Explaining the Immigrant-Native Wage Gap

Nicole Gorton and Sylvia Klosin

University of Chicago, Department of Economics

Abstract— **Do female immigrants earn as much as their native counterparts, and if not, why not? We establish the existence of a wage gap between female U.S. born and female immigrant workers, then try to explain what factors drive this gap. We consider the effect of skill, English language ability, state of settlement, and the bias of selection into the workforce. We find that English language ability and selection into the workforce have the largest impact on our measure of the immigrant wage gap; in fact, we find that immigrant women have a net wage advantage in the workforce when we consider these factors.**

I. Introduction

In 2013, immigrants represented nearly 13% of the United States population.[1] These immigrants come to this country for a variety of reasons and with different skills and experiences. On average, however, immigrants (both men and women) as a group earn lower wages than their native, American-born counterparts.[2] Why? There are a few possible explanations of this phenomenon. First, it could be the case that the labor market mistakenly sets wages too low initially when immigrants first arrive. Second, it could be the case that new immigrants lack the skills the labor market values when they first arrive in the United States. Third, the gap could be the result of selection bias into the workforce. Perhaps lower-skilled immigrants are over-represented in the workforce as they are forced to work to survive, while higher-skilled immigrants (and women, in particular) may choose not to work. In each of these cases, we would expect the gap to close over time: the labor market adjusts wages, workers gain skills over time (for example, English language ability) and low-quality workers drop out of the labor force altogether. However, as we will document, this is not the trend we see in the data: instead, the wage gap persists. Our primary inquiry attempts to explain why.

Much of the existing literature has explored the wage gap between native men and immigrant men, but we believe these results cannot be generalized for women without deeper analysis due to the unique selection challenges involved with women in the labor force. In our paper, we explore the trajectory and convergence of female immigrants' wages and seek to answer the following question: what characteristics explain the persistent wage gap between immigrant and native wages? This question is particularly difficult to answer for women who generally have a higher labor supply elasticity than men. While men are often the family breadwinners, women frequently opt out of the labor force and take on a more traditional role in the household. This is particularly true for immigrant women, who enter the country with a range of different standards of female labor force participation and gender roles based on the culture of their host country. Thus, the female labor market choice is more complicated and involves more considerations.

The explanation of the wage gap has important implications for immigrants and for policy makers. The presence of an unexplained wage gap has the potential to deter immigrants from participating in the workforce, or from immigrating to the United States altogether. Additionally, if the initial gap can be explained by immigrants' lack of skills and English language ability, then perhaps policies and programs could help immigrants improve their English fluency and gain the skills the labor market values so that their wages can more quickly approach those of natives. Additionally, if the gap is related to state of settlement (perhaps certain states are more conducive to immigrant success than others), then future work could determine which policies aide immigrants most effectively, and the government could implement those policies those on a national scale to ensure the workforce is as productive as possible.

Our empirical strategy involves three parts. First, we establish the existence of a wage gap between native and immigrant women. Second, we try to explain this gap by accounting for personal characteristics like skill, education level, and state of settlement. Third, we use a Heckman selection model to account for selection bias into the labor force. The Heckman decision model incorporates female culture factors from a woman's home country, which we believe impacts the decision to work. Throughout the paper we compare our findings about women with the trends in male immigrants documented by other studies.

II. Literature Review

Our primary motivation for this paper comes from Borjas' 2015 paper *The Slowdown in the Economic Assimilation of Immigrants: Aging and Cohort Effects Revisited Again*. Borjas studies the evolution of male immigrant earnings in the United States between 1970 and 2010. He finds that more recent cohorts are assimilating more slowly than earlier cohorts; that is, they are earning less and gaining less human capital stock. The basis of our study is modeled off of this paper: for example, we use the same data source (U.S. Census and ACS data) and we take the same approach

[1] www.migrationpolicy.org

[2] We will show this fact, but it has been documented by others as well. For example, see Anderson (2015).

to observe the raw gap in earnings between natives and immigrants. We will document this method in detail later on.

However, Borjas limits his study to immigrant men. Other work studies female immigrants and immigrant families in particular: for example, Francine Blau writes about another element of female work, one that we also examine in our paper, in her paper *Immigrants and Gender Roles Assimilation vs Culture*. She finds considerable evidence that an immigrant woman's source country gender culture influences her behavior in the United States: one such behavior is the decision to participate in the labor market. Blau uses fertility and GDP per capital of the host country to capture the gender culture. Her conclusions are robust to various efforts to rule out the effect of other unobservables. Due to the significance of the effect that she finds, we use these variables (among others) in the first stage of our Heckman Selection model.

Blau, Kahn, and Papps investigate the labor supply assimilation profiles of married adult immigrant women and men in their 2010 paper *Gender, Source Country Characteristics, and Labor Marker Assimilation Among Immigrants*. They find that women migrating from countries with high female labor force participation rates work substantially more than women coming from countries with lower female labor supply rates. They find this pattern also holds for women coming from countries with low fertility rates. Interestingly, these home country factors only impact the work decisions of female migrants and not male migrants, suggesting the robustness of the effect on women.

Our primary contribution to this literature is as follows: first, we extend portions of Borjas' analysis to women, and second, we further explore the wage gap by accounting for selection bias for women in the work force in our estimation of the wage equation. We include the country characteristics documented by Blau and Kahn as factors that affect female immigrants' decision to work.

III. Data

A. Construction of Base Sample

We construct our base data set as per Borjas 2014. Our data is a combination of US Census and American Community Survey data, as provided through the IPUMPS database. We use Census data from 1970, 1980, 1990, and 2000. The 1970 census data is a 3% sample, formed by pooling the Form 1 State, Metro, and Neighborhood databases. The 1980, 1990, and 2000 extracts are each 5% random population samples. We use the provided sampling weights in our estimates. Because the 2010 Census does not include all of our variables of interest, we create a proxy for the 2010 Census by pooling the American Community Survey from years 2009, 2010, and 2011. We limit our sample to those between ages 25 and 64.

Because our data is cross-sectional instead of panel, we construct immigrant cohort categories as per Borjas 2015. Immigrants who came to the United States in the same 5 year interval are considered to be a part of the same immigrant cohort; thus, cohorts are essentially categorical variables for year of immigration into the United States. With these groupings, we are able to track groups of immigrants through different survey years and observe how their wages change over time as they spend more time in the United States. There are 12 different cohorts in our dataset, ranging from entry years of 1940 to 2005. We are not tracking the same exact people over time, but by grouping people into cohorts we are constructing groups of people with similar characteristics, allowing us to do an almost panel-type analysis despite the data challenges posed by this cross-sectional sample. In total, our full sample includes about 30 million people, 10% of whom are migrants. This is a good approximation of the national sample. We define natives as those born in the United States and immigrants as those born outside the United States who immigrated after the age of 18.

