Gender Wage Gap Trends Among Continental United States Nations

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Abstract

This study examined income and earnings by gender for American Citizens working in STEM (Science, Technology, Engineering, and Math) careers. Variables identified and controlled equate to a formula known as "Human Capital." These variables are education attainment and year round full time work status. Raw data were derived from the American Community Survey from the 2010 decennial census at the county level. Resources used were the Bureau of Labor Statistics, American Nation (Woodard, 2011) and United States Census Bureau. "Human Capital" in three occupational sectors were overlain across the 11 Nations established by cultural geographer, Colin Woodard. These STEM sectors were Architecture and Engineering, Computer Science and Mathematics, and Life Sciences. Results varied by Nation and by sector. Computer Science and Mathematics proved to be the most controversial having the largest wage gap favoring men. The Life Sciences sector appeared to be the most gender neutral of the STEM sectors in wage comparisons. Architecture and Engineering had significant gender wage gap increases as educational attainment increased. Findings suggest gender wage gap is not the same in the three sectors that make up STEM. Further research and analyses should be focused on Computer Science, Mathematics, and the Architecture and Engineering sectors.

Introduction

The topic of Gender Inequality is a popular and generously researched field of study. A subset of Gender Inequality is the highly debated subject of a Gender Wage Gap. The general media often recites the statistic "Women earn 78 cents on the dollar." The April 2015 briefed "In 2013, the median woman working full-time all year earned 78 percent of what the median male working full-time all year earned" (Gender Pay Gap, 2015). Though extensive empirical evidence and scholarly research indicates there is a gap in pay between women and men, the formula whose result concludes a 78:100 ratio does not account for the many variables that affect a person's compensation. This statistic is a result from simply calculating the annual average rate of pay for women and men working a minimum of 37 hours per week. It does not account for education level, job sector or cultural differences.

An extensively researched variable of Gender Wage Gap is Occupational Segregation. Occupational Segregation is the separation of genders amongst occupational sectors. The phenomenon essentially identifies male-dominated and female-dominated sectors in the United States Labor Market. Accounting for this factor is important in understanding the "human-ness" of occupation selection for individuals. There are many debated theories as to what causes this phenomenon, but it did not fall into the

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scope of this study. What is needed to understand this study is the fact that STEM careers are heavily occupationally segregated. This particular study zeroed in on the STEM job sector. Occupations in STEM fields (Science, Technology, Engineering, and Mathematics) are substantially male-dominated. It is important to study STEM career trends because these occupations tend to compensate better than most female-dominated sectors.

Data compiled on years worked, educational attainment, full time employment status, job sector are all available from the United States Census Bureau. But, how can cultural differences be measured? In order to examine discrimination as a possible variable in the Gender Wage Gap, cultural geography must be explored. Discrimination is a result of human learned experiences from the surrounding cultural environment. Political boundaries (e.g. States, Census Tracts) in the United States do not properly delineate human cultural beliefs, standards, traditions, voting patterns, etc. Woodard (2011) studied human cultural patterns and delineated the United States population into Nations. In his book, "American Nations: A History of the Eleven Rival Regional Cultures of North America", Woodard paints a canvas of human geographical boundaries across North America. He examines regional ideals and historical roots to determine the boundaries of eleven Nations at a county-based resolution. These Nations are the geographical backdrop of this study. The purpose of using these boundaries was to determine if human culture plays a significant role in the gender wage gap. If human culture is a significant variable, one could deduce there is some level of discrimination occurring.

Definitions

"STEM" is the designated category of careers having to do with sciences and mathematics. It stands for Science, Technology, Engineering and Math. "Gender Wage Gap" is the difference in income between genders. "Nations" in reference to this study, are areas of the United States where ancestral backgrounds, cultural similarities and political beliefs cluster amongst the population. "Human Capital" is the formula by which a person is valued by an employer to determine compensation. "Occupational sector" is a group of job types recorded by the Bureau of Labor Statistics. "GEOID" is a unique identifier the US Census Bureau uses to assign geographical areas to tabular data.

Research Problem Description

Gender wage discrepancies were analyzed across the eleven North American Nations among three occupational sectors that make up STEM fields. The three sectors came from the 2010 decennial census: Computer Science and Mathematics, Architecture and Engineering, and Life Sciences. Variables utilized were: educational attainment, years worked and year-round employment status. 2010 was chosen because it is the most recent census data available at the time of this research.

Significance of Research

Though sexual discrimination seems to be still prevalent in United States, it is often difficult to prove with only circumstantial evidence available. Many cases go unreported. Some reports, though true, are anecdotal. In order to measure for discrimination, one must explore human culture with all other variables controlled.

Spatially analyzing "Human Capital" variables over carefully delineated cultural nations, used as discrimination predictions, can calculate the "human variable." Identifying this humanness factor can identify if behavioral choices are playing a role. There are scores of scholarly research studies locked away in academic libraries for "Human Capital" analyses in STEM occupations but these are not readily available to the general public.

Census data is difficult to organize, delineate and interpret. There is a possibility the "78:100" dollar statistic comes from generalization and misinterpretation of census data. A web-based geo application could prove to be enlightening for the public. Quantifying the true discrepancy between men and women in work compensation is crucial to the equality movement worldwide.

Delimitations of the Problem

There have been slews of variables explored in previous works regarding gender pay inequalities. Many delve into the psychological differences between men and women. Psychological variables such as negotiating strategies and personal career interests are difficult to quantify. Does a women ask for less compensation? Does the potential employer devalue women's human capital? Is their intimidation at play? Does society instill into youth the belief that female work is less valuable (Blau, 2012)? If this is the case, discrimination is built up overtime. It is not known whether the discrimination is stemming from the employer or employee herself or both. Nonetheless, the reason for these discrepancies, human culture is the root of these variables.

