The University of North Carolina Asheville
Journal on Undergraduate Research
Asheville, North Carolina
May 2020

Differences in Relative Manual, Abstract, and Routine Intensity of Occupations Influence on Economic Assimilation Rates of Immigrants

Nicholas Jeffrey Sarbaum
Economics
The University of North Carolina Asheville
One University Heights Asheville
North Carolina 28804 USA

Faculty Advisor: Dr. Jie Ma

Abstract

In recent years, there has been an increase in immigration to the United States, particularly among low skill workers from South and Central America fleeing violence or seeking better economic opportunities. Wages of migrants typically start off significantly lower than those of natives and take 10-15 years to reach parity[11]. The pace at which migrant wages reach parity is known as the assimilation rate. This paper investigates how the assimilation rates vary across different occupations due to variation in tasks intensities (manual, abstract and routine task intensities). This paper uses repeated cross-sectional data from the American Community Survey (ACS) and US Census merged with data from the Dictionary of Occupational Titles to estimate the different assimilation rates for detailed occupation groups. The paper finds that the assimilation rate is positively correlated with manual and routine task intensity, while there is a negative correlation between abstract task intensity and assimilation rate. The positive correlation indicates that immigrants in occupations that require less complex, or easier to learn, skills assimilate more rapidly, reaching wage parity with natives faster than their counterparts in occupations requiring more abstract skills.

1. Introduction

In recent years, there has been an increase in immigrants to the United States, particularly those of low skill immigrants from South and Central America[2]. Many of these immigrants are fleeing violence or looking for better economic opportunities. The earnings of immigrants, especially low skilled immigrants, tend to start off significantly lower than those of natives and on average take 10 - 15 years to catch up to the wages of natives[11]. For many of these low skill migrants, who will already suffer from relatively low wages in the United States due to lack of education, this wage penalty and sluggish assimilation can cause serious economic hardship. Recent policy changes have restricted the ability for immigrants to obtain a green card if they have received social assistance and restricted access to social services such as food stamps and Medicaid more heavily for non-citizens[8]. This disproportionately affects low income and low skill migrants, in particular those with families or children. This creates an incentive for immigrants to assimilate into the economy as fast as possible, because of this it is important to understand what occupations see the highest rate of economic assimilation. These occupations would be best suited for low skill immigrants seeking a more sustainable wage avoiding the need for social assistance which could place their naturalization in jeopardy. In addition to what occupations have the fastest rates of economic assimilation this paper also explores the microeconomic foundations of why assimilation rates vary across occupations. The estimation results find that differences in the manual, abstract, and routine task intensities of occupations have significant effects on the rate of assimilation.

1.1 Literature Review

The seminal paper Borjas[1], analyzes the ways in which the earnings of immigrants differ from those of natives and why these differences exist. Borjas[1] lays out three potential stories of immigration in his theoretical framework, positive, negative and refugee selection. In the case of positive selection, the “best” of a country immigrate to the United States and then proceed to outperform natives. Negative selection, on the other hand, occurs when those from the lower tail of earnings in their home country immigrate and proceed to underperform natives. This occurs when income distribution is less equal in the home country than the one a migrant is immigrating to. The final case Borjas[1] presents is that of refugee sorting, in which a person from the lower tail of income in their home country immigrated to the United States and proceeds to outperform natives, this would be something you may see after a communist revolution that redistributes income to lower classes. Through an OLS regression on US census data Borjas[1] is able to determine differentials between immigrant and native wages and how this gap closes over time defined as the rate of economic assimilation. The empirical model in this paper builds upon the seminal work of Borjas[1] and extends his specification by splitting the population into seventeen distinct occupation categories to investigate how these rates of assimilation vary across occupations.

In “Rethinking the Effects of Immigrants on Wages” Gianmarco Ottaviano and Geovani Peri[2] demonstrate that the impact of immigrants on natives varies highly depending on the degree of substitutability within an education group. This indicates that there is a factor other than education, such as skills within these groups that cause immigrants and natives to specialize into different occupations. Ottaviano and Peri[2] find that this specialization reduces competition between natives and immigrants and therefore mitigates losses experienced by natives from immigration. This means that there is a net benefit of immigration to natives even in the short run. They also find that the majority of losses are suffered by previous immigrant cohorts indicating that immigrants of similar education groups tend to sort into the same jobs. The reasoning behind this is investigated by Giovani Peri and Chad Sparber[3] in “Task Specialization, Comparative Advantages and the Effects of Immigration on Wages”.