We now provide an overview of control variables. Our control for ability to speak English is a binary variable, taking on a value of 1 if a person responded that he or she speaks only English, speaks English very well, or speaks English well and a value of 0 if a person responded that he or she does not speak English or speaks English poorly. Because this variable is only available post-1970, we can only use 1980+ survey years when we include this variable as a control. Our control variable for state of settlement is defined as the state in which the housing unit was located at the time of the survey. Thus, we cannot control for whether a specific person in a specific year has moved around the country; we observe only the state they currently live in. Skill groups are constructed by splitting education into five categorical variables, less than high school, high school graduate, some college, college graduate, and more than college and age into eight categorical variables, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64. We then sort individuals into one of 40 skill groups based on their respective age and educational categories. This skill group construction method is as per Borjas 2015. Basic summary statistics of our dataset are included in table 1 above.

TABLE I: Summary Statistics By Immigrant Status

	Non-Immigrants			Immigrants		
	Mean	Min.	Max.	Mean	Min.	Max.
Sex	0.52	0.00	1.00	0.52	0.00	1.00
Number of Children	0.95	0.00	9.00	1.24	0.00	9.00
Age	39.50	18.00	64.00	41.35	18.00	64.00
Age at Migration	NA	NA	NA	28.45	18.00	64.00
Hours Worked/Wk	31.19	0.00	99.00	29.62	0.00	99.00
Wks Worked/Yr	35.71	0.00	52.00	33.05	0.00	52.00
In Labor Force	0.76	0.00	1.00	0.71	0.00	1.00

Data from pooled US Census 1970-2000 and ACS 2009-2011

B. Construction of Country Indicators

An important element of our analysis is the relationship between host country characteristics and female labor market decisions. While societal attitudes towards men are fairly ubiquitous across the world, there is a significant amount of heterogeneity in attitudes towards women that may affect women's decisions to participate in the labor market once they arrive in the United States. To incorporate these factors, we associate each person in our dataset with country characteristics based on her country of birth: gross domestic product per capita, average years of schooling of women in the country, and the average fertility rate. GDP per capita and fertility rate data come from the World Bank's Development Indicators. Years of schooling data comes from Barro and Lee's Educational data set. For non-immigrants, the country is the United States; thus, the US country characteristics serve as a baseline in our analysis. Of course, these characteristics are not constant over time. In matching country characteristics to individual observations, we must also determine which year of characteristics is most appropriate. We consider that year to be the year of exposure; that is, the year that a person would have been most influenced by characteristics of a country. For example, it is unlikely that a five year old child would respond later in life to the culture of his country in the year that he was five. To account for this, we define the year of exposure as the year that a person was 18. We then merge country characteristics onto individual observations by country of birth and year of exposure.

Ideally, to capture the host country culture characteristics towards women that may directly impact immigrant women's working choices, we would have data on the percentage of women in the labor force in the host country or on the percentage of women represented in the national government. However, this data (also from the World Bank's Development Indicators) is only available beginning in the 1990s. Thus, we provide the below covariance matrix to demonstrate that fertility and year of schooling are reasonable proxies for these measures. Fertility has a correlation with the percentage women in parliament of 0.37, and and years of schooling has a correlation with women in the workforce of about about 0.33 and with women in the national parliament of about 0.13. Interestingly, our two measures of female attitude characteristics are not well-correlated at all: women in the workforce and women in national government have a correlation of -0.03.

	Fertility Rate	GDP Per Capita	Years of Schooling	Women in Labor Force	Women in Parliament
Fertility	1.00	0.51	0.02	-0.09	0.37
GDP Per Capita	0.51	1.00	0.16	-0.02	0.26
Years Schooling	0.02	0.16	1.00	0.33	0.13
Women in Labor Force.	-0.09	-0.02	0.33	1.00	-0.03
Women in National Gov.	0.37	0.26	0.13	-0.03	1.00

IV. Empirical Design

To estimate the wage gap and its determinants as precisely as possible, we construct our analysis in three stages. First, we estimate the most basic equation imaginable to establish the raw gap between immigrants and natives over time. This step is very similar to the approach used in Borjas 2015; thus, we begin by replicating his results which include only men, and then perform the same analysis on women. Like Borjas, we use consider immigrants in terms of cohorts, as described earlier, to track how wages change for different cohorts over time. Second, we consider a few factors that could explain the wage gap: for example, the ability to speak English, skill level, and stage of settlement. Finally, we consider the specific selection problems associated with estimating the wage equation for women. We use a Heckman selection model to take into account the affect that host country and other personal characteristics may have on participation. To account for heteroskedasticity in our error terms, we estimate robust standard errors. To account for within group correlation, we cluster our errors at the cohort level. We now report the results of this analysis.

V. Results

A. Part 1

First, we estimate the raw wage gap between immigrant workers and native workers. We begin by estimating age-adjusted weekly earnings by cohort, census year, and gender as in equation 1, where i corresponds to an individual and j corresponds to a cohort dummy:

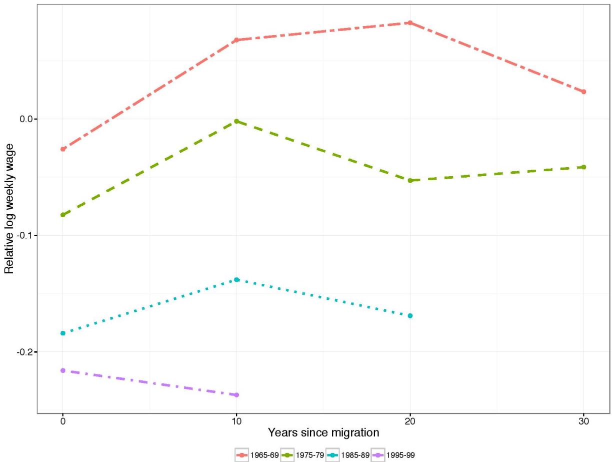
$$\ln(wage_i) = age + age^2 + age^3 + \Sigma_{j=1}^{12} cohort_{ij} \quad (1)$$

Estimates for men are a replication of a result from Borjas 2015, while the estimates for women are our own. This first estimate is obviously rough, but provides some indication of the wage gap. Results of the above equation are reported in tables 2 and 3 in the appendix; co-efficients on cohorts over time are reported through the plots below, which we will now describe in detail.[3]