Another inhibiting component of this research was the limited level of data available from the Bureau of Labor Statistics. The BLS does not compile detailed data on full time employment status. For example, a person who has 15 years full time employment status year round may have 10 years of experience in an Architectural job and 5 years of experience in a Business management job. Many researchers that have tackled the subject of employment have dealt with a myriad of factors playing into the hiring process. "The criteria governing entry are fairly responsive to external market conditions (Doeringer and Poire, 1971). For the purpose of this research, it is assumed that employment worked full time year round and all work was treated as equal experience for "Human Capital."

A third, possibly unquantifiable, phenomenon is the apparent growth of the gender wage gap over time. Again, the gap growth in itself is quantifiable, but the reason for the anomaly is not. In some job sectors, gender wage gap appears to grow over years worked. For example, a base or starting pay may be equal or with hardly any gap between genders, but over time men seem to be the promotion winners. This begs the question: Why are men "more successful" in their careers as time goes on? On one side, researchers claim the gap is due to women not asserting themselves enough for salary negotiations. Some say it is not equal work between genders because women take more leave for family reasons. The other side claims that women are not given the same opportunities to earn merit-based raises. An example given: high-profile, high-budget projects are given to men more often than women. This gives male employees more visibility to upper-management and more likely to merit promotions. This phenomenon was not explored. All incomes were derived from full time, US citizens between the ages of

25 and 69. It also did not attempt to explain the social and psychological reasons for the phenomenon.

Required Data and Availability

Raw data from the United States Census Bureau and the Bureau of Labor Statistics are the epicenter of gender wage gap research. Though there are several decades of freely accessible data, filtering and interpreting the data to the variables desired was laborious.

The subject of wage gap is heavily researched and many previous works have developed models to determine what factors play into compensation of an employee. Oaxaca (1973) developed a logarithm of earnings. It included variables of experience, education, training and hours. This study is a conglomerate of these models. Many models involved in calculating gender wage gap have overlapping variables, themes, and equations.

Methods

The methodology for this study consisted of five components. The first was the digitization of Woodard's Nations. Next, data from the Census Bureau were acquired and interpreted. Spatial and geostatistical analysis tools were utilized. Lastly, the results were explored over Woodard's Nations.

Digitization of Nations

Because Woodard's Nations were only accessible via a hardcopy map, it was digitized using a county dataset. ESRI's County dataset was brought into ArcMap from ArcGIS Online and exported as a feature class. An "American Nations" geodatabase was created to hold the newly digitized "Nations." Counties were selected according to the hardcopy map exported to the American Nations geodatabase. Figure 1 depicts a country-wide map of Woodard's Nations.

"The Left Coast," shown in gold is summarized as a combination of "Yankee faith in good government and social reform with a commitment to individual self-exploration and discovery." It was settled by New England merchants and Appalachian prospectors.

The "Far West" is depicted in red. It is far different from its western neighbor. This area was founded mostly by large businesses focused on exploiting the vast lands. "The region remains in a state of semi-dependency. Its political class tends to revile the federal government for interfering with its affairs" (Woodard, 2011).

"El Norte," in green, is the "Far West's" southern sister. It is the oldest of the Nations established by the Spanish empire in the 16th century. "Overwhelmingly Hispanic, it has long been a hybrid between Anglo- and Spanish America, with an economy oriented toward the United States rather than Mexico City" (Woodard, 2011).

The "Midlands" have fingers throughout the United States and is often called the "Heartland." Woodard states that the Midlands are "Arguably the most 'American' of nations." "Ethnic and ideological purity have never been a priority, government has been seen as an unwelcome intrusion, and political opinion has been moderate, even apathetic."

"Yankeedom" puts "great emphasis on education, local political control, and the pursuit of the 'greater good' of the community, even if it required individual self-denial" (Woodard, 2011).

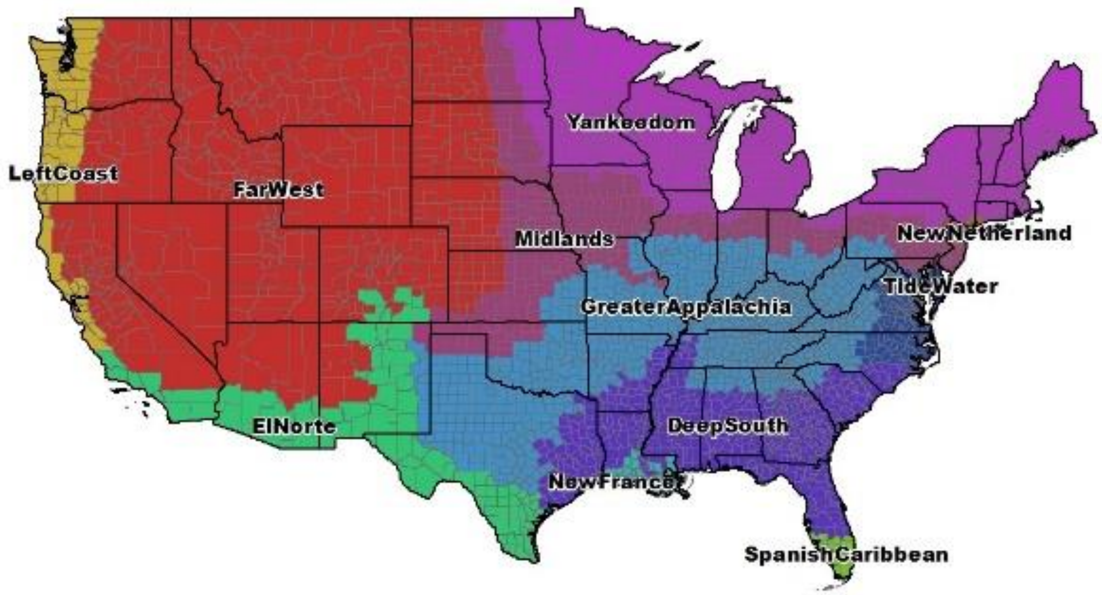


Figure 1. Colin Woodard's Nations of the United States.

