs and existing data." Although there have been proposals for improving migration data-quality, big changes have yet to be implemented (Santo Tomas et al 2009).

Some argue that refugee migration should be of the highest priority in international discussions such as the G20 summit (Goldstein and Venturini 2016). Refugee migration affects economies and societies on a growing scale. Understanding the factors which drive the assimilation paths of refugees and how they differ from those of economic migrants can inform migration policy reforms (Greyling 2016). Because of the sparsity of shortcomings in the research, little is definitively know about the differences between refugees and economic, "non-forced" migrants. As a result, policies on migrant admission, assimilation and welfare participation are not tailored to the needs of refugee arrivals (Greyling 2016).

Refugee migration studies in economics gained momentum due to the current refugee crisis in the Middle East (Martin 2017). The database of economics books and journal articles, *EconLit* shows that published research on refugees has grown over recent decades. A search for the word

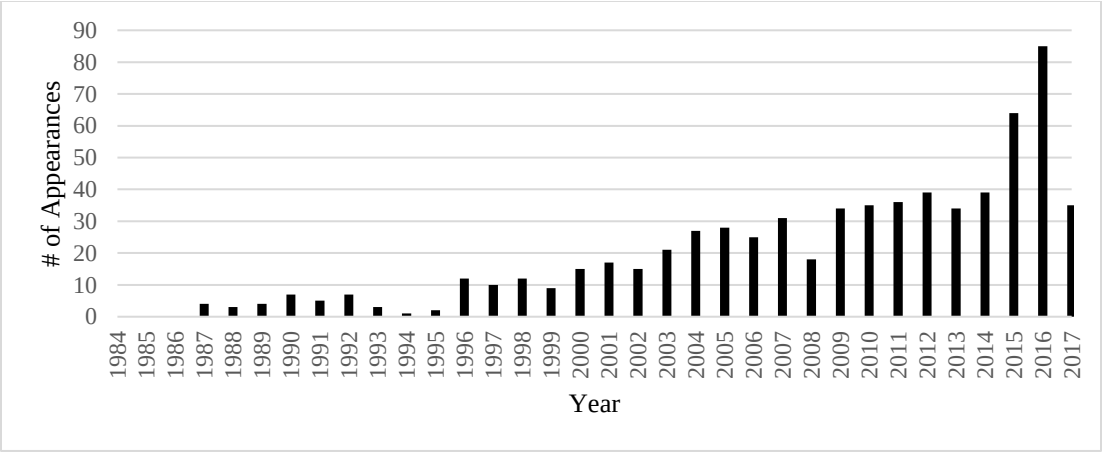
“refugee” or “forced migrant” in economic research shows the number of publications increasing rapidly since 1980 (See Graph 1a and 1b).

Graph 1a: "Refugee" and “Forced Migrant” Keyword Appearance in *EconLit* Search by Decade (1960s to 2010s)



Source: EconLit.com database. Data compiled by the author.

Graph 1b: "Refugee" and “Forced Migrant” Appearance in Abstract in *EconLit* Searches (1984-2010)



Source: EconLit.com database. Data compiled by the author.

The United States, as of 2013, had the largest resettlement program in the world, accepting over two thirds of refugee applicants, but research has been hindered because refugee data is strikingly poor. First and foremost, the Current Population Survey, the Census Public Use Micro Samples and the American Community Survey (the largest sources of data available to researchers) do not differentiate between refugees, economic immigrants and other foreign-born. Second, even when a sample of refugees is identified, there has been no long-term follow up. A very promising project, the New Immigrant Survey, funded by the U.S. Immigration and Naturalization Service, was designed as a longitudinal study of naturalized immigrants, but does not appear to have progress past the first year of questioning. And third, the few longitudinal studies of refugees have relatively small sample sizes (Evans 2017).

This paper develops a case-specific definition of refugees and applies a model of economic assimilation using data for Russian immigrants in the United States. The goal is to identify differences in assimilation paths for the two groups. The paper groups individuals as refugees or

economic immigrants based on historical context and immigrant flow statistics. Individuals are further divided into synthetic cohorts based on the number of years they had been living in the host country at time of survey. These groupings mitigate some effects and come with strong caveats, but the results provide a first look at further research into differences in assimilation. The research find that a model of assimilation based on key variables imputing personal income is a useful approach that could be used for future research. The paper concludes that there are indeed strong initial differences between refugees and economic immigrants at earlier duration, but that after immigrants spend more than 20 years in the host country, there are no statistical differences between different cohorts.

The paper is structured as follows: Section 2 analyzes how to define who is a refugee. Section 3 gives background on the sample of immigrants analyzed in the present research. Section 4 outlines previous research done in terms of refugee migration focusing on research design and results. Section 5 outlines the model for analysis. Section 6 describes the data used and presents preliminary statistics. Lastly, Section 7 sets out results of the model's application and of the statistical tests run. Section 8 concludes with the implication of the results and important next steps for this research.

2.Distinguishing Refugees from other Non-Forced Migrants

2a. Definitions

Nuances of migration make definitions such as "refugee" and "economic immigrant" more difficult than a binary distinction. One reason why it is difficult to formally track the world's refugee population comes from the question: how does one define a refugee[1]? The problem is that there are many different definitions and, more important, there are many different individual immigrants with varying reasons for moving.

To start with the definitions, the first hurdle is that different organizations and countries operate under different definitions. The initial one was established by the Geneva Convention in 1951, stating that a "refugee" is anyone with a:

> "well-founded fear of being persecuted for reasons of race, religion, nationality, membership of a particular social group or political opinion, is outside the country of his nationality and is unable or, owing to such fear, is unwilling to avail himself of the protection of that country; or who, not having a nationality and being outside the country of his former habitual residence as a result of such events, is unable or, owing to such fear, is unwilling to return to it." (Geneva Convention of 1949)

This definition is the root for most other classifications currently in use. The prevailing definition currently used by immigration departments is broader: refugees are people fleeing persecution or living under the threat or presence of violence. The United States' currently defines refugees as:

> "any person who is outside any country of such person's nationality, or, in the case of a person having no nationality, is outside any country in which such person last habitually resided, and who is unable or unwilling to return to, and is

[1] Note: Internally displaced persons and asylum seekers are often grouped with refugees but are dealt with in differently in migration counts and administrative/policy rules. This paper does not separate asylum seekers from refugees.

> unable or unwilling to avail himself or herself to the protection of that country because of persecution or a well-founded fear of persecution on accounts of race, religion, nationality, membership in a particular social group, or political opinion." (U.S. Immigration and Nationality Act 101(a))

Economic immigrants are equally hard to define: here too motivation and visa types are not recorded in the census. Economic immigrants generally move in search of better jobs, opportunities and economic security (Cortes 2004). Improving "quality of life" could be economic or social. This would include individuals entering on some of the following visas: visitor for business, temporary worker, intracompany transferee, religious worker etc. Issues of motivation are more complicated than the type of visa individuals enter the country on. Certain visas are easier to get and process than others, so individuals entering on expedited family reunification visas might in reality be moving for work. Similarly they might be refugees entering the US with work visas.

2b. Economic Theory

One of the reasons that refugee studies are only a recent development in the economics field is that classical economic modeling requires choice. The movement of refugees wasn't associated with autonomous decision-making and was therefore outside the scope of traditional models. But refugees are not individuals that have lost all autonomy over their decisions and this leads the core of the definitional issue.

The definitional difficulty is that each individual immigrant has a nuanced internal decision-making process. Refugee status is not a dichotomy but a continuum. With a few exceptions, all immigrants are economic immigrants, since the decision to move must involve the prediction that life will be better in a new land.

In the case of Jewish immigrants from the Soviet Union, for example, individuals may not have experienced direct, explicit violence, but implicit biases that individuals and the state may have. This influenced the balance of the promise of financial prosperity and social comfort, without driving the entirety of the decision. It is therefore a blunt, but necessary definitional tool to categorize individuals squarely either as refugees or economic immigrants.

For this study using micro-data, two factors are helpful in categorizing refugees: the presence of a push factor and the inability to return. One key difference between refugees and other immigrants is that refugees are pushed into emigration, while economic immigrants are pulled to a better life (Zimmerman 1996). The push factors include violence, property damage and fear of physical threats as well as experienced negative institutional discrimination. These factors are root causes of two observed differences in refugee migrants: less preparation and longer time horizons (Cortes 2004). These variables are hard to observe in census data, but there has been a recent effort to identify migration pushes. For example, in the New Immigrant Survey participants were asked if they had experienced any psychical harm, property damage, or abuse by officials and society before departure for the US.

But even with these differences, there is still overlap between motivations, push and pull factors and even time horizons (as will be discussed in detail later). This is the case of Soviet immigrants (who experienced persecution, could not return to their home country after leaving, but who were at the same time making decisions to move based in part on better economic and life opportunities expected outside the USSR[2]).

[2] As demonstrated by the author's parents and grandparents.

In this paper, the term “refugee” and “economic immigrant” are used broadly to denote forced and non-forced migration, based on the inherent differences in push/pull factors of an individual migration wave (year/country pair).

3. Background – Russian Immigrants [3]

Emigration from the USSR, and the fifteen states of the Former Soviet Union (FSU), to the United States is a case study which can provide previously unexplored definitional advantages (Cohen et al 2010). This paper broadly categorizes migrants based on historic context into waves of (or dominated by) refugees and waves of economic migrants. Most Soviet emigrants were Jewish, since closed border policies let out only ethnic Jews[4] they provide a valuable natural experiment (Polyan 2015). After the breakup of the Soviet Union, the characteristics of Russian migrants changed. Post-Soviet countries followed different political evolutions, some integrating into the European Union and some evolving into civil war, creating very dynamic groups of immigrants. The relative openness of US borders to Soviet emigrants and large size of the Soviet Union as a sending region means that we can observe a relatively large sample of migrants over an extended period. Furthermore, Russian immigrants are in some ways representative r all migrants to the US: the mean personal income of Russian migrants is close to that of all immigrants (see Graph 15 in Appendix).

Although looking at Jewish migration alone would yield more homogenous cohorts, it is impossible to distinguish Jewish and non-Jewish immigrants in any available dataset. The US census does not ask for religion or ethnic background, which makes identifying Jewish migrants virtually impossible. Jewishness in the Soviet Union was for many more an ethnicity than a religion. In the small sample of the New Immigrant Survey, none of the over 200 immigrants from Russia surveyed self-identified by religion as Jewish. It is therefore important to note the

[3] "Russian" is used here as a broad term used to denote immigrants from countries which have ties to Russian language, culture or history.

[4] Waves of Armenian and ethnic German immigrants were also let out in smaller numbers, but these immigrants largely moved to Armenia and Germany and very few immigrated to the US and therefore fall outside of the scope of this paper.

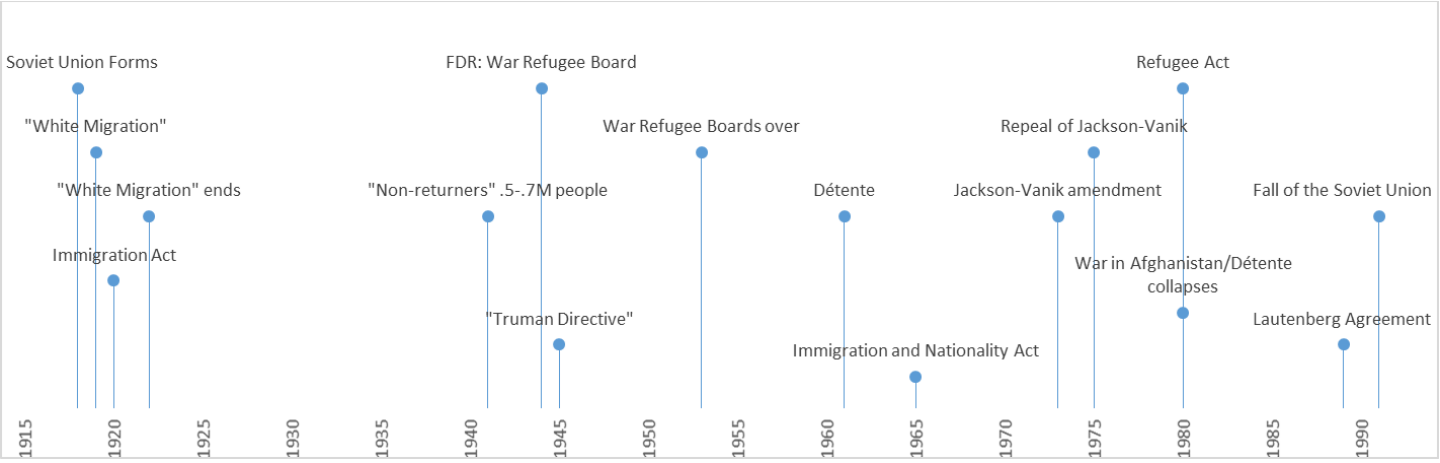
prevalence of Jewish migration in a historical context, but religion cannot play a role in the data analysis.

3a. History of Immigration from Soviet Union the United States

From the start of the Soviet Union (officially in 1918) to its dissolution in 1991 there were three commonly accepted waves of migration, with an unofficial fourth wave which took place after the union's break-up. These categorizations and observations are largely retrospective mostly because Russian literature and research on migration is just recently starting to evolve; during the Soviet Union, the subject of migration was a taboo topic, and writing was actively suppressed (Polyan 2015).

The first wave of migration took place between 1918 and 1922, and was spurred by the revolution and subsequent civil war. The second wave took place between 1941 and 1944: "non-returners" after the Second World War **(**Polyan 2015**)**. The third wave took place between 1948 and 1998/91, from the times of Stalin to Gorbachev. The fourth wave was characterized by open borders and started off with very poor economic conditions of the fledgling FSU states. Notable events are summarized in Graph 2 below and described in detail further.

Graph 2: Timeline of Russian Emigration



Source: observations compiled by the author.

In the first wave of Russian migration, which began shortly after the revolution in 1917 and lasted until 1922, over 100,000 Jews left the country over four years. Emigrants were self-selected; they left for socio-economic reasons rather than religious reasons (Polyan 2015). This wave was dubbed the "White Migration" after the two sides of the revolutionary war: the Reds (Bolsheviks) against the Whites. This first wave of migration can be categorized as a wave of refugees since individuals' prime motivation for leaving was a fear for their lives and most left with no possibility of return; most left through back-channels and escaped through unmonitored borders and on false papers.

The second accepted wave of emigration took place between 1941 and 1944. While this wave is hard to quantify as war tallies are inaccurate; current data estimate that between 500,000 and 700,000 people emigrated from Russia during this time (Polyan 2005). This wave can also be classified as refugee migrants since the circumstances of the war made people leave for non-premeditated reasons with no explicit preparation. Some were forcibly displaced during the war

and some found an opportunity to cross the border in the chaos of the fighting; most left expecting they would never be able to return.

The third migration wave lasted from 1948 to 1989, during which more than 1.5 million people left the Soviet Union. The size and length of this wave makes it harder to categorize; unlike the previous two waves, the "Third Emigration [was a] legal, organized and sustained movement" (Heitman 1993). Because of this wave's duration, it can be broken up further into three parts.

From 1948 to 1970, the "Soviet policy … was the result of foreign intervention – from Israel on behalf of the Jews" (Heitman 1993). Immigration was severely restricted; approximately 59,600 persons left during this time, with a vast majority moving to Israel, and some escaping to the US through available connections. Because of the difficulty of departure and the predominant anti-Semitism in the Soviet Union at the time, this group is also considered to be mostly refugees.

Between 1971 and 1980 the bulk of the movement occurred due to relaxed immigration policies, following the détente. The immigrants from the early 1970s were more likely to be emigrating from rural areas. More people were leaving as a result of discrimination based on religion. Family reunification was used as a visa justification and "many questionable claims to family reunification were winked at by the authorities" (Heitman 1993). The later 70s saw many more immigrants leaving from the bigger cities, chasing economic opportunity and freedom. For categorization, it serves to evaluate the first half of the 70s as a time of refugee migration and the later 70s as increasingly economic migration.

The third wave came between 1980 and the break-up of the Soviet Union. Between 1980 and 1986, the Soviet borders were closed and emigration quotas were significantly diminished as the USSR entered the war in Afghanistan and the previous détente broke down. In 1987 policies

of Perestroika (literally reconstruction) began to free up migration again. Emigration papers were still only available for ethnically Jewish migrants but "by this time most Jewish emigrants were clearly economic migrants who chose to resettle mainly in the United States" (Heitman 1993). On April 5, 1989, Assistant Attorney General Thomas Boyd wrote "the character of the [Russian] emigrant pool had changed. In particular, increasing numbers of people were leaving not to flee persecution, but solely for purposes of family reunion or economic opportunities". But the United States' official policy still gave most if not all refugee status. Those migrating between 1987 and 1991 are better considered "non-refugees" as their motivations had evolved. No presumptive refugee status was given after this time.

3b. Migration from Fifteen Post-Soviet States (Former Soviet Union or FSU) to the United States

The Soviet Union formally broke up on December 25, 1991. Fifteen independent countries were formed: Russia, Ukraine, Belarus, Latvia, Lithuania, Estonia, Armenia, Georgia, Moldova, Kazakhstan, Azerbaijan, Turkmenistan, Kyrgyzstan, and Uzbekistan. The creation of these new borders created arbitrary new citizenships for individuals who were not necessarily ethnically from the country they residing and working in. These situations made for fluid definitions of nationality and difficult migration paths.

Among the biggest problems that the post-communist states faced were privatization and the transition from command to market economies, both were almost universally botched. The privatization process was flawed; output sharply decreased, GDP dropped up to 40%, and poverty increased dramatically (World Bank 2002). The early 1990s were characterized by shortages of almost everything, including food and basic necessities. The unorganized transition process lent itself to corruption, exploitation and more. This led to many wanting to leave their homes as it became clear that the promises of democracy and prosperity were not being realized.