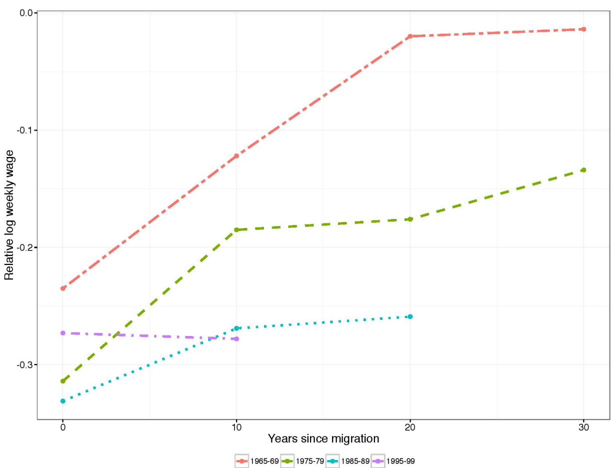
The x-axis of figure 1 is the year since the immigrant cohort arrived in the United States and the y-axis is the wage gap between that cohort's wages and native wages, controlling only for age, which is introduced as a third-order polynomial (as per Borjas 2015). It is important to note that because our samples are every 10 years, the initial wage gap for different cohorts do not represent their wages after they have been in the United States for the same number of years. For example, the first wages we observe of the 1960 and 1965 cohorts are their wages in 1970. At this time, one cohort has been in the U.S. for 5-10 years, while the other has been in the U.S. for only 1-5 years. We observe small differences in initial wages between cohorts in the 'initial' stages that can likely be attributed to differences in the amount of time different cohorts have been in the country. For both men and women, all cohorts earn wages below the native level when they first arrive in the United States. We also see that the initial wage gap is getting larger for new immigrant cohorts: the female immigrants who arrived in 2000 begin working at a much lower relative wage than previous cohorts. In fact, we see that every female cohort initially makes less than previous cohorts in comparison to natives. In particular, the 1965-1969 female cohort made only 2.6% less the natives in the first years since migration while the 1995-1999 cohort made 21.6% less than natives initially. For men there is a similar pattern, though the 1995-200 cohort did a bit better

[3]0's in tables simply indicate there are no observations for that cohort in that year (i.e. the survey was taken before such a cohort existed).

Fig. 1: Wage Assimilation, Men and Women



(a) Female



(b) Male

and reversed the downward trend. One potential explanation is that the quality of workers has changed – a hypothesis we will test later on.

Looking at initial wage gap gives us only limited insight into how the labor market values immigrants because of selection into immigration (a rich topic, but one not explored in this paper) and potential heterogeneity of skills between natives and immigrants (a topic we will explore later on). Thus, it is useful to consider the cohort-specific wage gap trend. If immigrants were lacking skills when they came to the United States, we would expect them to accumulate those skills – for example, English language fluency – over time. Even though we are not controlling for anything besides age in this stage of our analysis, tracking cohorts over time is a type of control in itself. Presumably, only the most able immigrant workers stay in the labor force over many years; as they do so, they acquire skills that the labor market values. Figure 1 shows that this is precisely what happened for the oldest male and female cohorts: we see that for both men and women, the 1965-1969, 1974-1979, and 1985-1989 cohorts have smaller wage gaps the longer they stay in the United States. For women the 1965-1969 cohort even ends up making more money than natives after living in the country 10 years. We see however, that later cohorts face larger wage gaps than earlier cohorts even over time. Later cohorts are closing the wage gap more slowly that earlier cohorts, or, in the case of the 1995 - 1999 cohort, making the wag gap larger over time. This trend is of particular interest to us, and is something we will try to explain in our following analysis.

Another element of particular interest to us is the notable differences between wage gap trends for women versus men. While Borjas 2015 discusses in detail elements of the male wage gap, the female plot is of particular relevance to our analysis. The wage trajectories for men and for women are quite different. While men's wages appear to (almost always) monotonically increase to the approach the native level, women's wages follow a far less logical path. For every cohort (except the most recent one), wages begin to increase, then fall back down again.

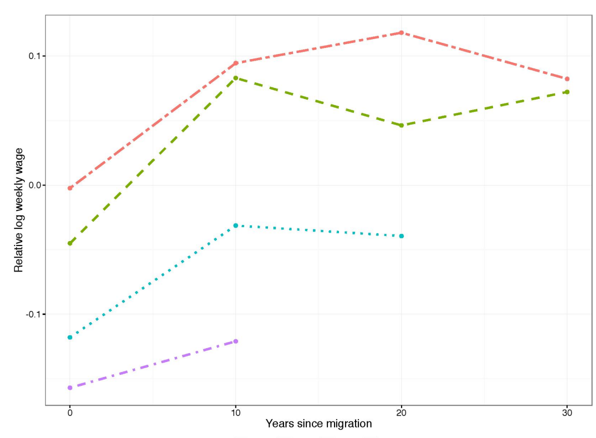
B. Part 2

To refine our analysis from section 1, we include controls for characteristics that could explain both the initial wage gap and the wage gap over time. Because our focus is on women, we no longer consider men as we did in part 1 (for a discussion of the wage gap for men, see Borjas 2015). First, we consider that skill differences may be driving the differences across cohorts. We construct 40 skill groups as defined earlier, sort individuals into groups, and estimate the following:

$$\begin{aligned} \ln(wage_i) = age + age^2 + age^3 + \\ \Sigma_{j=1}^{12} cohort_{ij} + \Sigma_{k=1}^{40} skill_{ik} \end{aligned} \tag{2}$$

Complete results are reported in table 4 in the appendix; coefficients for selected cohorts over time are reported below as before.

Fig. 2: Wage Assimilation Women Controlling for Skill

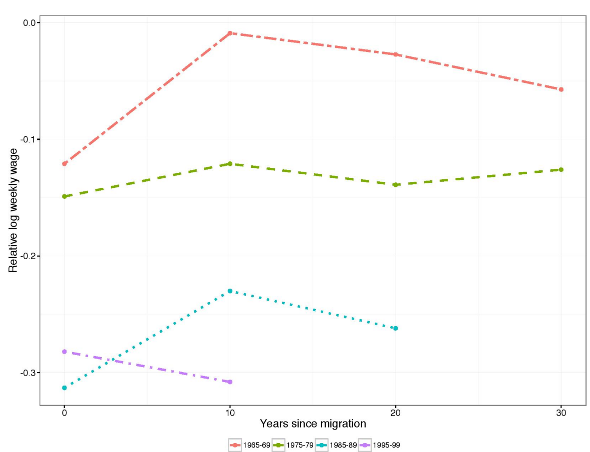


Our results suggest that controlling for skill decreases the wage gap a bit between natives and immigrant (the largest wage gap for woman in the baseline was -21.6% while now it is -15.7%). However, controlling for skill does not completely explain the wage gap either initially, or over time. It also does not explain the different wage gap patterns across cohorts because we still see that later cohorts are worse off than earlier cohorts in terms of initial wage. However, controlling for skill group does invert the slope of the 2000 cohort trend: in our initial analysis, we saw that the newest cohort actually did worse over time but now, we see an improvement. This result has implications we will discussion later on.

