Wage Change of Immigrants to the United States: A Human Capital Approach

by

Xu Zhu

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Professor William Easterly
Professor Marti Subrahmanyam
Professor Jens Hougaard
Professor Christina Wang
Professor Ye Jin

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Abstract

This research analyzes the wage change of the immigrants before and after the immigration, through the lens of human capital. Using the New Immigrants Survey (NIS), I am able to attain comprehensive individual level information. More specifically, I found that some critical aspects of human capital, education and language proficiency, survive the shock of changing labor market. These factors have deterministic effects on the wage, after controlling for countries of origin, and previous income. On the other hand, health, as well as interactions between the three features do not have a significant effect on the income. Moreover, I found that the income increase appears in both periods: from before immigration to right after immigration, and from right after immigration to several years after immigration. The result suggests that human capital is transferable in the form of certain features that are recognized across borders and labor markets, and the cause for the change is sustained over time. Given the nature of the NIS, I have applied several preprocessing methods and employed additional datasets that are merged respectively.

Contents

List of Figures

List of Tables

1 Introduction

Immigration has been a central part of the discourse in development accounting. As people move from one country to another, they most likely retain their personal traits. Using immigrants as samples, economists were able to separate the human part from the capital part in a production model (Hendricks and Schoellman 2017). In other words, immigration provides a natural experiment for cross-country income variation. However, one limitation of this approach is that the skills of the immigrants may not be perfectly transferable from one country to another. There may be issues such as loss of qualification as well as language barriers. This would downwardly bias the share of human capital in wage differences. Moreover, it is possible that some skills or features are less transferable than others so some jobs are less impacted by immigration. Additionally, immigrants generally have better jobs after their first job in the new country (Akresh 2008).

In this research, I will look into the effect of skill loss and regain among immigrants to the United States. Based on the human capital model, I would analyze three main determinants of human capital: education, cognitive abilities, and health (Caselli 2016) and how they affect the wage change before immigration, right after immigration, and several years afterward. To better fit into the context of immigration, I will also take into consideration factors such as English proficiency, type of immigration visa, and income of their home country. They may affect the transfer or regaining of the skills. Are some of these aspects more robust towards skill loss? How do they impact the wage recovery process? New Immigrant Survey (NIS hereafter) provides many variables that encapsulate the different aspects of human capital. I will use both NIS 2003-1, which interviewed a cohort of immigrants right after they gained legal permanent resident status in 2003 and 2004, and NIS 2003-2, a follow-up interview in 2007. This set of data provides the income of the respondents at various points of time, before and after immigration, as well as an extensive set of background variables, such as years of schooling, frequency of English usage, and self-evaluated health condition.

Schooling is an aspect of the human capital that is commonly tested. As we are looking at the immigrants, we could also analyze the differences between schooling in the US and abroad. Would skill loss be more significant for immigrants with higher or lower educational attainment? Can attaining education in the US allow immigrants to regain or gain new skills that place them in a better job? English education can be another factor to consider. Do immigrants that have better English suffer a smaller wage decrease and a higher wage overall? NIS not only asks the respondent about their overall English level but also specific instances where they use English (e.g. Do you speak English with friends/at home/at work?). I can determine which of these instances has the strongest impact on the wage rebound of immigrants. Additionally, I can test the interaction between education and English proficiency on wage changes after immigration.

Immigrants from different countries also display different wage decreases; immigrants from richer countries display a smaller wage decrease when they first arrived in the US (Hendricks and Schoellman 2017). I aim to further this discourse and analyze the wage of immigrants from different countries several years after their immigration.

Many researches on human capital look into the health of the workers. In traditional human capital accounting literature, researchers use pooled metrics such as adult survival rate (Weil

2007Campbell and Üngör 2020). In this case, I use more specific personal level information as NIS includes an entire section dedicated to the health of the immigrants. There are also self-reported perceptions on their own health. In most cases, the health situation does not change significantly over the 5 years period between the first and the second interview. Therefore we could test the effect of health on skill loss and regain of immigration. So far, there has not yet been any research that looks into the causality between health and immigrants income.

Admittedly, the cause behind the change of income of the immigrants is complex and involves many aspects beyond their own features. One notable cause is the change of physical capital. In fact, immigrants are frequently used as a measure of constant human capital to measure the proportion of physical capital. As immigrants move from one country to another, the physical stock change while human capital remains constant. However, the model that I consider include country specific terms for each of the aspects that measure human capital. Therefore, the wage difference pre-immigration and post-immigration pertains multiple aspects of between country differences. Additionally, I evaluate the income of the immigrants at two different points after immigration, providing an opportunity to difference out the market change effect. More specifically, by comparing and contrasting the income right after immigration and several years after immigration, I am able to find the effect of human capital features on income change after migration.