Peri and Sparber[3] demonstrate that due to imperfect communication skills yet similar manual skills immigrants have a comparative advantage in manual intensive tasks and natives have advantage in communicatively intensive tasks. Due to these different comparative advantages, when there is an influx of immigration, natives tend to specialize into more communicatively intensive tasks such as more supervisory and customer service occupations. This offers an explanation for why we do not see losses or mass migrations of natives when immigrants enter the economy as suggested by Borjas[2] and others. Peri and Sparber[3] accomplish this using measures on the relative manual and communicative intensity of census occupations from the US Census and the U.S Dictionary of Occupational Titles. This research expands upon their work to investigate how this differential in comparative advantage contributes to economic assimilation of immigrants as opposed to the impacts upon natives.

This research makes use of two datasets assembled by Dorn and Autor from their 2013 paper "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market.” Dorn and Autor seek to evaluate the causes of the pronounced rise in wage inequality seen in the United States and other developed nations beginning in the 1980s. To compare occupations across time Dorn and Autor create a reliable occupation cross-walk across 1980, 1990 and 2000 census along with the 2005-2008 ACS. In this paper, the crosswalk is applied to get a consistent occupation measure across years. Additionally, this paper makes use of data on manual, abstract, and routine task intensity aggregated by Dorn and Autor (2013) using the 1977 Dictionary of Occupational Titles to analyze how various occupational task intensities influence assimilation rate[10].

1.2 Descriptive Statistics

Due to the greater transferability of manually intensive skills and comparative advantage that immigrants hold it is expected that immigrants will sort into occupations utilizing these skills at a higher rate than other occupations, this is shown below in Figure 1.

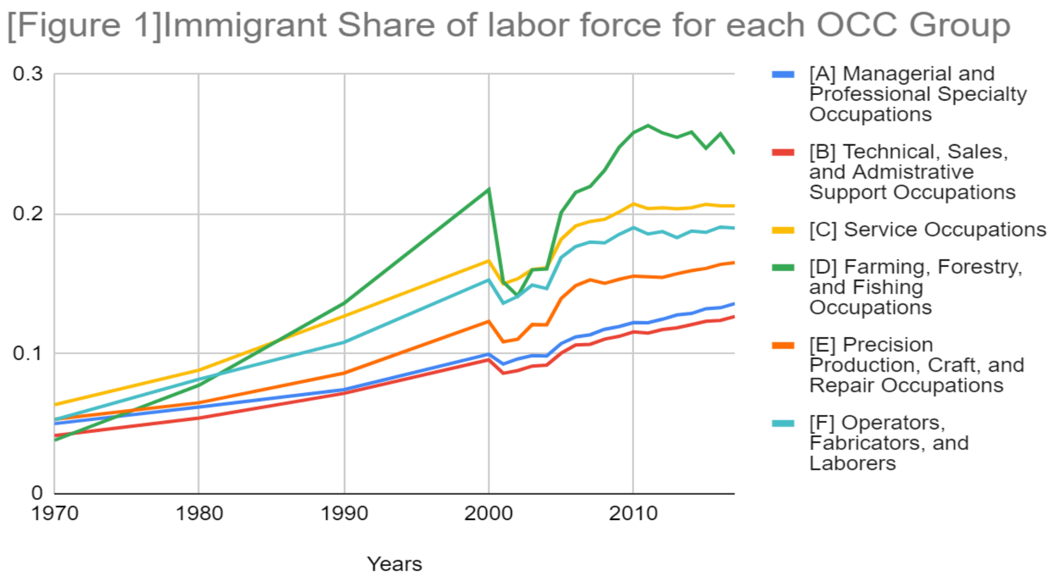

Figure 1. Immigrant share of labor force by general occupation group

This figure has an anomalous dip in all occupations right at the year 2000, this is likely caused by differences between the way immigrants are counted in the census survey and changes in sampling style compared to the ACS survey which is introduced in the year 2000. Because the drop is at the same time and of similar relative magnitude for all OCC groups it is likely not a meaningful change. This line chart demonstrates that, due to the greater transferability of manual skills, immigrants do indeed make up the largest share of the workforce in OCC groups D and F [Figure 2A and B], the occupations with the highest levels of manual intensity.