The "Greater Appalachians" (light blue) are a group founded in "individual liberty and personal sovereignty" (Woodard, 2011).

The "Deep South," in dark blue, is "the center of the states' rights movement, racial segregation, and labor and environmental deregulation" (Woodard, 2011). It is the least democratic of the eleven nations according to Woodard.

"Tidewater is the "Deep South's" disinclined ally and neighbor. It is another conservative nation that places a high value "on respect for authority and tradition and very little on equality or public participation in politics" (Woodard, 2011).

"New Netherlands" was originally a Dutch settlement that laid the foundation for the New York City Metropolitan area. From the beginning, it was a hub for global economics and business. It has always been a rainbow of religions and ethnicities.

"New France" is a unique nation with its foundation being French. Unlike the other nations, its reaches are not contiguous. "New French culture blends the folkways of ancient regime northern French peasantry with the traditions and values of the aboriginal people they encountered in northeastern North America" (Woodard, 2011).

Lastly, the "Spanish Caribbean" Nation is rich with Caribbean island culture. Many citizens are bilingual and of Latin-American ethnicity.

Census Bureau Data Mining

The Census Bureau has abundant data about US citizens. The decennial census collects economic and demographic data about US inhabitants. Data are available in tables that link to their geographic datasets with a primary key called "GEOID."

In order to find tables containing "Human Capital" data, the American FactFinder data tool was utilized. This tool provides the user with an easily-accessible search vehicle. It allows the user to choose from variety of topics, geographies, and demographics.

Factors chosen for the queries were Age and Sex and Income and Earnings (United States Census Bureau, 2010). Age was the factor signifying years of experience. Sex was used to determine the differences in Income and Earnings between genders. These queries were performed on each of the three Occupational Sectors that make up STEM: Computer Science and Mathematics, Architecture and Engineering, and Life Sciences. It should be noted that the Income and Earnings data were chosen for year-round full time employed legal US Citizens. The geography filter was set to "All US Counties."

Educational Attainment was the second query with the American FactFinder. This included median earnings by gender and age for year-round full time employed legal US Citizens. "All US Counties" was the chosen geography filter again.

Lastly, the 2010 US Counties file geodatabase (including economic and demographic data) was downloaded from the 2010 Census. This feature class was used to join the two previous tables.

Data Massaging

Tabular data from the Census Bureau were downloaded in CSV format and manipulated in Microsoft Excel. The demographic and economic data retrieved in August of 2017 was from the 2010 Census. Field/Column headers of the tables came coded and were interpreted using the table's metadata. The metadata for the Census Data contained definitions for field headers. E.g. "HD01_VD17" was a field header for the Educational Attainment table. The metadata contained the definition of "Estimate; Total: - Female: - Some college or Associate's degree." For ease of interpretation, aliases were created for field/column names. Unneeded fields like total population and income estimates for the total population were deleted. Pertinent fields, income estimates by gender and education were formatted to meet the needs of the study. E.g. GEOID data downloaded in numerical format but were transposed into string format during the import process in order to avoid the dropping of leading zeros.

All census data were added to a project in ArcMap. These included all counties in the continental United States along with tabular data that were queried from American FactFinder.

The American FactFinder CSV's were converted to .xlsx spreadsheets and then to .dbf files using the "Excel to Table" tool in ArcMap. Next, tables were joined to counties by GEOID. The final product contained data on the overall populations by age and gender, total populations for the three selected occupations (overall and by gender), the average income for the three selected occupations (overall and by gender), and average incomes for each level of educational attainment (overall and by gender). Income by Educational attainment was subdivided into five classes: No high school diploma (or equivalent), high school diploma (or equivalent), some college or Associate's degree, Bachelor's degree, and Graduate degree or higher.

Spatial Statistical Computations

In order to identify income trends within each American Nation, "Human Capital" was measured. For this research, the variables measuring "Human Capital" for

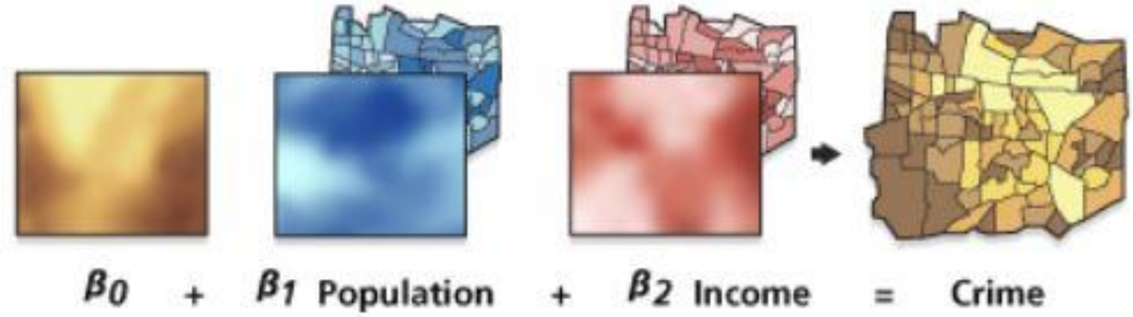


Figure 2. Infograph depiction of Geographically Weighted Regression in ArcGIS 10.5.1.

the three occupational sectors were: Educational Attainment, and years worked at full time employment status.

Geographically Weighted Regression (GWR) was used to elucidate understandings. The tool, illustrated in Figure 2, is specifically designed for calculating linear regression among spatial relationships as "GWR constructs a separate equation for every feature in the dataset incorporating the dependent and explanatory variables of features falling within the bandwidth of each target feature" (ArcGIS 10.5.1).