In this research, I am going to empirically examine the causes for wage changes after immigration. Based on the human capital model, I would analyze three main determinants of human capital: education, cognitive abilities, and health (Caselli 2016) and how they affect the wage change before immigration, right after immigration, and several years afterward. To better fit into the context of immigration, I will also take into consideration factors such as English proficiency, type of immigration visa, and income of their home country. They may affect the transfer or regaining of the skills. Are some of these aspects more robust towards skill loss? How do they impact the wage recovery process? New Immigrant Survey (NIS hereafter) provides many variables that encapsulate the different aspects of human capital. I will use both NIS 2003-1, which interviewed a cohort of immigrants right after they gained legal permanent resident status in 2003 and 2004, and NIS 2003-2, a follow-up interview in 2007. This set of data provides the income of the respondents at various points of time, before and after immigration, as well as an extensive set of background variables, such as years of schooling, frequency of English usage, and self-evaluated health condition. I assume that while all three of the human capital determinants (health, years of schooling, language proficiency) are affected by the skill loss, years of schooling would have the largest impact on both the wage loss and regain. Specifically, I will test two hypotheses: 1. Language proficiency augments the effect of Years of Schooling and health and their interactions are significant predictors for income and income change after immigration. 2. Health has a stronger impact on the income of immigrants working a lower-paying job. My findings suggest that while education and years of schooling has a persistent and positive effect on the wage of the immigrants, the effect of health is inconclusive, and the interactions between the three variables also do not exhibit a deterministic trend.

2 | Model

I consider a human capital model similar to the one used by Cacelli (2016):

$$h_{it} = \exp(\beta_{sit}s_{it} + \beta_{pit}p_{it} + \beta_{lit}l_{it}) \tag{2.1}$$

Where i is for each individual, t is for each time period (t=0 for pre-immigration, t=1 for the survey right after immigration, and t=2 for the second round of survey). h is a measure of human capital. s measures years of schooling, p measures health, and l measures language proficiency.

A "Mincerian" transformation of this model yields:

$$\log(w_{it}) = \beta_{sit}s_{it} + \beta_{hit}h_{it} + \beta_{lit}l_{it} \tag{2.2}$$

Where w represents wage at a given time for a certain individual. Given the dataset, this model can yield testable results via regression analysis. There are several notable differences between this model and the model used by Cacelli. First of all, I replaced the metric for cognitive skills with a measure of language proficiency. Secondly, I consider time-variant and individual data points instead of country-level data without a temporal dimension. Both of the changes reflect differences between the data and research motivation. Despite the wide range of metrics, NIS does not collect data that can demonstrate aptitude (such as PISA), and for immigrants, it is intuitive to consider their language proficiency to have an impact on their income. NIS provides extensive income data of the immigrants at different time points, and therefore we can compare the immigrants vertically, considering their economic outcome in different environments, as well as wage changes after immigration.

Given our sample of new immigrants that have jobs at all three points in time, I noticed that their attributes featured in this research do not change significantly. I have left out immigrants that have received education after immigration. Language proficiency may have more significant changes after immigration. However, due to lack of observation, I have not included a time-variant measurement of language proficiency.

Therefore, the fully specified model that I run tests with is as follows:

$$\log(w_{it}) = \alpha + \beta_h h_{i1} + \beta_s s_{i1} + \beta_l l_{i1} + \beta_{sl1} s_{i1} l_{i1} + \beta_{hl1} h_{i1} l_{i1} + \delta Z_{i1} + \epsilon_{it} \tag{2.3}$$

Where w_{it} is the income/occupation at a given period t (t=0 for pre-immigration, t=1 for the survey right after immigration, and t=2 for the second round of survey. h_{i1} indicates health of the immigrant at immigration. s_{i1} measures the years of schooling of the immigrant. l_{i1} measures the language proficiency of the immigrant.

I have also included interaction terms between language and schooling as well as health and language. This initial assumption is that if language impacts the job acquisition process, then the other human capital features will be impacted by the skills of communication, as reflected through the use of language, in this case English. My tests do not show a conclusive result on the effects of these interaction variables.

3 Data

3.1 Health

NIS includes a section dedicated to health with a wide array of self-reported variables on overall health condition, chronic diseases, and habits that could affect health. Following the precedent of major literature on health economics, I will focus on the health aspects that impact labor output. Different from the previous literature is the availability of individual level health data compared to national-level, pooled data, more specific aspects of health, as well as stronger exogenous assumption. As the immigrants' health is predetermined before their immigration, we can rule out the reverse causality between health and income. *health1* indicator will be the self-reported response to the question: Would you say your health is excellent, very good, good, fair, or poor? Answers 1-5 corresponds to excellent to poor. For each sample point, I summed the response to get a measure of their overall activity condition and flipped the term from one to five so that the higher the measure goes, the better the health is.

health1 captures the entirety of health, thus does not accurately represents the part of health that is directly related to work performance. Additionally, the respondents may not report their conditions accurately due to the vagueness of the question. However, given the extremely unbalanced nature of other indicators, I can only use *health1* to measure immigrant health.

