RE-EXAMINING IMPERFECT SUBSTITUTION BETWEEN IMMIGRANTS AND NATIVE-BORN WORKERS

By

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RE-EXAMINING IMPERFECT SUBSTITUTION BETWEEN

IMMIGRANTS AND NATIVE-BORN WORKERS

Abstract

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This paper re-examines the area approach in estimating the elasticity of substitution between native-

born and foreign-born workers. The area approach compares native-born workers' wages in

metropolitan areas with small inflows of immigrant workers to metropolitan areas with large

immigrant inflows. Using a nested CES production function, it finds that immigrants and native-born

workers are imperfect substitutes. The study, using the estimated parameters for the elasticity of

substitution between - immigrants and workers, workers with different experience groups, and

workers across different education levels, estimates that immigrant labor shocks have negligible and

even positive increases on native-born workers' weekly wages.

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Dedication

For my grandmother and mother.

CHAPTER ONE

INTRODUCTION

Immigration is a contested and often divisive topic, especially during the current political environment, which has seen a resurgence of nativist attitudes in the world's political regimes, with the United States and the United Kingdom being two prominent examples. The United States has over the past few years enacted a 'zero tolerance' position towards immigrants, which includes the infamous family separation policy in 2018 to deter immigration.

While the 2016-2020 administration appeared to have a poor view of immigration, in general, this is contrary to the view that most U.S. citizens have. According to a Pew Poll in 2019, 59% said that immigration is a positive to the U.S. economy, while 34% viewed immigration as a burden (*Around the World, More Say Immigrants Are a Strength Than a Burden* 2019). Still, in a later poll that same year, another Pew poll showed the dissonance amongst American attitudes towards immigration as most Americans also voiced support for more robust border security.

It is no surprise, then, that the divisive viewpoints are reflected in economic theory, where immigration is a contested topic. There are two main approaches in assessing immigration effects on native workers: a so-called 'area' approach and a 'national' approach. An essential difference between the two methodologies is that the area approach compares native-born workers' wages in metropolitan areas with small inflows of immigrant workers to metropolitan areas with large immigrant inflows. However, the national approach argues that it is impossible to account for both the movement of capital and workers between metropolitan areas.

However, there can be no debate that immigration and immigrant workers are a vital part of the American economy. With more than 40 million people born in a foreign country, the United States has more immigrants than any other nation as more than 13% of immigrants make up the population (*Key findings about U.S. immigrants* 2019). Nowhere is this perhaps best illustrated than in the agricultural industry, which has relied upon migrant workers to make up for labor shortages for decades. The bracero program that lasted from 1942 to 1964 saw well over 4 million labor contracts that permitted migrant workers from Mexico to work in the U.S. on a short-term basis (UCLA 2014). ¹More recently, the H-2A visa program that also allows foreign workers temporary visa status to work for agricultural employers has seen increased use in the U.S. (Crosscut 2019). Luckstead and Devadoss (2019) report that the program has seen an 18 percent growth each year since 2014, indicating that more than twenty percent of the agricultural labor force could be H-2A guest workers if the trend continues. Finding the impact that immigrants have on the United States' labor force is crucial to evaluating the benefits that programs such as the H-2A visa program yields to the U.S. economy.

¹ For a more in-depth discussion on the bracero program see Clemens, Lewis, and Postel (2017)

CHAPTER TWO

LITERATURE REVIEW

Borjas (2003) is a seminal paper on the national approach to immigration. Borjas (2003) finds that immigrant workers consistently depress the wages of native-born U.S. workers and that the geographic clustering of immigrant workers utilized by the area approach cannot account for the movement of both capital and U.S.-born workers in response to immigrant supply shocks to the labor force. Analogous with the model presented by Katz and Murphy (1992) that analyzes changes in the wage structure in the United States by aggregating workers into two groups: 'college equivalent workers' and 'high school equivalent workers', Borjas utilizes a production function with different levels of experience incorporated in a CES technology. Workers with comparable educational attainment but differing experience levels are aggregated to form an education group's labor supply, which is then aggregated to construct a national workforce (Borjas, 2003).

Borjas divides the labor force into four education groups and eight work-experience groups resulting in thirty-two skill-education groups. Using a production function framework, Borjas estimates the substitution levels that employers can substitute workers of different skills and educational attainment for one another. However, Borjas assumes that workers who are similarly educated but differ by experience are imperfect substitutes instead of immigrants and 'native' workers being imperfect substitutes as in Card (1990). His research finds that the immigrant 'influx' into the United States between 1980 and 2000 reduced the average native worker's wages by 3.2%, with immigration having a more significant adverse effect on lower education groups. The negative effect on native workers, particularly workers with low education levels, is consistent with his previous research (Borjas, Freeman, and Katz 1996, 1997; Borjas and Tienda 1987).

The area approach seeks to compare labor markets where immigrants make up a significant

Angeles or New York City vs Boise). However, as Raphael and Ronconi (2007) argue, the area approach faces several methodological issues in terms of selection bias. For instance, immigration rates are affected by pre-existing employment prospects in each city, the sensitivity of U.S. native workers to immigrants; and that regional economies may adjust to labor supply shocks diffusing immigration effects. Card (2009) finds that the evidence suggests that immigrants positively affect wages after controlling for spillover effects, city size effects, and immigrants being attracted to cities with strong labor markets. Similarly, in earlier research, Card (2001) finds that immigration has relatively negligible adverse effects on relative employment rates, with cities that have higher immigrant populations, such as Los Angeles, seeing only a 3% reduction in the relative employment rates for low skilled workers compared to cities with fewer immigrants, native-born workers only see only 1% decrease at most.

Still, there are justified criticisms regarding the shift-share instrument used by Card and others using an area approach. As used by Card and others, the shift-share instrument predicts immigration inflows as a weighted average of national inflow rates of immigrants from a country of origin and uses as weights the previous distribution of immigrant population shares. ²The use of shift-share instruments in studies such as in Card (2001), as Jaeger, Ruist, and Stuhler (2018) argue, is flawed. Without accounting for the serial correlation of immigrant populations, shift-share instruments conflate both the short and long run labor shocks caused by increases in immigrant populations because immigration rates are not exogenous. Accounting for this serial correlation Monras (2020) shows that in the short run, immigrant labor shocks negatively affect low-skilled native workers, while in the long run, he finds lingering adverse conditions for the same low-skilled

² For more on shift-share instruments see Adão, Kolesár and Morales (2018)

workers.

