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Abstract
This paper will use linear regression to analyze FRED's weekly earnings data and weekly hours data for 2017 and expects to find whether workers in different states earn a same level of income by performing the same jobs. It hypothesizes that bigger and wealthier states will pay higher compensation to workers, because the cost of living is higher and the state population size is bigger, which translates to a larger customer base for the health services industry. Some social issues, such as aging populations, and some policy implications are also discussed.

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I. INTRODUCTION

Health services cost has long been a burden for the United States (U.S.) for decades. From 2000 to 2016, health expenditures in the U.S. boomed from $1.369 trillion to $3.337 trillion, or $10,348 per person, and the growth rate of health expenditures increased continuously (Kamal & Cox, 2017). Of the total expenditure on health goods and health services, the latter accounts for two thirds. In fact, nearly half of health services cost is spent on compensating employees. This is even more astonishing if we compare the income of the U.S. physicians to that of other countries: a general-medicine physician in the U.S. earns $218,173 a year on average, and a typical specialist in the U.S. can earn $316,000 a year, while physicians and specialists in Australia and Sweden only earn half or even a third of that. (Knox, 2018). The Bureau of Labor Statistics has called for more research in investigating the relationship between the income of health service workers and the healthcare burden on employers and households. Understanding why some physicians in the U.S. can earn such a high income and where the compensation for employees in health services is the highest are very important. It is essential for political and social analysts who strive to reduce the burden of health expenditure to tackle this social problem. This paper will examine the differences in average productivity and average earnings per hour of employees in the United States in the field of health services and education between states. It also examines factors that may lead to these differences.

Workers in health services include all healthcare practitioners such as nurse and surgeons, and technical occupations such as health educators. For all these types of healthcare workers, annual salaries range from low to high. For example, the 2017 national median salary of household physicians was $23,130 on average, while that of a physician or a surgeon was more than $208,000 (BLS). In addition, workers doing the same work are earning different wages. For instance, the annual mean wage of health educators in Georgia was $82,950 in 2017, but the annual mean wage of health educators in Florida was only $53,750 in the same year (BLS, 2018). Therefore, there should be some other implicit state-level factors that also contribute to the high salaries of workers in the healthcare industry, and thus additional research focusing on state-level analysis is needed. This paper will include all workers in the health services industry and provide an analysis of the average productivity of workers in this field by state. Differences in functions among specific jobs are not considered in this research. Instead, this research will analyze whether the average expenditures in employee compensations in health services are different from state to state, and what factors may contribute to this difference.

This paper will use linear regression to analyze FRED's weekly earnings data and weekly hours data for 2017 and expects to find whether workers in different states earn a same level of income by performing the same jobs. It hypothesizes that bigger and wealthier states will pay higher compensation to workers, because the cost of living is higher and the state population size is bigger, which translates to a larger customer base for the health services industry. Some social issues, such as aging populations, and some policy implications are also discussed.

II. LITERATURE REVIEW

Analysis of the wage differences has been attracting academic attention. It was stated by Roback in 1982 that wage differences in a nation can be explained largely by local attributes. Firms must compensate employees for their willingness to live in a big and polluted city with fewer amenities (Roback, 1982). However, Roback's theory seems insufficient in explaining wage differences in the health services industry, so further developments and refinements have been made.

Rizzo and Blumenthal (1994) developed a specific relationship between employment and salaries. They measured the physician-to-population ratio by determining the need for the medical services through the size, density level, age, and gender distribution of the population, and found that a high physician-to-population ratio led to a slight decrease in wages of the physicians. With this finding, Rizzo and Blumenthal suggested that closely monitoring the physician-to-population ratio could control the spending on compensations for physicians. Moreover, another study by Kantarevic, Kraji, and Weinkauf (2008) also suggested that those who work in hospitals serving densely populated areas received higher wages and salaries than those serving less populated areas