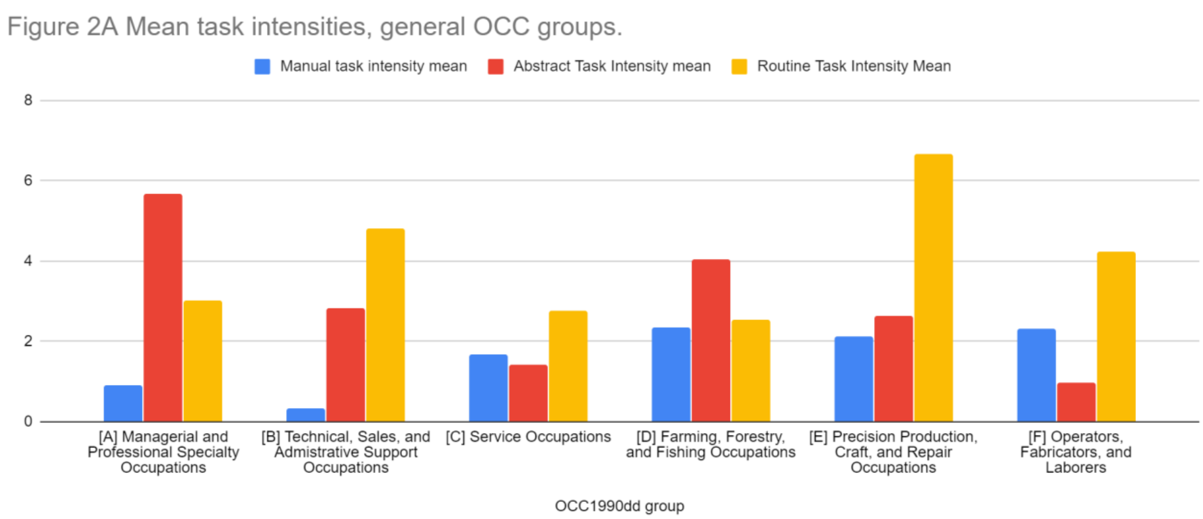

Figure 2A. Bar chart of occupational task intensities by general occupational groups

In Figure 2B below a more detailed bar graph shows the mean manual intensity, abstract intensity and routine intensity of 17 detailed occupation groups. It would be expected that the occupations with the highest manual, and routine intensity will see the fastest rates of assimilation due to the greater transferability and ease of learning these skills.

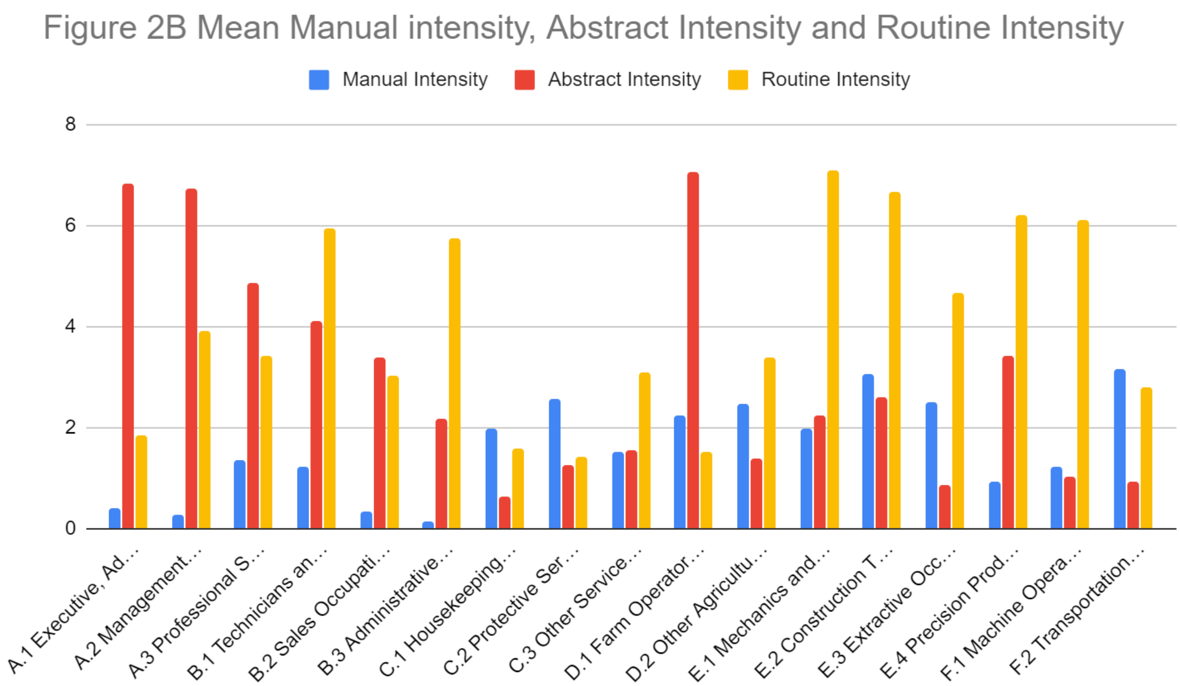

Figure 2B. Bar chart of occupational task intensities by detailed occupational groups

In this chart (2B) you can see that some of the occupations with the highest manual intensities are F.2, E.2, C.2, and D.2 (Transportation and material moving operations, Construction, Protective Service Occupations, and Other Agricultural related occupations which is primarily made up of farm laborers). The results section will demonstrate the positive correlation in detail.