After the breakup of the Soviet Union, the fifteen post-soviet countries followed different paths in the evolution of their political and economic systems: some became full-fledged democracies; others devolved into dictatorships and totalitarian regimes[5]. As of the 2002 World Bank transition report, the Post-Soviet countries spanned all four categories of political-economic systems[6]. Lithuania, Latvia and Estonia were competitive democracies. Their proximity and strong ties to Europe helped ease their transitions and establish strong, working democracies and fluid integration into the European Union. Russia, Ukraine, Moldova and Kyrgyzstan fall into the concentrated political regime category. Belarus, Kazakhstan, Uzbekistan, and Turkmenistan are non-competitive political regimes, with virtual dictators controlling the state. Lastly, Armenia, Georgia, Azerbaijan and Tajikistan became war-torn regimes. After 20002, though, most of post-soviet countries have subsequently evolved their status.

3c. Israel

Although migration to Israel falls outside the main scope of this paper, it was a factor in Soviet and Post-Soviet immigration. The migration of Russians to Israel is so striking that it can be used as a natural experiment (Fonarev 2017, Friedberg 2001, Smooha 2008). Israel was the only officially permitted destination for Soviet Jewish emigrants from the Soviet Union. This

[5] The World Bank, 2003, classifies the transitioning states could be categorized into four overarching categories: competitive democracies, concentrated political regimes, non-competitive political regimes, and war-torn regimes. Competitive democracies are the countries in which citizens participated in fair, multiparty elections and had a wide range of political and civil rights. Concentrated political regimes are the countries in which multi-party elections are held, but certain rights have been curtailed or restricted periodically, and even with elections, power is concentrated in one party and usually held by the executive branch of government. Non-competitive political regimes are systems in which one party controls the power; oppositional parties and activists aren't allowed any power and individual civil liberty is severely restricted. Lastly, war-torn regimes were those where the political climate was punctuated by internal and external conflict and war.

[6] Note these categorizations are as of 2002 and there has since been evolution and devolution in some countries, which are noted in the data, when classifying countries across refugee sending years.

established the foundations of path dependence for subsequent Russian immigrants. Israel, since its creation in 1948, has been a country of immigrants for immigrants. The United States did not always have an open border policy, going to Israel as a choice for all and to the US only for some. Israel's open immigration policy, the "Law of Return", was adopted in May 1950, and provided citizenship for any Jewish immigrants and their non-Jewish families wishing to immigrate to Israel (Cohen et al 2010). The policy created an open opportunity for Soviet and Post-Soviet Jews, especially the US borders were closed for emigrants who could not fake a family connection in the US. Thus immigrants arriving in the US were likely to have self-selected to go there, since migration to Israel was the default choice, requiring fewer steps and much less paperwork (Cohen and Haberfeld 2007).

3d. Short History of US Immigration Policy

America's "melting pot" history and its extended relationship with Russian immigrants creates an interesting case study. The willingness of the United States to accept immigrants varied over the span of the Soviet Union's existence and into the 21st century. Before the 1920s, the US was a safe-haven for immigrants from around the world, but in 1924 the Immigrant Act severely restricted migration, and isolationist policies prevailed until the outbreak of World War II. In January, 1944, Franklin Delano Roosevelt established the War Refugee Board ("United States Policy towards Jewish Refugees, 1941-1952" 2017). In 1945, the passage of the "Truman Directive" expedited visas for displaced persons, of which close to 40,000 were Jewish war refugees ("United States Policy…" 2017). These policies served as strong precedent for future refugee waves. In 1952, the passage of the Immigration and Nationality Act., also known as the McCarran–Walter Act, closed borders and returned the US to the quota systems established at the in the 1920s. Those quotas were in place until 1965, and the passage of the Immigration and Nationality Act, also known as the Hart-Celler Act ("Timeline in American Jewish History").

For Soviet immigrants open borders policies were the rule throughout the 20th century. Before 1980 "departure from the Soviet Union, by whatever means and for whatever reasons, was sufficient for possible admission into the United States" (Nelson 1988, Beyer 1991). Between 1980 and 1988 Soviet immigrants were granted "presumptive refugee status after perfunctory adjudications by the Immigration and Naturalization Service (INS) in Rome, Italy" (Beyer 1991). But after 1989, immigrants from the Soviet Union were no longer admitted on the presumption of refugee status and migrant flows from the now FSU significantly declined (Cohen et al 2010).

4. Literature Review

4a. Literature on Refugee Assimilation

By definition, there are differences between refugees and economic immigrants. Nevertheless problems arise when studying refugee assimilation as refugees are hard to categorize. Research on economic assimilation of refugees is still at an early stage (Martin 2017). A hurdle for relevant research is the lack of clear identification in available data when immigrants arrive in the US, the host-country. Although there are notable exceptions, like Sweden, most countries do not indicate refugee status on immigration papers outside of visa classification. Researchers have sought to identify proxy definitions for identifying refugees in order to study their assimilation (Godoy 2017).

One approach is to identify "refugee sending countries" based on their political and economic conditions (and social associations) (Cortes 2004, Potocky-Tripodi 2003). This approach captures large samples at the cost of including individuals emigrating for other reasons.

Kalina Cortes takes a notable first step towards more comprehensive literature on differences in assimilation for refugees. Although Cortes' work poses a very potent question: do economic immigrants assimilate differently than refugees. Her classifications of refugees and economic immigrants are broad, failing to encompass certain nuances. She denotes all immigrants from certain countries (Soviet Union, Vietnam, Afghanistan, Cuba, and others) as refugees, without accounting for evolving political situations in both the sending country and the United States (the receiving country). A problem is that this doesn't take into account the evolution of political and social situations in each countries. Even though was the US considered the Soviet Union a repressive regime throughout its existence, in some periods of relative freedom, individuals (particularly Jews) were allowed to legally leave (described in detail above).

A more nuanced approach includes generating year/country pairs which correspond to high levels of refugee acceptance (Capps et al 2015, Evans and Fitzgerald 2017). This way takes into account the political and cultural situations of each country together with US immigration statistics on categories of admission. Based on the Yearbook of Immigrant Statistics (put out by the Department of Homeland Security) years in which more than 70% of migrants were counted as refugees were used to created weighted samples of all refugees from said country (Evans and Fitzgerald 2017).

Other researchers look at case studies of single refugee waves. David Card's pioneering study examined a natural experiment of the Mariel Boatlift in which Cuban refugees came to Miami on April 23rd, 1980. A similar approach was used in other studies, such as Haitan refugees in 2010 (Figlio and Uzek 2017) and asylum seekers in Johannesburg, South Africa (Greyling 2016). Cohen et al (2010) look at the self-selection of Jewish immigrants leaving the FSU for Israel, Germany and the United States. Borjas and Monras (2017) look at the effects of four different shocks: the Marielitos in Miami in 1980; French repatriates and Algerian nationals in France in 1962, Jewish émigrés in Israel in the 1990s, and the exodus of refugees from the former Yugoslavia between 1991 and 2001. Lastly, there are a few instances of clear definitions, in which individuals are identified as refugees and subsequently tracked by the government as in Norway (Godoy 2017). Although these studies had clear definitions of refugees and were able to track them well, the focus of most of the research was the effect of such shocks on native populations and on other immigrants, not on the assimilation paths of the refugees themselves.

4b. Literature on Refugee Assimilation

A few comprehensive studies address the differences in outcomes of refugees and economic immigrants. Cortes uses census data to examine the wages and hours worked of two

cohorts of refugees and economic immigrants who entered the United States between 1975 and 1980. Following Hatton (2012), she identifies inherent definitional differences between the two groups. Cortes posits that the main difference is their time horizons in the host country: with refugees having longer foreseen stays than economic immigrants. She finds that in 1980, refugees "earned 6% less and worked 14% fewer hours than economic immigrants" but by 1990 refugees "earned 20% more, worked 4% more hours, and improved their English skills by 11% more than economic immigrants" (Cortes 2004). This is upheld by Cobb-Clark's (2006) analysis of new immigrants in Australia, Fix et al in (2000), as well as Aydemir's (2011) results in Canada: refugees earning less and experiencing higher unemployment rates in the first years of entry. These results are also corroborated by the in-depth analysis of Evans and Fitzgerald 2017. In their analysis of the largest sample of refugees to date, they find that refugees that enter between the ages of 19-24 and 23-28 struggle more than those entering at younger and older ages (Evans and Fitzgerald 2017).

Examining the effects of refugees on native populations and on other immigrants is another developing field of study. Card (1990) finds that a refugee labor supply shock had no significant effect on the local workforce. But revisiting the sample, Borjas (2017) finds an effect on the low-skill workers. Similarly, Russian Jews migrating to Israel had a big effect on the native population and workforce, but only in areas of skill-level crossover: where education and experience from home country aligns with opportunity in the host country (Borjas and Monras 2017). These results are relevant to refugee assimilation paths but do not relate directly to a comparison with economic immigrants.

Cohen and Haberfeld (2007) compare earning growth of immigrants in Israel and comparable natives. They contrast Jews in Israel, classified as refugees, and Jews in the United States, classified as economic immigrants. The key differentiation is that immigrants to the United

States could self-select, while those moving to Israel could not. They find that the "economic immigrants" in America assimilate better than the "refugees" in Israel, but these results are largely due to varying education levels (Cohen and Haberfeld 2007).

Research into the assimilation of Russian immigrants to Israel identifies important factors correlated with higher market mobility and economic assimilation. Cohen-Goldner, Eckstein, and Weiss focus on Israeli immigrants from the FSU twenty years after migration using the Israeli Labor Force Surveys and Income Surveys for 1989 and 2009 (Cohen-Goldner et al 2012). They find that in the long run there is high participation in the work force and low unemployment but wages never reach the natives' wages. In particular, many white collar immigrants are less likely to find employment. The factors most associated with long-term economic assimilation are place of residence, home ownership, and marriage patterns (Cohen-Goldner et al 2012). All of these are combinations of sociological and economic factors: language proficiency, cultural acceptance, and workplace opportunity are important measures in understanding the signals of immigrant assimilation. Those who move into enclaves are less likely to assimilate. And those who own homes are more likely to live in the periphery and thus are less likely to assimilate (although are more tied to Israel and more satisfied than average Israelis). Those who marry other immigrants are less likely to assimilate. Raijman and Semyonov take this analysis one step further and find similar results for two groups of migrants, the first arriving in Israel in 1979 and the second arriving in 1990. They find that the second, larger group of migrants experiences more occupational downgrading, but has wages comparable to those of the natives, even if never fully matching them (Raijman and Semyonov 1998).

Barry Chiswick (1998) looked at Hebrew proficiency as a determinant of earnings in Israel. He shows that there are multiple factors that lead to higher assimilation rates, as a function of

language proficiency. Other researchers have also identified language proficiency as the key variable and language proficiency has often been used as a predictor of earnings, and has a very strong positive effect on future earnings (Dustmann and Van Soest 2002).

Chiswick used data from the 1983 Israeli census to explore language skills compared to other variables as strong or weak predictors of economic and social assimilation. He finds that those who marry a native after immigration and those who have children are more likely to use Hebrew daily. Immigrants who live in enclaves, and those who come from English-speaking countries are least likely to use Hebrew at home (Chiswick 1998). The variables observed and their effects are discussed further in Section 4.

In a previous paper, I applied a version of Chiswick's model to Russian immigrants in Israel. The preliminary results confirmed the model's value for understanding economic assimilation (Fonarev 2017). Using microdata from the Israeli census of 1995, I constructed a test to explore the effects of refugee status on assimilation, but found no statistically significant difference between refugees and economic immigrants. There were two main problems with the initial approach: the definitions of the two groups were imprecise and the variable of duration confounded the results. Refugees were defined as anyone arriving to Israel before 1991, which is a strong assumption: different waves of immigration to Israel had significantly different characteristics. Furthermore, this definition of refugee status meant that all the refugees in the data had a higher duration in Israel (the host country). Since duration is one of the variables most closely tied to earnings, this approach did not yield significant results.

Using Chiswick's model, amended by substituting income for language as the dependent variable and including observable measures, I estimated preliminary results for a sample of Russian Jewish immigrants in Israel. In the data, duration was strongly correlated with income (See Graph 5 in Appendix). This strong confounding variable couldn't be controlled for, because

the data available were one cross section (no longitudinal data were available). Nevertheless, the observed results still significant implications in the effects of the control variables.

Multiple variables had an influence on earnings. Enclaves (living in non-metropolitan areas) has a slight negative impact on earnings. Years of education had a weak positive effect on earnings, with education in host country having a considerably stronger effect[7]. Home ownership was strong predictor of higher earnings, but could be due to correlation and not causation, as those with higher incomes are more likely to afford permanent housing.

Demographic characteristics were less predictive overall. Age at migration had a non-linear effect: those who arrived either very young, or in their 30s and 40s, had higher predicted earnings than those arriving between the ages of 18-24 or else much later in life. Gender had a minimal effect on earnings, balancing the higher education attained by women and the higher unemployment rates of women with families. Families of fewer than five had higher earnings. Marriage had a positive effect on earnings. Conversely, getting married in Israel (after migration) has a slight negative effect on earnings.

The sample of Russian immigrants in Israel differs from those in the US, but these preliminary associations are important as a context for my findings from the larger sample of American immigrants. Future research should compare the model predictions for these two samples and identify possible sources of differences.

[7] This is due to the nature of the immigrant sample; many skilled and highly educated Russian immigrants had a hand time crossing skills over into the Israeli economy (Cohen-Goldner 2007).

5. Methodology and Model

To test whether refugees differ from economic immigrants I propose a variation of the model employed by Chiswick (1998). Chiswick's model explores the effects of multiple variables on language ability, a proxy for assimilation. The following variables are included in the model: expected wage increment for language fluency, expected future duration, actual duration in destination, marriage to a native of destination, marriage to a native of origin, children, minority language concentration, destination language classes, linguistic distance of origin language, age at migration, education, and refugee status. While this model encompasses important controls, multiple variables are unobservable and therefore cannot be applied presently.

Since language ability isn't observed in the US census, I use the variable of personal income as the dependent variable. Earnings are a strong indicator of economic assimilation and provide measurable results (Greyling 2016). To create a testable set of control variables for assimilation, I amend Chiswick's model to include observable measures. The factors identified are a combination of demographics and measures of human capital. Demographics serve as important control measures. Place-specific human capital is a factor immigrants disproportionately invest in and has been previously identified as indicative of earnings (Duleep and Regets 1999). The model accounts for multiple important aspects of assimilation which are measured by the US census, but notably omits certain variables due to certain questions not being asked. The model is outlined here:

[Personal Income] = f(Employment, Education, Age, Gender, Married, Family Size, Higher Education, Age at Arrival, Welfare, Home Ownership, Location)

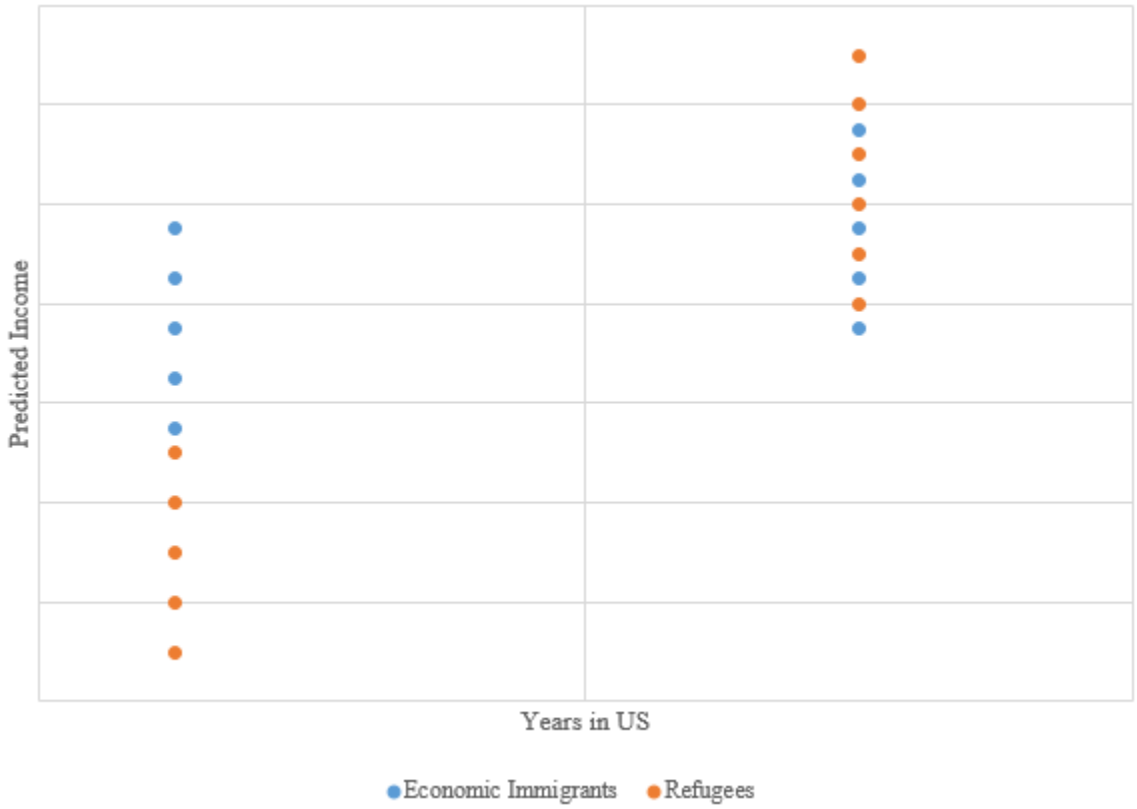
To analyze the differences between immigrants with variable durations, I employ cohort analysis. Based on previous research, cohort analysis depends on two driving factors: time of arrival and time since arrival. George Borjas in his analysis of the Marielitos and other refugee

shocks (2016) explores the effects of different arrival times. This cohort approach keeps homogenous cohorts, but mitigates the effects of different durations. Because the present research is focused on the effects of years spent in host country, the second effect is used presently. Grouping individuals by years since arrival (at the time of questioning) works under the strong assumption that different factors have similar effects in different decades (i.e. a higher education for an immigrant surveyed in 1950 has the same predicted effects as education for an immigrant surveyed in 2010). But although there are strong caveats to these cohort groupings, they function here as a starting point for further research.