Another strategy to examine the effect of immigration on native wages has been to look at incidents that have resulted in increased immigration rates (see, for example, Raphael and Lucas, 2007). A frequent example is the 'Mariel boatlift' that saw a spike in the number of (an estimated 125,000) Cuban immigrants to Miami, Florida (Clemens, 2017). The seminal paper on this incident by Card (1990) found 'virtually no effect' on native wages despite a seven percent increase in the metropolitan labor force of Miami. Card's study analyzes the employment and wage rates of the Miami labor market for 1979 to 1985 compared to four other cities that did not experience a Mariel boatlift-like incident in the same timespan: Atlanta, Los Angeles, Houston, and Tampa-St. Petersburg.

The study's findings have recently been subject to several revisions and reviews; Borjas (2015) finds that the Mariel incident decreased the average wages of low-skilled natives by 10 to 30 percent. However, in their update of Card's research using Synthetic Control Methods, Peri and Yasenov (2015) conclude that the evidence is insufficient to claim such significant adverse effects as Borjas does. Furthermore, Clemens and Hunt (2017) argue that Borjas' findings are biased due to his restriction of the sample used for his estimates that omits over 90% of low skill workers in the Miami area by excluding women, Hispanics, High School graduates, and only selecting workers between the ages of 25 and 59. Instead, they find that the Mariel boatlift can be explained by the contemporaneous change in the racial makeup of the labor force in the Miami area, with an increase in the share of black workers. They conclude that the evidence supports Peri and Yasenov (2015) that immigration's negative impact on native workers is negligible.

Recently, within the national approach, there have been further refinements in the methodology that resulted in estimates of immigrant effects on native workers to be negligible and

even slightly positive. In a simplistic model, if immigrants and domestic workers are assumed to be perfectly substitutable, any increase in immigrants' number is a supply shock to the labor force. This will decline all workers' wages since, in the supply-demand framework, labor supply will shift up while the demand for labor is downward sloping. The decreased wages will allow more workers to be hired by employers. The assumption that immigrants and domestic workers are perfect substitutes for one another is dubious. Immigrants differ from domestic workers in several ways and not simply by language or birthplace as immigrants are likely to differ in skills that are of value to employers, particularly since immigrants tend to be less formally educated than native-born workers (Raphael and Lucas 2007; Peri and Sparber, 2009). Once the assumption that immigrants and domestic workers are perfect substitutes is relaxed, the outcomes are less predictable.

In their reworking of the model by Borjas (2003), Ottaviano and Peri (2006) make two notable adjustments. First, they allow for the possibility that immigrants and native workers are not perfect substitutes. Second, they account for capital adjustment in both the short run and the long run. They find evidence that not only are immigrants and native workers imperfect substitutes across education and experience groups but that their effect on domestic workers is, for the most part, negligible as most of the adverse effects of immigration are borne on new immigrants since they compete with current immigrants for jobs. Similar results have been found in the U.K. (Manacorda, Manning, and Wadsworth, 2012), albeit with lower estimated values for the elasticity of substitution than those found in Card (2009) and Ottaviano and Peri (2012). The study still finds that immigration depresses the wages of previous immigrants, not native-born workers.

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CHAPTER THREE

THEORETICAL FRAMEWORK

Following the frameworks in Katz and Murphy (1992) and Borjas et al. (2003) and adopting from the research of Ottaviano and Peri (2006; 2012), I implement a nested CES production function to estimate the wage response to changes in the labor supply at a national level. The aggregate production of a national economy may be formulated as a Cobb- Douglas production function with constant returns to scale:

$$Y = AL^{\rho}K^{1-\rho} \tag{3.1}$$

where Y is the aggregate output, A is the total factor of productivity, L and K are aggregate inputs for labor and capital, respectively, and the elasticity of output is ρ . In the literature, the variable for labor L is treated as a nested CES comprised of varying labor types. Workers are partitioned into groups that differ by education and experience. This partitioning involves separating workers into main categories of education types—high school graduates or equivalents and more than high school. Within these two groups, there are two main sub-groups. The lesser or lower educated group are workers with less than a high school degree and those with exactly a high school diploma. The two subgroups are workers with some college but no degree and those with a college degree or more for the higher educated group.

Typically, in the literature, there are eight experience groups: 1-5 years, 6-10 years, 11-15 years, 16-20 years, 21-25 years, 26-30 years, 31-35 years, and 36-40 years (Borjas 2003; Borjas and Katz 2007; Ottaviano and Peri 2012). Domestic(native) workers and immigrants are separated into these groupings. Following the specification outline in Ottaviano and Peri (2012), the labor supply of each group, i.e., (the nested CES labor aggregate) may be written as:

$$L_{i(n)} = \left[\sum_{i(n+1)} \theta_{i(n+1)} \left(L_{i(n+1)}\right)^{\frac{\sigma_{n+1}-1}{\sigma_{n+1}}}\right]^{\frac{\sigma_{n+1}}{\sigma_{n+1}-1}}$$
(3.2)

where $\theta_{i(n)}$ is the relative productivity level of the i(n) group and Ottaviano and Peri standardize the productivity type following Card and Lemieux (2001) such that $\sum_{i(n)\in i(n-1)}\theta_{i(N)}=1$ and any multiplying factors are absorbed by the total factor productivity A, in the production function equation 3.1. The parameter $\sigma_n > 0$ is the elasticity of substitution between the different labor types. Thus, the wages of workers can be derived as follows:

$$ln(W_{i(N)}) = ln(\rho A k^{1-\rho}) + \frac{1}{\sigma_1} + \sum_{N=1}^{N} ln \ \theta_1 - \sum_{n=1}^{N-1} \left(\frac{1}{\sigma_n} - \frac{1}{\sigma_{n+1}}\right) ln(L_{i(N)})$$

$$-\frac{1}{\sigma_N} ln(L_{i(N)})$$
(3.3)

The parameter estimates for the elasticities of substitution can then be derived using data on wages and employment. The parameters are found by using the general equation:

$$ln\frac{w_{i(N)}}{w_{i(N)}} = ln \,\theta_{i(N)} / \,\theta_{j(N)} - \frac{1}{\sigma_N} ln \left(L_{i(N)} / L_{j(N)} \right) \tag{3.4}$$

