HOW DOES INFLUX OF IMMIGRANTS AFFECT NATIVE-BORN WAGES

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Abstract

This paper examines how the influx in immigrants impacts the native-born average hourly-wage. This was done by using the data set from Current Population Survey (CPS). I seek to see the effect of immigrant inflow on native wages by dividing the immigrants into newly-arrived immigrants and assimilated immigrants. This paper uses a cross-sectional survey data set across 121 MSA, 50 states and one year (2017). Using Ordinary least Squared (OLS) analysis, I built an initial understanding between influx of immigrants and native-born average hourly-wage. The study found an interesting sets of results. The newly-arrived immigrants had no statistical effect on native-born average hourly-wages whereas the assimilated immigrants had a negative effect on native-born hourly wage at 90% significant level. Theoretically this result is justified as an immigrant gets assimilated over time he/she become more substitutable to the native-born worker. When the three occupational groups (professional, service-related and manual labor) are included in the analysis the study finds a statistically significant effect on native-born average hourly-wages due to professional occupation. Thus, implying that high-skilled immigrants helps expand economy which in turn increases native wages. The results suggests a negative effect on native-born average hourly-wages due to manual labor. This parameter estimate supports the theory however was statistically insignificant. One-way fixed effect was used to see the difference in average hourly-wage across metro areas and states. The fixed effect result suggests that there is no effect on native-born average hourly-wage and influx on immigrants. However, the results do imply that presence of a high-skilled immigrant will increase the native wages by 2.23%. Overall, this study could be further enhanced with a 2-Staged Least Squared (2-SLS) model. Further, future studies could examine the effect on native-born average hourly-wages due to influx of immigrants over certain number of years.

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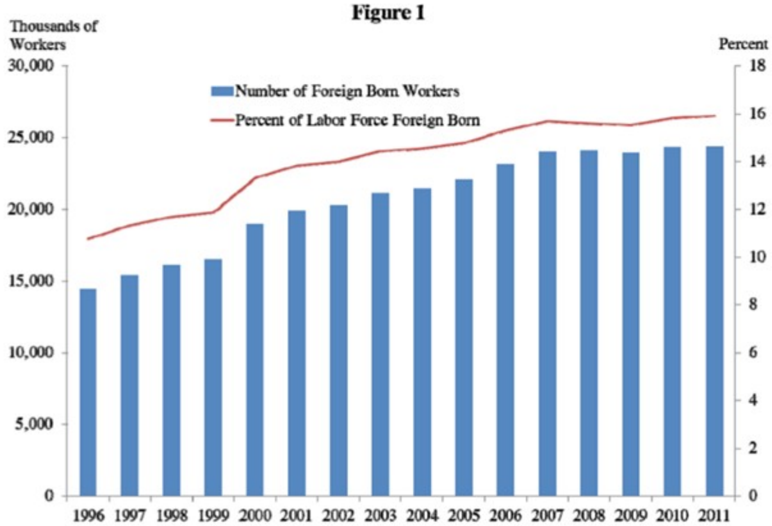
I. Introduction

Immigration has accounted for about 51% of total labor force growth in the United States from 1996 to 2011 (Orrenious & Zavodny, 2013). The United States is home to 91% of the world's immigrants (Orrenious & Zavodny, 2013). However, this influx of immigrants has been disproportionately larger in certain regions such as the Midwest and Southwest, where they accounted for about 66% of the labor force growth from 1996-2003 (Orrenious & Zavodny, 2013). While some believe that immigration has a detrimental impact on labor market outcomes of American born workers, others suggest that immigration boosts the US economy, enhances productivity, spurs innovation, helps consumers by keeping prices low, enhances US society, and increases the diversity of cultures. Immigrants have also been disproportionately concentrated in both ends of the skill level distribution, concentrated in both low skilled occupations (manual labor) and high skilled occupations (professionals) *(see figure 1)*. The increasing amount of immigrants and their concentration in certain regions and occupations ignites the question would an increase in the number of immigrants have an effect on the wages of native-born Americans?

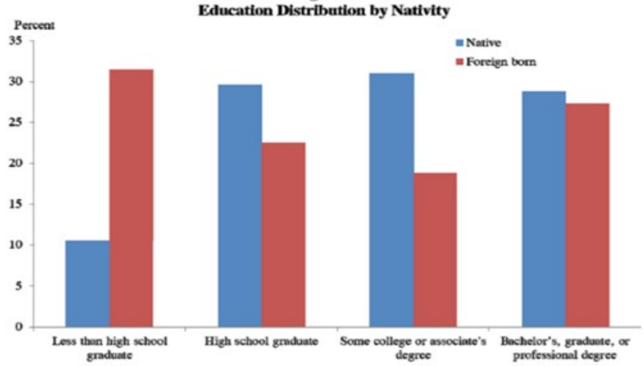
This paper will try to address this question by looking at the effect on native-born American's average hourly-wages by using the data on immigration inflows and natives average hourly-wages within three occupational groups. This research paper will replicate Pia & Zavodny (2007) study on immigration and its effect on natives wages. They conduct their research by looking at the amount of immigrant inflow in a given area by comparing it to the native-born American individual's average wage in that given area. This is a cross-section approach used in order to control for the unobserved variable as opposed to conducting it for one-year they do it for seven years (1994-2000). My goal will be to update the research by looking at 2017 data at MSA level and running a one-way fixed effect analysis across states.

Figure 1



Source: Bureau of Labor Statistics

Figure 2
Education Distribution by Nativity



Source: 2011 American Community Survey

II. <u>Literature Review</u>

"Does immigration affect wages? A look at occupation-level evidence" (Orrenius & Zavodny 2007) estimates the effect of immigration on native wages by three occupational groups (professionals, service-related & manual labor) at a metropolitan area level. They take occupation as a proxy to see its effect on skill level and regress the average earnings of natives in an occupational group. The variable *I* (Immigrant) is interacted with an indicator variable, occupational group, in order to allow the effect of immigration across different skill categories. Data used in the paper primarily comes from Current Population Survey (CPS) and is then merged with data from Immigration & Naturalization Service (INS). The INS data provides novelty to this study as it allows the author to distinguish between newly arrived immigrants and assimilated immigrants. It also helps construct the instrumental variable, immigrants, who are admitted in a given year as the spouse of an US citizen. Moreover, the authors use several years (1994-2004) of data whereas most previous literature relied on a cross-sectional approach. The availability of a panel dataset helped this study to control for unobserved local area effects. After running the OLS and 2SLS methodology they concluded that there was a small-negative impact of newly arrived immigrants on the wages of low-skilled natives (5.2%). Whereas, a positive impact on wages of high-skilled natives suggests a complementary relationship between newly-arrived immigrants and high-skilled natives. However, assimilated immigrants had a more negative effect on native wages suggesting that as the immigrants assimilate more and their status changes over time, they become more supplementary to native workers.