3.2 Language Proficiency

Many immigrants to the United States do not speak English as their first language. This may affect their job-seeking process. Skilled works typically would require more interactions and thus demand better English. Therefore, those who speak poor English but have a background in a high-paying job before immigration may sustain the largest wage drop. I assume speaking and listening have stronger impact on finding jobs. NIS asked the respondents to not only report their language proficiency but also ask them about their time spent using English outside of work. I use two types of measurement for language proficiency. *lang1* is the aggregate of the response to the two questions: How well would you say you understand English when someone is speaking to you? and How well would you say you speak English? (NIS 2003). I flipped the measurement, similar to the treatment of the health indicator. The second measure *lang2* uses the survey's questions on DVD watching, movie going, TV watching, radio listening, and newspaper reading in English. Since the respondents were randomly assigned into 5 groups and asked one of the five questions related, I normalized the responses into a scale from 1-5 with 5 being the most frequent and 1 being least frequent. My findings suggest that *lang1* generated more robust results compared to *lang2*.

3.3 Income and Profession

The dependent variable of this research is a value that measures the income and occupation of the immigrants. Since the research involve income of the same individuals in different countries, there are several ways of measuring income, each with different implications. Directly measuring wage allows us to use the measurement for cross-country human capital comparison. NIS reports income in a wide range of ways. For pre-immigration income, I use the PPP-adjusted income in USD provided by NIS-2. Using the amount and interval, I adjusted the income to a

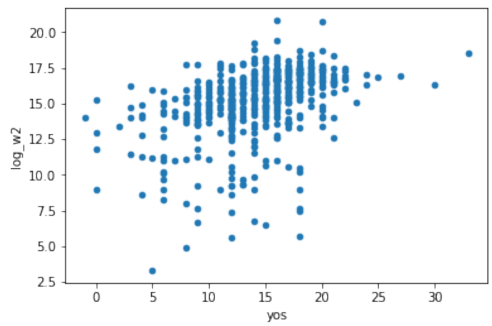

Figure 1: Years of Schooling and Income Distribution in Round 2

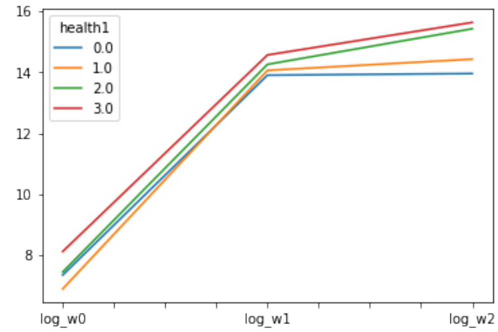

Figure 2: Health Indicator and Income Change from Pre-immigration to Round 2

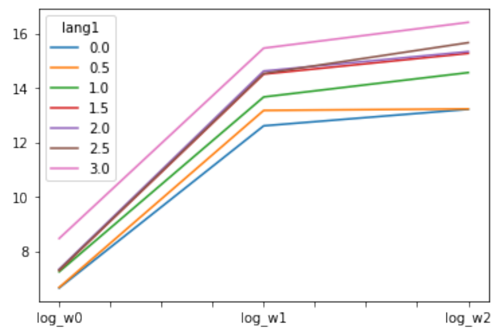

Figure 3: English Proficiency Indicator and Income Change from Pre-immigration to Round 2

per-week basis. This measurement allows us to see how distinct personal features either benefit/harm the immigrants their income. I use post-immigration weekly income in R1 and R2 as is. An alternative Akresh 2008 uses that focuses instead on occupational change is measuring the prestige of occupations as NIS provides information on the occupation of immigrants pre- and post-immigration. This measure omits income changes within the same broad industry and within the same job. Instead, occupation measurement focuses on job-skill mismatch that causes immigrants to suffer from sub-optimal job condition.

3.4 Control Variables

One advantage of using an immigration dataset is the relative lack of endogeneity issues, particularly in terms of reverse causality. The inclusion of control variables serves to mitigate potentially omitted variables. To better predict the model, I also include control variables for their home country, income at $t-1$ or $t-2$, as well as their age.