Fixed-time effects are assumed to account for the variation of both the aggregate terms and any variation specific to groups for the terms $\ln \theta_{i(n)}/\theta_{j(n)}$, where $\theta_{i(n)}/\theta_{j(n)}$ are the relative productivity levels for both immigrants and natives (2012). In both Borjas (2003) and Ottaviano and

Peri (2012), the experience-education specific productivity levels are also assumed to be invariant over time but can vary across the education-experience groups. Estimating the elasticity of substitution between domestic workers and immigrants is crucial to establishing evidence that immigrants and domestic workers are imperfect substitutes. In the nested structure, the effects of groups drop out if the estimated elasticity is equal to zero. So, in general, to estimate a nested CES, the starting point is at the lowest nest where the substitution parameter is estimated along with the relative efficiency parameters, which are then used to construct supply indexes as one moves through the levels in the nested structure

CHAPTER FOUR

DATA

4.1 Census Data

The data used comes from the integrated public use microdata samples (IPUMS) and the American Community Survey (IPUMS USA: Version 10.0 [dataset] 2020). The samples include the U.S. Decennial Census from 1960 to 2000 and the American Community Survey (ACS) data for 2010, 2015, and 2018. For the census samples for 1960 and 1970, the 1% state samples are used: the 5% state samples for the census samples for 1980, 1990, and 2000. The ACS 1% samples for 2010, 2015, and 2018 are used. Following the literature (Katz and Murphy 1992; Borjas, Grogger and Hanson 2008; Ottaviano and Peri 2008, 2012). I construct two samples used to generate both the hours worked and average wages of the labor groups. Each sample only includes workers who at least 18 to 66 years old, not living in group quarters, and who worked at least some positive number of hours during the previous year.

After accounting for the previous restrictions, the employment sample is generated by first grouping the census data into four education and eight experience groups. Importantly, they are also grouped by their birthplace. Those with foreign birthplaces are considered immigrants except those with U.S citizens as parents; for later census samples, this identification is based on the citizenship variable available by the IPUMS variable for citizenship status.

Table 4.1: Education Shares by gender and birthplace

Educational	Total	U.S. Men	Foreign	Foreign	U.S. Wome	nTotal U.S.
Attainment	Foreign		Men	Women		Born
Less than High	30.55	47.97	21.02	9.53	21.48	69.45
School						
	(21.35)	(17.44)	(14.82)	(6.54)	(5.01)	(21.35)
High School	9.42	55.55	5.7	3.72	35.03	90.59
	(5.67)	(6.12)	(3.54)	(2.14)	(3.63)	(5.67)
Some College	8.13	55.8	4.71	3.42	36.06	91.87
	(3.26)	(10.67)	(1.48)	(1.79)	(7.73)	(3.26)
College	11.00	56.48	6.84	4.16	32.51	89.00
	(4.85)	(13.88)	(2.12)	(2.74)	(9.19)	(4.85)

Labor shares are calculated by summing the total hours worked by the education group in a given census year. Parentheses report the standard deviations.

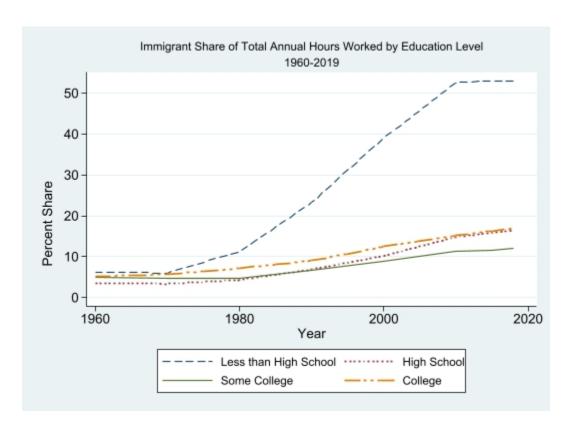


Figure 4.1 Plot figures show the total foreign (men and women) share of annual hours worked per census year.

Individuals who have not reached a grade 12 are grouped as having less than a High School education. Those with a grade of 12 are High School graduates; individuals who have between 1 to 3 years of college are grouped as having Some College. Finally, I consider college graduates as those with at least four years of college. However, it is entirely conceivable that with such broad definitions, some individuals are erroneously categorized into a group in which they do not belong (e.g., some people can finish a four-year bachelor's degree in 3 years).

In calculating hours and weeks worked in a given census, the codes used depend upon the census year. For 1960 and 1970, the variable available for weeks worked by an individual is a general variable given in intervals. So, I follow the procedure outlined by Ottaviano and Peri (2006) to create weeks worked by the median value for each interval, which is also the case for ACS data for years 2010, 2015, and 2018; otherwise, the census samples provide the exact number of weeks worked per

year. Hours worked is constructed using median intervals for census samples 1960 and 1970; otherwise, the exact number of hours reported by the sample is used.

Experience groups are formed as follows. Experience is defined as the age at which each worker entered the labor force: 17 for high school dropouts, 19 for high school graduates, 21 for workers with some college, and 23 for college graduates. Each worker's number of hours is the sum of each education-experience group's hours multiplied by the personal weight variable. The number of workers per education-experience group is the sum of each personal weight.

The wage sample is formulated using the same basic eliminations as the employment sample, but with further exclusions, the wage sample only includes individuals who report valid incomes greater than 0 and are not self-employed. Following these eliminations, the average wage for each education-experience group is calculated. Wages are deflated using the price deflator provided by IPUMS, which is in constant 1999 U.S. dollars. Deflators from 1960 to 2018 are: 5.725, 4.540, 2.314, 1.344, 1.000, .777, .704, and .679. Furthermore, top codes for the yearly wages in 1960, 1970, and 1980 are multiplied by 1.5, which is the precedent used in the literature to adjust those earnings (Borjas, Grogger, and Hanson, 2008).

Figure 4.1 shows the change in labor shares by immigrants by education level from 1960 to 2018. Table 4.1 reports the mean labor shares by education level from 1960 to 2018. There is a growing trend among immigrants to represent more significant shares of lower-educated workers, such that in 2018 53% of workers with less than a high school degree were immigrants. A separate trend is the increasing share of immigrants who make up highly educated workers, which shows how immigrants are disproportionately represented amongst both lower and higher education groups, a feature that is remarked upon in Peri (2016).