Another paper that agrees with the complementary nature of skilled immigrants and natives is Islam & Ngugen (2017). Using both individual and state level data, the paper considers innovation in terms of patents. They run two different models: first, they estimate the contribution of skilled immigrants within a specific skill group, the innovative capacity of the group, and its effect on the wages. Second, they estimate the indirect effect of skilled immigrants on a state-level wage rate through their contribution to a state's innovation. They do this to see which model is more efficient in answering the research question. In both cases they find positive and statistically significant evidence that skilled immigrants contribute to innovation which in turn increases the wage. Although they suggest that the aggregate outlook (state-level) is not very effective.

Basso & Perri (2015) also looks at the causal relation between immigration and labor market outcomes. They use the same methodology as Pia & Zavodny (2007), using data from 1970-2010 at a state level instead of the MSA level. Basso & Perri use the same 2SLS methodology with a cross-section approach but instead of occupation level they use education attainment. Their results are also similar to the previous two results. However, they suggest that using a Constant Elasticity of Substitution (CES) production function is more efficient to measure the effect of immigrants and natives wages. This second method allows them to estimate the impact of immigration on native wages by directly deriving the elasticity of substitution between immigrants and natives. This method was used by both Ottaviono & Peri (2008) and Peri & Spraber (2009). Ottaviono & Perri find that immigrants and native-born individuals are imperfect substitutes because they have different skills. When we consider the adjustment of physical capital, it shows that there is a positive effect on native wages in both the short and long run. On the contrary, Peri & Sparber conclude that immigration actually reduces the wages of native workers by 0.3% from 1990-2000. Both these papers believe that immigration policy plays a significantly large role in measuring the impact of immigration on wages. Therefore, I will be replicating the research study done by Pia & Zavodny (2007) and will look at the effect on average hourly-wages of natives due to assimilated immigrants and newly-arrived immigrants in the year 2017 by MSA.

III. Theoretical Model

My theory for the research question comes from "Labor Market Equilibrium." Labor Economics, by George J. Borjas, McGraw-Hill/Irwin, 2010. The simplest model of immigration assumes that immigrants and natives are perfect substitutes with the capital held fixed in a short -run. In this model, immigration shifts out the supply curve thus resulting in the native wage falling (see figure 3). In a sense, immigrants "take away" jobs from natives by reducing wage and convincing them that it is not worthwhile to work. However, the perfect substitute assumption in the short-run is ambiguous as the two types of workers may not be competing for the same jobs. For example: immigrants may be better fit for labor intensive jobs, freeing up the skilled native work force which was previously employed in labor intensive jobs. Hence, the presence of immigrants will increase native productivity by inducing specialization, making immigrants and native workers complements. Therefore, in the short-run the complementary relation between immigrants and natives shifts the demand curve for labor to the right, leading to a wage increase. (see figure 4)

In the long-run the effect of immigration can be differentiated from the short-run (see Fig. 3 & 4)

Figure 3

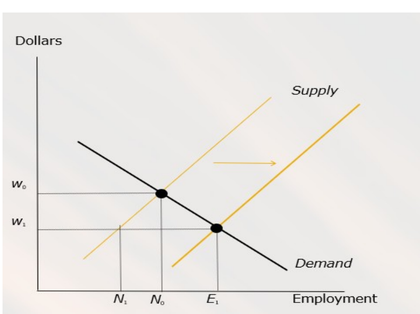
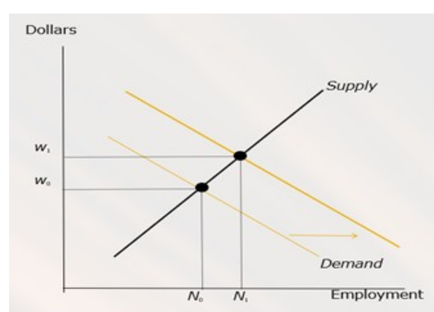


Figure 4



Suppose that immigrants and natives are perfect substitutes. In the short-run, addition of immigrants will lower the wage but increase the returns on capital by allowing the employers to hire workers at a lower wage. Over time, this increase in capital stock will shift the demand curve for labor to the right and compensate for the negative impact of initial labor supply shock. The magnitude of this demand curve shift can make the initial negative wage effect of immigration disappear (see figure 5). The extent which the labor demand curve shifts depends on the technology component in the production function. The production function of the receiving country can be defined by the Cobb-Douglas production function *(Eq.1)*

$$q = A k^{\propto} * L^{1-\propto} \qquad (A = \text{constant},\ 0 < \alpha < 1) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Equation 1}$$

$$r = \propto A\left(\frac{K}{L}\right)^{1-\propto} \quad w = (1-\propto) * A\left(\frac{K}{L}\right)^{\propto} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{Equation 2}$$

Note, the Cobb-Douglas production function has the property of constant returns to scale. The theory of factor demand in a competitive labor market implies that the price of capital and wage is given by marginal product of capital and labor. The short-run effect of immigration is simply that increase in the number of workers in the economy will decrease the wages. (*See Eq 1 and 2).* Over time, the higher rate of capital will increase the size of capital. Let's say in long-run after all the capital adjustments the capital falls back to its normal level. This implies that the capital is fixed in the long-run at the value *r.* However, The only way rate of capital can be fixed is if the ratio of K/L is also fixed in the long-run (*See Eq 1 and 2)*. This theoretical insight has very important implication for the labor market impact of immigration in the long-run. Consider if the Capital-Labor (K/L) ratio is constant than the wage also must be constant in the long run. This illustrates the previous point that immigration lowers the wage initially, but due to the capital and labor mix it will bring the economy back to where it was, having the same rate of return to capital and wage rate.

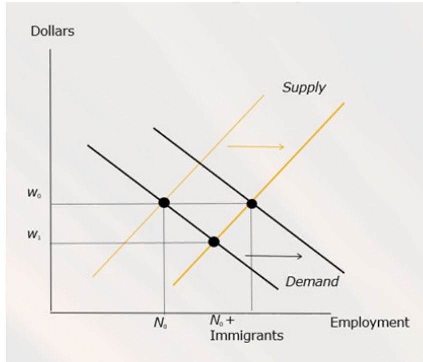


Figure 5

The key takeaway being that the immigration will have an adverse impact on wage to competing native workers, but in the long-run this adverse effect will weaken as the economy adjusts to an influx of immigrants. Thus the testable hypothesis being, that the influx of immigrants will decreases native wages.

IV. <u>Data & Empirical Model</u>

Insight for my data comes from the study done by Pia & Zavodny (2007). In order to see wage effect on natives I obtained my data from Current Population Survey (CPS) and Annual Social and Economic supplement (ASEC, secondary data set under CPS). I used a simple Ordinary Least Square (OLS) model and a one-way fixed effect model to estimate the effect on native hourly-wages by an influx of immigrants.