For present analysis, I divide Russian immigrants into cohorts depending on type of immigrant and years spent in the US at time of survey. Once ordinary least squares regressions are run on each cohort, a series of imputed incomes are generated, based on a function of a collection of control variables. Different imputed incomes for a cohort of refugees vs economic immigrants at a given duration would indicate that the difference is the make-up of the cohort, the only non-controlled for variable, refugee status (Left of Graph 3). Conversely, same predicted incomes would indicate that no inherent difference between the groups exists (Right of Graph 3).

My hypothesis is that at earlier durations, corresponding to fewer years spent in the host country, the refugee and economic migrant cohorts will experience different initial incomes and different rates of growth in income, due to inherent differences between refugees and economic immigrants. As duration and years spent in country increase, there will smaller differences between the two groups.

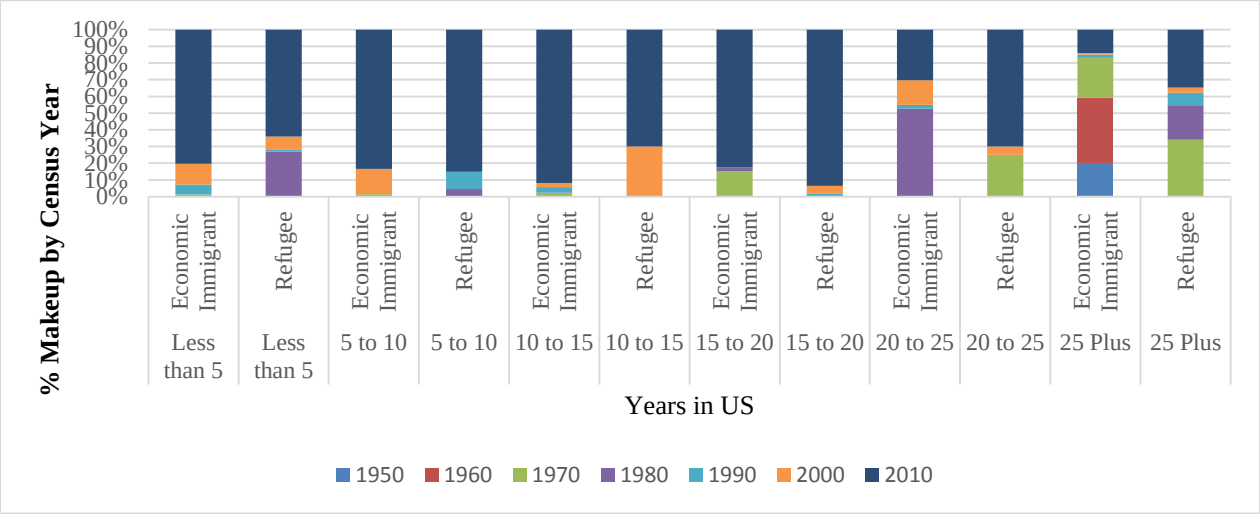
Graph 3: Cohort Make-Up and Explanation



Although this approach collects heterogeneous cohorts, in which the demographic characteristics of the immigrants are varied and predicted effects may be different, it provides a look at the differences between refugees and economic immigrants at different points in the assimilation paths, an effect which would not be readily apparent in a different approach. Another problem which cannot be currently addressed with the current data is that there is a possibility of attrition: as immigrants leave to other countries, return to their home countries, or die, the sizes of cohort may vary due to these exogenous variables.

Cohorts were summed across censuses and divided into five year increments starting with individuals who had lived in the United States for less than five years at the time of the survey and rising in five year increments to the cohort of individuals who have lived in the US for more than twenty five years. The cohorts are made up of observations in each category from US census micro-data for the decades 1950 to 2000 plus the ACS for 2001-2010. (See Graph 4).

Graph 4: Makeup of the Cohorts by Decade Surveyed



Source: IPUMS USA dataset. Data compiled by the author.

To test differences between the samples of refugees and economic immigrants at different durations, a Chow Test is conducted for each individual duration, allowing for conclusions as to whether economic immigrants' incomes are statistically significantly different, based on present models, than refugees at different points in their assimilation paths.

6. Data

To estimate the model I used micro-data from the Integrated Public Use Microdata Series (IPUMS USA). Data from the United States are available from 1950 to 2000 in ten year intervals and from 2000 to 2010 in one year intervals (due to a shift from the decennial census to the American Community Survey, ACS). Gathering relevant observations of immigrants from micro-data from the US Census (sample size: 1,190,265), the sample was further divided into imputed refugees (sample size 36,497) and imputed economic immigrant (sample size 34,457). The imputation was based on year of arrival in the US and country of origin. All data analysis and processing was completed in STATA 15 software.

I also used the New Immigrant Survey for descriptive statistics, verifying the findings from the IPUMS dataset. NIS data had clearer definitions of refugees and economic immigrants because it collected detailed data on visa types and motivation for migration, but contained significantly smaller sample sizes.

6a. Definitions

Defining refugees is difficult because the census does not ask detailed questions about of immigrants' characteristics. Immigrant status (refugee or economic migrant) is not a variable in the data, the classifications must be assigned. Any such imputation is inherently imperfect for reasons addressed in Section 2. Following Capps et al (2015) and Evans and Fitzgerald's (2017) approach of year/country pairs, individuals surveyed in the US census are grouped as refugees or economic immigrants. Using the Department of Homeland Security's "Yearbook of Immigrant Statistics" information of the total number of immigrants, refugees and asylum seekers was collected for all Post-Soviet states. For years in which more than 70% of Russian Immigrants were admitted as refugees or asylum seekers, I classified immigrants in the data from that sending year/country as refugees. Soviet immigrants were classified based on the waves of migration the migrant belonged to (defined in Section 3a).

This approach groups data for individuals entering the US in different decades. To address some of the problems, I adjusted personal income for inflation using 2010 as the base year, based on the Federal Reserve Economic Data (FRED) inflation index of the St. Louis Federal Reserve Bank. Furthermore, adjusted income doesn't take into account the effect of rising income in the US. To mitigate these effects, income was similarly weighted for the base year of 2010 (U.S. Bureau of Economic Analysis 2017). Other variables were harder to adjust for changes over time. Gender, age, education and other variables have a different impact on imputed earnings in 1950 compared to 2010. These flaws would be avoided with more homogenous cohorts, but due to small sample sizes cannot be controlled for in present analysis.

6b. Descriptive Statistics[8]

Descriptive statistics were generated based on the IPUMS dataset to understand the distribution and behavior of the key factors across samples which could influence individual imputed earnings. Basic descriptive statistics give good indications on the behavior of the variables and serve as a test of the validity of the model. The IPUMS sample of refugees and economic immigrants is made up of Russian immigrants for whom classification was possible and for a baseline measure, means for all foreign born, including non-Russian immigrants, were used to benchmark. Data from the New Immigrant Survey were used as a baseline, with NIS numbers noted separately throughout the descriptive statistics.

The sign of the expected effects of all independent variables in the model on earnings are shown in Table 1 and further discussed in detail below.

[8] See Appendix for full list of key variables and key statistics by cohort.

Table 1: Expected Effects of Control Variables

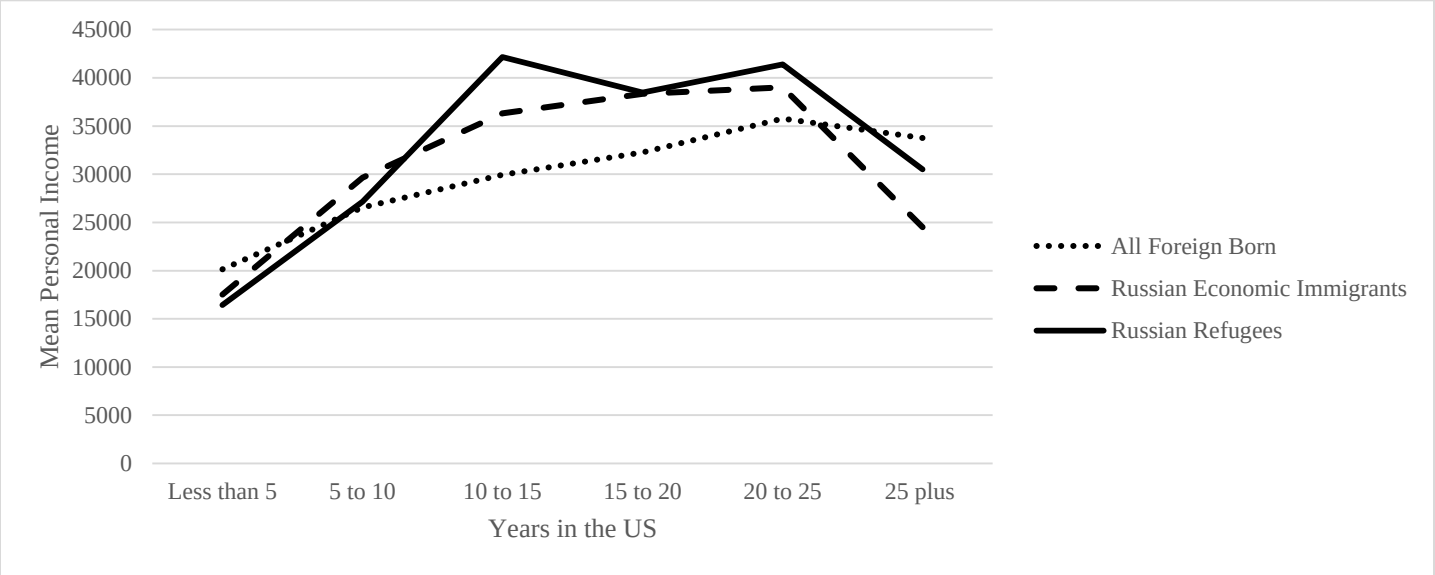
Employment	Education	Age	Gender	Married	Family Size	Higher Education	Age at Arrival	Welfare	Home Ownership	Location
+	+	?	-	+	?	+	?	-	+	+

Income

Personal income is the dependent variable and used as a proxy for economic assimilation. Income should increase as duration increases, but the paths of income growth are predicted to be different for refugees than for economic immigrants. In particular, Cortes predicts that refugees will start with lower incomes, but have a steeper rate of increase as duration increases (2004).

The IPUMS data samples show that refugees and economic immigrants follow a very similar path. Across groups, income increases with duration but the rate of growth declines as duration passes 25 years, which makes sense as the older the immigrant the more likely they are to approaching the age of retirement and lower employment rates (See Graph 5). As predicted by the hypothesis, refugees start off with incomes slightly lower than the mean for all foreign born, and lower than their economic immigrant counterparts. As duration in the US increases, their income grows at a faster rate than that of economic immigrants and much faster than average. At 15 to 20 years of duration the incomes of different groups converge and growth percentages start to equal out. At the 25 plus duration, cohorts all drop off in income, with slightly sharper declines for the sample of economic immigrants and refugees than for immigrant on average.

Graph 5: Personal Income by Years since Arrival



Source: IPUMS USA dataset. Data compiled by the author.

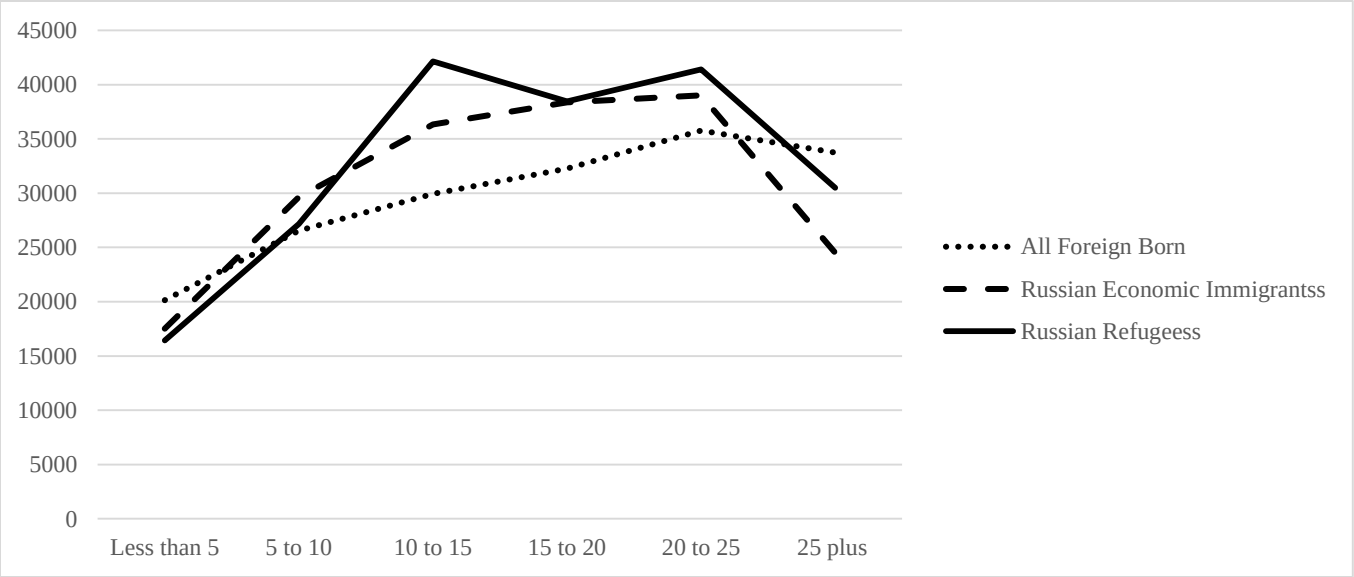
There are no apparent differences in the distributions of incomes across the cohorts (See Graph 17 in Appendix), rather, the distributions follow an even, normal distribution for all cohorts and variance is really small. This would indicate that individual variables play a strong role in individual incomes across cohorts.

Employment

Refugees have higher unemployment rates than economic immigrants across all cohorts (See Graph 6). This is inconsistent with the observations of higher average personal incomes for refugees in the later cohorts. Especially during times of crisis, male refugees tend to work more

hours than all foreign born on average, and more than natives (Capps et al 2015). Interestingly, unemployment does not go down significantly as duration increases. This may indicate that there are some strong confounding variables, especially for refugees, and a closer examination of the data is necessary. Some explaining factors are that refugee cohorts are slightly more female on average, and gender is strongly correlated with unemployment, especially for immigrants. It is also likely that self-reported employment might have glitches in data and coding.

Graph 6: Employment Rates by Years since Arrival



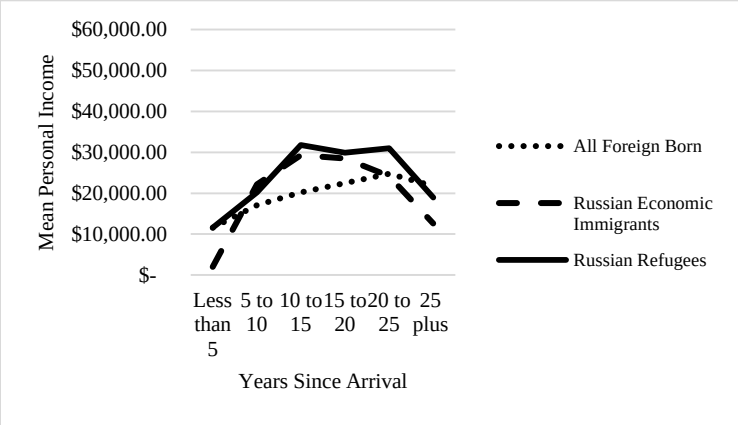
Source: IPUMS USA dataset. Data compiled by the author.

Gender

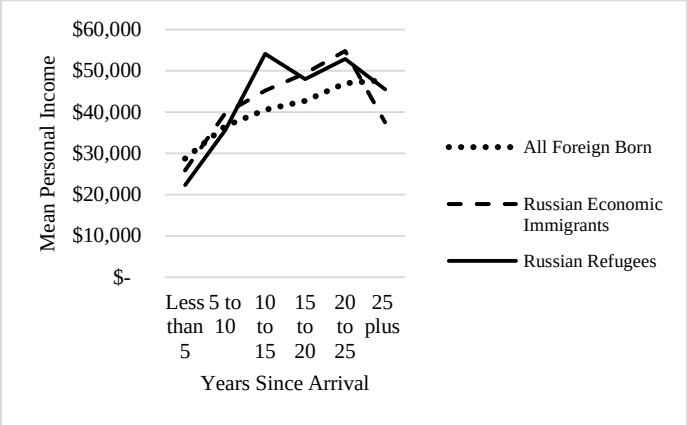
It is interesting to note that in this sample, males earn less than females on average, a finding which is generally inconsistent with the literature and general statistics. Others have found that immigrant men tend to work fewer hours in the first few years in the destination country, while women work more (Baker and Dwayne 1997). In addition, immigrant women's wages are higher relative to than their native women's wages than immigrant men's wages relative to native men (Cohen and Haberfeld 2007). The higher rates of income observed for refugees could be tied to the fact that is the refugee sample includes higher fraction of females.

Although there is some small variation across cohorts, the sample of refugees has a slightly higher percentage of female immigrants on average. While the economic immigrant sample is 55% male, the refugee sample is only 47% male. The sample of economic immigrants with the shortest durations has a stronger male population at 60% with all other cohorts at least 5 percent lower. There are not very large differences across cohorts, but the male self-selection for economic immigrants is as predicted. This was not the case for the sample of refugees surveyed by the New Immigrant Survey in which refugees and economic immigrants had very few differences in gender makeup across different durations. Looking at incomes across genders, women in the NIS data have higher incomes than men. Both genders' incomes follow paths very similar to those of the census average, with women have a slightly steeper income increase in income over time than men (See Graphs 7a and 7b). The effects of gender are discussed in more detail in a following section.