Another factor that could affect the wage gap over time is the state of immigrant settlement. For example, immigrants may be assimilating more slowly if they are settling in areas heavily populated with fellow immigrants. For example, Hispanic immigrants may settle in a state like Texas, with almost completely Hispanic areas, where they may have little incentive to learn English and assimilate to the rest of the United States. Heterogenity in state of settlement could explain why older cohorts assimilate differently than younger ones. To control for this effect, we estimate the following equation:

$$\ln(wage_i) = age_i + age_i^2 + age_i^3 + \Sigma_{j=1}^{12} cohort_{ij} + \Sigma_{k=1}^{49} state_{ik} \tag{3}$$

Fig. 3: Wage Assimilation Women Controlling for State

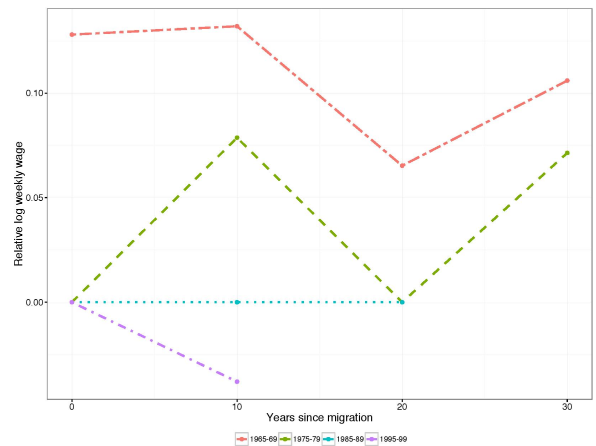


As before, we report all of the coefficients of this controlled regression in the appendix, but selected cohort coefficients over time are reported via figure 3. We see that controlling for controlling for the state settlement increased the wage gap above the baseline level. This suggests that the initial wage gap underestimates the differences between immigrants and natives. That is, the initial migrant coefficient may be hiding state effects. This is an unintuitive result, so in the future we would like to do further analysis with other more granular geographic measures. Then, we would be able to more closely estimate geographic effects.

Finally, we test whether the gap can be explained by immigrants' ability to speak English. In particular, it could be the case that the wage gap in the first years since immigration can be explained differing English language abilities. To test this effect, we estimate the following equation, where English is a dummy variable taking on a value of 1 if a person reported being able to speak English well:

$$\ln(wage_i) = age_i + age_i^2 + age_i^3 + \Sigma_{j=1}^{12} cohort_{ij} + english_i \tag{4}$$

Fig. 4: Wage Assimilation Women Controlling for English



As before, we report all of the coefficients of this controlled regression in the appendix, but the results can also be seen by looking at Figure 4. Please note that non-significant cohort coefficients are considered indicative of no wage gap (and indicated by a 0 in this figure). The idea is that there is no statistically significant difference between wages of these cohorts and of native workers, a finding that is particularly interesting considering how many observations are in our sample. In short, this result indicates that the statistical difference between immigrant and native wages begins to disappear once we control for English language ability.

Another important result from this stage of our analysis is the change in the benefit of English fluency over time, which is reported in the final row of table 3. In 1980, a person who spoke English well made 24.2% more than someone who did not. That advantage steadily increased over time, until 2010 when someone who spoke English well made more than 60% more than someone who did not. Of course, English language ability may be correlated with other skills valued by employers that we are not controlling for at this stage; nevertheless, the trajectory of the English language premium is significant and may be related to newer cohort's relative labor market disadvantage.

C. Part 3

Selection bias into the labor force complicates estimating the determinants of wage, particularly for women. In general, unobservable traits that induce people to work in the first place also impact wages. This issue is especially problematic for women, whose work decisions are complicated by social norms. These challenges are particularly pronounced for immigrant women, who arrive in the United States from countries with widely differing attitudes towards women working outside the home. Borjas limits his study to men precisely because these selection problems make the analysis of women a bit more difficult. We tackle those complications by using a Heckman Selection model.

First, we estimate the decision to work by means of a probit model, and second, we estimate the selection-bias corrected wage equation. A woman chooses to work if:

$$U(children_i + fertility_{ic} + schooling_{ic} + education_i + \eta_i) \geq 0 \tag{5}$$

where i is an individual and c corresponds to the individual's host country, as defined previously. In the first step, we include the number of children a woman has, a woman's education level, the fertility rate of home countries, and the education of women in the host countries. These last two variables are 'culture' variables and are used as indicators for attitudes towards women in an individual's country of origin. Cultural factors will impact a woman's decision to work, as discussed previously: for example, a woman from Saudi Arabia will have much different expectations for women working than a woman from Germany. Additionally, the more children a woman has, the harder it is for her to work outside the home. Lastly, we expect that a woman with higher education levels will be more likely to work outside the home. One important thing to note is that the country characteristics associated with natives are those of the United States; thus, we control for changes in attitudes towards women over time in the US (as large changes have occurred over the last 50+ years). Our probit specification takes the following form:

$$laborforce_i = children_i + fertility_{ic} + schooling_{ic} + education_i + \eta_i \tag{6}$$

From equation 6, we estimate the selection bias term, which is the inverse mills ratio evaluated at the probit model regressors and co-efficients, divided by the standard deviation of the error term η_i (as per Heckman 1979). Results are reported in table 9 for a few different specifications. We then add include this term as a regressor in the wage equation (as specified below) to account for selection bias. Similar to our previous analyses, we include a age introduced as a third-order polynomial, an immigrant indicator variable, and controls for education, race, English language ability, and GDP of home country. Before we can assume, however, that our adjusted wage equation is in fact free of selection bias, we must consider the assumptions of the Heckman selection model. The first major assumption is that at least one variable in the work decision model is exogenous to the wage equation. In the past, number of children has been used as such a variable. We also believe that the culture variables are exogenous. Even when we include country indicator variables as regressors in the wage equation, the country coefficients are insignificant, suggesting that GDP per capita is soaking up relevant country characteristics that affect wages. The second assumption is that errors are normally distributed; unfortunately this assumption is difficult to test. In this stage, results of which are reported in table 9, fertility of the host country had nearly 0 affect while number of children, education of women in a woman's home country, and a woman's own education had large and significant effects on her decision to enter the labor force. We then used the coefficients of these probit models to estimate the wage equation, pooling all of our surveys and adding a time fixed effect:

$$\ln(wage_i) = age_i + age_i^2 + age_i^3 + imm_i + education_i + race_i + english_i + bias_i + year_i + GDP_{ic} + \epsilon_i \tag{7}$$

where $bias_i$ is the inverse mills ratio as described previously. Results are reported in table 10. The first column is the base wage equation without accounting for selection bias; following columns correspond to probit specifications as reported in table 9. The first column provides results of the baseline wage equation without accounting for selection bias; the co-efficient on immigrant is -0.0721, indicating that even with controls, immigrant women make 7.21% less than native women. When only number of children is included in the probit stage, we find a modest but significant change in the wage disadvantage of being an immigrant: now, immigrant women make 5.573% less than native women. This co-efficient continues to fall as we include controls at the probit stage. When we include number of children and fertility of the host country, we find that native women make 1.16% less than native women. The following models all suggest that once other decision factors are included, immigrant women actually make more than their native counterparts. For example, when we include number of children, host country education, and a womans own education at the probit stage, we find that immigrant women make 2.88% more than native workers.