This study looks at the MSA level with a focus on one year, 2017. Using data from Current Population Survey (CPS) I created the two sets of immigrants (*Assimilated* and *New*). Individual hourly wage by MSA was gathered from CPS (ASEC). The dependent variable was created by averaging individual hourly-wage of native (16-64 years old) by occupational group by MSA, divided by total population in an MSA. The interest independent variables will include immigrants, which will be divided into newly-arrived immigrants and assimilated immigrants by occupational group by MSA. The use occupation as a proxy will allow us to see the effect of immigration by skill level. The occupation group is divided into 3 groups, professional (executives, doctors etc), service-related (electrical work, service worker) and manual labor (farm worker) by MSA. Education is also divided into 2 groups (high school and some college).

To examine the effect on average hourly wages of natives due to immigrants this study uses two models, OLS and one-way fixed effect models. This study uses one-way fixed effect model to see the difference in average hourly-wages due to immigrants across metro areas and states since only one year of data was used it is called a cross-sectional dataset. Usually fixed effect model works with area (i) and year (t) but because only one year was used in this data set dummy variables were created for 50 states (j) in order to see the effect across metro areas and states. It should be noted that the variables included in the study could create a certain degree of multicollinearity. However, these variables are appropriate to include considering that the previous literatures have also included similar variables.

OLS Model:

$$Lnwage = \beta_0 + \beta_1 new_{immigr_i} + \beta_2 Assimil_{immigr_i} + \beta_3 Professional_{Occ_i} + \beta_4 ServiceRelated_{Occ_i} + \beta_5 ManualLabor_{Occ_i} + \beta_6$$

Fixed Effect Model:

$$Lnwage_{ij} = \beta_0 + \beta_1 new_{immigr_{ij}} + \beta_2 Assimil_{immigr_{ij}} + \beta_3 Professional_{occ_{ij}} + \beta_4 ServiceRelated_{Occ_{ij}} + \beta_5 ManualLabor_{Occ_{ij}} +$$

Where:

Lnwage is the dependent variable in the empirical model which measures the aggregate hourly-wage of all the native individuals in a given MSA. The log of hourly wage is used because hourly-wage is highly skewed and taking log normalizes the data.

New_immigr measures the average number of newly-arrived legal immigrants that are present in a given MSA. This variable was created by accounting for the nativity of an individual as well as the amount of years that induvial has been living in the United States. According to Pia & Zavodny (2007) occupations and areas experiencing larger inflows of immigrants relative to the total number of workers in that occupation and area should experience a larger decline in wages and the magnitude of decline depends on how suitable immigrants are for other workers. Thus, the expected coefficient should have a negative effect on native hourly-wages.

Assimil_immigr measures the average number of assimilated immigrants that are present in a given MSA. This variable was created by accounting for the nativity of an individual that are present in a given MSA who have been living in United States for five or more years. Five years is used as a threshold because according to the US immigration policy it is likely for an immigrant to be a naturalized citizen in five years. The expected coefficient for this variable should be negative because as an immigrant starts to assimilate, they become more of a substitute to a native worker.

Professional_Occ, ServiceRelated_Occ & ManualLabor_Occ measure the skill level of an immigrant. These variables are important because they help to see how different skill levels affect native hourly wages. The variables were created after categorizing professional occupations (teachers, executive, doctors etc.), service related occupations (clerks, assistants etc.) and manual labor occupation (janitors, plumbers etc.). Professional occupation will have a positive relationship to native-wages as high-skilled immigrants tend to expand the economy compared to low-skilled immigrants. Hence there should be a negative relationship of service-related and manual labor occupation with native wages.

Some_highschool and some_college measure the average number of immigrants who graduated high-school and college. These variables represent graduation from some high school and graduation from some college. These variable help to show the difference in impact on native – wages by an immigrant who is a high school graduate as to an immigrant who is a college graduate. There is a negative relationship between native wages and an immigrant graduating from some high school as pointed out earlier in several above literatures that low-skilled immigrants decrease native wages. The coefficient for *some_college* should have a positive relationship with native wages.

Age, Female & Ethnicity_Latino are taken as a control for the model who are native female and of Latino ethnicity. Age consists of individuals working from 16-64 years of age and should have a positive sign. Females represents the sex with an expected negative sign. The variable also accounts for the effect of Latino ethnicity on the native wages and should have a positive sign.

V. <u>Results</u>

In this study, a semi-log OLS and a one-way fixed effect model were used to analyze whether the influx in immigrants in an MSA decrease the hourly-wage of native-born Americans. The model observes 121 MSA's in the year 2017. The results of both models can be seen in Table 5 of the Appendix.

To develop an initial understanding of the relationship between immigrants and wages of native-born Americans, an OLS model was used. It should be noted that running an OLS possess issues such as omitted variable bias. It also possess an issue of multicollinearity. In order to check for possible multicollinearity, a correlation test among the variables was run, these results can be seen in Table 6. From the results we see no variables suffer a high level of correlation but there seems to be a minor correlation between *ethnicity_latino and Manual labor*. After running the OLS model, the results in Table 3 are produced, accounting for 121 observation with a F-value of 2.07 and R-squared of 0.199 (See Table 5). The R-squared signifies that the independent variables used in the model account for roughly 20% of variance in hourly-wage of native-born Americans. From the table we can see the following variables with their respective significance *level professional_occ (99%), Assimil_immigr (90%) and Age (90%).*

In terms of my interest variables *(newly-arrived immigrants & assimilated immigrants)* the result did not show the expected sign for newly-arrived immigrants as predicted by the theory and it was also not significant on any level. However for assimilated immigrants, the result did predict an expected negative correlation with 90% significance. This may be because the assimilated immigrants become perfect substitutes to the native-born after a certain point in time. Therefore, an increase in assimilated immigrants in an area would decrease native hourly wage by 0.65%. As predicted by several previous literatures, high-skilled immigrants tend to have a positive effect on native wages and low-skilled immigrants have a negative effect on native wages. We can see in the OLS result that immigrant who has professional occupation increases native hourly wage by 1.73%, and an immigrant who is in manual labor related occupation decreases native hourly wage by 0.07% these effects are small in magnitude when it comes to the practical significance. The positive parameter estimate on high school graduate, college graduate and Latino ethnicity individual contradicts the theory. As high school graduate and Latino ethnicity should have a negative effect on wages, an individual who is a high school graduate would only be eligible for low-skilled jobs. Also, Latino ethnicity individuals who have been living in the United States are like to go for low-skilled jobs as suggested by various literatures. Instead of having a negative parameter estimate on college graduate, theory suggests that the relationship should be positive as high-skilled immigrants expand the economy (Pia & Zovadny 2013). These signs could be due to the estimated results from the OLS regression being biased and inefficient. It is likely that the model does not control for unobservable heterogeneity across MSA.

To account for difference across states, the same model is run using one-way fixed effect. The results can be seen in Table 4. The model contained 121 cross section over 50 states. The output produced an F-value of 116.08 (see Table 5). The R-squared signifies that the variables used in the model account for 97.9% of variance in native hour-wage. As seen in table 6 *Age*, *Professional_Occ and Female* are 99%, 95% and 90% significant respectively. However my interest variables (*newly-arrived immigrants* and *Assimilated Immigrants*) in spite of having the right parameter estimate for assimilated immigrants, were not significant. Newly-arrived immigrants did not have the right parameter estimate nor was it significant.