Country-level variance of income is widely studied (Hendricks and Schoellman 2017, Lagakos et al. 2012, Weil 2007) with different variables and controlling for different factors. In this research, as my focus is on individual human-capital features, I control the country effects. I used two methods to control for the home countries of the immigrants. Similar to Hendricks and Schoellman (2017), who worked on the same dataset, I divided the origin countries of the immigrants by their PPP-adjusted GDP per capita from PWT 7.1 in 2003 into five groups according to their ratio to that of the US.

An additional demographic control I consider is the concept of "Anglosphere." Nakagawa (2018) discusses the imperfect skill transfer among immigrants from non-Anglosphere countries to Anglosphere countries. The effect of language may be proxying for the cultural effect of Anglosphere, as America is considered as a part of this cultural region. My results show that the control does not perturb the results.

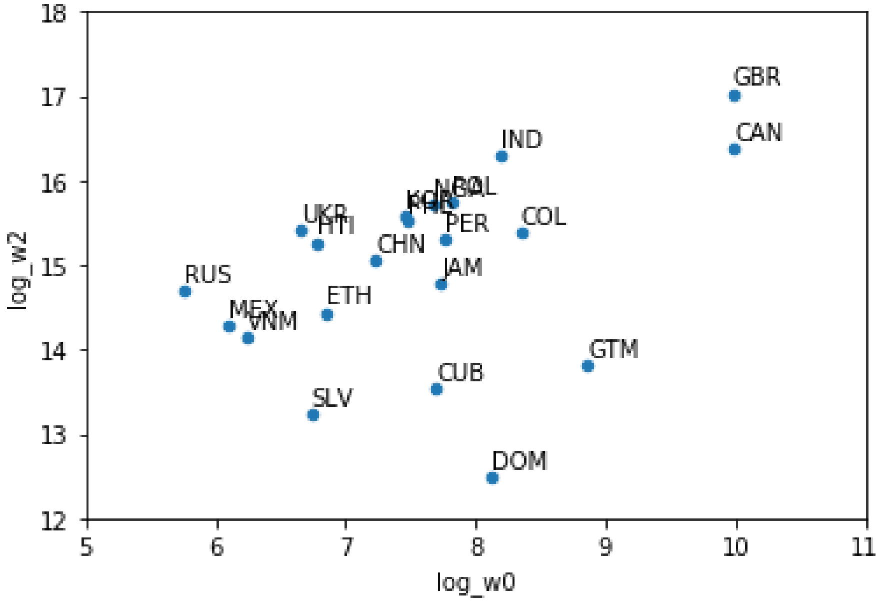

Figure 4: Log Wage at Round 2 Compared to Log Pre-Immigration Wage for Each Country

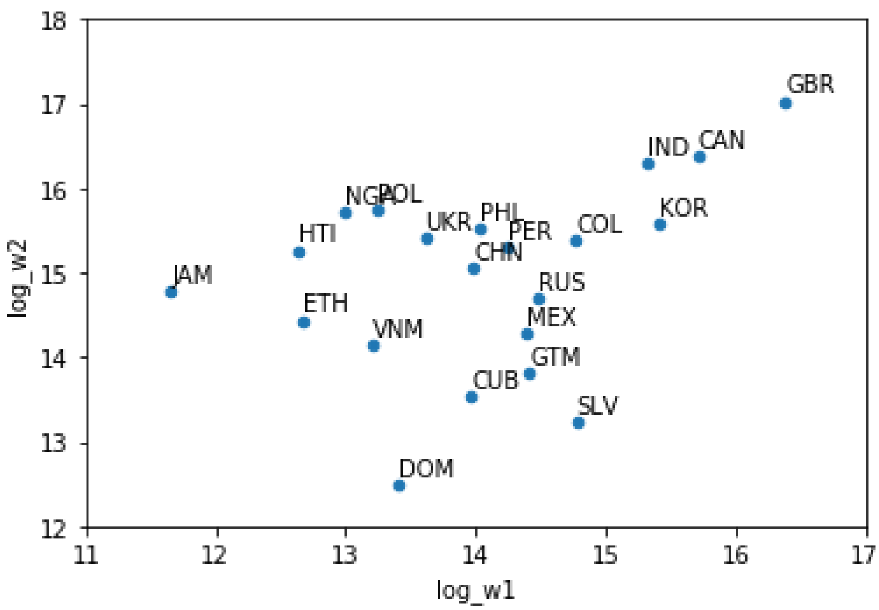

Figure 5: Log Wage at Round 2 Compared to Log Wage at Round 1 for Each Country

4 Result and Robustness Check

4.1 Result

As per my pre-analysis plan, I conducted the following regression tests:

Dependent Variables:					
	log(w2) - log(w1)	log(w2) - log(w0)	log(w1) - log(w0)	log(w2) - log(w1)	log(w2) - log(w1)
age	-0.032***	-0.036**	-0.004	-0.028**	-0.031***
	(0.012)	(0.015)	(0.015)	(0.011)	(0.012)
const	1.609**	9.547***	8.049***	2.351**	0.982
	(0.758)	(0.933)	(0.912)	(1.068)	(0.770)
countrygroup	-0.080	-0.348**	-0.257*	-0.149	-0.128
	(0.125)	(0.157)	(0.154)	(0.124)	(0.126)
health1	0.355**	-0.346**	-0.691***	-0.001	0.296**
	(0.139)	(0.175)	(0.172)	(0.256)	(0.129)
health1*lang1	0.077	-0.056	-0.132*		
	(0.064)	(0.082)	(0.080)		
health1*lang2				0.098	
				(0.077)	
lang1	0.454**	0.493*	0.038		-0.066
	(0.228)	(0.289)	(0.283)		(0.074)
lang2				-0.408*	-0.031
				(0.248)	(0.074)
logw0	-0.025			-0.032	-0.029
	(0.042)			(0.042)	(0.043)
yos	0.010	0.039	0.031	0.001	0.058*
	(0.034)	(0.042)	(0.041)	(0.057)	(0.031)
yos*lang1	-0.048***	-0.010	0.038**		
	(0.013)	(0.017)	(0.017)		
yos*lang2				0.014	
				(0.016)	
Observations	540	540	540	540	540
R^2	0.063	0.051	0.053	0.044	0.040
Adjusted R^2	0.049	0.039	0.041	0.030	0.028
Residual Std. Error	2.594(df = 531)	3.291(df = 532)	3.217(df = 532)	2.620(df = 531)	2.623(df = 532)
F Statistic	4.495*** (df = 8.0; 531.0)	4.112*** (df = 7.0; 532.0)	4.262*** (df = 7.0; 532.0)	3.085*** (df = 8.0; 531.0)	3.193*** (df = 7.0; 532.0)
Note:	*p<0.1; **p<0.05; ***p<0.01				

Table 1: Table of Regression Results

The results do not exhibit a robust correlation between the dependent variables and the main indicators. While *health1* appears to be consistently robust, further testing suggest that this maybe a result due to high collinarity between this term and its interaction term with *lang1* ($corr_{health1,health1*lang1} = 0.28$). To further test the model, I performed further tests with a modification on the dependent variables. In these tests in Table 1, the dependent variables are the differences between log wages at an earlier point. This approach implicates an assumption that the difference between the income in the two periods are one-to-one. I relieve the assumption in additional tests. The additional tests suggest that this implied assumption may not be valid, and as such, I will base on the unrestrained models for interpretation.

Dependent Variables:				
	log(w2)	log(w1)	log(w2)	log(w1)
age	-0.025***	0.008	-0.025***	0.006
	(0.009)	(0.009)	(0.009)	(0.009)
const	11.987***	12.235***	11.828***	12.823***
	(0.782)	(0.578)	(0.765)	(0.552)
countrygroup	0.066	0.164*	0.052	0.205**
	(0.095)	(0.096)	(0.095)	(0.096)
health1	0.113	-0.297***	0.129	-0.205**
	(0.107)	(0.106)	(0.097)	(0.099)
health1*lang1	-0.018	-0.114**		
	(0.050)	(0.049)		
lang1	0.418**	-0.040	0.225***	0.335***
	(0.174)	(0.174)	(0.057)	(0.056)
logw0		0.052		0.054*
		(0.032)		(0.033)
logw1	0.159***		0.152***	
	(0.043)		(0.043)	
yos	0.124***	0.133***	0.138***	0.090***
	(0.026)	(0.026)	(0.023)	(0.023)
yos*lang1	-0.011	0.044***		
	(0.011)	(0.010)		
Observations	540	540	540	540
R^2	0.281	0.224	0.279	0.193
Adjusted R^2	0.270	0.212	0.271	0.184
Residual Std. Error	1.987(df = 531)	1.978(df = 531)	1.986(df = 533)	2.013(df = 533)
F Statistic	25.953*** (df = 8.0; 531.0)	19.179*** (df = 8.0; 531.0)	34.400*** (df = 6.0; 533.0)	21.278*** (df = 6.0; 533.0)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 2: Table of Additional Tests