1.3 Theoretical Framework

As demonstrated in the Mincer earnings function (1), wages are a function of both skills acquired through labor market experience(x) and education(s). This equation can explain why immigrant wages start off significantly lower. Firstly, many American companies do not value foreign education as highly as those from American universities, thus, lowering the returns to education for immigrants. Secondly, immigrants tend to have imperfect communication skills which are particularly important for many high paying jobs, these skills, such as learning English, may take years to develop leading to stunted wages for immigrants[5]. In the following Mincer earnings function the left side of the function takes log wages for an individual, on the right side of the function w_0 represents the wages of an individual with zero education and experience, s represents years of education and x is years of labor market experience.

$$\text{Ln}(w) = lnw_0 + \rho s + \beta_1 x + \beta_2 x^2 \tag{1}$$

This paper extends the standard Mincer[5] earnings function by adding detailed job requirements performed by each worker. The extended Mincer earning equation captures both workers' skills and jobs' tasks as wage determinants, which is the new trend in the literature. The job requirements are split into three categories of occupational tasks as defined by Dorn and Autor from the 1977 Directory of Occupational Titles data: manual intensity which encompass tasks such as lifting and other manual labor, abstract intensity which include communication, planning and more complex thinking tasks, and finally routine intensity which is a measure of how repetitive one's tasks are[10]. Preliminary empirical evidence indicates that greater time is required to learn abstract and communicative skills versus manual and routine skills. This greater time will translate to slower rates of wage assimilation in occupations that are highly abstract. This skill differential has been demonstrated in previous literature by Ottaviano and Peri[2] and Peri and Sparber[3] showing that natives hold a comparative advantage in communication intensive occupations, and immigrants in more manually intensive occupations. This research takes this concept in a different direction considering instead how these comparative advantages and task differentials contribute to the assimilation rate of migrants rather than the impact upon natives.

Borjas[1] demonstrates how the wages of immigrants grow over time due to a variety of factors, this research focuses upon the economic assimilation rate of immigrants represented by α_1 and α_2 in Borjas' empirical model shown below in equation (2). In Borjas' model the left side takes values for log wages for individual *i* at time *T*, on the right side *Ii* acts an indicator variable for if someone is an immigrant or not, θ_T takes various socioeconomic home country characteristics defined by Borjas, *Yi* takes values for years since migration or the number of years an immigrant has been living in the United States, and finally C_i takes the cohort (birth year) of immigrants to control for the change in quality of immigrants over time.

$$lnw_{iT} = X_i\theta_T + \delta I_i + \alpha_1 I_i Y_i + \alpha_2 I_i Y_i^2 + \beta_1 I_i C_i + \beta_2 I_i C_i^2 + v_i \quad (2)$$

This paper expands upon Borjas' empirical model by looking at occupational factors in the US (manual, abstract, and routine task intensity) as opposed to home country factors that influence assimilation rate (X_i)[1]. This is accomplished by splitting the dataset by detailed oc1990dd groups defined by Dorn and Autor into seventeen categories then comparing assimilation rate (α_1) against measures of manual, abstract and routine task intensity to demonstrate how these occupational factors influence assimilation[10].

2. Empirical Methods

To show how assimilation rates differ across occupations influenced by task intensity, the two-stage estimation method proposed in by Borjas is utilized[1]. In the first stage, assimilation rate is estimated separately by occupation groups O_{1-17} using the following regression (3): (Results shown in Figure 3)

$$ln(w_{it}) = \beta_0 + \beta_1 I_i + \beta_2 Y_i + \beta_3 I_i Y_i 0_{1-17} + \beta_4 I_i Y_i^2 O_{1-17} + \beta_5 I_i C_i + \beta_6 I_i C_i^2 + X_{iT} + \varepsilon \quad (3)$$

The left side of the regression measures log wages for individual *i* at time *t*. On the right side of the regression I_i is a dummy variable for whether an individual is an immigrant or native-born taking a value of 1 for immigrant and 0 for native, this is important for isolating the effects of immigrants from natives. The occupation-specific assimilation rate is β_3 identified by running the estimated equation (3) separately for each detailed occupation group 1-17. β_4 represents how assimilation rate for each detailed occupation group changes over time. This regression additionally contains controls for cohort effects using C_i , I also include a squared version of this control to control for how cohort quality changes over time. Y_i takes values for years since migration, this is used in the determination of assimilation rate given by β_3. X_{it} captures other various control variables including year, sex, race, age, and educational variables. β_3 is the yearly rate of assimilation for occupation groups 1-17 and β_4 shows how this yearly assimilation rate changes over time, as immigrants assimilate into the economy it is expected that their rate of assimilation will decrease over time. These estimations show significant differences among assimilation rate across occupations. β_3 is then used in the second regression, regressed against the mean manual intensity, abstract intensity and routine intensity to evaluate how the assimilation rate of each OCC group is influenced by the manual, abstract, and routine and communicative intensity.