Therefore even though we see that newly-arrived immigrants has a minute positive effect on average hourly-wage of 0.95%, in reality it should have a negative effect. As immigrants increase in a given area at a given time the labor supply increases which decreases the native wages in the short-run. Based on this analysis, we cannot confirm with any empirical evidence that this will be the effect. In terms of skill level and its impact on wages we do know that from the previous literature and the empirical evidence obtained from this study that immigrants do affect native wages significantly on the high and low spectrum of skill level. From the Table 4 it is evident that high-skilled immigrants increase native-wages by 2.23% and low-skilled immigrants decrease native-wages by 0.003% which is negligible.

Looking at the control variables of native's who are female and of Latino ethnicity we do not see the predicted sign on the parameter estimate of *female*. The estimate implies that the presence of a female will increase native wages by 1.08%, but in reality it should decrease the native wages because again female entering the workforce will increase the labor supply which will decrease the average native wages. However, the predicted positive sign on Latino ethnicity is produced as based on theory, where the presence of a native Latino ethnic worker with increase the native wage by 0.74%. This can be justified by Borjas' theory, for example: The low-skilled immigrant workers who work at a construction site are most likely not fluent in English. Hence these set of workers require a native-born American as manager who is fluent in English. Therefore, increasing the wage of native-born. Some discrepancies in this model are due to omitted variable bias where not all aspects of immigrants are accounted for.

VI. Conclusion and Limitations

This study investigates the relationship between immigration and average native hourly-wage in United States, using a cross sectional survey from 121 MSA over a period of one year (2017). The results from OLS and one-way fixed effect suggest that there is no significant effect of newly- arrived immigrants. However we see that there is a minute yet significant negative effect on native-born average hourly-wages due to assimilated immigrants. Hence from the above analysis it is fair to assume that when new immigrants come to the United States there is no effect on native wages in the short term. However, as their time in United States increase we see small negative effect in long term. Some evidence from the early literature on the effect of native wages due to the skill level of immigrants are also seen. The above results are contrary to the results obtained in Pia & Zavodny (2007) there is a small and insignificant impact of low-skilled immigrants on native wages and a large and significant impact of high skilled immigrants on native-wages. These results can help restructure the immigration policies on United States by relaxing visa quotas on work-related immigrants and prioritizing them over visas given based on family ties. One cannot deny that economic benefits accrue from both high & low skilled immigration. High skilled immigration alleviates shortage and bottleneck in STEM occupation and provide positive fiscal impact as they pay more in taxes and consume less in publicly-provided services (Pia & Zavodny 2007). Immigration policies that promote more high skilled workers may slow outsourcing or off-shore production and attract more foreign investments.

Despite of this analysis there are some limitations to this study. First, it is difficult to accurately know the inflow of immigrants as there are several undocumented immigrants that enter the United States each year. Second, there is a high chance of heterogeneity as there are immigrant spouses that marry a Unites States citizen and these unobserved variable affect the hourly wage in an indirect manner which could be corrected by taking immigrant spouses who have converted to permanent visa from tourist visa as an instrument variable. Further just doing an analysis on one year does not provide expected significant results. Hence a study conducted over a certain number of years will provide with better understanding on how immigration will affect the native wages. Moreover I was not able to address this issue with 2SLS model as conducted by Pia & Zovadny (2007) due to the time constraint and the scenario of remote learning due to the COVID-19 pandemic. Running a 2SLS model would be a powerful econometric model as it is used in analysis of structural equation like this one. And is used when the dependent variable error terms are correlated with the independent variables. Therefore further research can be done which can account for correction of the above limitations and it would be interesting to conduct a research particularly pertaining to current situation as one would be able to observe an impact of immigration on native jobs post COVID-19 pandemic.

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VIII. Appendix

Table 1: Variable Definition and Source

Table 2: Descriptive Statistics

Varibale	N	Mean	Std Dev	Min	Max	Expected Signs
Lnwage	121	2.61	0.32	1.98	4.09	Dependent var
Hour_wage	121	14.49	0.07	7.25	60	Dependent var
New_immigr	121	0.017	0.049	0	1	-
Assimil_immigr	121	0.08	0.122	0	1	-
Professional_Occ	121	0.09	0.072	0	1	+
ServiceRelated_Occ	121	0.25	0.11	0	1	+
ManaulLabor_Occ	121	0.2	0.123	0	1	-
Age	121	40.14	3.707	16	64	+
Some_Highschool	121	0.31	0.131	0	1	-
Some_College	121	0.23	0.101	0	1	+
Female	121	0.53	0.095	0	1	-
Ethnicity_Latino	121	0.04	0.081	0	1	+

	Product of usual hours times usual hourly earnings. 999 being the maximum, $2358 per week, $150,000 a year	
New_Immigr	Dummy variable created for newly-arrived immigrant. Created using nativity & years of immigration.	CPS
Assimil_Immigr	Dummy created by using nativity and years of immigration. Foreign born lived in US for 5 or years	CPS
Professional_Occ	Dummy created by combining occupations like doctors, teachers, executives etc.	CPS
ServiceRelated_Occ	Dummy created by combining occupations like bank tellers, assistants etc	CPS
ManualLabor_Occ	Dummy created by combining occupations like janitors, construction worker etc	CPS
Age	Native-born individuals between age of 16 & 64	CPS
Some_Highschool	Immigrants with a high school degree	CPS
Some_College	Immigrants with a college degree	CPS
Female	Native born who are female in gender	CPS
Ethnicity_Latino	Native born with ethnicity- Latino	CPS

Table 3: OLS Regression Estimates

Variable	Parameter Estimate	Standard Error	t value	Pr > |t|
Intercept	2.9	4.91	7.57	<.0001
New_immigr	0.23	0.38	0.41	0.6842
Assimil_immigr	-0.65	0.56	-2.64	0.0094
Professional_Occ	1.73	0.24	3.26	0.0015
ServiceRelated_Occ	0.6	0.53	1.91	0.0594
ManaulLabor_Occ	-0.07	0.33	-0.23	0.8223
Age	-0.016	0.008	-2.01	0.0473
Some_highschool	0.27	0.26	1.07	0.2889
Some_College	-0.09	0.46	-0.2	0.8387
Female	0.04	0.31	0.15	0.8798
Ethnicity_Latino	0.4	0.43	0.93	0.3558

Table 4: Fixed Effect Estimates/NOINT				
Variable	**Parameter Estimate**	**Standard Error**	**t value**	**Pr > |t|**
Intercept	-	-	-	-
New_immigr	0.95	0.92	1.02	0.31
Assimil_immigr	-0.007	0.48	-0.02	0.9874
Professional_Occ	2.23	0.78	2.85	0.0058
ServiceRelated_Occ	0.4	0.48	0.84	0.4049
ManaulLabor_Occ	-0.003	0.54	0.01	0.9944
Age	0.02	0.008	3.68	0.0005
Some_highschool	0.41	0.399	1.04	0.3034
Some_College	0.49	0.71	0.69	0.4924
Female	1.08	0.41	2.62	0.00108
Ethnicity_Latino	0.74	0.78	0.95	0.345
Fixed Effects	Yes	Yes	Yes	Yes