Graph 7a: Personal Income by Years since Arrival (Male)



Graph 7b: Personal Income by Years since Arrival (Female)



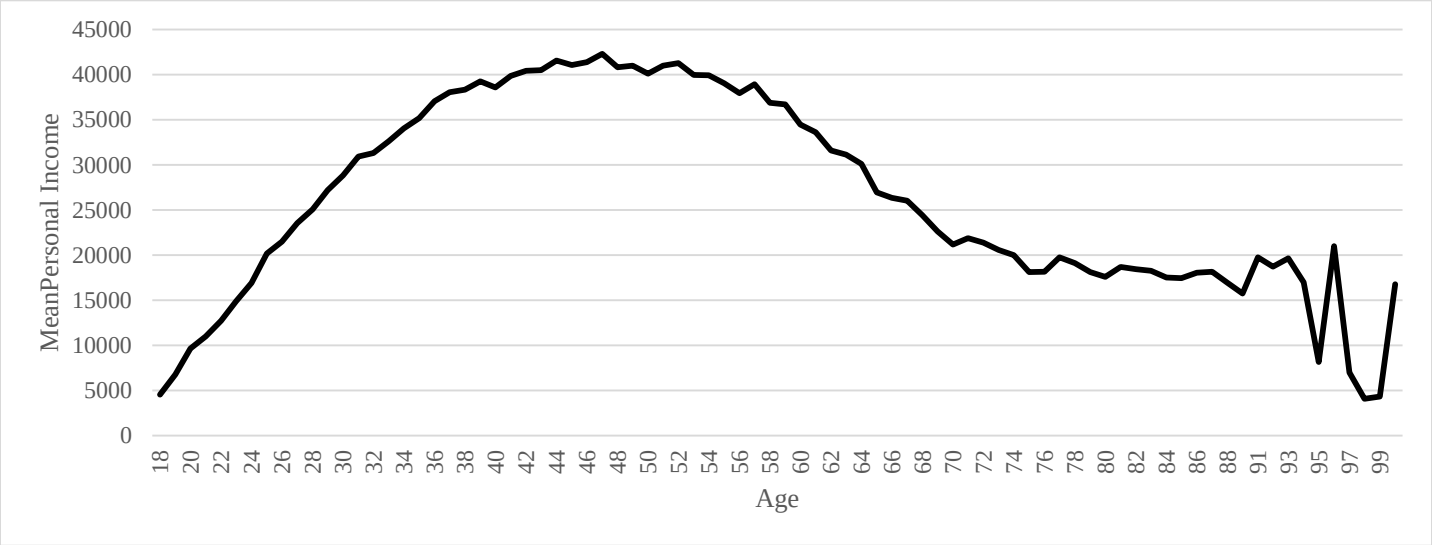
Source: IPUMS USA dataset. Data compiled by the author.

Age[9] and Age at Arrival

Age tends to have a non-linear effect on income as predicted by the lifecycle hypothesis. Age is predicted to follow a curve, with the lower ages (18-22) being individuals likely to be earning little to no income as they are often in school or just entering the workforce (Greyling 2016). Similarly, individuals over the age of 65 are at or near retirement and are thus less likely to be participating in the workforce. This is observed in the sample of all foreign born (See Graph 8).

[9] Note: Individuals below the age of 18 were not included in this analysis, as they are legally minors and less likely to be earning any personal income.

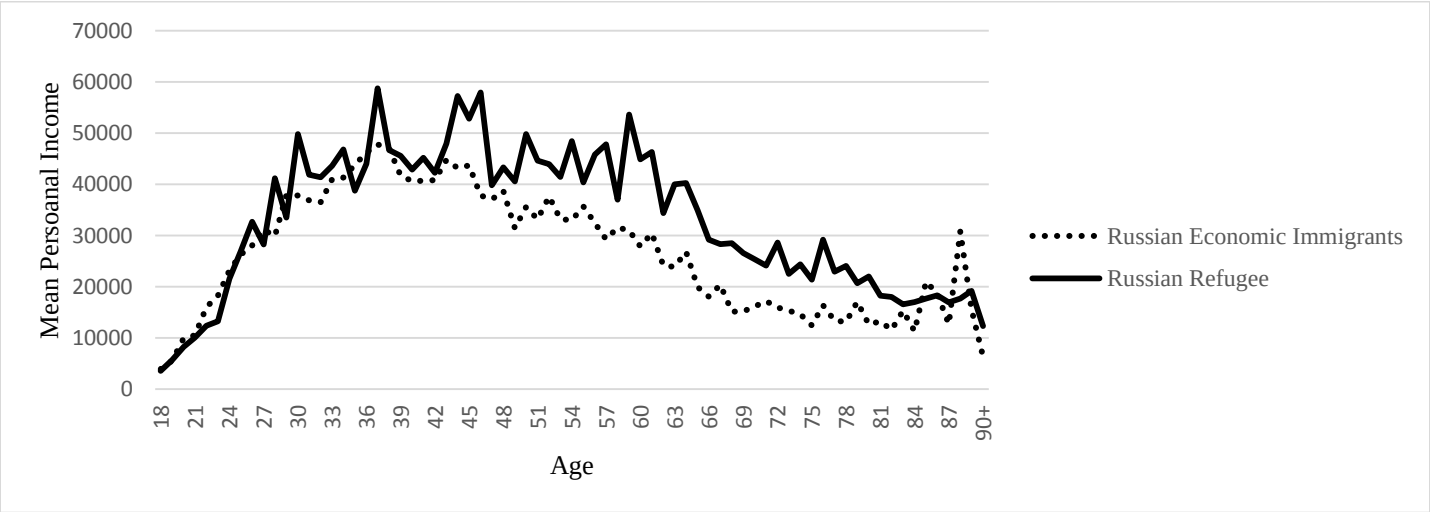
Graph 8: Mean Personal Income by Age



Source: IPUMS USA dataset. Data compiled by the author.

In the census data, economic immigrants are considerably older; with the mean age of 47 and refugee sample's mean age is only 40 and the mean age for all foreign born is 41. This is also true at individual cohorts: economic immigrants are slightly older while refugees are very similar to the mean of all foreign-born. The NIS data collaborates this finding, with economic immigrants slightly older on average than refugees. This also demonstrates itself in the higher incomes of economic immigrants in the shortest duration cohort and the sharper decrease in income and employment of economic immigrants in the longest duration cohort. Since observed individuals report ages as high as 100 years old, it is likely that many older immigrants (refugee or economic) will have left the workforce.

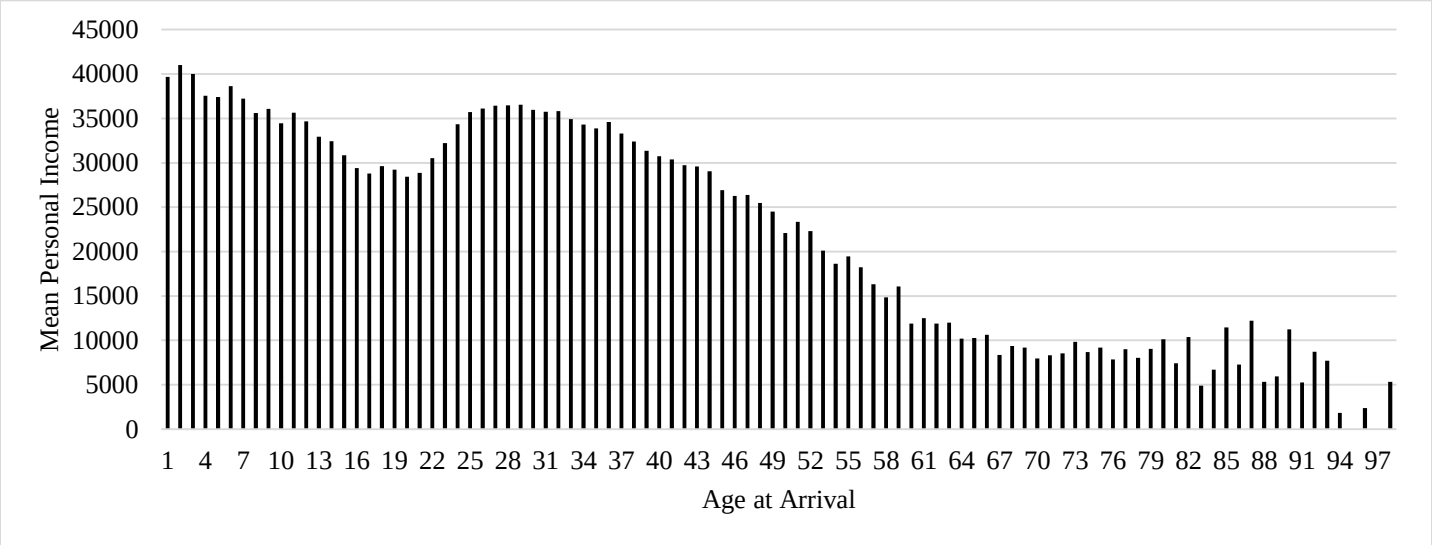
Graph 9: Mean Personal Income by Age and Refugee Status



Source: IPUMS USA dataset. Data compiled by the author.

Age at arrival (calculated from age and year of arrival by the author), similar to age in general, has a non-linear effect on income. Some effects to note are that arriving at a very young age allows the child to integrate easily into the culture of the host country, and the differences between immigrant children and native children become negligible in a short period of time. But as the age of arrival increases, assimilation rate slows for high school and college age young adults, and integration becomes considerably harder. But as immigrants enter working age, employment opportunities arise and income usually grows. Lastly, when arriving at an older age, entering the workforce and crossing over skills is often more difficult. These predictions are in fact clearly seen in the population of immigrants sampled (See Graph 10). But because age at migration has a very dynamic effect on earning potential, it should be very cautiously used as a predictive factor (Cohen and Haberfeld 2007).

Graph 10: Mean Personal Income by Age at Arrival



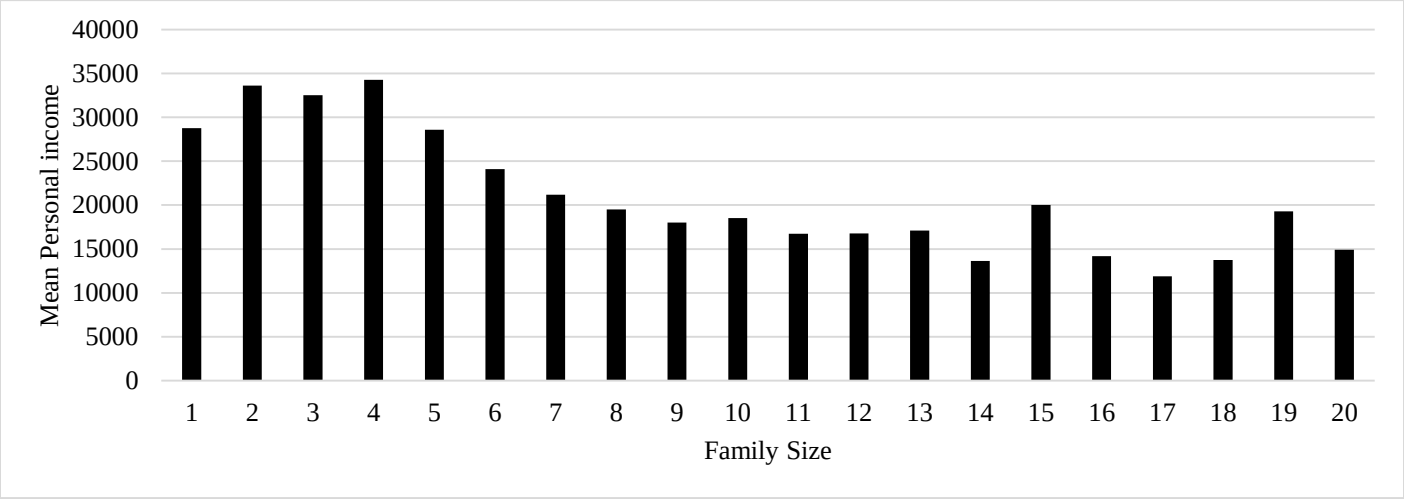
Source: IPUMS USA dataset. Data compiled by the author.

A trend similar to the one observed in age is seen in the average age of arrival of the samples. Economic immigrants tend to be older when they first arrive to the US than refugees: 32 for the former v 24 for the latter. Russian refugees entering the country in recent years (2002-2013) are likely to be young children, or of working age, with few young adults or older entrants (Capps et al 2015). This too makes sense in the context of forced migration, since economic immigrants are more likely to immigrate when they are most prepared to succeed, while refugees have little or no choice in their timing.

Family Size and Children

There is little research on the effect of family size on adjusted earnings; the research focuses more on birth order rather than number of children. Lampi and Nordblom have found that the number of siblings has a strong adverse effect on the future incomes of children (2009). Although this suggests that a bigger family size should decrease earnings, this is more of an indicative factor for siblings and future earnings than for family size. While there is no clear correlations in the immigrant sample between income and family size, families with fewer than five members do tend to have higher incomes than larger families (see Graph 11). The small sample size of the NIS shows very small differences in family size between refugees and economic immigrants.

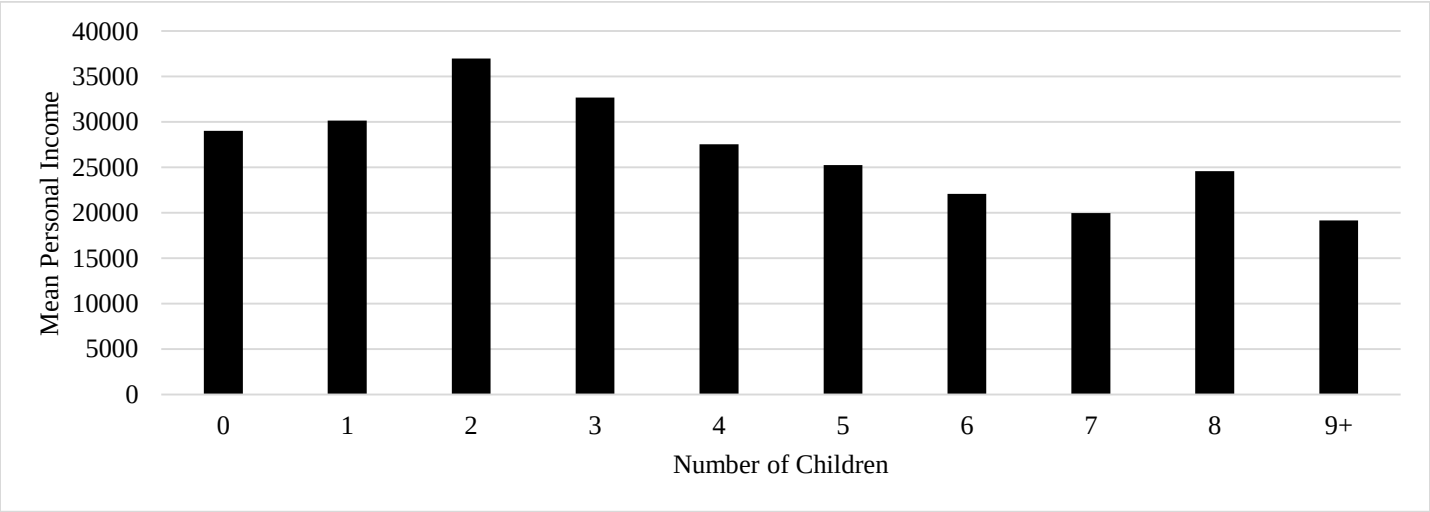
Graph 11: Mean Personal Income by Family Size



Source: IPUMS USA dataset. Data compiled by the author.

Similarly, the number of children should indicate higher earnings, as having children could indicate the means to support a larger family size, but there is no express correlation. Children also have strong indirect effects on earning. Since younger children acquire language skills very easily, the language (and subsequent human capital) can be brought into the home and absorbed by parents and older siblings. Conversely, children may serve as intermediaries and interpreters for parents and may subsequently have a negative effect of language acquisition (Chiswick 1998). Children also provide an incentive to work and stay longer in a country, as parents might not want to disturb the child's development by interrupting school, friends, etc. Overall there should be a positive effect from children, as they increase language assimilation and earnings (Chiswick 1998). The sample of immigrants shows that income increases with number of children, peaks at two and then drops off with increased number of children (see Graph 12).

Graph 12: Mean Personal Income by Number of Children in the Household



Source: IPUMS USA dataset. Data compiled by the author.

On average the refugee sample has more children than the sample of economic immigrants or the general foreign born population. Refugees have 1.6 children on average while economic immigrants have .85 on average and foreign born overall have 1.2. The same trend holds for the numbers of children under the age of five. Refugees have more, young children on average: 0.36 compared to the economic immigrants average of 0.14 and the all foreign born average of 0.28. Conversely, in the NIS sample, economic immigrants report more children on average than refugees. As duration increases, the number of younger children decreases, which correlates to higher birth rates as age increases. These large sample differences are difficult to explain through cultural variables and imply a stronger effect of migrations factors.

Marriage

Marriage has a dynamic effect on assimilation. In general, marriage is associated with higher earnings (Chiswick 1998). New married immigrants follow different trends according to gender: women tending to work more and men less in the first few years (Baker and Dwayne 1997). Another important effect of marriage, which is difficult to model, is that being married increases the earning potentials of the couple (Eckstein and Yoram 2002). Overall this creates a pretty strong positive effect of marriage on earnings. Another difference which is unobservable with the given data is the effect of marrying a fellow immigrant compared with marrying a native. Marriage to a native strongly predicts increased assimilation, while marrying an immigrant, especially from the same origin country, predicts decreased assimilation rates (Chiswick 1998). In the observed data, without accounting for any external variables, marriage is associated with a significantly higher income (See Table 2).