In the second stage, the objective is to identify job characteristics that predict the cross-occupation heterogeneity of assimilation rates, by regressing the occupation-specific assimilation rate on task intensity measures. A positive result for manual (α_1) and routine (α_2) intensities supports the hypothesis of a faster rate of assimilation for manually intensive occupations whereas a negative result would indicate the opposite.

$$AssimRate(\beta_3)_{1-17} = \beta_0 + \alpha_1 M_{1-17} + \alpha_2 A_{1-17} + \alpha_3 R_{1-17} + \epsilon_i \quad (4)$$

The assimilation rate measure on the left side of this equation comes from β_3 of equation (3). On the right side the main variables of interest are α_1 and $\alpha_3$which will demonstrate by occupation how the measures of manual task intensity (M_{1-17}) and routine task intensity (R_{1-17}) influence occupational assimilation rate. These values are expected to be positive due to the greater transferability and ease of learning manual and routine tasks. A_{1-17} gives a measure of the impact of abstract task intensity on assimilation rate but is expected to have a negligible or negative impact on assimilation rate.

4. Data

The data used in the empirical section is the 5% IPUMS census sample from 1980 to 2000 and the ACS surveys from 2000 to 2017[12].This switch to the ACS allows for more detailed year to year data as the survey is conducted yearly as opposed to the once per decade Census. The 5% sample is used to maintain statistical significance when splitting the data into smaller universal OCC groups, in particular for OCC groups C1, D1, and D2 (housekeeping/cleaning jobs, farm managers, and farm labor) due to their smaller relative populations. The dataset is restricted to natives and immigrants of primary working age, 18-65. Additionally, child immigrants (those that migrate before the age of 18), who likely have skills more similar to natives than their fellow immigrants, are excluded. The dataset is additionally restricted to those actively within the labor force excluding "discouraged" and "marginally attached" workers. The job task data set used for determining the task intensities for each detailed occ1990dd group was assembled by Autor and Dorn (2013). This dataset uses information from the US Dictionary of Occupational Titles which provides measures as determined by industry professionals on the manual, abstract, and routine task intensity of occ1990dd census occupation codes. In order to get these universal occ1990dd codes this research uses crosswalk files provided by Dorn and Autor which make conversions from each census year's OCC code to the universal occ1990dd code allowing for intertemporal comparisons of occupations and occupational task intensities[10].

For the stage 1 and 2 regressions occupations are grouped into seventeen occupational groups listed below:
A1 Executive, Administrative, and Managerial Occupations, A.2 Management Related Occupations, A.3 Professional Specialty Occupations, B.1 Technicians and Related Support Occupations, B.2 Sales Occupations, B.3 Administrative Support Occupations, C.1 Housekeeping and Cleaning Occupations, C.2 Protective Service Occupations, C.3 Other Service Occupations, D.1 Farm Operators and Managers, D.2 Other Agricultural and Related Occupations, E.1 Mechanics and Repairers, E.2 Construction Trades, E.3 Extractive Occupations, E.4 Precision Production Occupations, F.1 Machine Operators, Assemblers, and Inspectors, and F.2 Transportation and Material Moving Occupations.

5. Results

Figure 3 below shows the assimilation rate of immigrants by occupation group (β_3) in column 1, beneath each assimilation rate value is the two tailed P value indicating that these assimilation rates are statistically significant. Column 2 provides values showing how these assimilation rates over time from equation 1 (β_4) a negative value indicates that the wages of immigrants increase at a decreasing rate. In column 3 is the immigrant indicator variable (β_1)this gives a measure of the general wage penalty suffered by immigrants as compared to natives, interestingly occ1990dd groups C.3, C.1, and D.1 see a wage boost for immigrants, possibly due to decreased demand amongst natives for these occupations or due to the comparative advantage immigrants hold in these occupations.