The co-efficient on the selection bias correction term (the inverse mills ratio) also provides some insight into sign of the selection bias. In every case, the mills ratio is negative, suggesting that the error term of the decision to work model and of the wage equation model are negatively correlated. Thus, unobserved characteristics that induce people to work actually lower their wages. Unfortunately, in this specification, the bias term is not immigrant specific, so we cannot draw any conclusions on selection bias for only the immigrant group.

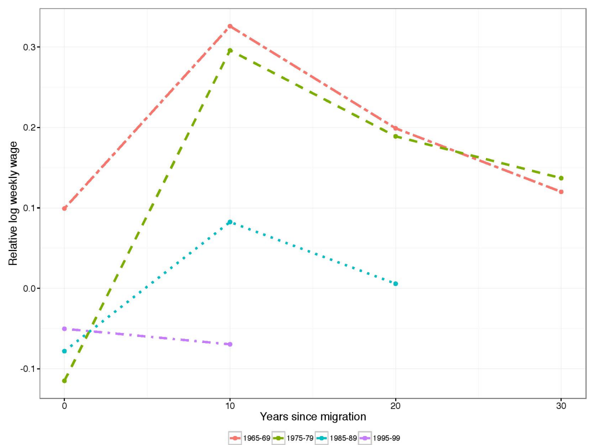
After estimating Heckman selection models for immigrants in general, we use our final probit specification to estimate the survey-specific wage equations with cohort dummies as in our previous analysis. We estimate the following equation for each survey year:

$$\ln(wage_i) = age_i + age_i^2 + age_i^3 + \Sigma_{j=1}^{12} cohort_{ij} + education_i + race_i + english_i + bias_i + GDP_{ic} + \epsilon_i \tag{8}$$

Results are reported in table 11, and the trajectory of the cohort-specific wage gap is depicted in the plot below.

Our results from this specification show that the increase in the initial wage level many of the cohorts is now either above zero, or increases rapidly to a positive value after that

Fig. 5: Wage Assimilation Women Controlling for Selection Bias



initial year. The effect decreases after a few years but wages remain above the native level for older cohorts.

VI. Discussion

We began our analysis in part 1 with an overview of the wage gap by studying immigrant cohorts over time. We hypothesized that, as immigrants spend more time in the United States, wages would converge to those of natives. There are a few different reasons why we expected this to be the case. First, while immigrants accumulate the desired skills as they continue to live in the United States, their wages would approach the level of native workers. Second, only the highest performing immigrants would stay in the work force over time. The immigrants who are making the least and and are not seeing their wages improve may drop out of the workforce. Therefore, when we look at migrant wages ten years after they migrate we may be observing the wages of the best off immigrants, and so we would expect a convergence to native wages. Nevertheless, that is not the trend we observed for women. Thus, we extended our analysis to try to explain why.

In parts 2 and 3 of our analysis, we proposed a few explanations for the trends we observed in part 1. Table 2 below shows the initial and final cohort co-efficients for the four specifications we considered. Yellow highlight includes the specification with the most positive co-efficient for each cohort. First, we controlled for skill groups. We hypothesized that different education and experience levels among immigrant cohorts could explain different time trends, and that different education levels in immigrants as opposed to natives could explain the initial wage gap. Controlling for skill did have an significant effect on the slope of the newest cohort's wage trend: in part 1, we found that this cohort actually made less after they'd been in the country for 10 years. Controlling for skill, we find that they make more in the following period, which is the trend we would expect as immigrants gain skills over time. However, the wage gap for newer cohorts controlling for skill is still very large: skill does not explain the large gaps between recent and older cohorts or the initial gap between immigrants and native. This result further suggests that the quality of immigrant cohorts has not fallen significantly over time; otherwise, controlling for skill would put all cohorts nearly on par with each other. Additionally, skill does not have a large impact on explaining trend fluctuations; for example, we still see a lack of monotonicity with older cohorts.

We then considered the effect of state of settlement,

TABLE II: Wage Gap By Cohort, Initial and Final, All Specifications

	Initial Wage Gap					
Cohort	**Baseline**	**Skills**	**English**	**State**	**All**	**Heckman**
1960	3.52%	7.32%	7.62%	-4.58%	2.28%	7.1%
1965	-2.60%	-0.24%	12.80%	-12.10%	6.30%	9.93%
1970	2.62%	7.25%	10.20%	-4.01%	3.43%	6.87%
1975	-8.24%	-4.51%	0.70%	-14.90%	-8.17%	-11.5%
1980	-9.28%	0.50%	1.24%	-21.80%	-8.46%	14.9%
1985	-18.40%	-11.80%	-5.73%	-31.30%	-20%	-7.81%
1990	-16.50%	-8.32%	-2.32%	-24.50%	-11.60%	3.81%
1995	-21.60%	-15.70%	-4.74%	-28.20%	-16.70%	-5.03%
2000	-30.20%	-18.50%	-6.91%	-37.00%	-18.30%	-10.9%
2005	-31.60%	-24.30%	-6.83%	-38.40%	-23.90%	-20%

	Final Wage Gap (as of 2010)					
Cohort	**Baseline**	**Skills**	**English**	**State**	**All**	**Heckman**
1960	9.77%	-4.00%	10.50%	-7.35%	-16.80%	39.2%
1965	8.94%	9.69%	10.60%	0.82%	2.51%	12%
1970	10.07%	11.10%	7.71%	-0.74%	3.62%	14.7%
1975	4.14%	7.21%	7.14%	-12.60%	10.10%	13.7%
1980	-9.30%	2.00%	4.70%	-18.20%	-3.46%	7.57%
1985	-16.90%	-3.95%	0.12%	-26.20%	-8.26%	5.76%
1990	-19.20%	-6.71%	-3.78%	-27.50%	-9.63%	-2.46%
1995	-23.70%	-12.10%	-6.91%	-30.80%	-13.50%	-6.96%

Newest cohorts omitted from final gap as initial = final.

hypothesizing that perhaps immigrants have been settling in different places over time. Different states are likely to receive immigrants differently; thus, differences in cohorts could be explained by heterogeneity of state of settlement among cohorts. However, controlling for state increased the wage gap substantially for almost every cohort. This result suggests that the real wage gap between natives and immigrant may be larger than our baseline predicts, however this unintuitive result needs to be explored further with other geographic measures.

Finally, we controlled for the ability to speak English. This had the most significant effect on both the initial and final wage gap for nearly every cohort. In some cases, the gap between immigrants and natives was no longer significant. Table 2 highlights the significant effect of English on the wage gap. The fact that gap was not closed over time unless we controlled for English language ability suggests that English is perhaps not a skill that immigrants naturally acquire after time in the labor force. Otherwise, our initial analysis would have revealed the relationship that we found in this stage. This is one area in particular where better access to language learning programs could have a large impact on immigrant assimilation.