Table 5: Native wages & Immigrants		
Model		
Variables	OLS	FIXED EFFECT
Intercept	2.9*** (7.57)	**NOINT**
New_immigr	0.23 (0.41)	0.95 (1.02)
Assimil_immigr	-0.65* (-2.64)	-0.007 (-0.02)
Professional_Occ	1.73*** (3.26)	2.23** (2.85)
ServiceRelated_Occ	0.6 (1.91)	0.4 (0.84)
ManaulLabor_Occ	-0.07 (-0.23)	-0.003 (0.01)
Age	-0.016 * (-2.01)	0.02*** (3.68)
Some_highschool	0.27 (1.07)	0.41 (1.04)
Some_College	-0.09 (-0.2)	0.49 (0.69)
Female	0.04 (0.15)	1.08* (2.62)
Ethnicity_Latino	0.4 (0.93)	0.74 (0.95)
N	121	121
R-Sq	0.19999	0.979
F-Value	2.07***	116.08***
T-values in the pranthesis. *,**,*** are the significance level for 90%,95% & 99% respectively.		

Table 6: Pearson Correlation Coefficients, N=121 Prob>|r| under H0: Rho= 0										
	New_immigr	**Assimil_immigr**	**Professional_Occ**	**ServiceRelated_Occ**	**ManaulLabor_Occ**	**Age**	**Some_highschool**	**Some_College**	**Female**	**Ethnicity_Latino**
New_immigr	1	0.18691 0.0037	0.05497 0.3966	0.05252 0.4179	-0.04351 0.5023	-0.08009 0.2163	-0.04752 0.4637	0.05166 0.4257	-0.06648 0.3051	0.03222 0.6194
Assimil_immigr	0.18691 0.0037	1	0.20693 0.0013	0.09855 0.1279	-0.00648 0.9204	-0.14011 0.0300	-0.26348 <.0001	-0.10406 0.1078	-0.20777 0.0012	0.17963 0.0053
Professional_Occ	0.05497 0.3966	0.20693 0.0013	1	-0.09412 0.1460	-0.21714 0.0007	-0.155 0.0163	-0.33731 <.0001	-0.08788 0.1748	-0.20235 0.0016	-0.03079 0.6350
ServiceRelated_Occ	0.05252 0.4179	0.09855 0.1279	-0.09412 0.1460	1	-0.46785 <.0001	0.06574 0.3154	-0.08032 0.2150	-0.05598 0.3879	0.20471 0.0014	-0.09746 0.1322
ManaulLabor_Occ	-0.04351 0.5023	-0.00648 0.9204	-0.21714 0.0007	-0.46785 <.0001	1	0.12921 0.0455	0.18577 0.0039	0.22456 0.005	-0.21073 0.001	0.50119 <.0001
Age	-0.08009 0.2163	-0.14011 0.0300	-0.155 0.0163	0.06574 0.3105	0.12921 0.0455	1	0.33979 <.0001	-0.07482 0.2482	0.00716 0.9121	-0.07987 0.2176
Some_highschool	-0.04752 0.4637	-0.26348 <.0001	-0.33731 <.0001	-0.08032 0.215	0.18577 0.0039	0.33979 <.0001	1	-0.41884 <.0001	0.1964 0.0022	-0.24101 0.0002
Some_College	0.05166 0.4257	-0.10406 0.1078	-0.08788 0.1748	-0.05598 0.3879	0.22456 0.0005	-0.07482 0.2482	-0.41884 <.0001	1	-0.09679 0.1349	0.28072 <.0001
Female	-0.06648 0.3051	-0.20777 0.0012	-0.20235 0.0016	0.20471 0.0014	-0.21073 0.001	0.00716 0.9121	0.1964 0.0022	-0.09679 0.1349	1	-0.18354 0.0043
Ethnicity_Latino	0.03222 0.6194	0.17963 0.0053	-0.03079 0.635	-0.09746 0.1322	0.50119 <.0001	-0.07987 0.2176	-0.24101 0.0002	0.28072 <.0001	-0.18354 0.0043	1