OCC GROUP	ASSIMILATION RATE	CHANGE IN ASSIMILATION RATE OVER TIME	IMMIGRANT	YEARS OF EDUCATION	YEAR	AGE	SEX	COHORT EFFECT	R2
A.1	0.0059928 (0.000)	-0.000127 (0.000)	-0.0214424 (0.014)	0.1091735 (0.000)	0.0358457 (0.000)	0.0196671 (0.000)	X	X	0.4046
A.2	0.0138241 (0.000)	-0.0002378 (0.000)	-0.168041 (0.000)	0.1024212 (0.000)	0.0336363 (0.000)	0.0158816 (0.000)	X	X	0.3517
A.3	0.0244228 (0.000)	-0.0004448 (0.000)	-0.2295749 (0.000)	0.1291362 (0.000)	0.0330388 (0.000)	0.0218352 (0.000)	X	X	0.3583
B.1	0.0326522 (0.000)	-0.0005058 (0.000)	-0.3285592 (0.000)	0.0949319 (0.000)	0.0326522 (0.000)	0.0236489 (0.000)	X	X	0.4217
B.2	0.0131697 (0.000)	-0.000302 (0.000)	-0.1167609 (0.000)	0.1330192 (0.000)	0.0269688 (0.000)	0.0308914 (0.000)	X	X	0.3692
B.3	0.0184845 (0.000)	-0.0003367 (0.000)	-0.2021831 (0.000)	0.0647214 (0.000)	0.0285958 (0.000)	0.0247151 (0.000)	X	X	0.3223
C.1	0.0061541 (0.000)	-0.0002949 (0.000)	0.304787 (0.000)	0.02631 (0.000)	0.0347522 (0.000)	0.016694 (0.000)	X	X	0.2682
C.2	0.0330931 (0.000)	-0.0005145 (0.000)	-0.5242118 (0.000)	0.1262047 (0.000)	0.0289941 (0.000)	0.02483 (0.000)	X	X	0.3492
C.3	0.0104811 (0.000)	-0.0003409 (0.000)	0.1335399 (0.000)	0.0537046 (0.000)	0.0278765 (0.000)	0.0269107 (0.000)	X	X	0.2473
D.1	0.0290514 (0.000)	-0.0005338 (0.000)	-0.1335034 (0.027)	0.070982 (0.000)	0.0351267 (0.000)	0.0137327 (0.000)	X	X	0.2287
D.2	0.0161061 (0.000)	-0.0005098 (0.000)	0.1154282 (0.000)	0.0514929 (0.000)	0.03363 (0.000)	0.0219257 (0.000)	X	X	0.2949
E.1	0.0184575 (0.000)	-0.0003784 (0.000)	-0.1166411 (0.000)	0.0649931 (0.000)	0.0272072 (0.000)	0.0189552 (0.000)	X	X	0.3093
E.2	0.0189108 (0.000)	-0.000421 (0.000)	-0.0432014 (0.000)	0.060035 (0.000)	0.0266624 (0.000)	0.0174851 (0.000)	X	X	0.2317
E.3	0.0256285 (0.000)	-0.0005103 (0.000)	-0.2723983 (0.001)	0.0586885 (0.000)	0.0343573 (0.000)	0.0158544 (0.000)	X	X	0.3562
E.4	0.0196972 (0.000)	-0.0003912 (0.000)	-0.2050448 (0.000)	0.0608211 (0.000)	0.0289577 (0.000)	0.0184602 (0.000)	X	X	0.372
F.1	0.0232501 (0.000)	-0.0004958 (0.000)	-0.2312765 (0.000)	0.0488457 (0.000)	0.0284295 (0.000)	0.0191002 (0.000)	X	X	0.3638
F.2	0.0185804 (0.000)	-0.0004265 (0.000)	-0.1001144 (0.000)	0.0459076 (0.000)	0.0234896 (0.000)	0.026802 (0.000)	X	X	0.274

Figure 3. Results of first stage regression.

	MANUAL INTENSITY	ABSTRACT INTENSITY	ROUTINE INTENSITY
ASSIMILATION RATE	0.2775	-0.1052	0.3931
SIGNIFICANCE LEVEL	(0.2809)	(0.6878)	(0.1186)

Figure 4. Correlation using equation (5)

Figure 4 shows the correlation between manual, abstract, and routine intensities correlated with assimilation rate for each occupational group (1-17) weighted by the number of individuals in each occupation. This is calculated using the equation (5) where the correlation coefficient shown in row 1 of figure 4 is $\hat{p}$:

$$\hat{p} = \frac{\sum_{i=1}^{n} w_i(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=I}^{n} w_i(x_i - \bar{x})^2}\sqrt{\sum_{i=I}^{n} w_i(y_i - \bar{y})^2}} \tag{5}$$

This provides a measure of how each value of task intensity tends to move in relation to assimilation rate. A positive value for manual intensity indicates that the more manually intensive an occupation is the higher the assimilation rate would be whereas a negative coefficient would indicate that the more manually intensive an occupation is the slower the assimilation would be.