In order to perform Geographically Weighted Regression analysis, it is pertinent to execute and analyze the results of a collinear regression like Exploratory Regression or Ordinary Least Squares (OLS). The purpose of running a collinear regression prior to GWR is to delineate which variables are statistically significant and which are redundant or insignificant. To get a well-rounded outlook on the GWR, both Exploratory Regression and Ordinary Least Squares were undertaken. OLS and Exploratory Regression are similar analyses, but display outputs are subtly different. ArcGIS 10.5.1 help documents summarize Exploratory Regression as a tool that "...evaluates all possible combinations of the input candidate explanatory variables, looking for OLS models that best explain the dependent variable within the context of user-specified criteria." This is very similar to their description of OLS as a linear regression to generate a model a dependent variable in terms of its relationships to a set of explanatory variables. variables." Both models have measures by which the results are examined to find the best goodness of fit, model performance, etc. The Ordinary Least Square test was used on the Male and Female populations working in the Computer Science and Mathematics occupational sector. The dependent variable was the male or female average income. The explanatory variables were the overall average incomes for the sector and average incomes at educational attainment classes: Some College, Bachelor's Degree and Graduate Degree. These same variables were then used with GWR. Exploratory Regression was undertaken on the same Computer Science and Mathematics sector. The dependent and explanatory variables had the same inputs as the OLS model respectively.

Each of the three sectors were divided up by gender, age group and the three education levels (Some College/Associate's degree, Bachelor's degree, Graduate degree or Higher). The explanatory variables were the incomes for the particular sector, and age group (years worked).

Finally, the Geographically

Table 1. Ordinary Least Square test results using Computer Science and Mathematics sector data.

Ordinary Least Squares Diagnostics			
Input Features:	**OccIncEdu2010**	**Dependent Variable:**	**M_AvgIncCompMath**
Number of Observations:	2164.00	Akaike's Information Criterion (AICc)[d]:	46622.50
Multiple R-Squared [d]:	0.67	Adjusted R-Squared [d]:	0.67
Joint F-Statistic [e]:	772.30	Prob(>F), (6,2157) degrees of freedom:	0.00
Joint Wald Statistic [e]:	2128.90	Prob(>chi-squared), (6) degrees of freedom:	0.00
Koenker (BP) Statistic [f]:	30.37	Prob(>chi-squared), (6) degrees of freedom:	0.00
Jarque-Bera Statistic [g]:	193169.77	Prob(>chi-squared), (2) degrees of freedom:	0.00

Weighted Regression analysis results were compared for each Nation by examining the coefficients. A summary of each GWR result was created for each Nation using a model. For example, the discrepancy between male and female incomes for Computer Science and Mathematics in the Far West was compared with each other Nation.

Results

Results of pre-tests, Ordinary Least Squares, Exploratory Regression and Spatial Autocorrelation, paved the way for successful Geographically Weighted Regression analysis. Pre-testing determined if GWR would be statistically significant or biased.

Ordinary Least Squares

The results of the Ordinary Least Squares analysis were interpreted in six steps (Table 1). Model performance was measured first using Multiple R-Squared (Coefficient of Determination) and Adjusted R-Squared. Values range between 0.0 and 1.0. Because the OLS test had multiple Explanatory Variables, the Adjusted R-Squared value was the measure assessed to determine model performance. OLS was only performed on the Computer Science and Mathematics job sector. Results were exported to a PDF document. The Adjusted R-Squared for Males in Computer Science and Mathematics was .66. This value meant educational attainment accounted for about 66.6% of the model variability.

Next, each explanatory example was examined using three measures. The Correlation Coefficient output which "reflects both the strength and type of relationship the explanatory variable has to the dependent variable." (ArcGIS 10.5.1). It determines whether the variable has a positive or negative correlation with the dependent variable. The coefficient for the overall average incomes in Computer Science and Mathematics was positive, 0.85 ($P<.001$). Small p-values probability (p)-values suggest the coefficient is important for the model (ArcGIS 10.5.2). The Variance Inflation Factor (VIF) should be under a value of 7.5 to determine whether the explanatory value is redundant. All of the explanatory values for the OLS test in Computer Science and Mathematics had VIF values of 3.13 and lower. Model significance was measured by the Joint-F Statistic and the Joint Wald Statistic. The Joint-F Statistic is only valid if the Koenker Statistic is insignificant. In the case of explanatory variable Average Income of Computer Science and Mathematics, the Joint-F Statistic was unreliable. The Joint Wald Statistic was instead used to determine the model's significance. The model was significant with a Joint Wald value of $P<.001$.

Stationarity is the fourth step in the

OLS analysis. It is the measure by which relationship consistency is tested between the dependent variable and its geographical or data area. Stationarity is calculated with the Koenker Statistic and determines if the explanatory variables relate to the same degree across space and data. Because the Koenker Statistic was significant (P<.001), the model was assumed to have significant non-stationarity and therefore a good candidate for GWR.

Model bias was calculated in OLS with the Jarque-Bera Statistic. It determines if the difference between the dependent variables and the predicted values are normally distributed. If the Jarque-Bera probability is less than .05, the residuals are not normally distributed. This means the model is biased. The Jarque-Bera Statistic was less than .05 thus the model was biased.

The last step in the OLS analysis identified spatial correlation. This was performed outside the OLS tool with the Spatial Autocorrelation (Moran's I) tool. The z-score showed a less than 1% chance the clusters were random (Figure 3). This determined the data were clustered and therefore had statistically significant spatial autocorrelation. This result indicated that the model might not be biased, but instead misspecified.