After considering these controls, we implemented a Heckman selection model to account for female selection bias into the work force, a factor that may affect determinants of the wage equation. We began by running a probit model with a few different specifications, including different explanatory variables. We found that selection bias has a large affect on the wage disadvantage of immigrants; in particular, we found that immigrants actually earn more than native workers after controlling for characteristics and selection bias. We then extended this basic analysis to the cohort setup of our earlier models, using the last probit specification as our selection stage. This model seems to explain much of the wage gap; in fact, many of the selection-adjusted cohort coefficents are positive, suggesting that controlling for selection, immigrants are actually making more than natives, even in the earliest years.

VII. Conclusion

At the start of our analysis, we defined the wage gap to be the difference in wages between immigrants and natives. After controlling for a range of personal characteristics and selection bias, we uncovered another gap of sorts: after controlling for selection bias, we found that immigrant women actually made *more* than their native counter parts after being in the country for a number of years. At no point in our analysis were we able to 'close' the wage gap completely. Specifically, we were not able to completely explain the wage gap trend for newer immigrant cohorts. This may have to do with the fact that we do not have data on wages 10-20 years after arrival, due to how recent these cohorts have arrived. Nevertheless, the initial wage gap is striking, and we look forward to looking at these cohorts later on once more data becomes available. Additionally, we believe there is further work to be done in explaining the positive wage gap that we have uncovered.

English language ability had a large impact on the significance of the difference between immigrants and native workers. Furthermore, even when we control for selection bias and our control variables, including English, we find the Heckman cohort coefficients tend to be smaller on average than the baseline. These results, which are similar to Borjas' finding for male immigrants, suggests that there is a substantial labor market premium to learning English. But since we did not observe wage convergence without controlling for language ability, even though we would expect that to be a naturally accumulated trait, English language programs may be crucial for immigrants' success and assimilation.

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Appendix

TABLE III: Establishing the Wage Gap: Men

	Dependent Variable: Log Weekly Wage				
	1970	1980	1990	2000	2010
Age	0.320***	0.337***	0.259***	0.207***	0.346***
	(0.00295)	(0.00389)	(0.00587)	(0.0149)	(0.0123)
Age^2	-0.00727***	-0.00729***	-0.00508***	-0.00409***	-0.00719***
	(0.0000735)	(0.0000926)	(0.000159)	(0.000397)	(0.000329)
Age^3	0.0000538***	0.0000520***	0.0000333***	0.0000274***	0.0000499***
	(0.000000575)	(0.000000679)	(0.00000134)	(0.00000329)	(0.00000277)
<1950	0.130***	0.143***	0	0	0
	(0.00134)	(0.00464)			
1950-1960	0.0364***	0.0324***	0.0996***	0.147***	0
	(0.000213)	(0.00245)	(0.00285)	(0.00957)	
1960-1964	-0.0597***	-0.0408***	0.0458***	0.0738***	0.567***
	(0.000534)	(0.000766)	(0.00365)	(0.00427)	(0.0187)
1965-1969	-0.243***	-0.122***	-0.0204***	-0.0135*	0.194***
	(0.000637)	(0.000357)	(0.00321)	(0.00499)	(0.00996)
1970-1974	0	-0.223***	-0.124***	-0.128***	-0.0603***
		(0.000869)	(0.00196)	(0.00616)	(0.00414)
1975-1979	0	-0.314***	-0.185***	-0.176***	-0.138***
		(0.000910)	(0.000320)	(0.00467)	(0.00416)
1980-1984	0	0	-0.285***	-0.236***	-0.206***
			(0.00104)	(0.00225)	(0.00528)
1985-1989	0	0	-0.331***	-0.269***	-0.263***
			(0.00141)	(0.00158)	(0.00491)
1990-1994	0	0	0	-0.269***	-0.271***
				(0.00347)	(0.00297)
1995-1999	0	0	0	-0.273***	-0.280***
				(0.00404)	(0.000814)
2000-2004	0	0	0	0	-0.352***
					(0.00278)
2005-2011	0	0	0	0	-0.325***
					(0.00399)
Observations	969469	2002074	2373285	2708438	1653425
R^2	0.017	0.041	0.059	0.043	0.052

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE IV: Establishing the Wage Gap: Women

	Dependent Variable: Log Weekly Wage				
	1970	1980	1990	2000	2010
Age	0.0385***	0.0961***	0.117***	0.0278	0.220***
	(0.00239)	(0.00724)	(0.00730)	(0.0178)	(0.0184)
Age^2	-0.00152***	-0.00264***	-0.00249***	-0.000300	-0.00482***
	(0.0000623)	(0.000166)	(0.000188)	(0.000454)	(0.000475)
Age^3	0.0000167***	0.0000231***	0.0000174***	0.000000517	0.0000351***
	(0.000000517)	(0.00000121)	(0.00000153)	(0.00000366)	(0.00000385)
<1950	0.0819***	0.100***	0	0	0
	(0.00111)	(0.00188)			
1950-1960	0.0478***	0.0250***	0.0128***	0.173***	0
	(0.000270)	(0.00144)	(0.00154)	(0.00836)	
1960-1964	0.0352***	0.0358***	0.0610***	0.0429***	0.0977***
	(0.000654)	(0.000401)	(0.00215)	(0.00316)	(0.0178)
1965-1969	-0.0260***	0.0677***	0.0825***	0.0233***	0.0894***
	(0.000841)	(0.000858)	(0.00181)	(0.00397)	(0.00920)
1970-1974	0	0.0262***	0.0420***	-0.0256***	0.0107**
		(0.000627)	(0.000932)	(0.00492)	(0.00339)
1975-1979	0	-0.0824***	-0.00205***	-0.0529***	-0.0414***
		(0.000334)	(0.000187)	(0.00365)	(0.00435)
1980-1984	0	0	-0.0928***	-0.100***	-0.0930***
			(0.000483)	(0.00158)	(0.00557)
1985-1989	0	0	-0.184***	-0.138***	-0.169***
			(0.000547)	(0.00122)	(0.00448)
1990-1994	0	0	0	-0.165***	-0.192***
				(0.00198)	(0.00220)
1995-1999	0	0	0	-0.216***	-0.237***
				(0.00233)	(0.00108)
2000-2004	0	0	0	0	-0.302***
					(0.00243)
2005-2011	0	0	0	0	-0.316***
					(0.00318)
Observations	517816	1473205	2005078	2401329	1519415
R^2	0.006	0.002	0.004	0.008	0.017

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE V: Explaining the Wage Gap: Women, Controlling for Skill Groups