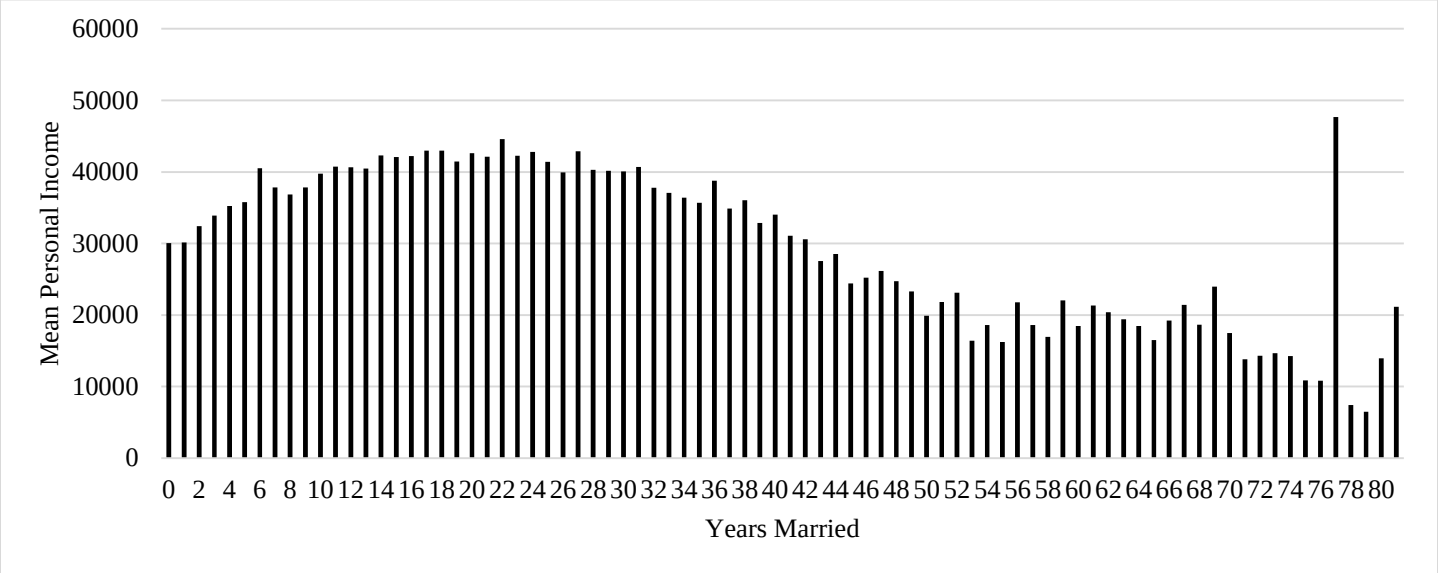
Table 2: Mean Personal Income for Married and Not-Married

Marriage	Mean Personal Income
Not Married	$24,161
Married	$34,390

Source: IPUMS USA dataset. Data compiled by the author.

The marriage rates are similar across groups and across cohorts. The refugee sample reported that 72.3% were married, and economic immigrants reported that 68% were married. According to the selected samples from the NIS there were no inherent differences in marriage rates between types of immigrants. Refugees and economic immigrants tend to be married longer than the all immigrant on average by about 5 years (with refugees married slightly longer than economic immigrants). The opposite is the case for the samples of refugees and economic immigrants in the NIS sample, with economic immigrants being married about 5 years longer than refugees. This is in accordance with the number of children, as marriage rates and duration are correlated with more children.

Graph 13: Mean Income by Number of Years Married



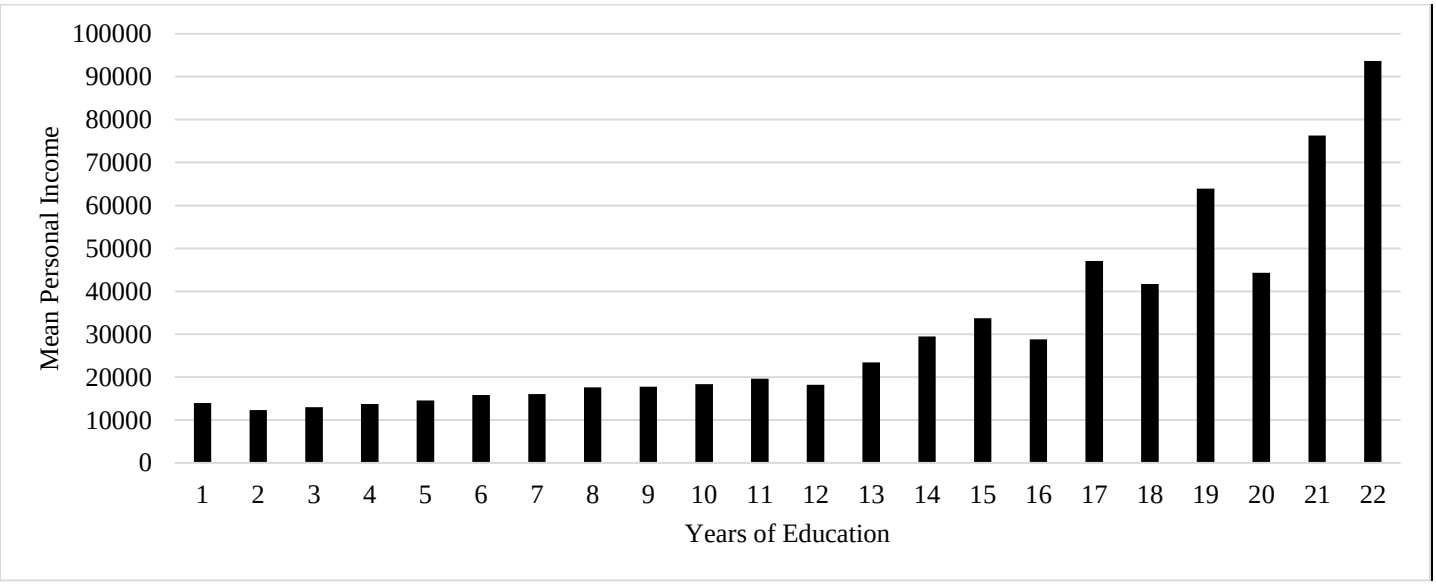
Source: IPUMS USA dataset. Data compiled by the author.

Education

Education has been shown to have a strong positive effect on earning potential (Chiswick 1998, Fonarev 2017). Although there are a few outliers, higher education leads to more job prospects and availability. An element which is highly indicative of earnings, but is not observed in the sample, is education in the host country as opposed to country of origin. Receiving education in the country of birth is important, but the effect on income of learning in the host country is marginally higher (Chiswick 1998). Although education in the host country is not observed in the census, it is self-reported in the NIS data. According to the survey, refugees have on average 1.3 years of education in the US while economic immigrants only have .9 year. This is observed in the data of immigrants: income increases with years of education (see Graph 14). It also seems that

income increases very moderately with schooling up until the achievement of a high-school degree, and then starts to increase exponentially with higher education. There are certain inconsistencies in the data, largely due to the evolving value of education over the extended period of observation.

Graph 14: Mean Personal Income by Years of Education



Source: IPUMS USA dataset. Data compiled by the author.

Economic immigrants and refugees report similar education rates, with economic immigrants slightly more educated, and both samples reporting higher education levels than immigrants on average. Economic immigrants report 13.3 years of education on average while refugees report 13.6 years on average compared to the general sample's 12.2 years. The NIS data

show similar results, with difference between refugee and economic immigrant's levels of education is less than one year. It is interesting that both samples report on average more than primary education while immigrants on average do not. This is likely coming from the context of Soviet migrants as education was of a high quality and universally free. The one cohort outlier is the refugee immigrants with duration of 20 to 25 years, in which the average education level was only 9.4 years which agrees with the considerably lower levels of college education in the same cohort (only 23% compared to the average 58%). This is difficult to explain and might be due to expected data reporting inconsistencies.

Higher Education

College education and post-graduate education indicate higher earning (Chiswick 1998, Fonarev 2017). This sample of immigrants is not an exception, with higher levels of education indicating significantly higher levels of earnings (See Table 3 and Table 4). Interestingly, those classified as refugees report very low levels of college and post-graduate degrees, while still reporting above average years of schooling. In the last decade, Russian refugees report considerably more higher education degrees than non-refugee migrants (Capps et al 2015). Economic immigrants report that they have received some college education slightly more often than refugees: 66% and 58% respectively. All foreign born in general report low levels of college degrees: only 43% having some college education. Across cohorts there is little variance, although the older refugee cohorts report significantly lower levels of college education than others. The numbers are even more constant for post-graduate degrees, with the means being very close: 22% of economic immigrants report post-graduate degrees while 20% of refugees report post-graduate degrees. The NIS samples show that economic immigrants have higher graduate and post-graduate educations than refugees, but the variance is small, with differences around two percent. Here the difference is in the comparison with the means for all foreign born: both refugees and economic

immigrants report close to twice as many individuals achieving post-graduate degrees than the average foreign born individual.

Table 3: Mean Personal Income by College Degree Attainment

College Education	Mean Personal Income
No College Degree	$19,726
College Degree	$48,385

Source: IPUMS USA dataset. Data compiled by the author.

Table 4: Mean Personal Income by Post-Graduate Degree Attainment

Post Graduate Education	Mean Personal Income
No Post-Graduate Degree	$25,718
Post-Graduate Degree	$77,083

Source: IPUMS USA dataset. Data compiled by the author.

Location[10]

Enclaves are strong indicators of lower levels of assimilation, but since enclaves are not expressly observed in the sample data, the research explores the effect of metropolitan or non-metropolitan residence. Those living in the urban areas are likely to be earning less, and more likely to be unemployed (Cohen-Goldner et al 2002). This is reflected in the data, as immigrants living in metropolitan areas report higher incomes on average (See Table 5).

[10] Locations are divided into metropolitan and non-metropolitan residencies.

Table 5: Mean Personal Income by Residence Location

Location	Mean Personal Income
Non-Metropolitan	$22,776
Metropolitan	$31,310

Source: IPUMS USA dataset. Data compiled by the author.

Economic immigrants are more likely to live in more central locations: 93% of the sample chooses to reside in the center. Refugees and immigrants on average are more likely to live on the periphery. In the context of forced migration and self-selection as economic immigrants are more likely to choose to live where there are more job opportunities. It is also intuitive that with the cohorts that are in the country longer, tend to live more in the periphery than the other cohorts, an intuitive observation with age and comfort.

Home Ownership

Owning a home is associated with both of higher income and greater permanence in a locality (See Table 6). Owning a home is likely to be an effect of an immigrant's higher income, but also is associated with satisfaction with and bonds to the host country and increased expected duration there (Cohen-Goldner et al 2012). A bond to the host country predicts more investment in place-specific human capital, a choice associated with a longer time horizon and long run increases in expected income. Based on the sample of immigrants: owning a home is correlated with higher personal incomes, but the direction of causation is far from clear.

Table 6: Mean Personal Income by Home Ownership

Home Ownership	Mean Personal Income
Do Not Own Home	$22,389
Own Home	$37,049

Source: IPUMS USA dataset. Data compiled by the author.

Refugees are considerably less likely to own a home than economic immigrants or foreign born on average: 33% ownership compared to 51% and 50%. This is interesting because it does not account for the aspect of future duration, since it would be predicted that economic immigrants are more likely to leave the host country than refugees, based on definition alone.

Food-Stamps

Using food-stamp enrollment as a proxy for welfare recipients, it is predicted that participation in the program is associated with lower income. This is the case for the sample of foreign born, as those who report food-stamp enrollment also report significantly lower levels of income than those not enrolled in such programs (See Table 7).

Across cohorts it is observed that economic immigrants and refugees are more likely to be enrolled in food stamp programs than all foreign born, which doesn't fit with previous observations in the context of the employment and income rates. There are likely data issues based on the nature

of self-reporting welfare participation, as there is a lot of missing observations and misreported data.

Table 7: Mean Personal Income by Food Stamp Enrollment

Food Stamp Participation	Mean Personal Income
Not on Food Stamps	$35,589
On Food Stamps	$14,418

Source: IPUMS USA dataset. Data compiled by the author.

6c. Variables Not Observed in IPUMS Dataset:

Due to the selection of questions asked by the US census and the coding of the data, there are certain variables that are either not observed at all or have too many missing values to be significant. These factors are important to include in a model of assimilation, but cannot be included in the present regression analysis.

The most notably omitted variable is language ability, which is the dependent variable in Chiswick's original model. Some important household information is also unobservable or recoded poorly. Household income reporting in the US census has means too high to be plausible and therefore is not useful in regression analysis. Mean household income is reported as $248,522[11] which is disproportionately higher than the mean income in the US which in 2010 was reported to be $ 49,445 by the US Census (DeNavas-Walt et al 2011). Another important factor which is predictive of assimilation is the nationality of one's spouse, with individuals marrying natives having higher assimilation rates and immigrants that marry within the immigrant community (especially those of the same country of origin) have harder times assimilating as

[11] This is largely due to underreporting for households of one individual, which skew the data to higher incomes coming out of combined homes.

discussed previously. The US census doesn't identify spousal birthplace, so the effect is unobservable.

An important factor which is identified by Chiswick's model is "expected future duration", which is inherently unobservable without pointed survey questions focusing on migration. It is also an important measure at the root of the difference between refugees and economic immigrants, especially with Cortes' postulation that the longer time horizons of refugees drives the differences in their assimilation paths. For the purpose of this model, expected future duration is included into observed differences between refugees and economic immigrants, and used as a definitional tool to drive statistical tests, and not as an independent variable.

7. Results

Applying the model to the observed data yields significant results and discloses the variables predicted effects on earnings. Individually, the variables are usually statistically significant, and individual regressions show high levels of significance. The variables included show no unexpected auto-correlation (See Table 8).

Table 8: Variable Correlations

	Log Income	Education	Age	Gender (% Male)	% Married	Years Married	Family Size	Number of Children	% College	% PhD	% Central	% on Foodstamps	% Own Home	% Employed	Age at Arrival
Log Income	1														
Education	0.3543	1													
Age	-0.1055	-0.0947	1												
Gender (% Male)	-0.2606	-0.0006	0.0709	1											
% Married	0.0825	0.0896	-0.2526	-0.206	1										
Years Married	-0.1362	-0.1431	0.8389	0.1315	-0.2424	1									
Family Size	-0.0237	-0.1377	-0.3091	-0.0906	0.2791	-0.2283	1								
Number of Children	0.0349	-0.0902	-0.3264	-0.0675	0.1987	-0.2419	0.7599	1							
% College	0.3153	0.7859	-0.0872	0.0007	0.0857	-0.1313	-0.1071	-0.0681	1						
% PhD	0.293	0.5304	-0.0316	-0.0639	0.0747	-0.0638	-0.0776	-0.048	0.4079	1					
% Central	0.0516	0.0589	-0.0009	-0.001	-0.0015	-0.0081	0.0325	0.0175	0.0468	0.0286	1				
% on Foodstamps	-0.1924	-0.1663	-0.0026	0.0178	-0.0938	0.0092	0.1337	0.1044	-0.1438	-0.0885	-0.0057	1			
% Own Home	0.1763	0.1391	0.1731	0.0412	0.1148	0.1565	0.0954	0.0432	0.119	0.0661	-0.0243	-0.1678	1		
% Employed	0.4032	0.152	-0.5348	-0.1331	0.1857	-0.4873	0.1926	0.2276	0.137	0.0852	0.0227	-0.1177	-0.0023	1	
Age at Arrival	-0.1691	-0.0556	0.3949	0.0024	-0.0645	0.2957	-0.0742	-0.122	-0.0453	0.0177	0.0785	0.0835	-0.1066	-0.1943	1

Source: IPUMS USA dataset. Correlation results generated by STATA 15.

The ordinary least squares regressions provides a glimpse into the model's validity. Overall, the independent variables perform as expected. There are small differences across cohorts and samples, but the average coefficients follow the predictions. On average, the P-values for the variables are low and hence significant. The variables that are less significant are years of schooling and undergraduate degrees, but we also find a high significance levels for post-graduate education attainment. The regression results are reported below (See Table 9: A-Q in appendix).

Age at arrival and years of schooling have small effects on income. The age effects are small due to the fact that the variables have non-linear predicted effect on income. Age at arrival only has a strong positive effect on income at the lowest levels of duration, in which older individuals have higher predicted earnings. This may be caused by the fact that at the earliest durations, experience and work ability are more likely to be indicative of employment opportunity. Years of education has a small effect, which is surprising. But considering the diminishing value of only high-school education and the increasing need of higher education, the variables of graduate and post-graduate educations are better predictive factors, and this is evident in the data as the coefficients are considerably higher for those variables. One outlier is the sample of refugees which have been in the country between 10 and 15 years for whom years of schooling have a small negative effect on predicted earnings, but the outlier is mitigated since it is not statistically significant (with a P-value of .496).

Gender, family size, and participation in welfare programs show relatively large negative effects on expected income, as predicted by the model. Considering the immigrant samples, income has been historically lower for men than women, especially in the earlier years of being in the host country. Being male has a stronger negative effect on earnings for the earlier cohorts and is lower for refugees than for economic immigrants. Food stamp participation, as a proxy of

enrollment in welfare programs, has the expected negative effect on earnings. Welfare has a higher negative impact for refugees than for economic immigrants and decreases as duration increases, with a peak up at the longest duration cohorts. These observations are also expected, as refugees are more likely to be dependent on welfare programs and as duration increases, so does age and unemployment. Family size has a smaller negative effect on earnings, and is not considerably stronger of a predictive factor across cohorts or samples, especially due to its non-linearity.