Dependent Variables:											
	log(w2)	log(w2)	log(w2)	log(w2)	log(w2)	log(w2)	log(w1)	log(w2)	log(w1)	log(w2)	log(w1)
age	-0.024***	-0.025***	-0.025***	-0.025***	-0.024***	-0.025***	0.003	-0.025***	0.006	0.004	-0.025***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
const	12.190***	12.592***	12.287***	12.556***	12.200***	11.000***	8.470***	10.887***	11.383***	7.574***	11.013***
	(0.712)	(0.534)	(0.840)	(0.532)	(0.712)	(0.908)	(0.829)	(0.709)	(0.535)	(0.950)	(1.006)
countrygroup	0.084	0.075									
	(0.097)	(0.096)									
health1	0.205	0.090	0.093	0.092	0.203	0.131	-0.183*	0.131	-0.201**	-0.175*	0.131
	(0.186)	(0.099)	(0.099)	(0.099)	(0.186)	(0.097)	(0.098)	(0.097)	(0.100)	(0.098)	(0.098)
health1*lang1	-0.074				-0.071						
	(0.100)				(0.100)						
inanglosphere										-0.840*	0.013
										(0.439)	(0.438)
lang1	0.827**	0.549***	0.566***	0.565***	0.808**	0.457***	0.726***	0.459***	0.713***	0.786***	0.456***
	(0.353)	(0.111)	(0.109)	(0.109)	(0.352)	(0.112)	(0.108)	(0.112)	(0.110)	(0.112)	(0.118)
logcgdp			0.025			-0.012	0.265***			0.324***	-0.013
			(0.059)			(0.059)	(0.058)			(0.066)	(0.068)
logw0	0.027	0.026	0.029	0.030	0.031		0.046		0.065**	0.054*	
	(0.033)	(0.032)	(0.032)	(0.032)	(0.032)		(0.032)		(0.032)	(0.032)	
logw1						0.156***		0.154***			0.156***
						(0.043)		(0.042)			(0.043)
yos	0.161***	0.150***	0.150***	0.150***	0.158***	0.138***	0.084***	0.138***	0.091***	0.084***	0.138***
	(0.039)	(0.023)	(0.023)	(0.023)	(0.039)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)
yos*lang1	-0.009				-0.007						
	(0.021)				(0.021)						
Observations	540	540	540	540	540	540	540	540	540	540	540
R^2	0.264	0.263	0.262	0.262	0.263	0.279	0.217	0.279	0.186	0.222	0.279
Adjusted R^2	0.253	0.255	0.254	0.255	0.253	0.271	0.208	0.272	0.179	0.212	0.269
Residual Std. Error	2.010(df = 531)	2.008(df = 533)	2.009(df = 533)	2.007(df = 534)	2.010(df = 532)	1.986(df = 533)	1.984(df = 533)	1.984(df = 534)	2.020(df = 534)	1.979(df = 532)	1.988(df = 532)
F Statistic	23.814*** (df = 8.0; 531.0)	31.685*** (df = 6.0; 533.0)	31.586*** (df = 6.0; 533.0)	37.928*** (df = 5.0; 534.0)	27.123*** (df = 7.0; 532.0)	34.339*** (df = 6.0; 533.0)	24.584*** (df = 6.0; 533.0)	41.273*** (df = 5.0; 534.0)	24.471*** (df = 5.0; 534.0)	21.700*** (df = 7.0; 532.0)	29.378*** (df = 7.0; 532.0)
Note:	*p<0.1; **p<0.05; ***p<0.01										

Table 3: Table of Additional Tests (con't)

The additional tests suggest a much more robust landscape for the human capital features. Both language and years of schooling appear to have a positive and statistically significant effect on the income, regardless of the control variables. Interaction effects, however, do not seem to be of significant effects. Insofar as this sample is concerned, I observe no consistent health effects on the income at $t = 2$. Rather unexpectedly, health has a consistent negative effect on the income at $t = 1$. In terms of the control, I have experimented with several different setups. The first attempt is categorizing the origin countries of the expatriates into different income groups by their GDP per capita. The second one is using the per capita GDP of each country as is. This approach offers more variance in the control variables, thus stronger controlling effect. Under either control, the results are robust.

4.2 Robustness Checks

In terms of internal validity, we need to consider the different experiments with income at each period separately, as the driving force of wage changes may be different. Between $t = 0$ to $t = 1$, the immigrants moved, and found a new job in the new country and labor market. Consider the standard production function per worker and recall the human capital measure I use:

$$y_{it} = \frac{K_{it}}{Y_{it}} * A_{it} * h_{it}$$

$$h_{it} = \exp(\beta_{sit} s_{it} + \beta_{pit} p_{it} + \beta_{lit} l_{it})$$

The coefficient β is likely different for different labor markets. The most intuitive example would be that English language proficiency would naturally be a critical trait in a English-speaking labor market, and much less in a labor market with a different *lingua franca*. Thus, as the immigrants move from one country to another, it is unsure whether the difference can be attributed to the difference of Total Factor Productivity, or the difference between capital expense ratio, or different preference for a certain human capital feature. However, all three of the differences would not be correlated with individual level human capital features. One feature that is omitted and could be correlated with the human capital features is experience accumulated through working at a job or a certain labor market. Akresh (2008) and Lagakos *et al.* (2012) have both discussed the effect of experience on income among immigrants. However, it is likely that age would contain the effect of experience, as proxied by years of working. Moreover, Lagakos *et al.* (2012) observed that the work experience acquired from wealthier countries would be more effective on wage gains. Therefore by including a country-level income control, I have also mitigated the potential of omitted variable bias from working experience. As for $t = 2$, the income difference is not driven by the change of job market, and instead by the change on individual level. One concern may be that since the two periods have a difference of three years, the features themselves may change upwards over time. These changes may be positively correlated with their current levels, causing a misalignment in the interpretation of the effects of the variables. Given the availability of the data, I am unable to rule out such possibilities, or to include a time-variant term for the features. Given the relatively short time-span, I would argue that it is unlikely for any of the features to change significantly.

5 | Discussion and Conclusion

From the research, we can conclude that education and language proficiency, as a part of the human capital, positively impact the income of the immigrants. Previous researches have leveraged immigration data to determine cross-country differences in terms of human capital percentage and efficiency (Hendricks and Schoellman 2017, Lagakos et al. 2012) Other researches use cross-country labor data (Caselli 2016, Campbell and Üngör 2020) with a "disassembled" human capital measurement. It remains unanswered how the human capital transfer across border. More specifically, what parts of it are transferable, and what is not. This research allows us to find that education and language proficiency survive immigration and change of labor market, whereas health does not.

I observe increase in income across the board. On average, the income rise by 2.5 times. Notably, the income increase after immigration is more significant, suggesting that either that human capital features are marred by poor job searching experience as an immigrant. Frijters, Shields, and Price (2005) observe that in the UK job market, immigrants suffer from less optimal job searches compared to the natives. More importantly, they mark the trend that chance of successful job searches increase as the years after immigration increase. This would explain the wage increase from $t = 1$ to $t = 2$. Moreover, since my model does not directly consider the job search factors (although language skills might be positively correlated with job search successes), it is likely that $t = 2$ presents a more accurate image of the magnitude of the human capital impact.

From $t = 0$ to $t = 1$, the positive effect on income from the human capital features suggests

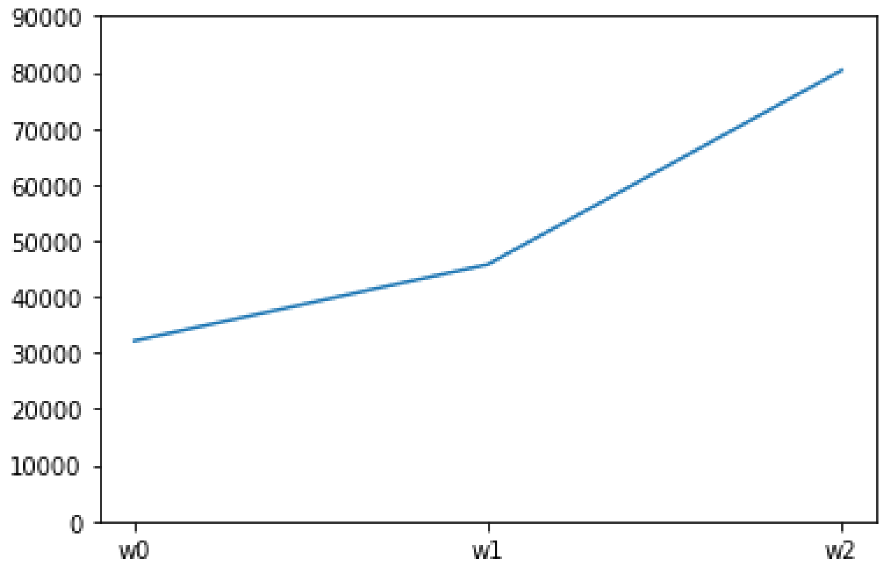

Figure 6: Average Wage in all Three Periods

several possibilities. For one, higher language proficiency and more years of schooling can make an individual more adaptive and suffers less shock from immigration. An alternative scenario is that these two features could potentially be correlated with the visa type, and that subsequently affects wage, in particular right after immigration. From $t = 0$ to $t = 2$ and $t = 1$ to $t = 2$ regression tests, we can infer that since the effect persists over time, it is more likely that regardless of visa types, the human capital matters to career development of immigrants.