	Dependent Variable: Log Weekly Wage				
	1970	1980	1990	2000	2010
Age	-0.0810***	-0.0149*	0.0141***	0.0148*	0.0468**
	(0.00559)	(0.00593)	(0.00212)	(0.00489)	(0.0114)
Age^2	0.00198***	0.000471*	0.0000873	0.000220	-0.000249
	(0.000141)	(0.000150)	(0.0000654)	(0.000115)	(0.000324)
Age^3	-0.0000149***	-0.00000383*	-0.00000353***	-0.00000532***	-0.00000326
	(0.00000108)	(0.00000116)	(0.000000585)	(0.000000906)	(0.00000270)
<1950	0.0653***	-0.156***	0	0	0
	(0.00103)	(0.00457)			
1950-1960	0.0780***	0.0367***	0.0600***	0.132***	0
	(0.000780)	(0.00134)	(0.00247)	(0.00332)	
1960-1964	0.0723***	0.0502***	0.0891***	0.0965***	-0.0400*
	(0.00150)	(0.000439)	(0.00233)	(0.00392)	(0.0130)
1965-1969	-0.00241	0.0944***	0.118***	0.0822***	0.0969***
	(0.00131)	(0.00112)	(0.00186)	(0.00503)	(0.00444)
1970-1974	0	0.0725***	0.111***	0.0564***	0.111***
		(0.00207)	(0.000602)	(0.00497)	(0.00275)
1975-1979	0	-0.0451***	0.0829***	0.0462***	0.0721***
		(0.00181)	(0.00156)	(0.00286)	(0.00456)
1980-1984	0	0	0.00501	0.00602***	0.0200**
			(0.00285)	(0.000706)	(0.00450)
1985-1989	0	0	-0.118***	-0.0314***	-0.0395***
			(0.00264)	(0.00283)	(0.00171)
1990-1994	0	0	0	-0.0832***	-0.0671***
				(0.00496)	(0.00207)
1995-1999	0	0	0	-0.157***	-0.121***
				(0.00553)	(0.00543)
2000-2004	0	0	0	0	-0.185***
					(0.00837)
2005-2011	0	0	0	0	-0.243***
					(0.00961)
Observations	517816	1473205	2005078	2401329	1519415
R^2	0.114	0.069	0.120	0.133	0.163

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE VI: Explaining the Wage Gap: Women, Controlling for English Language Fluency

	Dependent Variable: Log Weekly Wage			
	1980	1990	2000	2010
Age	0.0928***	0.114***	0.0232	0.210***
	(0.00396)	(0.00412)	(0.0131)	(0.00866)
Age^2	-0.00255***	-0.00242***	-0.000186	-0.00458***
	(0.0000837)	(0.000109)	(0.000335)	(0.000226)
Age^3	0.0000225***	0.0000168***	-0.000000384	0.0000332***
	(0.000000560)	(0.000000916)	(0.00000272)	(0.00000186)
<1950	0.101***	0	0	0
	(0.00313)			
1950-1960	0.0459***	0.0288***	0.179***	0
	(0.00292)	(0.00364)	(0.00647)	
1960-1964	0.0762***	0.0912***	0.0639***	0.105***
	(0.00432)	(0.00779)	(0.00389)	(0.00891)
1965-1969	0.128***	0.132***	0.0653***	0.106***
	(0.00670)	(0.0122)	(0.00916)	(0.00446)
1970-1974	0.102***	0.111***	0.0412*	0.0771***
	(0.00917)	(0.0163)	(0.0139)	(0.00480)
1975-1979	0.00699	0.0787**	0.0352	0.0714***
	(0.0113)	(0.0185)	(0.0162)	(0.00909)
1980-1984	0	0.0124	0.00667	0.0470**
		(0.0239)	(0.0174)	(0.0112)
1985-1989	0	-0.0573	-0.0111	0.00121
		(0.0288)	(0.0185)	(0.0122)
1990-1994	0	0	-0.0232	-0.00261
			(0.0201)	(0.0120)
1995-1999	0	0	-0.0474	-0.0380**
			(0.0239)	(0.0110)
2000-2004	0	0	0	-0.0691***
				(0.0119)
2005-2011	0	0	0	-0.0683***
				(0.0123)
Speaks English Well	0.243***	0.332**	0.411***	0.613***
	(0.0306)	(0.0760)	(0.0625)	(0.0348)
Observations	1473205	2005078	2401329	1519415
R^2	0.003	0.006	0.013	0.030

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE VII: Explaining the Wage Gap: Women, Controlling for State of Settlement

	Dependent Variable: Log Weekly Wage				
	1970	1980	1990	2000	2010
Age	0.0527***	0.0911***	0.116***	0.0204	0.219***
	(0.00199)	(0.00789)	(0.00776)	(0.0182)	(0.0194)
Age^2	-0.00186***	-0.00251***	-0.00246***	-0.000108	-0.00478***
	(0.0000520)	(0.000182)	(0.000199)	(0.000467)	(0.000503)
Age^3	0.0000192***	0.0000220***	0.0000169***	-0.00000109	0.0000346***
	(0.000000450)	(0.00000133)	(0.00000161)	(0.00000378)	(0.00000408)
<1950	0.0102**	0.0659***	0	0	0
	(0.00141)	(0.00122)			
1950-1960	-0.0242***	-0.0226***	-0.0648***	0.119***	0
	(0.000613)	(0.00243)	(0.00292)	(0.00635)	
1960-1964	-0.0485***	-0.0165***	-0.0359***	-0.0178*	-0.0735**
	(0.000440)	(0.00140)	(0.00503)	(0.00556)	(0.0204)
1965-1969	-0.121***	0.00905***	-0.0273***	-0.0573***	0.00822
	(0.00107)	(0.000607)	(0.00428)	(0.00963)	(0.00595)
1970-1974	0	-0.0401***	-0.0765***	-0.111***	-0.0736***
		(0.00117)	(0.00458)	(0.0123)	(0.00807)
1975-1979	0	-0.149***	-0.121***	-0.139***	-0.126***
		(0.00194)	(0.00562)	(0.0131)	(0.0141)
1980-1984	0	0	-0.218***	-0.187***	-0.182***
			(0.00460)	(0.0102)	(0.0152)
1985-1989	0	0	-0.313***	-0.230***	-0.262***
			(0.00350)	(0.00712)	(0.0134)
1990-1994	0	0	0	-0.245***	-0.275***
				(0.00462)	(0.00966)
1995-1999	0	0	0	-0.282***	-0.308***
				(0.00259)	(0.00531)
2000-2004	0	0	0	0	-0.370***
					(0.00319)
2005-2011	0	0	0	0	-0.384***
					(0.00218)
Observations	344931	1473205	2005078	2401329	1519415
R^2	0.032	0.014	0.036	0.028	0.039

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE VIII: Explaining the Wage Gap: Women, All Controls