Marriage, children, graduate and post-graduate education, and home ownership are all strongly indicative of higher earnings, consistent with earlier predictions. Marriage and children predict slightly higher earnings consistently across groups with the one outlier being the last cohort. For all Russian immigrants that have lived in the country for over 25 years, there is in fact a small negative impact of marriage on earnings. Children have a ubiquitously positive effect on earnings, but tend to be more indicative of higher income for the economic immigrant population than for refugees across all durations. College education has a positive effect on earnings, and post-graduate education has an even stronger one. Post high school education seems to be more indicative of higher earnings for refugees than for economic immigrants. One outlier is the effect of higher education for economic immigrants in the 20 to 25 year cohort in which the effect switched to a slightly negative effect on earnings. This correlates to the unexplained descriptive statistics for education in these cohorts. This may be due to coding errors, poor self-reporting or could stem from the small sample size for this cohort. Home ownership might have an inverse causation with income, but is consistent with the expected positive effects predicted by the model. Arguably the most indicative positive factor for income is employment, which holds true for the data across samples and cohorts; the employment variable is also consistently statistically significant with P-values at zero across the board.

To test whether the samples of refugees and economic immigrants are statistically different, a Chow Test was employed. Running the regressions across each sample and pooled samples of cohorts gives the following residual sum of squares and counts. The model has eleven degrees of freedom. Sample sizes are consistently significant with only two cohorts with fewer than 300 observations (see Table 10).

Table 10: Residual Sum of Squares and Number of Observations by Cohort

Years in US	Type	Residual Sum of Squares	Number of Observations
Less than 5	Economic Immigrant	1328	1,133
Less than 5	Refugee	331	301
Less than 5	All Russian	1665	1,434
5 to 10	Economic Immigrant	1905	2,166
5 to 10	Refugee	345	369
5 to 10	All Russian	2267	2,535
10 to 15	Economic Immigrant	2468	2,788
10 to 15	Refugee	243	286
10 to 15	All Russian	2730	3,074
15 to 20	Economic Immigrant	1036	1,178
15 to 20	Refugee	567	637
15 to 20	All Russian	1616	1,815
20 to 25	Economic Immigrant	108	141
20 to 25	Refugee	353	407
20 to 25	All Russian	476	548
25 Plus	Economic Immigrant	968	1,161
25 Plus	Refugee	806	1,240
25 Plus	All Russian	1785	2,401

Source: IPUMS USA dataset. Correlation results generated by STATA 15.

Conducting the Chow Test for each durational cohort, gives the F-values demonstrated in Table 11.

Table 11: F-Value by Cohort

Cohort	F-Value
Less than 5	1302.85
5 to 10	1.62
10 to 15	2864.88
15 to 20	1695.97
20 to 25	1.80
25 Plus	1.74

Source: IPUMS USA dataset. Correlation results generated by STATA 15.

With 11 degrees of freedom, the critical value for the F-statistic is 2.818 at a 5% significance level and 4.462 for a 1% significance level. For the cohorts with durations of less than 5 years, 10 to 15 years, and 15 to 20 years, the F-values are high and we reject the null hypothesis: the samples are statistically significantly different. For the remaining cohorts we fail to reject the null hypothesis, and cannot say that the samples of economic immigrants and refugees are significantly different.

With the exception of the 5 to 10 year cohort[12], the results are consistent with the hypothesis: at earlier durations economic immigrants and refugees are significantly different in their economic assimilation, but as duration increases, they converge to very similar paths.

[12] Further investigation into the cause of the outlier has not yielded a full explanation, save for a slightly skewed distribution of observations, with older individuals and slightly smaller sample sizes.

Although there is no definitive way to test the statistical validity of the regressions, some precautions were taken. First, test for multicollinearity were run. The tolerance inflation factor (VIF) for each regression shows little cause for alarm, as no values cross the conservative threshold of 10, and mean VIF for each regression is between the acceptable 1 and 2. There seems to be no indication of multicollinearity. Further regression diagnostics as suggested by Belsley et al (1980) show no significant indicators of multicollinearity as covariance ratios are largely within estimated errors.

8. Conclusion

The economic literature on refugees has lacked empirical research, largely stemming from the inherent difficulties in providing working definitions and comprehensive tracking systems. Since tracking refugees (especially in the long term) is both difficult and costly, empirical findings are replaced by oversimplifications and blanket classifications. The research is starting to grow and delve deeper into the issues of refugee migration analysis, and there have been significant steps forward in resolving definitional issues, but large holes remain. Improving data quality and tracking systems would be an important step but policy has been slow to catch up. Addressing these problems and evolving the literature is very important for the resolution of pressing policy issues of the future and today, especially as refugees are coming to the forefront of many international policy discussions. Many questions regarding refugee assimilation have yet to be answered, and more definitive research would make for more socially beneficial policy decisions both in the emigration and assimilation processes.

As the number of refugees in the world continues to increase, policy makers need to understand differences (or lack thereof) between forced and non-forced migrants. This study has shown there to be differences between populations of immigrants which do not share similar

decision making. Some of the most notable differences are the migration decision and the ability to prepare more fully for immigration and the differences in time horizons in the host country.

The research presented here attempts to provide some clarity on some of the problems with the research methods in the field of refugee migration study and to provide preliminary results on the differences between refugees and other migrants. Although there are still many flaws in the present data, the narrowing of samples to Russian immigrants and the more nuanced look at specific waves of migration allows the definitions to circumvent some of the bigger problems in the research: namely the ability to track individuals based on their driving motivations for migration. Comparing waves of immigrants from the Soviet Union, during which Jews fled the oppressive communist regimes with little hope of return, to immigrants from the fifteen post-soviet states (accounting for the evolution of socio-political transitions from communism) creates a natural experiment in which refugees and economic immigrants are more readily identifiable.

Gathering information from individuals surveyed in the American census between 1950 and 2010, Russian immigrants in US census data were classified as refugees and economic immigrants and subsequently allocated to synthetic cohorts based on the time they had spent in the United States (their destination country), at the time of the survey. This allowed us to observe difference across cohorts in key variables influencing income. The statistical regression analysis was used to model differences in the impact of the independent variables across the refugee and economic migrant samples.

As predicted by the hypothesis, and consistent with previous research, the data show refugees and economic immigrants following different paths in economic assimilation. Although refugees start with lower incomes at arrival than economic immigrants, the trajectory of increase is higher for refugees. Refugees' incomes surpass the incomes of economic immigrants and of all

foreign born as duration increases. The present research does contain a strong outlier, in the group of migrants who have lived in the host country between 10 and 15 years, for whom there is no statistically significant difference between forced and non-forced migrants. These results are may be attributable to small sample sizes and other inherent problems in the data.

It is valuable to identify the explanatory variables which affect predicted earnings and assimilation for different populations and different individuals. In terms of evolving migration policies and quotas, especially for the expanding implementation of point systems, it is important to note which factors effect assimilation trajectories. Applying an amended version of Chiswick's model to the data shows multiple predictive variables functioning as expected to predict earnings for refugees and economic immigrants.

Especially for refugees, the following variables are strong predictors of higher earnings: gender, post-graduate education, and home ownership. Although there are some other elements at play, understanding these key variables would serve to create better policy. Since female refugees tend to work more and earn more, especially in early years, this could suggest amendments to gender quotas, and could serve as a base for gender-specific employment programs. Since post-graduate education is very indicative of future earnings, quotas could be constructed accordingly, and encouragement of post-graduate education in the host country would be important. Home-ownership could have some unobserved effects, but subsidized housing could be very important for refugees, as the extended time-horizon associated with home-ownership would be a strong indicator of higher employment and future earnings.

Conversely, variables that have little or no effect on earnings could be given less weight in policy measures. Age at arrival and schooling (when no post high-school education has been achieved) should be given less weight in migration decisions and should be excluded from quota analysis, as there is little indication of positive or negative effects on future earnings.

These results, in the context of research conducted by Kalina Cortes, Capps et al, and Evans and Fitzgerald, point us in the right direction for policy change. With the conclusion of the differences between assimilation rates of refugees and other immigrants, it would be important for policy-makers to acknowledge certain salient differences. In the context of "internal" policy – policy towards migrants admitted to the country – policymakers should explore the implications that increased support during earlier years for refugees would be balanced out by decreased needs as duration increases. Furthermore, the high earning potentials for longer duration refugees are important motivators for policy supporting longer expected duration for refugee groups. For "external" policy – questions of who to let in and on what conditions – it is important to know which identifiable (observable) factors predict assimilation, higher earnings and more.

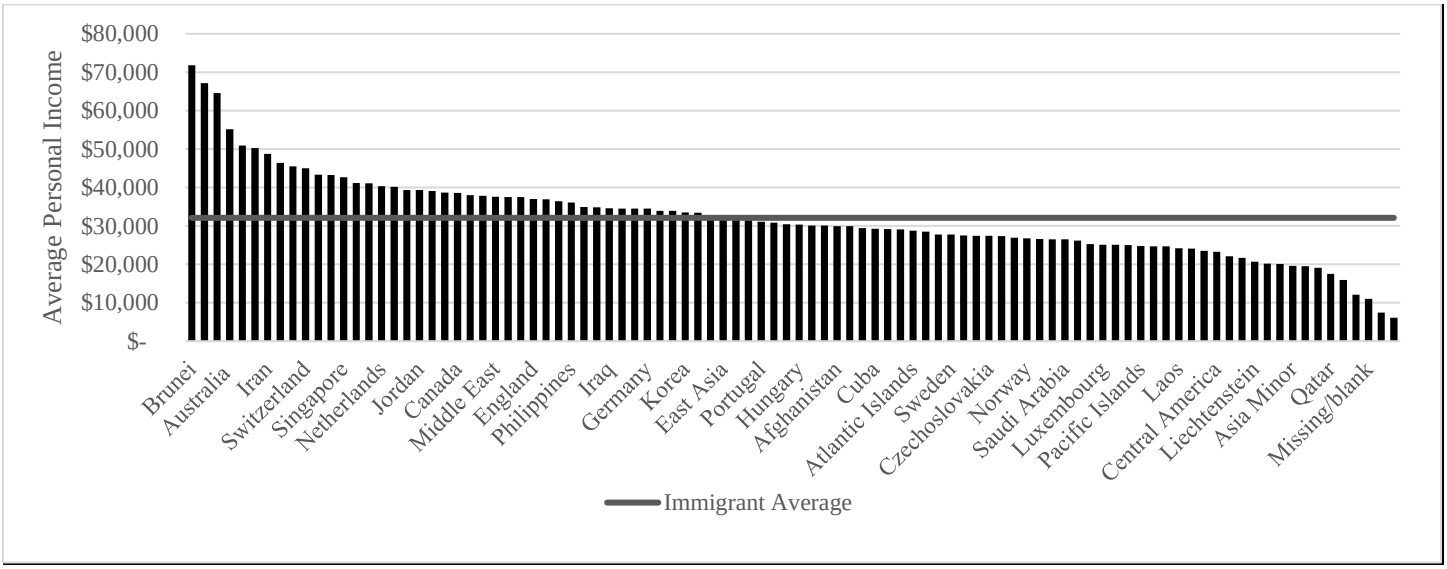
Although more research needs to be done, and definitional issues need to be resolved more universally, natural experiments such as the case of Russian Immigrant to the United States, and to some extent Israel, provide important first glimpses into identifying tangible differences and similarities between economic immigrants and refugees.

While the results are consistent with previous research, it is important to remember the strong caveats associated with the data used. Because the definitions of refugees and economic immigrants are imputed, the data reflect trends and cannot account for individual motivation. An important problem with the data is the homogeneity of the sample. This study limited the data to only immigrants from the Soviet Union may reflect factors that are specific to this group which are not generalizable to other groups of refugees and economic immigrants. Furthermore, research design, the effects of the decade of arrival are excluded making it difficult to account for possibly changing effects of the independent variables over time. Although the results demonstrated in this

paper are by no means conclusive, they are steps towards more progressive and holistic research and policy on refugee migration.

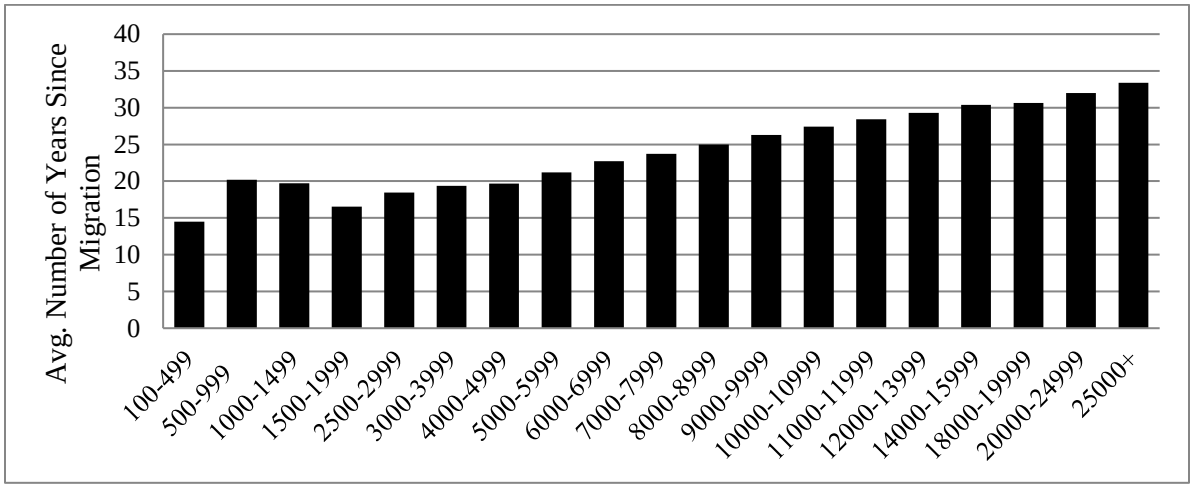
Appendix:

Graph 15: Average Personal Income by Country of Birth



Source: IPUMS USA dataset. Data compiled by the author.

Graph 16: Average Duration for Each Income Bracket[13]



Source: IPUMS International (Israeli Census) dataset. Data compiled by the author.

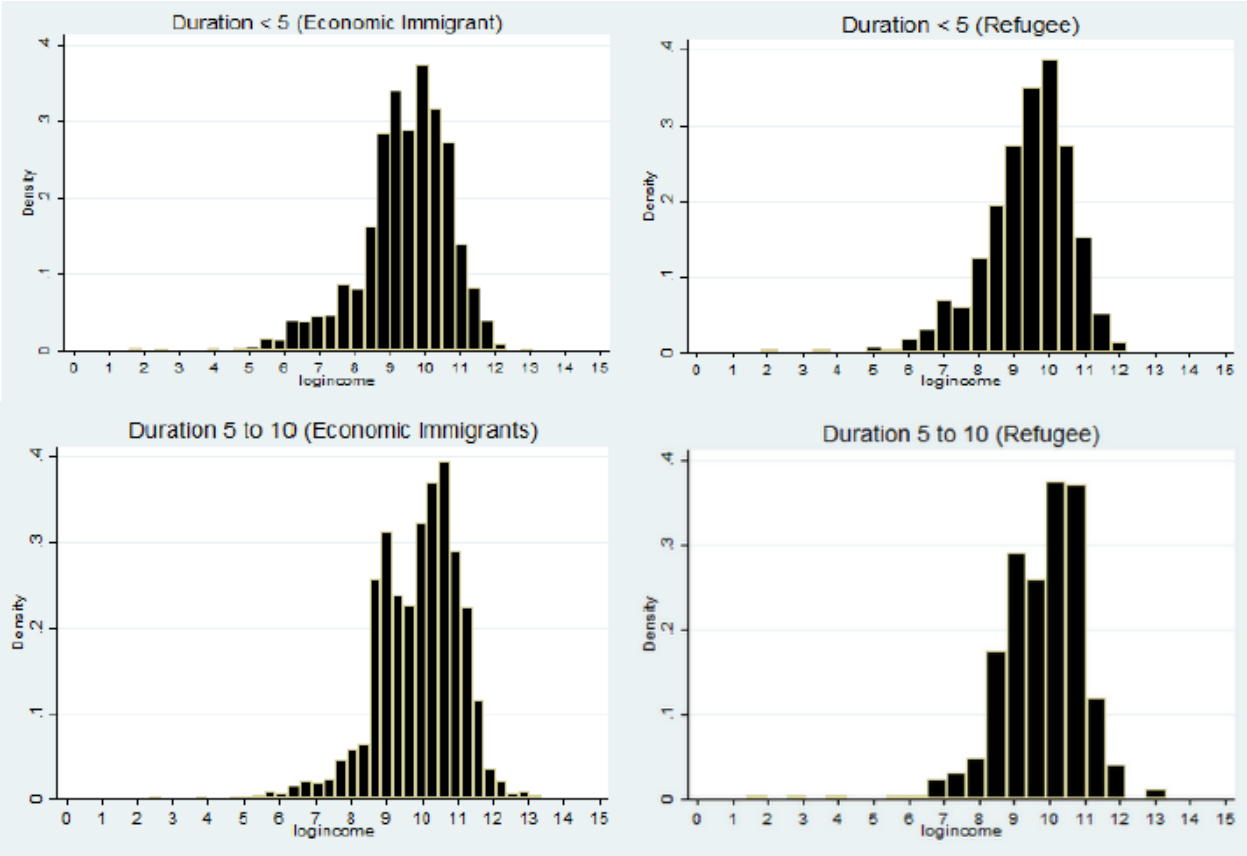
[13] Income brackets based on Israeli New Shekel