The model passed five of the six tests in the Ordinary Least Squares Regression model. The test it did not pass was model bias, the Jarque-Bera statistic. Because the model was identified as biased/misspecified, explanatory variables were re-examined. It was concluded pre-testing should be performed using the Exploratory Regression analysis.

Exploratory Regression

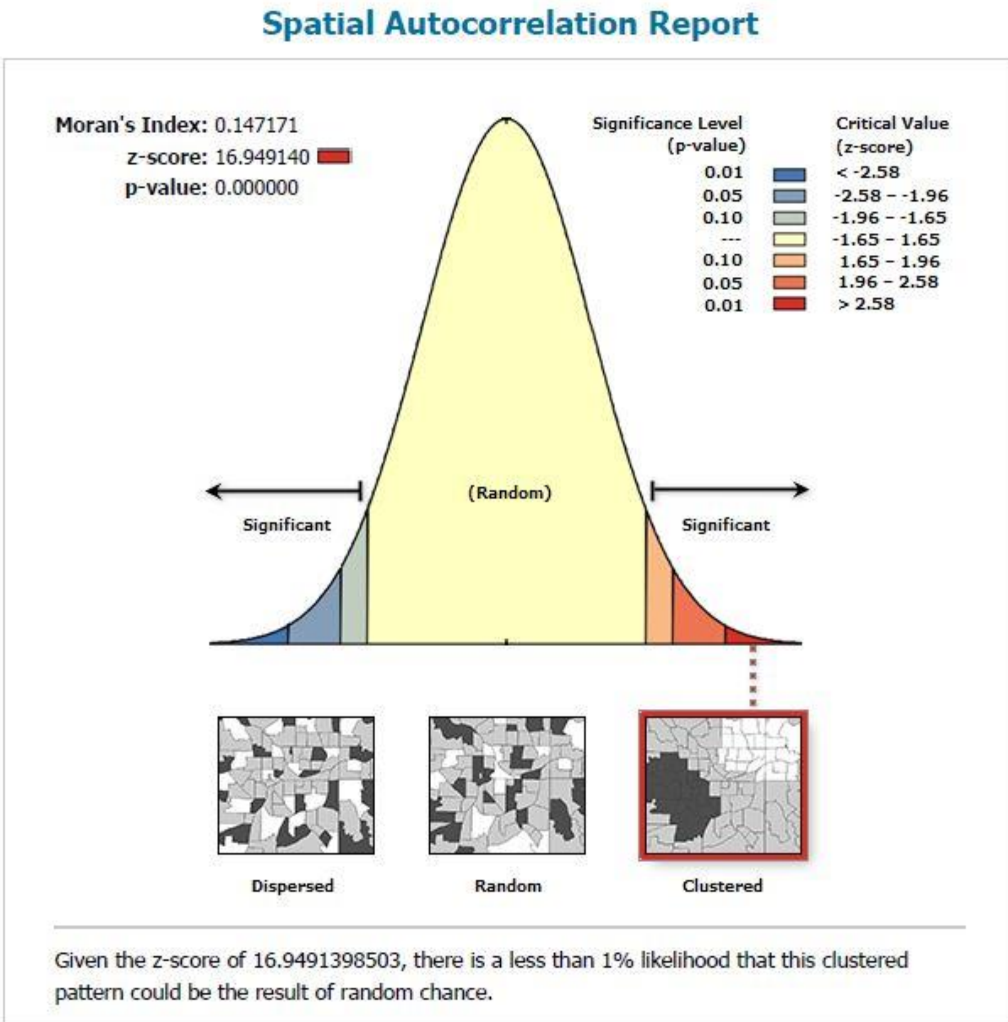
The Exploratory Regression (ER) tool was used to analyze which explanatory variables were making the model biased. The tool was first run using the exact explanatory variables used in the OLS model. Again, the Jarque-Bera (JB) Statistic failed every variable which verified the model's bias. However, it identified Educational Attainment levels of "Associate's Degree or Some College," "Bachelor's Degree" and "Graduate Degree or Higher" as having a statistical significance of 100 percent. This result was the reason for using these three Education Attainment levels in the Geographically Weighted Regression analysis.

Because the JB Statistic was still showing model bias, but had significant spatial autocorrelation, it was deduced the model might be missing key explanatory variables. Educational attainment, gender, age, and citizenship accounted for the "Human Capital" explanatory variables. When a model passes all steps in OLS and ER except model bias, it is suggested that Geographically Weighted Regression should be examined to find the missing explanatory variable(s). The model was not considered to be biased, but alternatively, misspecified. Misspecified means to have a missing explanatory variable that is most likely spatial.

Geographically Weighted Regression

The combination of the Spatial Autocorrelation (Moran's I) test and Exploratory Regression Analysis determined the misspecified model was clustered spatially. Geographically Weighted Regression was the last step in statistically computing the gender wage gap in STEM occupations (Figures 4-8).

GWR was conducted using heat symbology on the coefficients to identify



Global Moran's I Summary

Moran's Index:	0.147171
Expected Index:	-0.000461
Variance:	0.000076
z-score:	16.949140
p-value:	0.000000

Figure 3. Global Moran's test for spatial correlation.

spatial patterns across the Continental United States (CONUS). The symbology was classified using standard deviation. Counties with no data were given hollow symbology. Counties with no data were simple counties with no reported persons of a particular gender working in 2010 in the relative occupational sector. Counties with data were symbolized up to 2.5 standard deviations away from mean center. This was done to identify the gap as it compares to its county average for the