4.2 Washington State Data

The estimates concerning Washington State come from the Current Population Survey available from IPUMS (2020). While CPS contains national-level data, I restrict the data to a single state using the state of Washington's FIPS code. The samples include yearly data from 1994 to 2020. As with the census data, a wage and employment sample are constructed using the same basic procedures, aside from a few minor changes owing to the differences between the CPS and census and ACS data sets that I will mention. I only consider years from 1994 to 2020 since the variables that yield information on the birthplace and citizenship status are only available in these years. I eliminate those who report living in group quarters or vacant units and again only consider those in the working age. Foreign status is given to those who reported being not a citizen and or a naturalized citizen.

The four education groups are constructed in the following manner. Those in the less than high school group are those who do not report having a High school diploma or report a grade of less than 12. High school graduates are those who report having a High school diploma or equivalent. I group those into the 'some college group' as those who report having less than 4 years of college, including those with an associate degree. Finally, college graduates are those who have a bachelor's degree or higher. Both samples use the available variables that provide the exact number of weeks and hours worked last year to calculate hours worked and wage data. The wage sample as before drops invalid incomes or individuals who report no income and only considers workers who are not self-employed or unpaid family workers. Average weekly wages are calculated in 1999 dollars using the deflator variable provided by IPUMS. Individual weights are used to calculate hours worked and wage data.

Figure 4.2 shows the labor shares for immigrants by educational level. As with 4.1, we can

see the same trends visible for the U.S. immigrants make up a large portion of the less educated labor force and increasingly make up a significant portion across all four education groups.

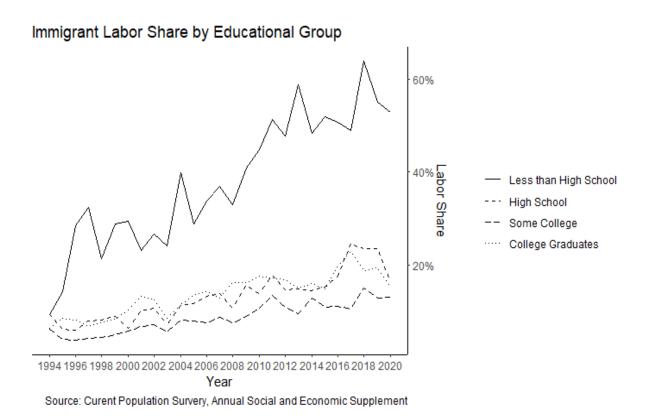


Figure 4.2 Plot shows the Washington State immigrant labor shares by educational attainment by body count.

CHAPTER FIVE

RESULTS

5.1 Estimate of σ_N

The parameter estimate of σ_N represents in the Ottaviano and Peri nested CES model the lowest level amongst aggregate groups. At this level, workers differ by place of birth, so both immigrants and natives are grouped in the same education and experience skill groups. Using equation 3.4, the elasticity of substitution between natives and immigrants can be estimated using the following specification:

$$\ln \frac{w_{F_{it}}}{w_{D_{it}}} = \lambda_i + \lambda_t - \beta \ln \left(\frac{L_{F_{it}}}{L_{D_{it}}}\right) + \varepsilon_{it}$$
(5.1)

where β is the variable of interest $1/\sigma_N$ and $ln(w_{Fit}/w_{Dit})$ is the relative average wages between immigrants and natives in education-experience group i and census year t. The education-experience group is all 32 education by experience groups in any given census year. Fixed effects for education and experience are represented by λ_i and time effects λ_t and the error term is ε_{it} . λ_i is the set of education by experience fixed effects that are assumed to account for the relative productivity between immigrants and native workers $\frac{\theta_{Fit}}{\theta_{Dit}}$. Relative productivity can vary over time across groups but is assumed to be constant over time λ_t .

Figure 5.1 shows the scatterplot between the relative wages of immigrants to natives and the relative hours of immigrants to natives; there is a negative correlation between the two groups across both groups and census years, indicating that there is imperfect substitution with an elasticity of substitution of 17. Table 5.1 shows the estimation results using equation 5.1 using different fixed

effects but all using ordinary least squares. The parentheses report the robust standard errors, each of the estimates uses as weights (using aweight in STATA) the level of employment for each group except where stated.

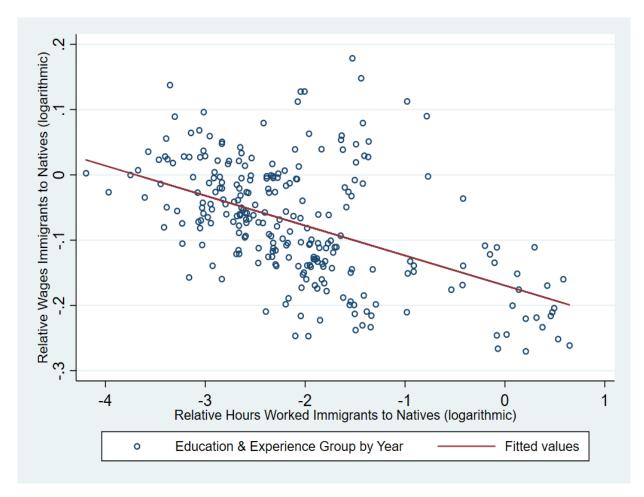


Figure 5.1 Scatter plot showing the relative wages of foreign workers plotted against domestic workers' relative hours.

The results in column (1) represent the estimated parameter without including fixed effects, column (2) reports estimate including fixed effects λ_i and λ_t in the regression. Column (3) displays estimates that include fixed effects in the regression but without weighting. For all columns, only those who are not self-employed are included in the regressions; workers are comprised of both full-time and part-time employment levels. For the top four rows, σ_N is assumed to be constant across

each group; subsequent rows allow σ_N to vary across education groups and experience groups.