	Dependent Variable: Log Weekly Wage			
	1980	1990	2000	2010
Age	-0.0161*	0.0184***	0.0110	0.0502***
	(0.00626)	(0.00205)	(0.00503)	(0.0106)
Age^2	0.000494*	-0.0000149	0.000314*	-0.000313
	(0.000159)	(0.0000635)	(0.000119)	(0.000307)
Age^3	-0.00000394*	-0.00000275**	-0.00000607***	-0.00000287
	(0.00000124)	(0.000000563)	(0.000000936)	(0.00000259)
<1950	-0.182***	0	0	0
	(0.00299)			
1950-1960	0.00798***	0.000386	0.0924***	0
	(0.00124)	(0.00271)	(0.00468)	
1960-1964	0.0228***	0.0169**	0.0531***	-0.168***
	(0.00109)	(0.00381)	(0.00624)	(0.0137)
1965-1969	0.0630***	0.0347***	0.0220**	0.0251***
	(0.00147)	(0.00321)	(0.00623)	(0.00453)
1970-1974	0.0343***	0.0202***	-0.00565	0.0362***
	(0.00172)	(0.00369)	(0.00633)	(0.00234)
1975-1979	-0.0817***	-0.00763	-0.0118	0.0101*
	(0.00238)	(0.00409)	(0.00577)	(0.00346)
1980-1984	0	-0.0846***	-0.0478***	-0.0346***
		(0.00344)	(0.00461)	(0.00335)
1985-1989	0	-0.200***	-0.0786***	-0.0826***
		(0.00388)	(0.00292)	(0.00175)
1990-1994	0	0	-0.116***	-0.0963***
			(0.00244)	(0.00327)
1995-1999	0	0	-0.167***	-0.135***
			(0.00195)	(0.00630)
2000-2004	0	0	0	-0.183***
				(0.00820)
2005-2011	0	0	0	-0.239***
				(0.00927)
Speaks English Well	0.0842***	0.0962**	0.125***	0.214***
	(0.00606)	(0.0206)	(0.0238)	(0.0226)
Observations	1473205	2005078	2401329	1519415
R^2	0.078	0.142	0.146	0.177

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE IX: Probit Models of Labor Force Choice; First Step Heckman

	Dependent Variable: Participation in Labor Force				
Independent Vars.	(1)	(2)	(3)	(4)	(5)
Number of Children	-0.108***	-0.124***	-0.128***	-0.124***	-0.106***
	(0.000253)	(0.000280)	(0.000316)	(0.000280)	(0.000285)
Female Years of Schooling, Home Country		0.0936***		0.0936***	0.0753***
		(0.000274)		(0.000274)	(0.000280)
Fertility Rate, Home Country			0.0000111***		
			(4.39e-08)		
Education					0.242***
					(0.000346)
Observations	15671499	13455455	11657698	13455455	13455455

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE X: Heckman Wage Equations, Accounting for Selection

		Dependent Variable: Log Weekly Wage				
Independent Vars.	Base Wage Equation	(1)	(2)	(3)	(4)	(5)
Immigrant	-0.0721***	-0.0573***	-0.0116*	0.122***	0.0526***	0.0288***
	(-15.66)	(-12.49)	(-2.50)	(25.08)	(11.17)	(6.13)
Age	0.249***	0.289***	0.287***	0.280***	0.286***	0.285***
	(196.40)	(225.01)	(223.11)	(218.38)	(223.02)	(220.88)
Age^2	-0.00506***	-0.00585***	-0.00578***	-0.00567***	-0.00578***	-0.00579***
	(-150.74)	(-173.27)	(-171.19)	(-168.28)	(-171.48)	(-170.87)
Age^3	0.0000336***	0.0000381***	0.0000376***	0.0000373***	0.0000378***	0.0000381***
	(118.94)	(134.95)	(133.01)	(132.12)	(133.76)	(134.40)
GDP Per Capita	-0.00000172***	-0.00000155***	-0.00000633***	-0.00000241***	-0.00000473***	-0.00000430***
	(-9.71)	(-8.82)	(-35.33)	(-13.50)	(-26.52)	(-24.16)
Black	0.00845***	0.0188***	0.0180***	0.0166***	0.0181***	0.0162***
	(5.92)	(13.15)	(12.61)	(11.63)	(12.65)	(11.35)
Asian	0.0607***	0.0580***	0.0526***	0.0757***	0.0613***	0.0517***
	(20.62)	(19.74)	(17.85)	(25.57)	(20.75)	(17.49)
Other	0.00677**	0.0173***	0.0161***	0.0215***	0.0194***	0.0195***
	(2.58)	(6.57)	(6.12)	(8.17)	(7.36)	(7.41)
English	0.153***	0.138***	0.146***	0.132***	0.140***	0.109***
	(39.23)	(35.26)	(37.35)	(33.47)	(35.54)	(27.72)
Education	0.264***	0.254***	0.255***	0.256***	0.255***	0.131***
	(595.66)	(564.94)	(566.75)	(571.38)	(566.90)	(121.50)
1990	0.207***	0.195***	0.190***	0.190***	0.189***	0.185***
	(142.23)	(134.78)	(130.90)	(129.88)	(129.74)	(126.72)
2000	-0.0315***	-0.0462***	-0.0562***	-0.0588***	-0.0587***	-0.0633***
	(-13.29)	(-19.53)	(-23.63)	(-24.52)	(-24.59)	(-26.44)
2010	-0.434***	-0.449***	-0.463***	-0.468***	-0.467***	-0.472***
	(-127.38)	(-131.87)	(-135.39)	(-135.78)	(-135.98)	(-137.42)
Bias Term		-1.542***	-1.248***	-1.103***	-1.220***	-1.174***
		(-163.08)	(-164.62)	(-151.64)	(-165.69)	(-141.02)
Observations	8396309	8396309	8390003	8394583	8388293	8388293

t statistics in parentheses. Specification Numbers correspond to probit specifications above.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE XI: Heckman Wage Equations, Accounting for Selection: By Cohort

	Dependent Variable: Log Weekly Wage			
	1980	1990	2000	2010
Age	0.212***	0.0244**	0.0107**	0.0418***
	(5.64)	(3.13)	(3.13)	(10.43)
Age^2	-0.00565***	0.000145	0.000231**	-0.000186*
	(-4.74)	(0.68)	(2.75)	(-2.00)
Age^3	0.0000521***	-0.00000624**	-0.00000449***	-0.00000334***
	(4.18)	(-3.25)	(-6.72)	(-4.73)
1960-1964	0.0710***	0.265***	0.155***	0.392*
	(3.83)	(15.27)	(7.82)	(2.09)
1965-1969	0.0993***	0.326***	0.199***	0.120***
	(7.45)	(27.02)	(15.91)	(4.04)
1970-1974	0.0687***	0.351***	0.199***	0.147***
	(5.60)	(34.60)	(20.23)	(8.40)
1975-1979	-0.115***	0.296***	0.189***	0.137***
	(-8.72)	(30.90)	(21.14)	(10.44)
1980-1984		0.149***	0.135***	0.0757***
		(15.78)	(15.91)	(6.52)
1985-1989		-0.0781***	0.0825***	0.00576
		(-7.77)	(10.31)	(0.52)
1990-1994			0.0381***	-0.0246*
			(4.77)	(-2.36)
1995-1999			-0.0503***	-0.0696***
			(-6.00)	(-6.63)
2000-2004				-0.109***
				(-10.11)
2005-2011				-0.200***
				(-16.26)
Bias Term	-1.120***	-1.707***	-0.643***	-0.499***
	(-145.44)	(-164.63)	(-51.95)	(-20.56)
Observations	868401	1800003	2489203	1665505

t statistics in parentheses. Controls included for race, host country GDP, and English language ability.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$