IX. SAS Codes

Codes pertaining to PROC MEANS and averaging the variables by MSA

```
/* libname from previous program */
data IPUMS.D2;
set IPUMS.cps_00007;

if SEX= 2 then Female= 1;
 else Female= 0;

if POPSTAT= 1 then Adult_Civilian= 1;
 else Adult_Civilian= 0;
if POPSTAT= 2 then Armed_Forces= 1;
 else Armed_Forces= 0;
if POPSTAT= 3 then Child= 1;
 else Child= 0;

if RACE= 100 then White= 1;
 else White= 0;
if RACE= 200 then Black= 1;
 else Black= 0;

if EDUC= 073 then Some_highschool= 1;
 else Some_highschool= 0;
if EDUC= 111 then some_college= 1;
 else some_college= 0;



if OCC2010= 0010|OCC2010= 0020|OCC2010= 0030|OCC2010= 0100|OCC2010= 0110|
OCC2010= 0120|OCC2010= 0130|OCC2010= 0140|OCC2010= 0150|OCC2010= 0160|OCC2010=
0205|OCC2010= 0220|OCC2010= 0230|OCC2010= 0300|OCC2010= 0310|OCC2010= 0330|
OCC2010= 0350|OCC2010= 0360|OCC2010= 0410|OCC2010= 0430|OCC2010= 0500|OCC2010=
0560|OCC2010= 0600|OCC2010= 0620|OCC2010= 0700|OCC2010= 0710|OCC2010= 0730|
OCC2010= 0800|OCC2010= 0810|OCC2010= 0820|OCC2010= 0830|OCC2010= 0840|OCC2010=
0850|OCC2010= 0900|OCC2010= 0910|OCC2010= 0940|OCC2010= 0950|OCC2010= 1000|
OCC2010= 1010|OCC2010= 1020|OCC2010= 1050|OCC2010= 1060|OCC2010= 1200|OCC2010=
1220|OCC2010= 1230|OCC2010= 1240|OCC2010= 1300|OCC2010= 1320|OCC2010= 1350|
OCC2010= 01360|OCC2010= 1400|OCC2010= 1410|OCC2010= 1420|OCC2010= 1430|
OCC2010= 1440|OCC2010= 1450|OCC2010= 1460|OCC2010= 1520|OCC2010= 1530|OCC2010=
1550|OCC2010= 1560|OCC2010= 1600|OCC2010= 1610|OCC2010= 1640|OCC2010= 1650|
OCC2010= 1700|OCC2010= 1710|OCC2010= 1720|OCC2010= 1740|OCC2010= 1760|OCC2010=
1800|OCC2010= 1820|OCC2010= 1830|OCC2010= 1840|OCC2010= 1900|OCC2010= 1910|
OCC2010= 1920|OCC2010= 1930|OCC2010= 1980|OCC2010= 2000|OCC2010= 2100 then
professional_Occ= 1;
 else professional_Occ= 0;
if OCC2010= 2010|OCC2010= 2020|OCC2010= 2040|OCC2010= 2050|OCC2010= 2060|
OCC2010= 2140|OCC2010= 2150|OCC2010= 2200|OCC2010= 2300|OCC2010= 2310|OCC2010=
```

```
2320|OCC2010= 2330|OCC2010= 2400|OCC2010= 2430|OCC2010= 2440|OCC2010= 2540|
OCC2010= 2600|OCC2010= 2700|OCC2010= 2720|OCC2010= 2740|OCC2010= 2750|OCC2010=
2760|OCC2010= 2800|OCC2010= 2810|OCC2010= 2825|OCC2010= 2840|OCC2010= 2850|
OCC2010= 2860|OCC2010= 2900|OCC2010= 2910|OCC2010= 2920|OCC2010= 3000|OCC2010=
3030|OCC2010= 3040|OCC2010= 3050|OCC2010= 3060|OCC2010= 3110|OCC2010= 3120|
OCC2010= 3130|OCC2010= 3140|OCC2010= 3150|OCC2010= 3160|OCC2010= 3200|OCC2010=
3210|OCC2010= 3220|OCC2010= 3230|OCC2010= 3240|OCC2010= 3260|OCC2010= 3300|
OCC2010= 3310|OCC2010= 3320|OCC2010= 3400|OCC2010= 3410|OCC2010= 3500|OCC2010=
3510|OCC2010= 3520|OCC2010= 3530|OCC2010= 3600|OCC2010= 3610|OCC2010= 3620|
OCC2010= 3630|OCC2010= 3640|OCC2010= 3650|OCC2010= 3700|OCC2010= 3710|OCC2010=
3720|OCC2010= 3730|OCC2010= 3740|OCC2010= 3750|OCC2010= 3800|OCC2010= 3820|
OCC2010= 3900|OCC2010= 3910|OCC2010= 3930|OCC2010= 3940|OCC2010= 3950|OCC2010=
4000|OCC2010= 4740|OCC2010= 4750|OCC2010= 4760|OCC2010= 4800|OCC2010= 4810|
OCC2010= 4820|OCC2010= 4830|OCC2010= 4840|OCC2010= 4850|OCC2010= 4900|OCC2010=
4920|OCC2010= 4930|OCC2010= 4940|OCC2010= 4950|OCC2010= 4965|OCC2010= 5000|
OCC2010= 5010|OCC2010= 5020|OCC2010= 5030|OCC2010= 5100|OCC2010= 5110|OCC2010=
5120|OCC2010= 5130|OCC2010= 5140|OCC2010= 5150|OCC2010= 5160|OCC2010= 5165|
OCC2010= 5200|OCC2010= 5220|OCC2010= 5230|OCC2010= 5240|OCC2010= 5250|OCC2010=
5260|OCC2010= 5300|OCC2010= 5310|OCC2010= 5320|OCC2010= 5330|OCC2010= 5340|
OCC2010= 5350|OCC2010= 5360|OCC2010= 5400|OCC2010= 5410|OCC2010= 5420|OCC2010=
5700|OCC2010= 5800|OCC2010= 5810|OCC2010= 5820|OCC2010= 5840 then
ServiceRelated_Occc= 1;
 else ServiceRelated_Occ= 0;
if OCC2010= 4010|OCC2010= 4030|OCC2010= 4040|OCC2010= 4050|OCC2010= 4060|
OCC2010= 4110|OCC2010= 4120|OCC2010= 4130|OCC2010= 4140|OCC2010= 4150|OCC2010=
4200|OCC2010= 4210|OCC2010= 4220|OCC2010= 4230|OCC2010= 4240|OCC2010= 4250|
OCC2010= 4300|OCC2010= 4320|OCC2010= 4330|OCC2010= 4340|OCC2010= 435|OCC2010=
4400|OCC2010= 4420|OCC2010= 4430|OCC2010= 4460|OCC2010= 4500|OCC2010= 4510|
OCC2010= 4520|OCC2010= 4530|OCC2010= 4540|OCC2010= 4600|OCC2010= 4610|OCC2010=
4620|OCC2010= 4720|OCC2010= 5500|OCC2010= 5510|OCC2010= 5520|OCC2010= 5530|
OCC2010= 5540|OCC2010= 5550|OCC2010= 5560|OCC2010= 5610|OCC2010= 5620|OCC2010=
5630|OCC2010= 5860|OCC2010= 5900|OCC2010= 5910|OCC2010= 6005|OCC2010= 6050|
OCC2010= 6100|OCC2010= 6130|OCC2010= 6200|OCC2010= 6210|OCC2010= 6220|OCC2010=
6230|OCC2010= 6240|OCC2010= 6250|OCC2010= 6260|OCC2010= 6300|OCC2010= 6330|
OCC2010= 6355|OCC2010= 6400|OCC2010= 6420|OCC2010= 6430|OCC2010= 6440|OCC2010=
6500|OCC2010= 6515|OCC2010= 6520|OCC2010= 6530|OCC2010= 6600|OCC2010= 6660|
OCC2010= 6700|OCC2010= 6710|OCC2010= 6730|OCC2010= 6740|OCC2010= 6765|OCC2010=
6800|OCC2010= 9620|OCC2010= 9640|OCC2010= 9750 then ManualLabor_Occ= 1;
 else ManualLabor_Occ= 0;

if HISPAN= 100|HISPAN= 102|HISPAN= 200|HISPAN= 300|HISPAN= 400|HISPAN= 500|
HISPAN= 401|HISPAN= 410 then Ethnicity_Latino= 1;
 else Ethnicity_Latino= 0;

/* create newly-arrived immigrants */
if NATIVITY= 5 & YRIMMIG >= 2013 then new_Immigr= 1;
 else new_Immigr= 0;

/* create assimilated immigrants */

if NATIVITY= 5 & YRIMMIG < 2013 then Assimil_immigr= 1;
 else Assimil_immigr= 0;

/* REMEMBER= make salary of immigrants missing */
if new_Immigr= 1|Assimil_immigr= 1 then HOURWAGE= .;
if HOURWAGE= 999.99 then HOURWAGE= .;
/* Averaging all the interest variables for means procedure */
```

```
run;
Proc Means Data= IPUMS.D2 noprint;
CLASS METAREA YEAR;
VAR HOURWAGE new_immigr Assimil_immigr professional_Occ ServiceRelated_Occ
ManualLabor_Occ AGE No_schooling Some_highschool some_college Female Black
Ethnicity_Latino;
OUTPUT OUT= IPUMS.D2Reg(where=(_type_=2))       mean=;
run;
```