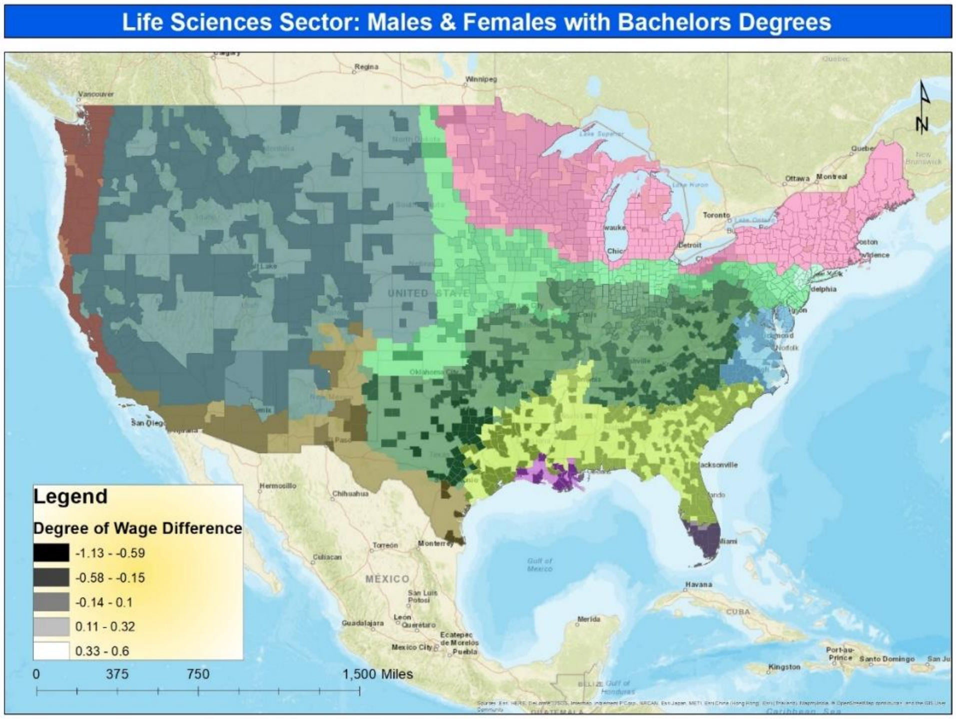


Figure 4. Degree of wage difference between genders in Life Sciences with Bachelor's degrees.

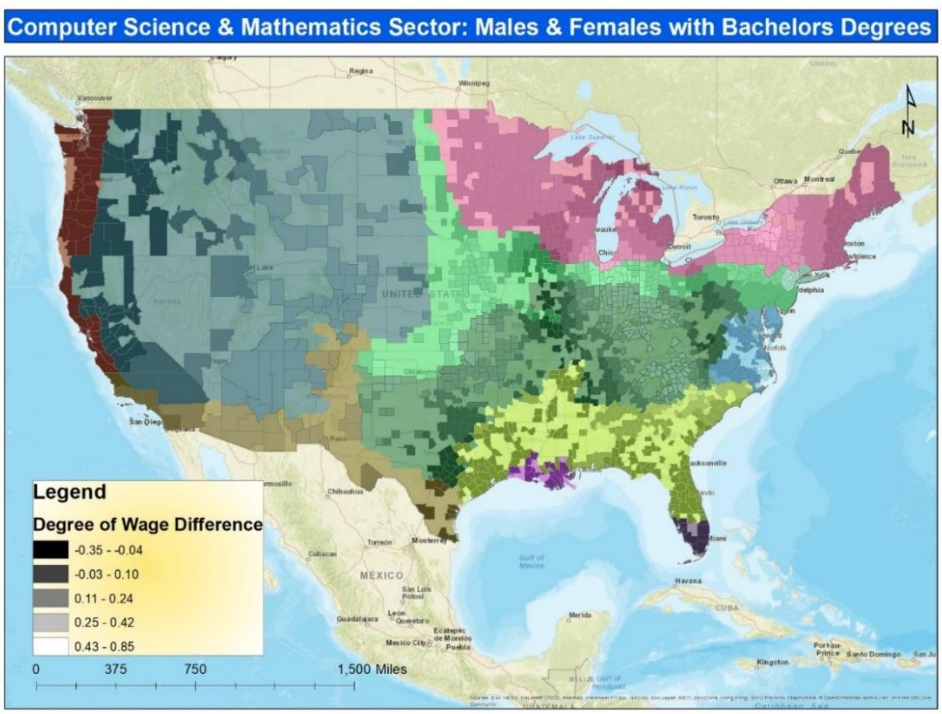


Figure 5. Degree of wage difference between genders in Computer Science and Mathematics with Bachelor's degrees.

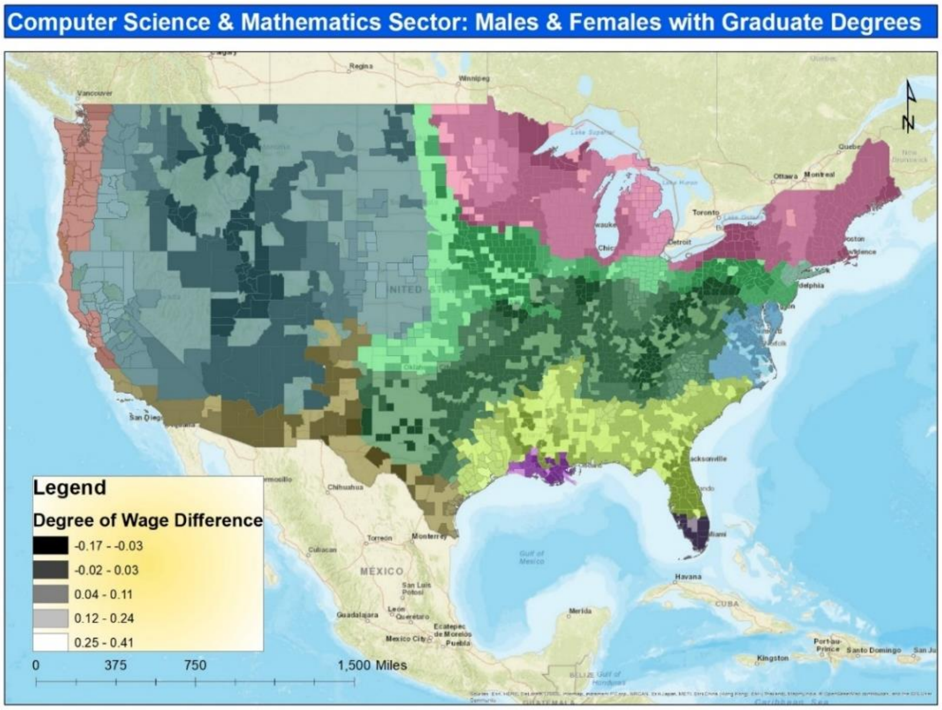


Figure 6. Degree of wage difference between genders in Computer Science and Mathematics with Graduate degrees.