Table 5.1 Parameter Estimate of σ_N

Table 5.	i Parameter E	Stilliate of ON	
Wage Group	(1) Simple	(2) Fixed Effects	(3) Unweighted
Men	-0.05***	-0.06***	-0.05***
	(0.01)	(0.01)	(0.01)
Women	-0.04***	-0.07***	-0.07***
	(0.01)	(0.01)	(0.01)
Men & Women	-0.03***	-0.05***	-0.04***
	(0.01)	(0.01)	(0.01)
Men (Relative			
Employment)	-0.05***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)
Less than High school	-0.07***	-0.07***	-0.06***
	(0.00)	(0.01)	(0.01)
High school	-0.10***	-0.09***	-0.10***
	(0.01)	(0.02)	(0.02)
Some College	-0.09***	-0.09***	-0.10***
	(0.01)	(0.02)	(0.02)
College	0.03	0.06**	0.05**
	(0.02)	(0.02)	(0.02)
Experience 0 - 10 years	0.01	-0.13***	-0.14***
	(0.02)	(0.03)	(0.03)
Experience 11 - 20 years	-0.02	-0.07**	-0.07**
	(0.02)	(0.03)	(0.03)
Experience 21 - 30 years	-0.05***	-0.06**	-0.06**
	(0.01)	(0.02)	(0.02)
Experience 31 - 40 years	-0.08***	-0.04**	-0.05**
. 1 1 11 1	(0.01)	(0.02)	(0.02)

Note: Estimates are based on all workers (full-time and part-time). Parentheses report the robust standard errors; the method is OLS using 3.4. Experience and education groups only consider men. Weights are by average employment. Fixed effects are education by experience and time-specific effects. Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01

The estimates show that the parameter σ_N for gender groups is significant at the 1% level for each of the different regressions. Furthermore, the results are significant even when accounting for the fixed effects. The R^2 , which is not shown, ranges from a low of 0.001 when estimating the parameter for Men with 0 to 10 years of experience to 0.83. The range of the estimates is between -

0.03 to -0.07, with an average of -0.06, suggesting an elasticity of substitution of 17, which is commensurate to the findings of Ottaviano and Peri (2012).

Since most of the literature focuses on the effect of immigrants on the young and lower educated part of the workforce, it is worth discussing the estimates for the less experienced and educated groups. Rows for Less than High School to College Graduates show estimates when education levels group the sample: a significant result is that even when fixed effects are included, all the estimates are significant at the 5% level with evidence of imperfect substitution up to workers with at least some college where the estimate is -0.10 suggesting an elasticity of substitution of 10. The estimate for college graduates is imprecise and does not provide any evidence for imperfect substitution. The subsequent rows show the estimates when experience levels group the sample. Here the estimates are insignificant for younger workers when fixed effects are not included but significant for older workers at the 1% level. Including fixed effects yields significant results for all experience groups.

The estimates for $-1/\sigma_N$ are more significant in value for less experienced workers than for the more experienced groups: for those with 0 - 10 years of work experience, the estimate is -0.13 compared to -0.04 for the 31 – 40-year group. The results suggest that there are lower levels of substitution between immigrants and native-born workers among the less educated and inexperienced groups.

5.2 Estimates of $\sigma_{EXP} \& \sigma_{EDU}$

Using the results from the previous estimation, the parameter σ_{EXP} can be found. This parameter is the elasticity of substitution between workers with the same education level but with differing years of experience. The systematic, time-invariant levels of productivity for both immigrants and natives are inferred from the estimates of the fixed effects λ_i and λ_t obtained from equation 5.1. From imposing the standardization that productivity levels sum to 1:

$$\widehat{\theta}_{F,k} = \frac{\exp(\widehat{\lambda}_i)}{1 + \exp(\lambda_i)}, \widehat{\theta}_{D,k} = \frac{1}{1 + \exp(\widehat{\lambda}_i)}$$
(5.2)

Using equation 3.3, the predicted values for $\hat{\theta}_{D,k}$ and $\hat{\theta}_{F,k}$ and the estimate for $\hat{\sigma}_N$ the aggregate labor index can be found. Fixed effects assumed to control for the variation of $\ln(\rho A k^{1-\rho}) + \frac{1}{\sigma_1} \ln(L)$ and any group-specific group aggregates $\sum_{N}^{n-1} \left(\frac{1}{\sigma_N} - \frac{1}{\sigma_N} + \frac{1}{\sigma_N} - \frac{1}{\sigma_N} + \frac{1}{$

 $\frac{1}{\sigma_N+1}\ln(L_{i(n)})-1/\sigma_n\ln(L_{i(n)})$. Education by experience fixed effects is assumed to capture the relative productivities $\ln\sigma_N$ that is also assumed to be constant over time. The estimation can then be written as:

$$\ln(\overline{w}_{it}) = \lambda_i + \lambda_t - \beta \ln(\widehat{L}_{it}) + \varepsilon_{it}$$
(5.3)

where β is the estimated elasticity of substitution $^{1}/_{\sigma_{EXP}}$ and \overline{w}_{it} is the average wage, and λ_{i} , λ_{t} are the fixed effects that absorb the specified terms. The resulting estimation is then the elasticity of substitution between workers with the same level of education but with differing experience levels.

In a similar fashion, and moving another level up, the parameter for σ_{EDU} can be estimated once the estimates for the experience by education fixed effects are obtained from equation 5.3.

Again, if variation in $ln(\rho Ak1 - \rho) + 1/\sigma_{EDU}ln(Lt)$ can be captured by a time-trend and that the relevant productivity $ln\theta_{i(n)}$ is likewise absorbed by an education-specific fixed effect then the estimation model can be written as:

$$\ln(\overline{w}_{it}) = \lambda_i + \lambda_t - \beta \ln(\widehat{L}_{it}) + \varepsilon_{jt}$$
(5.4)

Where β is the estimated elasticity of substitution between different education groups σ_{EDU} . I estimate σ_{EXP} with and without including the fixed effects and these results are reported in tables 5.2 and 5.3, respectively. Each estimation method is 2SLS using the logarithm of hours worked by immigrants as an instrument for the labor aggregate. As Ottaviano and Peri explain (2008), after accounting for the dummy variables, immigration is a pure supply shock. Thus, they argue that it is an appropriate instrument to account for the endogenous variable hours worked by immigrants and native workers (Ottaviano and Peri, 2006). I report robust standard errors that are clustered by education and experience groups in my results. The reported estimates indicate an elasticity of substitution for workers of different experience levels of around 6.25.

Before discussing my results, it is worthwhile to refer to previous studies that have estimated this parameter. Katz and Murphy (1992) and Card and Lemieux (2001) being two prominent references. Katz and Murphy (1992) find an estimate of -0.342(0.032), while Card and Lemieux (2001) get an estimate between -0.107(0.048) and -0.237(0.033). Earlier research by Welch (1979) gets similar results with ranges for this parameter between -0.080 and -0.218. Although these studies primarily use samples that only include men, they are informative as a reference point.