Codes Pertaining to OLS and Fixed effect

```
data work.Malav;
set IPUMS.D2Reg;
ODS pdf file= 'c:\Users\Malav Desai\Desktop\SP\Lnwage_results2.pdf';

if METAREA= 0060|METAREA= 0320|METAREA= 0640|METAREA= 0641|METAREA= 0840|
METAREA= 0841|METAREA= 1240|METAREA= 1241|METAREA= 1710|METAREA= 1880|METAREA=
1920|METAREA= 1921|METAREA= 1922|METAREA= 2310|METAREA= 2920|METAREA= 3360|
METAREA= 3361|METAREA= 3362|METAREA= 3810|METAREA= 3811|METAREA= 4080|METAREA=
4420|METAREA= 4421|METAREA= 4600|METAREA= 4880|METAREA= 4881|METAREA= 5800|
METAREA= 5801|METAREA= 7240|METAREA= 7640|METAREA= 8620|METAREA= 8750|METAREA=
8800|METAREA= 9050 then Texas=1;
 else Texas= 0;
if METAREA= 0080|METAREA= 1320|METAREA= 1321|METAREA= 1640|METAREA= 1641|
METAREA= 1680|METAREA= 1681|METAREA= 1840|METAREA= 2000|METAREA= 2001|METAREA=
2002|METAREA= 3200|METAREA= 3400|METAREA= 4320|METAREA= 4440|METAREA= 4800|
METAREA= 5640|METAREA= 8400|METAREA= 9000|METAREA= 9320|METAREA= 9321 then
Ohio= 1;
 else Ohio= 0;
if METAREA= 0500|METAREA= 0120|METAREA= 0501|METAREA= 0520|METAREA= 0521|
METAREA= 0600|METAREA= 0601|METAREA= 1560|METAREA= 2905|METAREA= 4680|METAREA=
4681|METAREA= 4682|METAREA= 7520|METAREA= 8700 then Georgia= 1;
 else Georgia= 0;
if METAREA= 0160|METAREA= 0960|METAREA= 1280|METAREA= 1281|METAREA= 2281|
METAREA= 2940|METAREA= 3610|METAREA= 3611|METAREA= 3830|METAREA= 5606|METAREA=
5607|METAREA= 5660|METAREA= 5950|METAREA= 6460|METAREA= 6461|METAREA= 6840|
METAREA= 8160|METAREA= 8680|METAREA= 8930 then New_York=1;
 else New_York= 0;
if METAREA= 0240|METAREA= 0280|METAREA= 1390|METAREA= 2360|METAREA= 3240|
METAREA= 3241|METAREA= 3680|METAREA= 4000|METAREA= 6160|METAREA= 6161|METAREA=
6280|METAREA= 6680|METAREA= 7560|METAREA= 7610|METAREA= 9140|METAREA= 9280|
METAREA= 9281 then Pennsylvania= 1;
 else Pennsylvania= 0;
if METAREA= 0380 then Alaska= 1;
 else Alaska= 0;
if METAREA= 0400|METAREA= 1020|METAREA= 1602|METAREA= 2330|METAREA= 2440|
METAREA= 2760|METAREA= 3480|METAREA= 3890|METAREA= 5020|METAREA= 7800|METAREA=
8320 then Indiana= 1;
 else Indiana= 0;
if METAREA= 0440|METAREA= 0780|METAREA= 0870|METAREA= 0871|METAREA= 2160|
METAREA= 2161|METAREA= 2640|METAREA= 3000|METAREA= 3001|METAREA= 3002|METAREA=
```

```
3003|METAREA= 3520|METAREA= 3720|METAREA= 3721|METAREA= 4040|METAREA= 5220|
METAREA= 5320|METAREA= 5321|METAREA= 6960|METAREA= 6961 then Michigan= 1;
 else Michigan= 0;
if METAREA= 0450|METAREA= 0451|METAREA= 0580|METAREA= 1000|METAREA= 1001|
METAREA= 1940|METAREA= 2030|METAREA= 2650|METAREA= 2651|METAREA= 2880|METAREA=
5160|METAREA= 5240|METAREA= 8600 then Alabama= 1;
 else Alabama= 0;
if METAREA= 0460|METAREA= 0461|METAREA= 0462|METAREA= 2290|METAREA= 3080|
METAREA= 3620|METAREA= 3621|METAREA= 3870|METAREA= 4720|METAREA= 5080|METAREA=
5081|METAREA= 6600|METAREA= 8940 then Wisconsin= 1;
 else Wisconsin= 0;
if METAREA= 0480|METAREA= 1300|METAREA= 1520|METAREA= 1521|METAREA= 2560|
METAREA= 2980|METAREA= 3120|METAREA= 3121|METAREA= 3122|METAREA= 3150|METAREA=
3290|METAREA= 3291|METAREA= 3600|METAREA= 6640|METAREA= 6641|METAREA= 6642|
METAREA= 9200 then North_Carolina= 1;
 else North_Carolina= 0;
if METAREA= 0720|METAREA= 0721|METAREA= 0722|METAREA= 1305|METAREA= 3180|
METAREA= 3181|METAREA= 7130 then Maryland= 1;
 else Maryland= 0;
if METAREA= 0740|METAREA= 0741|METAREA= 1120|METAREA= 1122|METAREA= 1123|
METAREA= 1124|METAREA= 1125|METAREA= 1200|METAREA= 2600|METAREA= 2601|METAREA=
5400|METAREA= 6480|METAREA= 6483|METAREA= 8000|METAREA= 8001|METAREA= 9240
then Massachusetts= 1;
 else Massachusetts= 0;
if METAREA= 0760|METAREA= 3350|METAREA= 3351|METAREA= 3880|METAREA= 3960|
METAREA= 5200|METAREA= 5260|METAREA= 5561|METAREA= 7680|METAREA= 7681 then
Louisiana= 1;
else Louisiana= 0;
if METAREA= 0860|METAREA= 1150|METAREA= 3790|METAREA= 4430|METAREA= 5270|
METAREA= 5910|METAREA= 6441|METAREA= 7600|METAREA= 7601|METAREA= 7840|METAREA=
8200|METAREA= 9260 then Washington= 1;
else Washington= 0;
if METAREA= 0900|METAREA= 2400|METAREA= 4890|METAREA= 6440|METAREA= 6442|
METAREA= 7080 then Oregon= 1;
else Oregon= 0;
if METAREA= 0920|METAREA= 3560 then Mississippi= 1;
else Mississippi= 0;
if METAREA= 1010|METAREA= 1530|METAREA= 3260|METAREA= 4640|METAREA= 5720|
METAREA= 5721|METAREA= 6760|METAREA= 6761|METAREA= 6800|METAREA= 9220 then
Virginia=1;
else Virginia=0;
if METAREA= 1040|METAREA= 1041|METAREA= 1340|METAREA= 1400|METAREA= 1401|
METAREA= 1601|METAREA= 1603|METAREA= 1604|METAREA= 1605|METAREA= 2040|METAREA=
3740|METAREA= 3741|METAREA= 6120|METAREA= 6880|METAREA= 7880 then Illinois= 1;
else Illinois= 0;
if METAREA= 1130|METAREA= 4280|METAREA= 4520 then Kentucky= 1;
else Kentucky= 0;
if METAREA= 1140|METAREA= 2020|METAREA= 2021|METAREA= 2680|METAREA= 2700|