It can be seen from Figure 3 that the occupation with the highest rate of assimilation is C.2 (Protective services Occupations) lines up with our prediction of occupations with higher manual intensities having higher assimilation rates. Looking at the values of Figure 3 for occupation C.2, a value of 0.0330931 means that each year an immigrant in occupation C.2 will catch up to the wages of natives by 3.3% associated with their economic assimilation into the US economy. The value in column 2 of -0.0005145 means that every year this assimilation wage growth slows by .0515%. These values are small but statistically significant, and there are many other factors that can contribute to an immigrant's ability to catch up to the wages of natives faster, including education, and age.

Figure 4 shows that while not statistically significant, there is a positive correlation between assimilation rate and both manual and routine intensities. It also demonstrates a slight negative correlation between assimilation rate and abstract intensity which is consistent with previous literature stating that immigrants have a comparative advantage in more manually intensive tasks as compared to abstract ones.

Figure 5 shows the regression results from stage 2 of the two-stage regression proposed earlier, while also statistically insignificant due to small sample size (17 observations), this regression supports the findings of the correlation in Figure 4 demonstrating the positive relationship between assimilation rate and both manual and routine intensity and the negative relationship between assimilation rate and abstract intensity.

	MANUAL INTENSITY	MANUAL INTENSITY	ROUTINE INTENSITY
COEFFICIENT	0.0039395	0.0009997	0.0012336
P	(0.121)	(0.369)	(0.272)

Figure 5. Results of second stage regression

This trend can be seen in Figure 6 below showing a scatter plot of manual intensity correlated with assimilation rate by occupation. The horizontal axis is manual intensity and the vertical axis is the assimilation rate from the first stage regression. This scatter plot is then weighted by sample size shown by the size of the circle as estimates from a larger sample are more precisely estimated and should be weighted more.

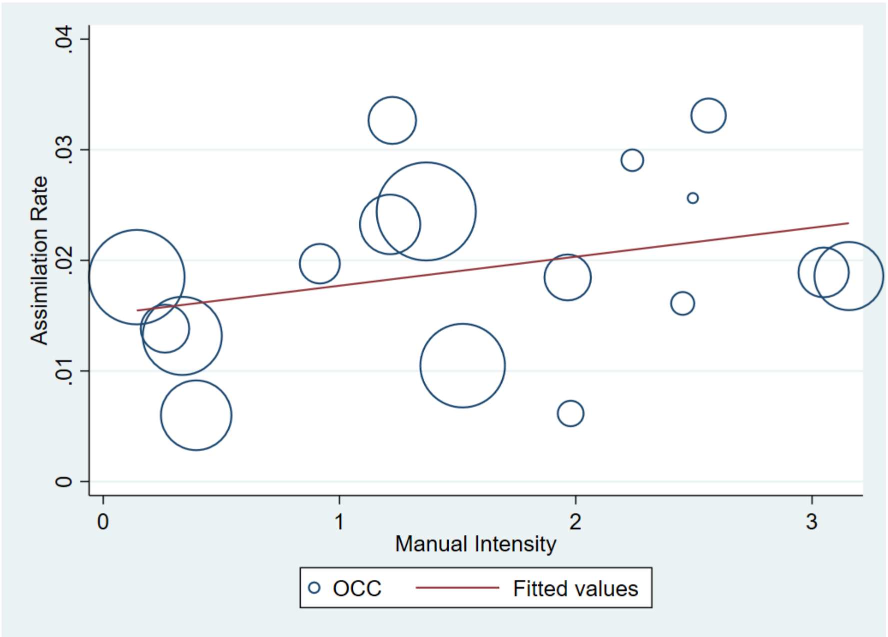

Figure 6. Weighted scatter of relationship between assimilation rate and occupational manual intensity

Figure 7 below shows this positive trend between routine intensity and assimilation rate also weighted by sample size due to greater accuracy of estimates.