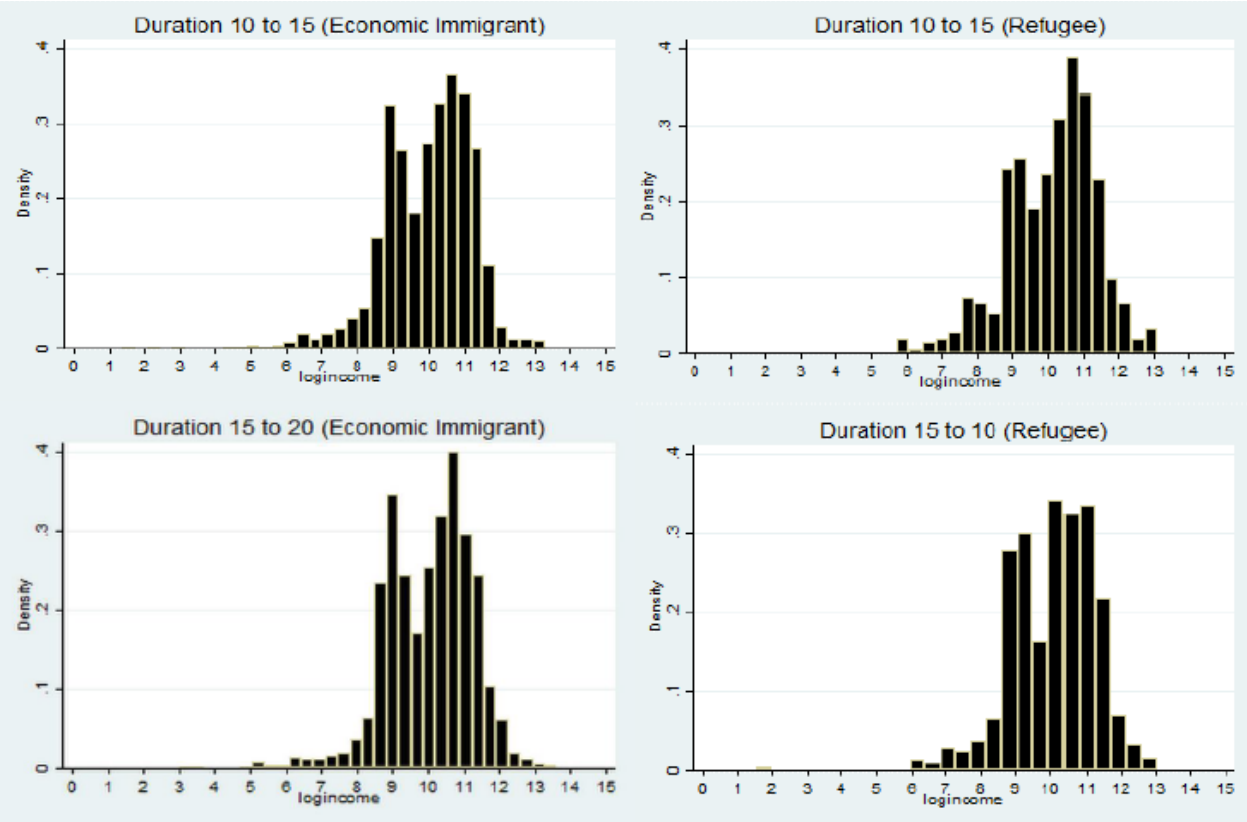
Table 12 : Descriptive Statistics across Key Variables

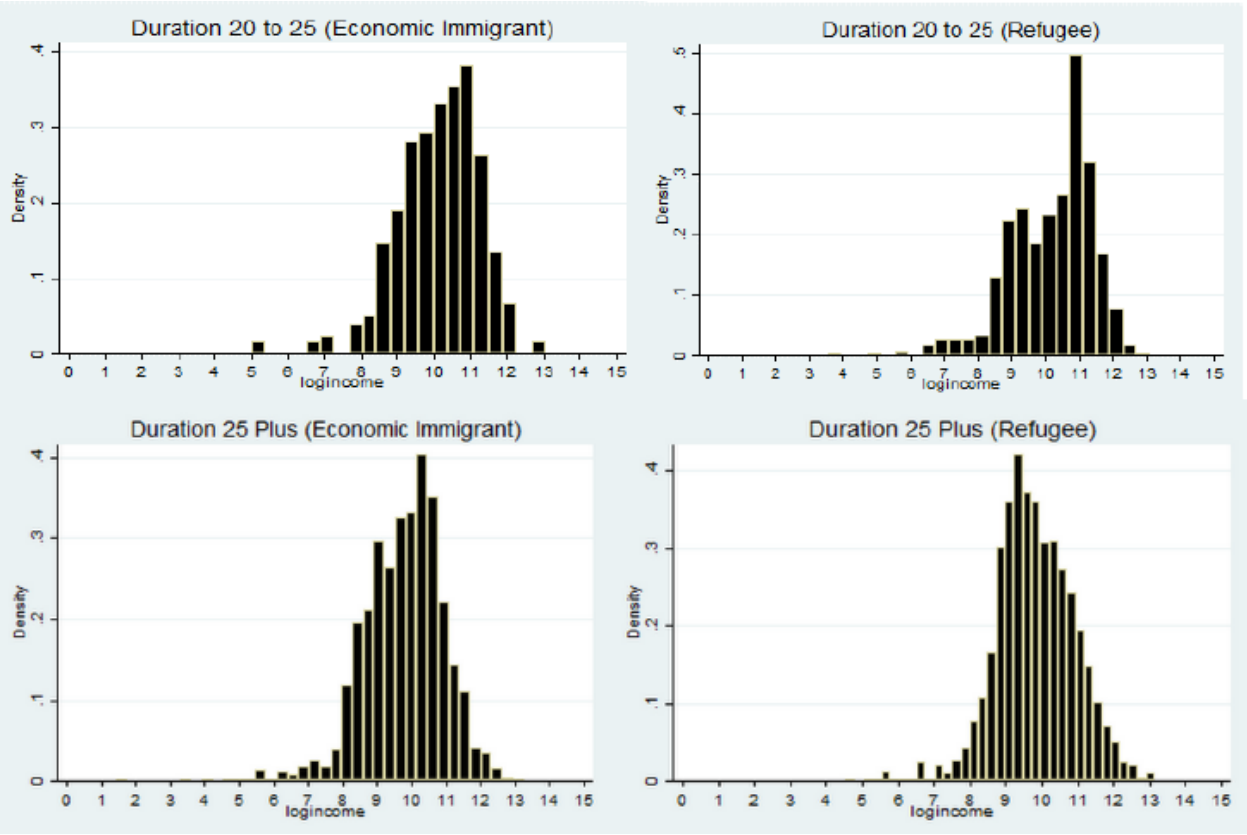
	Duration	Less than 5		5 to 10		10 to 15		15 to 20		20 to 25		25 plus	
		Economic Immigrant	Refugee	Economic Immigrant	Refugee	Economic Immigrant	Refugee	Economic Ir	Refugee	Economic Immigrant	Refugee	Economic Immigrant	Refugee
	Count	2,264	898	3,827	5,304	3,646	5,341	1,980	7,294	575	5,674	21,110	11,986
Age	Min	18	18	18	18	18	18	18	18	20	20	18	18
	Max	94	93	94	90	94	94	94	94	94	94	100	100
	SD	(15.4)	(15.4)	(16.4)	(11.4)	(18.4)	(12.4)	(18.4)	(12.4)	(16.4)	(12.4)	(14.4)	(16.4)
	Average	**37.38**	**36.51**	**41.35**	**32.28**	**45.72**	**35.36**	**48.12**	**37.98**	**53.86**	**42.12**	**55.62**	**56.62**
Age at Arrival	Min	14	14	9	9	4	4	0	0	0	0	0	0
	Max	92	89	89	84	84	81	79	77	74	73	68	68
	SD	(15.4)	(15.4)	(16.4)	(11.4)	(18.4)	(12.4)	(18.4)	(12.4)	(16.4)	(12.4)	(14.4)	(13.4)
	Average	**35.17**	**34.62**	**34.31**	**24.83**	**33.89**	**23.38**	**31.76**	**21.06**	**32.58**	**20.49**	**25.88**	**19.69**
Gender	SD	(49%)	(50%)	(50%)	(50%)	(50%)	(50%)	(50%)	(50%)	(50%)	(50%)	(50%)	(50%)
	Average	**60%**	**55%**	**57%**	**45%**	**56%**	**46%**	**54%**	**44%**	**52%**	**45%**	**49%**	**48%**
Years of Education	Min	4	4	4	4	4	4	4	4	4	4	4	4
	Max	17	17	17	17	17	17	17	17	17	17	17	17
	SD	(2.4)	(3.4)	(2.4)	(2.4)	(2.4)	(2.4)	(3.4)	(3.4)	(3.4)	(3.4)	(4.4)	(4.4)
	Average	**14.15**	**13.83**	**14.44**	**13.82**	**14.54**	**14.19**	**14.21**	**14.22**	**13.40**	**14.10**	**9.40**	**11.53**
% College	SD	(45%)	(46%)	(43%)	(20%)	(44%)	(18%)	(46%)	(17%)	(50%)	(21%)	(31%)	(41%)
	Average	**61%**	**40%**	**61%**	**6%**	**73%**	**7%**	**70%**	**7%**	**57%**	**9%**	**11%**	**10%**
% PhD	SD	(46%)	(50%)	(48%)	(28%)	(44%)	(27%)	(42%)	(27%)	(39%)	(30%)	(18%)	(45%)
	Average	**19%**	**14%**	**22%**	**2%**	**25%**	**2%**	**23%**	**2%**	**18%**	**4%**	**3%**	**3%**
% Married	SD	(47%)	(48%)	(47%)	(47%)	(48%)	(44%)	(47%)	(43%)	(46%)	(41%)	(45%)	(44%)
	Average	**68%**	**65%**	**67%**	**66%**	**65%**	**74%**	**66%**	**76%**	**69%**	**79%**	**73%**	**73%**
Years Married	Min	0	0	0	0	0	0	0	2	1	1	0	1
	Max	67	57	80	60	71	70	78	64	71	76	74	81
	SD	(15.4)	(17.4)	(14.4)	(14.4)	(16.4)	(18.4)	(16.4)	(16.4)	(17.4)	(16.4)	(18.4)	(18.4)
	Average	**14.08**	**20.90**	**14.96**	**16.74**	**22.39**	**24.72**	**25.26**	**24.39**	**25.08**	**27.63**	**35.14**	**39.81**
Number of Children	Min	0	0	0	0	0	0	0	0	0	0	0	0
	Max	9	9	9	9	9	9	9	9	5	9	9	9
	SD	(1.4)	(1.4)	(1.4)	(2.4)	(1.4)	(2.4)	(1.4)	(2.4)	(1.4)	(2.4)	(1.4)	(2.4)
	Average	**0.83**	**1.07**	**0.90**	**1.17**	**0.78**	**1.73**	**0.79**	**1.95**	**0.71**	**2.04**	**1.08**	**1.69**
Number of Children Under 5	Min	0	0	0	0	0	0	0	0	0	0	0	0
	Max	4	3	3	4	4	4	3	4	3	4	4	4
	SD	(1.4)	(1.4)	(1.4)	(1.4)	(.4)	(1.4)	(.4)	(1.4)	(.4)	(1.4)	(.4)	(.4)
	Average	**0.21**	**0.28**	**0.21**	**0.51**	**0.15**	**0.54**	**0.13**	**0.41**	**0.10**	**0.29**	**0.08**	**0.12**
% Living in Center	SD	(26%)	(30%)	(23%)	(32%)	(17%)	(32%)	(20%)	(34%)	(28%)	(34%)	(32%)	(36%)
	Average	**92%**	**90%**	**95%**	**88%**	**97%**	**89%**	**96%**	**87%**	**91%**	**87%**	**89%**	**84%**
% Own Home	SD	(46%)	(42%)	(49%)	(41%)	(50%)	(45%)	(49%)	(48%)	(45%)	(49%)	(50%)	(50%)
	Average	**29%**	**22%**	**43%**	**21%**	**55%**	**28%**	**60%**	**36%**	**73%**	**41%**	**44%**	**50%**
% on Foodstamps	SD	(37%)	(41%)	(38%)	(41%)	(39%)	(37%)	(40%)	(36%)	(36%)	(35%)	(24%)	(21%)
	Average	**17%**	**21%**	**18%**	**22%**	**19%**	**16%**	**19%**	**15%**	**15%**	**14%**	**6%**	**5%**
% Employed	SD	(50%)	(47%)	(49%)	(33%)	(49%)	(33%)	(49%)	(46%)	(50%)	(49%)	(50%)	(46%)
	Average	**49%**	**34%**	**59%**	**12%**	**62%**	**12%**	**62%**	**30%**	**55%**	**39%**	**45%**	**29%**

Source: IPUMS USA dataset. Descriptive statistics generated by the author.

Graph 17: Distribution of Income across Cohorts




Duration 10 to 15 (Economic Immigrant)
Duration 10 to 15 (Refugee)
Duration 15 to 20 (Economic Immigrant)
Duration 15 to 10 (Refugee)
Density
logincome



Source: IPUMS USA dataset. Histograms generated by STATA 15.

Table 9: Ordinary Least Square Regressions

Source: IPUMS USA dataset. Regression results generated by STATA 15.

A) All Foreign Born – Less than 5 Years in US

Source	SS	df	MS			
				Number of obs	=	1,447
				F(11, 1435)	=	45.96
Model	625.405799	11	56.8550727	Prob > F	=	0.0000
Residual	1775.3178	1,435	1.23715526	R-squared	=	0.2605
				Adj R-squared	=	0.2548
Total	2400.7236	1,446	1.66025145	Root MSE	=	1.1123

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.00742	.0174392	0.43	0.671	-.0267891	.0416291
gender	-.5385203	.0604776	-8.90	0.000	-.6571542	-.4198864
married	.1091657	.0705324	1.55	0.122	-.0291919	.2475233
familysize	-.1300346	.0258065	-5.04	0.000	-.1806571	-.0794121
numchildren	.2232194	.0349408	6.39	0.000	.1546788	.29176
college	.1094157	.09586	1.14	0.254	-.0786251	.2974565
phd	.4098294	.1208515	3.39	0.001	.1727649	.6468938
agearrival	.0051132	.0023089	2.21	0.027	.0005841	.0096423
foodstmp	-.3432208	.091106	-3.77	0.000	-.5219359	-.1645056
ownhome	.0425735	.067911	0.63	0.531	-.090642	.175789
empstat	.9000909	.0686594	13.11	0.000	.7654073	1.034775
_cons	8.054043	.2498261	32.24	0.000	7.56398	8.544107

B) All Foreign Born 5 to 10 Years in US

Source	SS	df	MS			
				Number of obs	=	2,559
				F(11, 2547)	=	119.45
Model	1188.60557	11	108.055052	Prob > F	=	0.0000
Residual	2304.04735	2,547	.904612229	R-squared	=	0.3403
				Adj R-squared	=	0.3375
Total	3492.65291	2,558	1.36538425	Root MSE	=	.95111

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0341108	.0111447	3.06	0.002	.0122572	.0559645
gender	-.3816524	.0382819	-9.97	0.000	-.4567193	-.3065855
married	.1026446	.0441207	2.33	0.020	.0161284	.1891608
familysize	-.1269083	.0176148	-7.20	0.000	-.1614492	-.0923675
numchildren	.1727829	.0234252	7.38	0.000	.1268485	.2187173
college	.1119212	.062988	1.78	0.076	-.0115918	.2354342
phd	.2553586	.0751388	3.40	0.001	.1080193	.4026978
agearrival	.0052896	.0014429	3.67	0.000	.0024602	.008119
foodstmp	-.2926963	.057508	-5.09	0.000	-.4054636	-.179929
ownhome	.1229563	.0422376	2.91	0.004	.0401328	.2057798
empstat	.980166	.049199	19.92	0.000	.8836918	1.07664
_cons	7.89406	.1577682	50.04	0.000	7.584693	8.203427

C) All Foreign Born 10 to 15 Years in US

Source	SS	df	MS
Model	1908.68717	11	173.517016
Residual	2767.99112	3,093	.894921152
Total	4676.6783	3,104	1.50666182

Number of obs	=	3,105
F(11, 3093)	=	193.89
Prob > F	=	0.0000
R-squared	=	0.4081
Adj R-squared	=	0.4060
Root MSE	=	.946

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.019516	.0102298	1.91	0.057	-.0005419	.0395739
gender	-.2825478	.0345345	-8.18	0.000	-.3502606	-.2148349
married	.1805826	.0409676	4.41	0.000	.1002562	.260909
familysize	-.1761349	.016855	-10.45	0.000	-.209183	-.1430867
numchildren	.2449031	.0232781	10.52	0.000	.1992611	.2905452
college	.2095073	.0594803	3.52	0.000	.0928824	.3261322
phd	.2909639	.0676966	4.30	0.000	.1582291	.4236987
agearrival	.0048323	.0013094	3.69	0.000	.0022648	.0073998
foodstmp	-.2648572	.0525543	-5.04	0.000	-.367902	-.1618124
ownhome	.1939632	.0402445	4.82	0.000	.1150545	.2728719
empstat	1.166646	.0467908	24.93	0.000	1.074902	1.25839
_cons	8.010625	.1430053	56.02	0.000	7.73023	8.29102

D) All Foreign Born 15 to 20 Years in US

Source	SS	df	MS
Model	1166.34834	11	106.031667
Residual	1636.41485	1,815	.901605981
Total	2802.76319	1,826	1.5349196

Number of obs	=	1,827
F(11, 1815)	=	117.60
Prob > F	=	0.0000
R-squared	=	0.4161
Adj R-squared	=	0.4126
Root MSE	=	.94953

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0109484	.0137001	0.80	0.424	-.0159213	.0378181
gender	-.2692144	.0450792	-5.97	0.000	-.357627	-.1808018
married	.2391532	.0539452	4.43	0.000	.133352	.3449545
familysize	-.1410433	.0211441	-6.67	0.000	-.1825127	-.099574
numchildren	.1953436	.0294556	6.63	0.000	.1375731	.253114
college	.2810735	.0778808	3.61	0.000	.128328	.4338189
phd	.3278007	.0909307	3.60	0.000	.1494608	.5061405
agearrival	.0049643	.0016867	2.94	0.003	.0016563	.0082724
foodstmp	-.2528163	.0726533	-3.48	0.001	-.3953092	-.1103234
ownhome	.2153794	.0532469	4.04	0.000	.1109477	.3198111
empstat	1.158482	.0632001	18.33	0.000	1.034529	1.282434
_cons	7.978861	.187408	42.57	0.000	7.611303	8.346419