METAREA= 2710|METAREA= 2711|METAREA= 2750|METAREA= 2751|METAREA= 2900|METAREA=
3980|METAREA= 4900|METAREA= 4901|METAREA= 5000|METAREA= 5001|METAREA= 5340|
METAREA= 5341|METAREA= 5740|METAREA= 5790|METAREA= 5960|METAREA= 6010|METAREA=
6011|METAREA= 6080|METAREA= 6081|METAREA= 6580|METAREA= 7510|METAREA= 7511|
METAREA= 8240|METAREA= 8280|METAREA= 8740|METAREA= 8960 then Florida= 1;
else Florida= 0;
if METAREA= 1160|METAREA= 1161|METAREA= 1930|METAREA= 3280|METAREA= 3283|
METAREA= 3284|METAREA= 3285|METAREA= 5480|METAREA= 5481|METAREA= 5481|METAREA=
```

```
5482|METAREA= 5520|METAREA= 5760|METAREA= 5770|METAREA= 8040|METAREA= 8880
then Connecticut= 1;
 else Connecticut= 0;
if METAREA= 1360|METAREA= 1960|METAREA= 2120|METAREA= 3500|METAREA= 7720|
METAREA= 8920 then Iowa=1;
 else Iowa= 0;
if METAREA= 1440|METAREA= 1760|METAREA= 2660|METAREA= 3160|METAREA= 3161|
METAREA= 3162|METAREA= 3163|METAREA= 3310|METAREA= 5330|METAREA= 5331 then
South_Carolina=1;
 else South_Carolina= 0;
if METAREA= 1480|METAREA= 5260|METAREA= 9000 then West_Virginia= 1;
 else West_Virginia= 0;
if METAREA= 1560|METAREA= 1661|METAREA= 1685|METAREA= 3660|METAREA= 3661|
METAREA= 3661|METAREA= 3662|METAREA= 3840|METAREA= 4920|METAREA= 5360|
METAREA=5361 then Tenessea= 1;
 else Tenessea= 0;
if METAREA= 0680|METAREA=2300|METAREA=2840|METAREA=3220|METAREA=4480|
METAREA=4481|METAREA=4482|METAREA=4483|METAREA=4484|METAREA=4700|METAREA=4940|
METAREA=5170|METAREA=6690|METAREA=6780|METAREA=6920|METAREA=6921|METAREA=7120|
METAREA=7121|METAREA=7320|METAREA=7321|METAREA=7360|METAREA=7361|METAREA=7362|
METAREA= 7363|METAREA=7364|METAREA= 7365|METAREA= 7400|METAREA= 7401|
METAREA=7460|METAREA=7461|METAREA=7470|METAREA=7471|METAREA=7472|METAREA=7480|
METAREA=7481|METAREA=7500|METAREA=8120|METAREA=8730|METAREA=8731|METAREA=8780|
METAREA=8781|METAREA=9270|METAREA=9340 then California= 1;
 else California= 0;
if METAREA= 1720|METAREA= 2080|METAREA= 2081|METAREA= 2082|METAREA= 2083|
METAREA= 2670|METAREA= 3060|METAREA= 6560 then Colorado=1;
 else Colorado=0;
if METAREA= 1740|METAREA= 3710|METAREA= 3760|METAREA= 7040|METAREA= 7920 then
Missouri= 1;
 else Missouri= 0;
if METAREA= 0200|METAREA= 2540|METAREA= 4100|METAREA= 7490 then New_Mexico= 1;
 else New_Mexico= 0;
if METAREA= 2580|METAREA= 2581|METAREA= 2720|METAREA= 4400|METAREA= 6250 then
Arkansas= 1;
 else Arkansas= 0;
if METAREA= 2190|METAREA= 9160 then Delaware= 1;
 else Delaware= 0;
if METAREA= 3320|METAREA= 3715|METAREA= 8640 then Hawaii= 1;
 else Hawaii=0;
if METAREA= 4150|METAREA= 4770|METAREA= 8440|METAREA= 9040 then Kansas= 1;
 else Kansas= 0;
if METAREA= 2240|METAREA= 2241|METAREA= 5120|METAREA= 5121|METAREA= 6980 then
Minnesota= 1;
 else Minnesota= 0;
if METAREA= 4360|METAREA= 5920|METAREA= 5921 then Nebraska= 1;
 else Nebraska= 0;
if METAREA= 4120|METAREA= 4130|METAREA= 6720|METAREA= 6721 then Nevada= 1;
 else Nevada= 0;
if METAREA= 4200|METAREA= 5880|METAREA= 8560 then Oklahoma= 1;
 else Oklahoma= 0;
if METAREA= 6482|METAREA= 6484 then Rhode_Island= 1;
 else Rhode_Island= 0;
if METAREA= 6520|METAREA= 7000|METAREA= 7160|METAREA= 7161|METAREA= 7162 then
Utah= 1;
 else Utah= 0;
```

```
if HOURWAGE="." then delete;
if hourwage >0 then Lnwage=log(hourwage); Else Lnwage=.;
run;
proc corr data= work.Malav;
var lnwage new_Immigr Assimil_immigr professional_Occ ServiceRelated_Occ
ManualLabor_Occ AGE Some_highschool some_college Female Ethnicity_Latino;
title 'correaltion';
run;
proc means data= work.Malav;
run;
proc reg data= work.Malav;
model LNwage= new_Immigr Assimil_immigr professional_Occ ServiceRelated_Occ
ManualLabor_Occ AGE Some_highschool some_college Female Ethnicity_Latino;
run;
ODS pdf close;

ODS pdf file= 'c:\Users\Malav Desai\Desktop\SP\Fixed_Lnwage_results1.pdf';
proc reg data= work.Malav;
Model LNwage = new_Immigr Assimil_immigr professional_Occ ServiceRelated_Occ
ManualLabor_Occ AGE Some_highschool some_college Female Ethnicity_Latino
Texas Ohio Georgia New_York Pennsylvania Indiana Michigan Alabama Wisconsin
North_Carolina Maryland Massachusetts Louisiana Washington Oregon Mississippi
Virginia Illinois Kentucky Florida Connecticut Iowa South_Carolina
West_Virginia Tenessea California Colorado Missouri New_Mexico Arkansas
Delaware Hawaii Kansas Minnesota Nebraska Nevada Oklahoma Rhode_Island
Utah/NOINT;

test
Texas=Ohio=Georgia=New_York=Pennsylvania=Indiana=Michigan=Alabama=Wisconsin=No
rth_Carolina=Maryland=Massachusetts=Louisiana=Washington=Oregon=Mississippi=Vi
rginia=Illinois=Kentucky=Florida=Connecticut=Iowa=South_Carolina=West_Virginia
=Tenessea=California=Colorado=Missouri=New_Mexico=Arkansas=Delaware=Hawaii=Kan
sas=Minnesota=Nebraska=Nevada=Oklahoma=Rhode_Island=Utah=0;
run;

ODS pdf close;
```