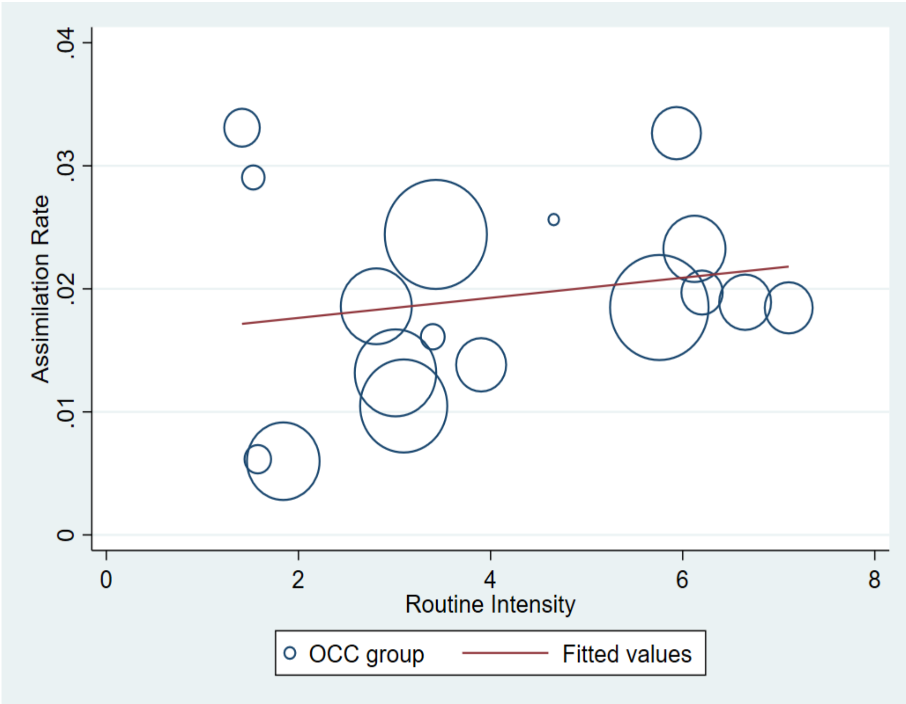

Figure 7. Weighted scatter of relationship between assimilation rate and occupational routine intensity

6. Conclusion

Through the use of a two-stage regression on the assimilation rate of immigrants as split by occupation group OCC A.1 - F.2 and comparison against the mean task intensities of these occupations derived from DOT data. This paper demonstrates statistically significant heterogeneity of assimilation rates across the seventeen occupational groups previously defined. This is useful for immigrants determining what occupations they should seek if desiring the fastest route to wage parity with natives the data suggests that jobs within OCC category C.2 (Protective Service Occupations) is the fastest route. Additionally, while stage two demonstrates no statistically significant results in equation (4) or the correlation preformed using equation (5) , it indicates a positive correlation between an immigrant's assimilation rate and the manual intensity of their occupation of 0.2775, and a positive correlation between assimilation rate and routine intensity of 0.3931 while demonstrating a small negative to negligible correlation between an immigrant's abstract intensity and assimilation rate. This reinforces the findings of previous literature by demonstrating real world effects of an immigrant's comparative advantages held in manually intensive tasks on their wages and assimilation rate. The major shortcomings of this paper come from the small sample size (17) for the second stage regression. This results in a lack of statistical significance and a somewhat weak trend between manual intensity and assimilation rate, this could be improved upon by splitting occupations into smaller groups or running each occupation individually to provide a more detailed view.

7. References

1. Borjas, George. "Self-Selection and the Earnings of Immigrants." *The American Economic Review* 77, no. 4 (September 1987): 531–53. https://doi.org/10.3386/w2248.

2. Ottaviano, Gianmarco I.p., and Giovanni Peri. "Rethinking the Effects of Immigration on Wages." *National Bureau of Economic Research*, no. 12497 (August 2006). https://doi.org/10.3386/w12497

3. Peri, Giovanni, and Chad Sparber. "Task Specialization, Comparative Advantages, and the Effects of Immigration on Wages." *National Bureau of Economic Research*, no. 13389 (September 2007). https://doi.org/10.3386/w13389.

4. Autor, David, Frank Levy, and Richard Murnane. “The Skill Content of Recent Technological Change: An Empirical Exploration.” *Quarterly Journal of Economics*, (November 2003). https://doi.org/10.3386/w8337.
5. Mincer, Jacob. “Investment in Human Capital and Personal Income Distribution.” *Journal of Political Economy* 66, no. 4 (1958): 281–302. https://doi.org/10.1086/258055.
6. Borjas, George J. “The Economic Analysis of Immigration.” *Handbook of Labor Economics*, 1999, 1697–1760. https://doi.org/10.1016/s1573-4463(99)03009-6.
7. Fessler, Pam, and Joel Rose. “Trump Administration Rule Would Penalize Immigrants For Needing Benefits.” NPR. NPR, August 12, 2019. https://www.npr.org/2019/08/12/748328652/trump-administration-rule-would-penalize-immigrants-for-using-benefits.
8. US Department of Homeland Security. *Inadmissibility on Public Charge Grounds.* Washington, DC: August 14, 2019. CFR 103,8 CFR 212 to 214,8 CFR 248. Accessed December 2, 2019.
9. https://www.regulations.gov/docket?D=USCIS-2010-0012
10. David Autor and David Dorn. "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market." *American Economic Review*, 103(5), 1553-1597, 2013.
11. Chiswick, Barry R. “The Effect of Americanization on the Earnings of Foreign-Born Men.” Journal of Political Economy 86, no. 5 (1978): 897–921. https://doi.org/10.1086/260717.
12. Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.2 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D020.V7.2