E) All Foreign Born 25 Years or more in US

Source	SS	df	MS			
				Number of obs	=	2,440
				F(11, 2428)	=	123.91
Model	1011.6318	11	91.9665276	Prob > F	=	0.0000
Residual	1802.13062	2,428	.742228428	R-squared	=	0.3595
				Adj R-squared	=	0.3566
Total	2813.76243	2,439	1.15365413	Root MSE	=	.86153

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0165215	.0073483	2.25	0.025	.0021119	.0309311
gender	-.5415192	.0364519	-14.86	0.000	-.6129992	-.4700392
married	-.1218992	.0426933	-2.86	0.004	-.2056184	-.0381801
familysize	-.0803678	.0253325	-3.17	0.002	-.1300433	-.0306923
numchildren	.0803751	.038279	2.10	0.036	.0053123	.1554379
college	.1457401	.0535164	2.72	0.007	.0407977	.2506826
phd	.2639125	.0619617	4.26	0.000	.1424093	.3854157
agearrival	-.0079568	.0013567	-5.87	0.000	-.0106171	-.0052965
foodstmp	-.4331897	.087272	-4.96	0.000	-.6043249	-.2620545
ownhome	.3646515	.045039	8.10	0.000	.2763326	.4529703
empstat	.7774478	.042195	18.43	0.000	.6947058	.8601898
_cons	9.114156	.1020107	89.35	0.000	8.914119	9.314193

F) Economic Immigrants Less than 5 Years in US

Source	SS	df	MS			
				Number of obs	=	1,141
				F(11, 1129)	=	36.32
Model	500.499169	11	45.4999245	Prob > F	=	0.0000
Residual	1414.44263	1,129	1.25282784	R-squared	=	0.2614
				Adj R-squared	=	0.2542
Total	1914.9418	1,140	1.67977351	Root MSE	=	1.1193

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0075308	.020366	0.37	0.712	-.0324286	.0474902
gender	-.5890156	.068565	-8.59	0.000	-.7235448	-.4544864
married	.0789726	.0794632	0.99	0.321	-.0769396	.2348848
familysize	-.1335606	.0301632	-4.43	0.000	-.1927427	-.0743784
numchildren	.2414852	.0407149	5.93	0.000	.1615998	.3213706
college	.1142963	.1098896	1.04	0.299	-.1013145	.3299072
phd	.3861864	.1390789	2.78	0.006	.1133043	.6590686
agearrival	.0035463	.002603	1.36	0.173	-.001561	.0086536
foodstmp	-.3571821	.1045572	-3.42	0.001	-.5623303	-.1520339
ownhome	.0181447	.0767298	0.24	0.813	-.1324043	.1686938
empstat	.8925327	.078165	11.42	0.000	.7391677	1.045898
_cons	8.160077	.288989	28.24	0.000	7.593061	8.727093

G) Economic Immigrants 5 to 10 Years in US

Source	SS	df	MS			
				Number of obs	=	2,185
				F(11, 2173)	=	100.36
Model	984.001035	11	89.4546396	Prob > F	=	0.0000
Residual	1936.91296	2,173	.891354331	R-squared	=	0.3369
				Adj R-squared	=	0.3335
Total	2920.914	2,184	1.33741483	Root MSE	=	.94412

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0359943	.0120809	2.98	0.003	.0123031	.0596856
gender	-.3669831	.0411728	-8.91	0.000	-.4477254	-.2862408
married	.1004117	.0471874	2.13	0.033	.0078746	.1929488
familysize	-.1371878	.0199482	-6.88	0.000	-.1763073	-.0980682
numchildren	.1897882	.0266896	7.11	0.000	.1374484	.2421281
college	.1277527	.0690717	1.85	0.065	-.0077008	.2632062
phd	.2377995	.0807894	2.94	0.003	.0793668	.3962321
agearrival	.0041136	.0015769	2.61	0.009	.0010213	.0072059
foodstmp	-.2745292	.0639762	-4.29	0.000	-.3999901	-.1490684
ownhome	.1119064	.0453468	2.47	0.014	.0229787	.2008341
empstat	.9413787	.0528949	17.80	0.000	.8376487	1.045109
_cons	7.959042	.1703061	46.73	0.000	7.625062	8.293022

H) Economic Immigrants 10 to 15 Years in US

Source	SS	df	MS			
				Number of obs	=	2,819
				F(11, 2807)	=	176.53
Model	1731.46841	11	157.406219	Prob > F	=	0.0000
Residual	2502.95993	2,807	.891685047	R-squared	=	0.4089
				Adj R-squared	=	0.4066
Total	4234.42834	2,818	1.50263603	Root MSE	=	.94429

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0179746	.0105992	1.70	0.090	-.0028085	.0387578
gender	-.2699262	.0361746	-7.46	0.000	-.3408578	-.1989946
married	.1655361	.0426149	3.88	0.000	.0819763	.2490959
familysize	-.1787061	.0176624	-10.12	0.000	-.2133388	-.1440735
numchildren	.2323115	.0242869	9.57	0.000	.1846895	.2799334
college	.2250637	.0627728	3.59	0.000	.1019781	.3481493
phd	.2815018	.0703787	4.00	0.000	.1435025	.4195011
agearrival	.004836	.0013743	3.52	0.000	.0021413	.0075308
foodstmp	-.2650657	.0547565	-4.84	0.000	-.3724327	-.1576987
ownhome	.2081573	.0422273	4.93	0.000	.1253576	.290957
empstat	1.186222	.0497301	23.85	0.000	1.088711	1.283733
_cons	8.010827	.1482848	54.02	0.000	7.720069	8.301585

I) Economic Immigrants 15 to 20 Years in US

Source	SS	df	MS			
				Number of obs	=	1,184
				F(11, 1172)	=	78.99
Model	780.68435	11	70.9713046	Prob > F	=	0.0000
Residual	1052.98171	1,172	.898448561	R-squared	=	0.4258
				Adj R-squared	=	0.4204
Total	1833.66606	1,183	1.55001358	Root MSE	=	.94787

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0318469	.018077	1.76	0.078	-.00362	.0673137
gender	-.2264312	.0558445	-4.05	0.000	-.3359975	-.1168649
married	.2123435	.0663642	3.20	0.001	.0821376	.3425495
familysize	-.1278861	.0262755	-4.87	0.000	-.1794384	-.0763339
numchildren	.2084318	.0365613	5.70	0.000	.1366989	.2801646
college	.1414254	.101106	1.40	0.162	-.0569435	.3397943
phd	.2462573	.1157723	2.13	0.034	.0191131	.4734015
agearrival	.0063906	.0020921	3.05	0.002	.0022859	.0104953
foodstmp	-.2100199	.0877869	-2.39	0.017	-.382257	-.0377829
ownhome	.2124042	.0664156	3.20	0.001	.0820975	.342711
empstat	1.24229	.0798818	15.55	0.000	1.085562	1.399017
_cons	7.603444	.2426749	31.33	0.000	7.127318	8.079569

J) Economic Immigrants 20 to 25 Years in US

Source	SS	df	MS			
				Number of obs	=	141
				F(11, 129)	=	6.44
Model	59.5727555	11	5.41570505	Prob > F	=	0.0000
Residual	108.46849	129	.84084101	R-squared	=	0.3545
				Adj R-squared	=	0.2995
Total	168.041246	140	1.20029461	Root MSE	=	.91697

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.1382691	.0710352	1.95	0.054	-.0022758	.2788141
gender	-.3869105	.1621608	-2.39	0.018	-.7077497	-.0660713
married	.223879	.2204899	1.02	0.312	-.2123656	.6601237
familysize	-.2344296	.1082034	-2.17	0.032	-.4485126	-.0203466
numchildren	.298003	.1534766	1.94	0.054	-.0056542	.6016602
college	-.5064438	.3107114	-1.63	0.106	-1.121194	.1083064
phd	-.1860662	.4288297	-0.43	0.665	-1.034516	.6623839
agearrival	-.0117981	.0064214	-1.84	0.068	-.0245029	.0009067
foodstmp	.1639331	.3147055	0.52	0.603	-.4587194	.7865856
ownhome	.2135366	.2107119	1.01	0.313	-.2033622	.6304353
empstat	.8296636	.1870635	4.44	0.000	.4595539	1.199773
_cons	7.949713	.8703528	9.13	0.000	6.227699	9.671727

K) Economic Immigrants 25 Years or more in US

Source	SS	df	MS			
				Number of obs	=	1,187
				F(11, 1175)	=	60.02
Model	549.129701	11	49.9208819	Prob > F	=	0.0000
Residual	977.211297	1,175	.831669189	R-squared	=	0.3598
				Adj R-squared	=	0.3538
Total	1526.341	1,186	1.28696543	Root MSE	=	.91196

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0020052	.0111541	0.18	0.857	-.0198788	.0238893
gender	-.443889	.0549976	-8.07	0.000	-.5517934	-.3359846
married	-.030143	.0646166	-0.47	0.641	-.1569198	.0966338
familysize	-.0760111	.0345891	-2.20	0.028	-.1438744	-.0081478
numchildren	.0684308	.0513624	1.33	0.183	-.0323414	.1692031
college	.2189416	.0823353	2.66	0.008	.057401	.3804823
phd	.3138	.0916849	3.42	0.001	.1339157	.4936844
agearrival	-.0071512	.0020545	-3.48	0.001	-.0111822	-.0031203
foodstmp	-.4763311	.1235564	-3.86	0.000	-.7187469	-.2339153
ownhome	.3244042	.0684349	4.74	0.000	.1901361	.4586724
empstat	.8380429	.0637406	13.15	0.000	.7129848	.9631011
_cons	9.108439	.1577313	57.75	0.000	8.798972	9.417905

L) Refugee Less than 5 Years in US

Source	SS	df	MS			
				Number of obs	=	306
				F(11, 294)	=	10.18
Model	133.818388	11	12.165308	Prob > F	=	0.0000
Residual	351.472727	294	1.19548546	R-squared	=	0.2757
				Adj R-squared	=	0.2487
Total	485.291115	305	1.59111841	Root MSE	=	1.0934

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0093727	.0341841	0.27	0.784	-.0579039	.0766492
gender	-.3568897	.130235	-2.74	0.007	-.6132007	-.1005787
married	.2229445	.1578107	1.41	0.159	-.0876373	.5335263
familysize	-.1091841	.050984	-2.14	0.033	-.2095239	-.0088442
numchildren	.1538181	.0697507	2.21	0.028	.0165442	.291092
college	.0752156	.2014575	0.37	0.709	-.3212661	.4716972
phd	.4650959	.251963	1.85	0.066	-.0307839	.9609756
agearrival	.0104055	.005075	2.05	0.041	.0004176	.0203934
foodstmp	-.3011855	.1890611	-1.59	0.112	-.6732702	.0708992
ownhome	.1241393	.1508809	0.82	0.411	-.1728042	.4210829
empstat	.9164041	.1457179	6.29	0.000	.6296218	1.203186
_cons	7.661497	.5065582	15.12	0.000	6.664557	8.658437

M) Refugee 5 to 10 Years in US

Source	SS	df	MS			
				Number of obs	=	374
				F(11, 362)	=	20.09
Model	213.491404	11	19.4083095	Prob > F	=	0.0000
Residual	349.730094	362	.966105232	R-squared	=	0.3791
				Adj R-squared	=	0.3602
Total	563.221498	373	1.50997721	Root MSE	=	.98291

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.022489	.0290955	0.77	0.440	-.0347285	.0797065
gender	-.4897181	.1037706	-4.72	0.000	-.6937869	-.2856492
married	.1564268	.1265166	1.24	0.217	-.092373	.4052267
familysize	-.0889488	.0393266	-2.26	0.024	-.1662862	-.0116115
numchildren	.1193074	.0517029	2.31	0.022	.0176316	.2209832
college	-.0390069	.1565282	-0.25	0.803	-.3468256	.2688118
phd	.3750037	.2056707	1.82	0.069	-.0294558	.7794631
agearrival	.0106734	.0038425	2.78	0.006	.0031171	.0182297
foodstmp	-.3610358	.1404098	-2.57	0.011	-.6371572	-.0849144
ownhome	.1764341	.1161529	1.52	0.130	-.0519852	.4048533
empstat	1.244128	.1334597	9.32	0.000	.981674	1.506581
_cons	7.573908	.4246255	17.84	0.000	6.738866	8.408951

N) Refugee 10 to 15 Years in US

Source	SS	df	MS			
				Number of obs	=	286
				F(11, 274)	=	19.68
Model	192.856241	11	17.5323856	Prob > F	=	0.0000
Residual	244.055411	274	.890713177	R-squared	=	0.4414
				Adj R-squared	=	0.4190
Total	436.911652	285	1.53302334	Root MSE	=	.94378

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0498288	.0402355	1.24	0.217	-.0293811	.1290387
gender	-.391097	.1144427	-3.42	0.001	-.6163957	-.1657983
married	.2873788	.1507999	1.91	0.058	-.0094949	.5842526
familysize	-.1245919	.0582663	-2.14	0.033	-.2392983	-.0098854
numchildren	.3412363	.0826404	4.13	0.000	.1785455	.5039271
college	.0865057	.1937702	0.45	0.656	-.2949619	.4679734
phd	.3882844	.249271	1.56	0.120	-.1024455	.8790142
agearrival	.0082694	.0044095	1.88	0.062	-.0004114	.0169501
foodstmp	-.3195545	.1900001	-1.68	0.094	-.6935999	.054491
ownhome	-.0466494	.1407961	-0.33	0.741	-.3238289	.2305302
empstat	.9741472	.1387471	7.02	0.000	.7010014	1.247293
_cons	7.662539	.5561165	13.78	0.000	6.567735	8.757343

O) Refugee 15 to 20 Years in US

Source	SS	df	MS			
				Number of obs	=	643
				F(11, 631)	=	40.12
Model	398.782119	11	36.2529199	Prob > F	=	0.0000
Residual	570.141782	631	.903552745	R-squared	=	0.4116
				Adj R-squared	=	0.4013
Total	968.923901	642	1.50922726	Root MSE	=	.95055

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	-.0145384	.0211615	-0.69	0.492	-.0560939	.0270171
gender	-.3464117	.0764407	-4.53	0.000	-.4965206	-.1963028
married	.2738491	.0929531	2.95	0.003	.0913142	.4563841
familysize	-.1664562	.0357992	-4.65	0.000	-.2367562	-.0961561
numchildren	.1802788	.0498092	3.62	0.000	.082467	.2780907
college	.4863236	.1228786	3.96	0.000	.2450232	.727624
phd	.4255663	.1502895	2.83	0.005	.1304382	.7206944
agearrival	.0023625	.0028651	0.82	0.410	-.0032638	.0079888
foodstmp	-.2890214	.1316315	-2.20	0.028	-.5475102	-.0305325
ownhome	.2069588	.0893052	2.32	0.021	.0315874	.3823302
empstat	1.024675	.1035378	9.90	0.000	.8213548	1.227996
_cons	8.515659	.3010319	28.29	0.000	7.924513	9.106804

P) Refugee 20 to 25 Years in US

Years in US: 20 to 25
Immigrant type: Refugees

Source	SS	df	MS			
				Number of obs	=	413
				F(11, 401)	=	31.34
Model	308.104099	11	28.0094635	Prob > F	=	0.0000
Residual	358.424593	401	.893826914	R-squared	=	0.4623
				Adj R-squared	=	0.4475
Total	666.528691	412	1.61778809	Root MSE	=	.94542

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0200737	.0250918	0.80	0.424	-.0292542	.0694015
gender	-.2270918	.0963407	-2.36	0.019	-.4164877	-.0376958
married	.1549821	.1130131	1.37	0.171	-.06719	.3771542
familysize	-.101841	.0658289	-1.55	0.123	-.2312539	.0275718
numchildren	.1780674	.0813646	2.19	0.029	.018113	.3380218
college	.3737862	.1669073	2.24	0.026	.0456634	.7019089
phd	.0284758	.1715024	0.17	0.868	-.3086804	.365632
agearrival	.0036375	.0034733	1.05	0.296	-.0031907	.0104656
foodstmp	-.2728762	.1554947	-1.75	0.080	-.5785627	.0328104
ownhome	.2855685	.1217109	2.35	0.019	.0462972	.5248397
empstat	1.32021	.1219906	10.82	0.000	1.080389	1.560031
_cons	7.861131	.3450812	22.78	0.000	7.182737	8.539526

Q) Refugee 25 Years or more in US

Source	SS	df	MS			
				Number of obs	=	1,253
				F(11, 1241)	=	66.23
Model	476.11482	11	43.2831655	Prob > F	=	0.0000
Residual	810.981709	1,241	.653490498	R-squared	=	0.3699
				Adj R-squared	=	0.3643
Total	1287.09653	1,252	1.02803237	Root MSE	=	.80839

logincome	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
yrsschool	.0308515	.0096413	3.20	0.001	.0119363	.0497666
gender	-.6392434	.0481311	-13.28	0.000	-.7336707	-.5448161
married	-.2109408	.0571721	-3.69	0.000	-.3231054	-.0987763
familysize	-.0867903	.0381779	-2.27	0.023	-.1616906	-.0118899
numchildren	.0989957	.059686	1.66	0.097	-.018101	.2160923
college	.0791076	.0692654	1.14	0.254	-.0567826	.2149978
phd	.2246548	.0836376	2.69	0.007	.0605681	.3887415
agearrival	-.007665	.0019033	-4.03	0.000	-.011399	-.003931
foodstmp	-.3690726	.1247826	-2.96	0.003	-.6138808	-.1242644
ownhome	.3952303	.0593038	6.66	0.000	.2788836	.5115771
empstat	.7344087	.057327	12.81	0.000	.6219402	.8468773
_cons	9.081185	.1340456	67.75	0.000	8.818205	9.344166

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