Table 5.2 Parameter Estimate of $(-1/\sigma_{EXP})$ No Fixed Effects

	mineter Estimate	01 (2 /0 <i>E</i> M) 1	10 I med Bire	200
Wage Group	Men	Women	Men &	Men(Relative
			Women	Employment)
Estimate	0.25**	0.39***	0.20***	0.18*
	(0.09)	(0.08)	(0.07)	(0.10)
First stage	0			
F-Statistic	216.78	216.78	216.78	192.98
\mathbb{R}^2	0.46	0.46	0.46	0.43
Observations	256	256	256	256

Note: Parentheses report the robust standard errors clustered by the education-experience group, estimation method 2SLS, immigrant labor supply as an instrument. * p<0.10, ** p<0.05, *** p<0.01

Table 5.3 Parameter Estimate of $(-1/\sigma_{EXP})$ Fixed Effects

Table 5.5 I attained in 17 DEAT) I fixed Effects				
Wage Group	Men	Women	Men &	Men(Relative
			Women	Employment)
Estimate	0.01	0.20***	0.04	0.03
	(0.04)	(0.07)	(0.05)	(0.05)
First stage	0			
F-Statistic	51.06	51.06	51.06	43.29
\mathbb{R}^2	0.94	0.94	0.94	0.93
Observations	256	256	256	256

Note: Parentheses report the robust standard errors clustered by the education-experience group, estimation method 2SLS, immigrant labor supply as an instrument. Fixed effects are education by experience and time effects. * p<0.10, ** p<0.05, *** p<0.01

The reported results are surprising and mostly imprecise when fixed effects are included. None of the reported results suggests evidence of imperfect substitution between experience groups, contrary to previous research findings. The estimate for men is close to 0, with a reported value of 0.01 but is insignificant even at the 10% threshold. Surprisingly, the only significant result is for women, who have an estimate of 0.2. The results indicate that perhaps the data does not suit the specification of narrow experience groups of 1-5 years. Using OLS to estimate equations 5.3 and 5.4 would likely lead to biased results since Borjas, (2003) notes the supply of workers is likely to be endogenous given the span of periods using the census data. Therefore, previous research has used as the preferred instrument the supply of foreign workers in the relevant skill group. The first stage F-statistic using the number of hours worked as the measure for the supply of foreign workers for rows 1-3 is 121.02. When estimating the parameter using relative employment as the measure of labor supply for men the instrument is the level of employment of immigrants and the F-statistic in this instance is 114.56. In either case the F-statistic shows that the instrument is valid.

Similarly, my results for the estimation of σ_{EDU} are mixed while they are consistent in their values. The lack of statistical significance for much of the estimates is likely due to the lack of observations available using census data, a point that is remarked on by several previous studies as a drawback to using census data (Borjas, Grogger, and Hanson, 2008; Ottaviano and Peri, 2012; Card, 2009). Card (2009) notes it could very well be the case that the data does not support four education groups specified in this nested CES structure and that instead, the college-high school wage is best specified using the two skills group as shown in both Acemoglu (2002) and Katz and Murphy(1992). That said, prior estimates for σ_{EDU} by (Borjas, 2003) using the 4 education groups find two estimates: -0.741 (standard error 0.646) and -0.0759 (standard error of 0.582), while Borjas and Katz (2007) report an estimate of 0.413 (standard error 0.312). Katz and Murphy (1992), using only two

education groups, get an estimated elasticity of substitution of 1.4. While Ottaviano and Peri (2012) also using four education groups to report several estimates for this parameter which range between -0.02 to -0.43 depending upon the fixed effects included in the regression and the nesting CES structure.

Table 5.4 Parameter Estimate of $(-1/\sigma_{EDU})$

Parameter Estimate	Men	Women	Men & Women	Men by Employment
Education & Time Trends				
Coefficient	-0.09	-0.08	08	08
	(0.08)	(0.12)	(0.07)	(.07)
\mathbb{R}^2	0.99	0.99	0.99	0.99
Education Trends				
Men	-0.34*	-0.38*	-0.35*	-0.34
	(0.12)	(0.15)	(0.13)	(0.21)
\mathbb{R}^2	0.98	0.97	0.97	0.91
Observations per group	32	32	32	32

Note: Estimates use the corresponding wage as a dependent variable, the labor aggregate as the explanatory variable. Parentheses report the robust standard errors clustered by the education level; the estimation method is 2SLS using foreign workers as an IV for the relative education group. * p<0.10, ** p<0.05, *** p<0.01

The results reported in table 5.4 show estimates by both including fixed effects for a time trend and education specific time trends or only including fixed effects for education. The different sets of results show the remarked upon the sensitivity of this parameter to fixed effects. By including both sets of fixed effects, the estimates are insignificant and noticeably decrease their values.

Comparing these results to those reported by Borjas (2003), Ottaviano and Peri, 2012; Borjas and Katz, 2007) show that they are similar in magnitude ranging from -0.382 to -0.336 with an average value of -0.352. The results suggest an elasticity of substitution around 5, which is within the range reported in other studies, including the estimates found by Card and Lemieux, 2001.

5.3 Estimated Wages Changes

Using CPS data for Washington state for 1994 and 2020, I calculate the overall percentage wage changes for native-born U.S. workers and immigrants using 1994 as the base year. I also estimate the percentage changes for the United States using the same data. The estimated wage changes assume that capital adjusts to the shock of immigrant labor supply, which means that overall, the long run's wage effect is zero. In the short run, it is entirely conceivable that immigrant labor shocks depress native wages even further, as illustrated by Monras (2020).

The calculated wage changes are made with minor adjustments to the structure of the CES production function framework. There are two broad groups of workers, high school and college equivalents, which are further differentiated into high school and college graduates. The estimated wages for Table 5.5 show the results using my parameter estimates in column 2 and the estimates taken from the literature, except for the estimated parameter for the elasticity of substitution between immigrants and natives of the same skill group.