occupational sector instead of comparing the wage to the overall sector average in CONUS. It normalized the data to give appropriate perspective at a county resolution.

Within the Architecture and Engineering Sector, the gender wage gap was wider favoring men in the Far West and Greater Appalachia. The gap spread wider both in income and in space as the educational attainment increased. However, as educational attainment increased for men, a gap in favor towards women was identified in the Left Coast.

The gender wage gap in favor of men in Computer Science and Mathematics was widespread and significant right away at the first level of educational attainment. The only Nations with little gender wage gap in this sector were New Netherlands, El Norte and the Spanish Caribbean. The only Nation to improve as educational attainment increased was the Left Coast. In all other Nations, the gap widened and spread across the Nation with an increase of educational attainment. Adversely for males, El Norte showed men being below the average for the sector at Some College or Associate's degree, but improved as educational attainment increased.

Lastly, the Life Sciences Sector seemed to favor women more than the other two sectors. Again, though, the gap increased with educational attainment. Most of the gender gap inequality towards women was scattered throughout southern Greater Appalachia and New France. Men did not bode well in northern parts of Greater Appalachia, the Far West or even areas of Yankeedom.

Discussion

It is clear STEM employees are not all experiencing discrimination to the same

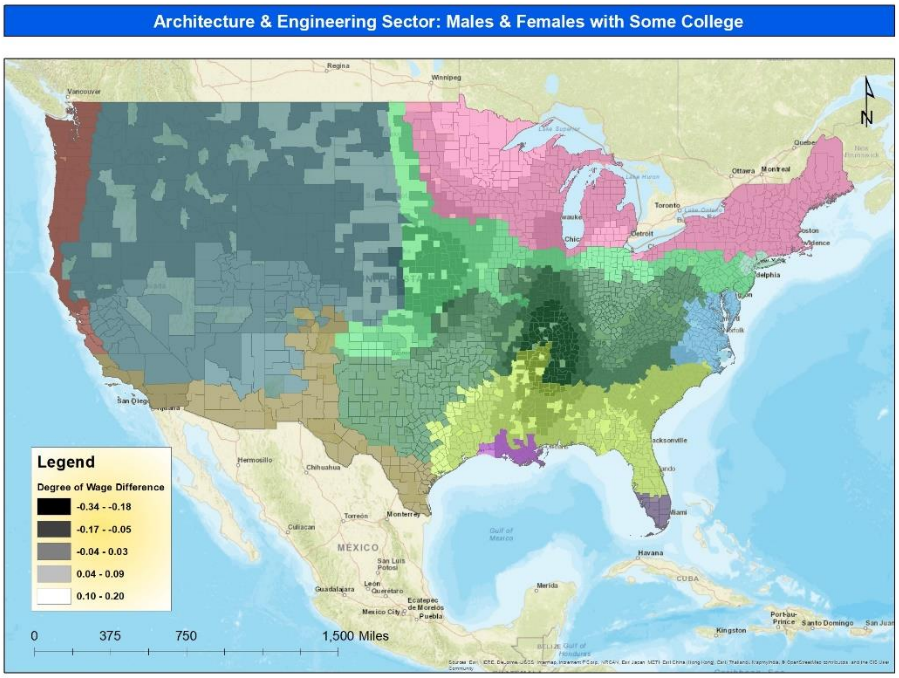


Figure 7. Degree of wage difference between genders in Architecture and Engineering with some college.

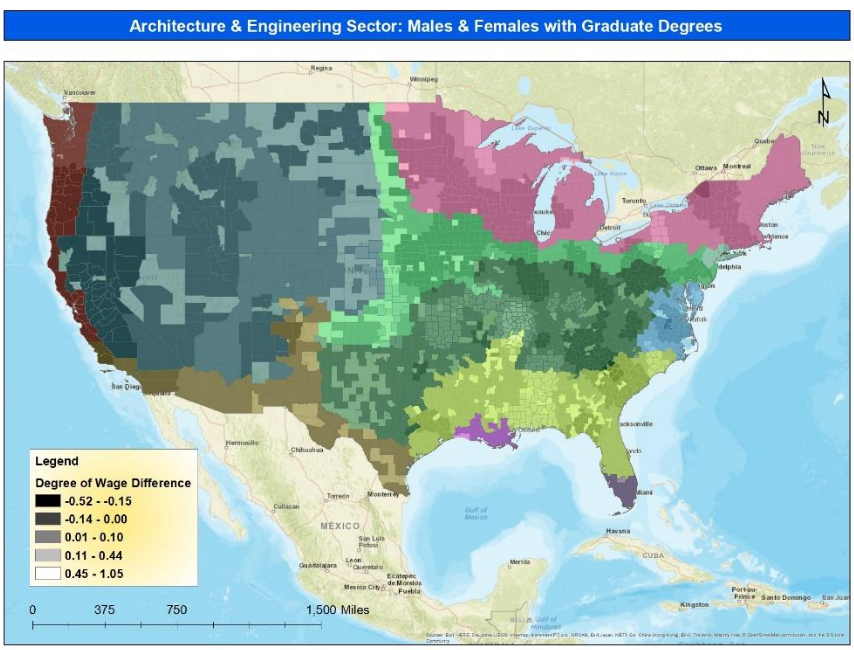


Figure 8. Degree of wage difference between genders in Architecture and Engineering with Graduate degrees.

degree, if at all, and should be continually examined. However, because the three sectors differ so greatly, it is suggested that every occupational sector be analyzed individually. Grouping so many disciplines is too generalizing for the radical differences of work culture in each occupation.