$t = 1$ to $t = 2$ tells a similar story. Education and language can also facilitate wage growth in the relative long term. This may be either caused by faster experience gains during work, or faster recovery from the initial shock and mismatched jobs. The second possibility is similar to the cause of wage increase from $t = 0$ to $t = 1$, whereas the first one is different. To differentiate these among immigrants requires an analysis on the type of job/industry they are working at $t = 0, 1, 2$. Akresh (2008) has performed said analysis, and her research suggests that a downward trend of occupation does exist, and it rebounds afterwards. This does not mean that only one effect is in play here, nor does she suggest that this may be different for those that are educated better or have higher English proficiency. In fact, research on experience acquisition shows workers in general acquire wage-enhancing skills, and it is hard to imagine that immigrants are exception in it.

Admittedly, some features do not exhibit statistically significant effects, contrary to my hypotheses. While it may suffice to say that hypotheses are often misaligned, it is also important to consider why some of them do not exhibit the expected trends. This research cannot bring forth a conclusive reason why I cannot reject the null hypothesis that health does not have an effect on the income post-migration. One possibility is that all of the immigrants in NIS are legal immigrants, and they would be more likely to work at a job that is less physically demanding. Another possibility is that the health measure, based on self-response, may not be perfectly accurate. A person who feels unhealthy may not be actually unhealthy, and vice versa. Lastly, while my research concerns workers on an individual level, Weil (2007) measures income and health difference on a national level. The aggregate health effect may have a positive effect, compared to individual level. For instance, a healthier population in general could boost the country's Total Factor Productivity, or that having colleagues with better health can boost the efficiency of the working space. For the interaction effects, the inconclusive results may be caused by the high collinearity. Alternatively, this may also suggest that the language effect may not "augment" the effect of other features of human capital, and instead affects wage in an independent manner. That is to say, good communication does not may the work more monetarily appreciated, and conversely, bad communication does not may good work less valuable. It is unsure whether this is a particular effect among immigrants, or non-native speakers in the workforce. This result calls for future research on the effect of language and communication in human capital accounting.

Additionally, the incoming-gaining human features of the immigrants (good education and good language skills) is consistent with the human capital features of stationary workers. The variables are modeled off that of Caselli (2016), who analyzes inter-country income differences with local workers. They appear to be of the trend. However, this research will be agnostic about the extents to which the human capital features matter to the immigrants compared to the domestic workers. Such comparisons would call for immigrant and non-immigrant data collected with the same methodology, and the sampling also has to be consistent. American Community Survey or Decennial Census are good candidates for such comparisons. However, they are not as comprehensive in the collection of pre-immigration information. Comparison of human capital effects on immigrants and locals presents an interesting research direction to pursue.

In general, my research presents a composite view on how human capital impacts the income of the immigrants, using a human capital model. By applying a typically country-level model to individuals, I found that some of the features (schooling and language proficiency) have a robust and strong impact on wage, while health does not. Further researches have to be conducted to determine whether this is a matter with the data, or it is a recurrent trend. By focusing on the divergent features of the immigrants themselves, instead of using them as an instrument of constant human capital, I can better understand how human capital is broken down, and what specific aspects affect income.

Bibliography

Akresh, Ilana R. (2008). "Occupational Trajectories of Legal US Immigrants: Downgrading and Recovery." In: *Population and Development Review* 34.3, pp. 435–456. DOI: 10.1111/j.1728-4457.2008.00231.x..

Campbell, Susanna G. and Murat Üngör (2020). "Revisiting Human Capital and Aggregate Income Differences." In: *Economic Modelling* 91, pp. 43–64. DOI: 2020.05.016..

Caselli, Francesco (2016). "Accounting for Cross-Country Income Differences." In: DOI: 10.1596/26105..

Frijters, Paul, Michael A. Shields, and Stephen Wheatley Price (Nov. 2005). "Job Search Methods and their Success: A Comparison of Immigrants and Natives in the UK". In: *The Economic Journal* 115.507, F359–F376. ISSN: 0013-0133. DOI: 10.1111/j.1468-0297.2005.01040.x. eprint: https://academic.oup.com/ej/article-pdf/115/507/F359/26502832/ejf359.pdf. URL: https://doi.org/10.1111/j.1468-0297.2005.01040.x.

Hendricks, Lutz and Todd Schoellman (2017). "Human Capital and Development Accounting: New Evidence from Wage Gains at Migration." In: *The Quarterly Journal of Economics* 133.2, pp. 665–700. DOI: 10.1093/qje/qjx047.

Lagakos, David et al. (2012). "Experience Matters: Human Capital and Development Accounting." In: *NBER Working Paper*. DOI: 10.3386/w18602.

Nakagawa, Mariko (2018). "Skill Transference and International Migration: A theoretical analysis on skilled migration to the Anglosphere." In: *The Research Institute of Economy, Trade and Industry*.

Weil, David N. (2007). "Accounting for the Effect of Health on Economic Growth." In: *The Quarterly Journal of Economics* 122.3, pp. 1265–1306. DOI: 10.3386/w11455.