Table 5.5	Estimated	Wage	Changes
I upic o.o	110 tilliated	v v u S C	Circuit

σ_{HL}	5	2
G EDU	5	10
σ_{EXP}	6.25	6.25
σ_N	17	17
United States		
Natives		
Less than HS	1.7%	5.8%
High School	1.9%	5.7%
Some college	2.1%	6.1%
College	0.4%	4.1%
Average	1.3%	5.2%
Immigrants		
Less than HS	-0.1%	4.0%
High School	-5.8%	-1.9%
Some college	-4.6%	-0.6%
College	-13.6%	-10.0%
Average	-8.2%	-4.3%
Washington		
Natives		
Less than HS	-0.1%	-0.7%
High School	0.0%	-1.6%
Some college	0.4%	-1.8%
College	-0.3%	-1.2%
Average	0.0%	-1.5%
Immigrants		
Less than HS	-3.8%	-6.9%
High School	-6.8%	-9.8%

Some college	-4.9%	-7.7%
College	-16.8%	-19.6%
Average	-7.9%	-10.8%

The results based on my estimates show that nationally, native workers saw on average slight overall positive change. In Washington state, native workers saw slightly adverse effects by education groups but saw, for the most part, minor changes. Using the parameters from the literature to estimate the effect of immigration on wages results in a slightly more significant reduction in wages on average by 1.5%. Immigrants, especially those in Washington, bore most of the losses due to immigration increases. These results lead to the conclusion that immigrant labor shocks negatively affected the wages of previous immigrants and not native-born workers; this is more evident and surprising when considering the college-educated group of immigrant workers who saw more significant losses than those with less than a high school education of around -13.6% to -10% nationally and even greater losses for those immigrants residing in Washington state. To reiterate, the overall effect of immigration from 1994-2020 saw a modest positive gain for native-born workers and reduced foreign-born workers' wages.

CHAPTER SIX

CONCLUSION

The United States has seen great change over the past fifty years, not the least of which is the dramatic change in its population makeup. Despite the rhetoric of many political groups, it is hard to disentangle the adverse effects immigrants may or may not have on native-born citizens. However, by employing a nested CES function that has gained traction in the national area approach one can begin to analyze the effect immigrants have on native-born workers.

This study's results corroborate previous research that finds evidence of imperfect substitution between immigrants and native-born workers within education and experience groups. The estimated elasticity of substitution of 17 is close to the findings of both Card (2009) and Ottaviano and Peri (2012), with smaller estimates for less-educated workers. The findings reported in this study are not conclusive. In particular, the assumption of four education or skill groups while using census data is a known issue within the labor economics literature, and the findings in this study make no strong claims that this is not the case. Furthermore, in estimating the elasticity of substitution across experience groups, the narrowly assumed experience groups are not supported by the results, indicating an alternative nesting structure that inverts the order as discussed in (Ottaviano and Peri, 2012) is perhaps more suitable.

Finally, it is worth noting that the estimated wage changes assume that the economy fully adjusts to immigrant labor shocks. Since the underlying Cobb-Douglas production function is linearly homogenous, the elasticity of substitution parameters does not directly enter the average wage change. Therefore, the model does did not consider the complete impact immigrant labor shocks have in the short run. This is a crucial drawback of the model framework presented in this paper; further study would need to consider how the economy dynamically adjusts to labor shocks

to address the concerns that immigrant population rates are not exogenous.

BIBLIOGRAPHY

- **Acemoglu, Daron.** 2002. "Directed Technical Change." *The Review of Economic Studies*, 69(4): 781–809.
- Around the World, More Say Immigrants Are a Strength Than a Burden.

 2019a.https://pewresearch.org/global/2019/03/14/around-the-world-more-say-immigrants-are-astrength-than-a-burden/
- **Borjas, George J.** 2003. "The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market." *The Quarterly Journal of Economics*, 118(4): 1335–1374.
- **Borjas, George J.** 2015. "The Wage Impact of the Marielitos: A Reappraisal." National Bureau of Economic Research Working Paper 21588.
- **Borjas, George J., and Lawrence F. Katz.** 2007. "The Evolution of the Mexican-Born Workforce in the United States." *Mexican Immigration to the United States*, 13–56. University of Chicago Press.
- Borjas, George J., Jeffrey Grogger, and Gordon H. Hanson. 2008. "Imperfect Substitution between Immigrants and Natives: A Reappraisal." National Bureau of Economic Research Working Paper 13887.
- Card, David. 1990. "The Impact of the Mariel Boatlift on the Miami Labor Market."

 ILR Review, 43(2): 245–257.
- **Card, David.** 2001. "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics*, 19(1): 22–64.

- Card, David. 2007. "How Immigration Affects U.S. Cities." Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London CReAM Discussion Paper Series 0711.
- Card, David. 2009. "Immigration and Inequality." The American Economic Review, 99(2): 1–21.
- Card, David, and Thomas Lemieux. 2001. "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *The Quarterly Journal of Economics*, 116(2): 705–746.
- **Clemens, Michael.** 2017. "There's no evidence that immigrants hurt any American workers: The debate over the Mariel boatlift, a crucial immigration case study, explained."
- Clemens, Michael A, and Jennifer Hunt. 2017. "The Labor Market Effects of Refugee Waves:

 Reconciling Conflicting Results." National Bureau of Economic Research Working Paper
 23433.
- Clemens, Michael A, Ethan G Lewis, and Hannah M Postel. 2017. "Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion." National Bureau of Economic Research Working Paper 23125.
- Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. 2020.

 Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset].

 2020b.https://doi.org/10.18128/D030.V8.0, Minneapolis, MN: IPUMS.
- **Jaeger, David A, Joakim Ruist, and Jan Stuhler.** 2018. "Shift-Share Instruments and the Impact of Immigration." National Bureau of Economic Research Working Paper 24285.
- Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply

- and Demand Factors." The Quarterly Journal of Economics, 107(1): 35–78.
- Key findings about U.S. immigrants. 2019b.
- **Luckstead, Jeff, and Stephen Devadoss.** 2019. "The Importance of H-2A Guest Workers in Agriculture." *Choices*, 34(1): 1–8.
- Manacorda, Marco, Alan Manning, and Jonathan Wadsworth. 2012. "THE IMPACT OF IMMIGRATION ON THE STRUCTURE OF WAGES: THEORY AND EVIDENCE FROM BRITAIN." Journal of the European Economic Association, 10(1): 120–151.
- **Monras, Joan.** 2020. "Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis." *The Journal of political economy*, 128(8): 3017–3089.
- Ottaviano, Gianmarco, and Giovanni Peri. 2006. "Rethinking the Effects of Immigration on Wages." National Bureau of Economic Research Working Paper 12497.
- Ottaviano, Gianmarco, and Giovanni Peri. 2012. "RETHINKING THE EFFECT OF IMMIGRATION ON WAGES." *Journal of the European Economic Association*, 10(1): 152–197.
- **Peri, Giovanni.** 2016. "Immigrants, Productivity, and Labor Markets." *The Journal of Economic Perspectives*, 30(4): 3–29.
- Peri, Giovanni, and Chad Sparber. 2009. "Task Specialization, Immigration, and Wages."