Life Sciences shows a wide gender wage inequality favoring men mainly in Greater Appalachia. Figure 4 shows some clustering of a wider gap in pay. There was a narrower gap in the Far West and Deep South, but for most liberal Nations, Life Sciences compensated women equally and possibly higher in some cases. The gap did not seem to significantly increase or decrease with education. Jobs in Life Sciences, though prestigious, do not compensate as competitively on average compared to jobs in the other two STEM occupational sectors. Without devaluing the pockets of gender wage gap in Life Sciences, it could be suggested this sector requires less focus on inequalities than Computer Science and Mathematics and Architecture and Engineering. Computer Science and Mathematics, on the other hand, typically compensates employees very competitively compared to other occupational sectors. The sector is growing exponentially as innovations in technology soar. It is important that women have an equal opportunity to these high-paying jobs and an equal opportunity to climb the ladder with increased experience and education. This sector is significantly lacking in wage equality in even so-called liberal-leaning Nations. The Left Coast is a tech hub for the Computer Science and Mathematics sector. Google, Amazon, Microsoft are just a few of the giants that make their home in the northwest of the United States. They employ hundreds of thousands of people in tech jobs. Figure 5 displays concentrated dark spots of wide gender gaps for citizens with a Bachelor's degree were obvious in Computer Science and Mathematics.

These results mean that entry level jobs were paying men more than women. The gap diminished in this sector for the Left Coast as education increased, but this begged a new question, why? Did the same women starting off being paid less eventually "earn their equality"? Or were jobs requiring a higher level of education paying more equally? The answer to those questions would tell two very different stories.

Interestingly, as this gap decreased in the Left Coast, the Far West, Greater Appalachia, El Norte, and Yankeedom all began to experience wider wage gaps as education increased (Figure 6.) This phenomenon was seen across many occupational sectors across the board, not just in STEM. It can be argued the cause is rooted in choices women make as they age. If women choose to have families, taking maternity leave or working less hours is looked upon as less committed to work. It also can cost a company more money in health benefits for a women bearing children. If those reasons are truly the reason for this widening gap, it is clear discrimination. Further research in a widening gap overtime would be very beneficial to women in Computer Science and Mathematics.

The Architecture and Engineering sector results told even another story. The concentrations of gender wage gap clustered mostly in Greater Appalachia and some areas of Yankeedom for citizens with an Associate's degree in Architecture and Engineering (Figure 7).

These Nations have very different cultures, yet seem to hold the same poor standards for compensation. As education increased for workers in this sector, the gap did not diminish. The wage gap began to appear in El Norte and the Far West for those with a Bachelor's degree. Workers with a Graduate degree felt a gap widening even further (Figure 8.) Just as Computer science and Mathematics felt a widening gap with increased education, more research would benefit workers in Architecture and Engineering jobs.

Lastly, further research could examine the trends throughout time among the Nations. Predictions have the ability to offer proactive measures as opposed to reactive. With data from historical censuses, the living story of the income discrepancy for equal "Human Capital" could be told. With a temporal perspective, predictions of a widening gap could be used to cull future generations of women experiencing compensation inequalities.

Conclusions

As Woodard (2011) explains, the Nations have become more concentrated and segregated over time. "For generations these distinct cultural hearths developed in remarkable isolation from one another, consolidating characteristic values, practices, dialects, and ideals." There is no question why so much polar political conflict remains within the United States today. Understanding these human cultures can help to explain human differences over space.

Overlaying "Human Capital" onto Woodard's Nations proved there is a significant spatial correlation between income and gender. The inequality even seems to intensify as educational attainment increases in several cases. Controlling the explanatory variables and normalizing the data is important in gaining a clearer picture of gender wage inequality.

Every employment sector should be examined independently. This research concluded that each of the three sectors that make up STEM should be dissected separately. The Architecture and Engineering favors higher wages for men in the generally conservative Nations. The Computer Science and Mathematics sector has the widest gap and is prevalent in nearly all Nations, liberal and conservative. Life Sciences was the most gender neutral throughout the Nations, with small patches of inequality in conservative Nations. It is crucial to strive for truly "equal pay for equal work."

The general statement of "78 cents on the dollar" is indeed an inaccurate depiction of gender wage inequality. Some regions of the United States experience a wider pay gap between genders than others. These gaps also vary by employment sector. In order to understand the true discrepancy of pay between genders, regions and occupations, each should be examined independently.

References

Blau, F. 2012. Gender, Inequality, and Wages. Oxford, United Kingdom: Oxford University Press.

Oaxaca, R. 1973. Male-Female Wage Differentials in Urban Labor Markets. International Economic Review 14(3), 693-709.

Doeringer, P. B., and Piore, M. J. 1971. Internal Labor Markets and Manpower Analysis. Lexington, MA: D.C. Health.

Woodard, C. 2011. American Nations: A History of the Eleven Rival Regional. New York, NY: Penguin Books.

United States Census Bureau Data. 2010. 2010 Census Economic and Demographic Data. Retrieved August 14, 2017 from https://www.census.gov/geo/maps-data/.

Gender Pay Gap. 2015. Recent Trends and Explanations. Council of Economic Advisers Issue Brief, April 2015.