 American Economic Journal: Applied Economics, 1(3): 135–169.
- **Peri, Giovanni, and Vasil Yasenov.** 2015. "The Labor Market Effects of a Refugee Wave: Applying the Synthetic Control Method to the Mariel Boatlift." National Bureau of Economic Research Working Paper 21801.
- Raphael, Steven, and Ronconi Lucas. 2007. "THE EFFECTS OF LABOR MARKET

COMPETITION WITH IMMIGRANTS ON THE WAGES AND EMPLOYMENT OF NATIVES: What Does Existing Research Tell Us?" *Du Bois Review: Social Science Research on Race*, 4(2): 413—432.

- Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas and Matthew Sobek. 2020. IPUMS USA: Version 10.0 [dataset]. 2020a.https://usaipumsorg/usa/, Minneapolis, MN: IPUMS.
- **Shierholz, Heidi.** 2010. "IMMIGRATION AND WAGES: Methodological advancements confirm modest gains for native workers." Economic Policy Institute Briefing Paper 255.
- W.A. farmers and laborers are struggling under the H-2A guest worker program and it may get worse. 2019c.
- **Welch, Finis.** 1979. "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust." *Journal of Political Economy*, 87(5): S65–S97.

APPENDIX A

Marginal Product of Labor

In a competitive economy both capital and labor are paid their marginal products. Thus, the real wage paid to workers is equal to the marginal product of labor (MPL). Assuming that the production for an economy can be represented by the Cobb-Douglas production function:

$$y = AL^{\rho}K^{1-\rho}$$

where ρ and $1-\rho$ are the share of income to labor and capital, respectively, then taking first order conditions we can derive the marginal product of labor:

$$\frac{\partial y}{\partial L} = \rho A L^{\rho - 1} K^{1 - \rho}$$

$$MPL = w = \rho A \left(\frac{K}{L}\right)^{1-\rho}$$

Where the capital to labor ratio can be written as $\frac{K}{L} = k$ and since the MPL equals the real wage W, we can express the wage as the marginal condition:

$$w = \rho A(k)^{1-\rho}$$

Differentiating with respect to L and taking natural logarithms where L is the nested function:

$$L_{i(n)} = \left[\sum_{i(n+1)} \theta_{i(n+1)} \left(L_{i(n+1)}\right)^{\frac{\sigma_{n+1}-1}{\sigma_{n+1}}} \right]^{\frac{\sigma_{n+1}}{\sigma_{n+1}-1}}$$

Yields:

$$ln(W_{i(N)}) = ln(\rho A k^{1-\rho}) + \frac{1}{\sigma_1} + \sum_{N=1}^{N} ln \ \theta_1 - \sum_{n=1}^{N-1} \left(\frac{1}{\sigma_n} - \frac{1}{\sigma_{n+1}}\right) ln(L_{i(N)}) - \frac{1}{\sigma_N} ln(L_{i(N)})$$

Long Run Wages Effects

The total long-run effects of immigration on wages of domestic native-born and foreign-born workers follow the derivation given in Ottaviano and Peri (2008). w_{Djkit} is the average weekly wages of native workers and w_{Fjkit} is the average weekly wages of immigrant workers for main education group j, sub-education group k in time, experience group i, and in time t. F_{jkit} is the total hours worked for foreign workers, with ΔF_{jkit} the change between two time periods in total hours worked for immigrant workers. s_{Fjkit} is the share of total wages paid to immigrant workers, where the relevant parameters for the elasticity of substitution are given by σ_{HL} for the elasticity of substitution between the two main education groups j, $\sigma_{EDU,k}$ is the elasticity of substitution between the subgroups k, σ_{EXP} is the elasticity of substitution between workers of the same education group with different experience levels, and σ_{IMMI} is the elasticity of substitution between native and immigrant workers within the same skill group. The percentage change in weekly wages is then given by:

$$\left(\frac{\Delta w_{Djkit}}{w_{Djkit}}\right)^{Total}$$

$$= \frac{1}{\sigma_{HL}} \sum_{HL} \sum_{EDU} \sum_{EXP}^{8} \left(s_{Fcqit} \frac{\Delta F_{cqit}}{F_{cqit}}\right) + \left(\frac{1}{\sigma_{EDUk}} + \frac{1}{\sigma_{HL}}\right) \sum_{EDU} \sum_{EXP} \left(s_{Fjqit} \frac{\Delta F_{jqit}}{F_{jqit}}\right)$$

$$+ \left(\frac{1}{\sigma_{EXP}} + \frac{1}{\sigma_{EDUj}}\right) \sum_{EXP} \left(s_{Fjnit} \frac{\Delta F_{jnit}}{F_{jnit}}\right) + \left(\frac{1}{\sigma_{IMMI}} - \frac{1}{\sigma_{EXP}}\right) \left(s_{Fjkit} \frac{\Delta F_{jkit}}{F_{jkit}}\right)$$

for native workers and the percentage change for immigrant workers is given by:

$$\begin{split} &\left(\frac{\Delta w_{Fjkit}}{w_{Fjkit}}\right)^{Total} \\ &= \frac{1}{\sigma_{HL}} \sum_{HL} \sum_{EDU} \sum_{EXP}^{8} \left(s_{Fcqit} \frac{\Delta F_{cqit}}{F_{cqit}}\right) + \left(\frac{1}{\sigma_{EDUj}} - \frac{1}{\sigma_{HL}}\right) \sum_{EDU} \sum_{EXP} \left(s_{Fjqit} \frac{\Delta F_{jqit}}{F_{Fjqit}}\right) \\ &+ \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_{EDUj}}\right) \sum_{EXP} \left(s_{Fjnit} \frac{\Delta F_{jnit}}{F_{jnit}}\right) + \left(\frac{1}{\sigma_{IMMI}} - \frac{1}{\sigma_{EXP}}\right) \left(s_{Fjkit} \frac{\Delta F_{jkit}}{F_{jkit}}\right) \\ &- \frac{1}{\sigma_{IMMI}} \frac{\Delta F_{jkit}}{F_{jkit}} \end{split}$$