A recent empirical urban/regional analysis, also known as the "open city' model, has been used to determine wages differences across cities or states in the US (Goodman & Smith, 2017). Goodman and Smith summarized the geographical differences in salaries and test the relationship between wages and hospital characteristics, such as the number of hospitals and health professionals in a specific region. It has been found that healthcare professionals are unevenly distributed across geographical areas, and areas with low residential densities receive fewer healthcare professionals. In addition, the "open city" model of Goodman and Smith suggests that there is higher productivity in metropolitan areas and this leads to higher wages for labor in these areas. Therefore, wages vary across states or cities depending on the size and density in predictable ways. The findings of Goodman and Smith contradict with the findings of Roback. For Goodman and Smith, higher earning is due to higher productivity, but for Roback, high salary is related to fewer amenities in big cities.

Besides analysis of population distribution and regional characteristics, the most recent study of Qin and Chernew (2014) looks into another variable: health insurance of employees. Qin and Chernew examined the number of employees whose health insurances were or were not sponsored by their employers and their wages from 1992 to 2011. After dividing the employees into two categories— with and without the employer-sponsored health insurance— Qin and Chernew found that, while earnings for employees increased dramatically from 1992 to 2011, there was a wage gap between employees with and without the employer-sponsored health insurances. The wages of employees with the employer-sponsored health insurances grew significantly faster than those of employees without the employer-sponsored health insurances.

Some other urban economic literature has used the concept of increasing return to scale in production and the agglomeration of activities to address the wage differentials in health services industry.

Until it is constrained by production factors like inadequate spaces and congestion, the agglomeration of production leads to enhanced productivity, hence more profits and residual income, which in turn lead to higher wages to motivate the healthcare workers (Folland, Goodman, & Stano, 2018; Dranove & Lindrooth, 2003).

This research will use employment rate, population, and health insurance coverage as independent variables, and use wage as dependent variables. It uses linear regression to analyze which variable is most significant in contributing to the wage differentials. In addition, while other studies focused on a specific region throughout a long period of time, the data used in this paper is categorized by state and focuses specifically on 2017.

III. DATA AND METHODOLOGY

The 2017 state data of average weekly earnings in dollars and average weekly hours of workers in the field of health services and education were acquired from GeoFred, which extracted and summarized data from ESRI, Tele Atlas, U.S. Census Bureau, and Natural Earth. These two sets of data are used because they are very inclusive, and thus are able to represent the overall level of compensation for health services workers in each state. However, only comparing average weekly earnings between states is not reliable, because employees in different states work unequal hours per week, as shown in Table 1. For example, employees in California work 33.7 hours per week and workers in Georgia work 35.3 hours per week. However, professionals in California earn an average of $1004.93 per week while employees in Georgia only earn a weekly wage of $985.58. California health professionals earn a higher wage rate even if they work fewer hours. This paper will explore why this phenomenon exists. To study this issue, an average productivity, or average hourly earnings, of health services workers (APT) was computed using the two sets of data from GeoFred, by dividing average weekly earnings by average weekly hours in Excel. Alaska, Nevada, and District of Columbia are not included in this paper due to the lack of data.

The maximum and minimum of APT are summarized in Table 1. APT across the states fluctuates between $19.78 per hour in Missouri and $30.23 per hour in Rhode Island. Therefore, differences in APT do exist between states. This paper will look at 5 variables that may have caused gaps in APT: the health care employment rate, the percentage of people age 65 and above, population size, the cost of living, and the uninsured rate. The health care employment rate by state was extracted from the BLS and is measured by people employed in the healthcare industry over the total labor force in each state. The percentage of people age 65 or over and population of each state are summarized by the American Census. The percentage of elderly people is included because older people need more health treatment than others and may affect the demand for health services. Figure 1 plots the percentage of people aged 65 and above with APT, and shows no strong correlation. To measure the cost of living, a cost of living index was used. It is extracted from the BLS and measures the price levels paid for products and services. The cost of living may matter because employers often offer a higher compensation rate to workers if that state has a higher cost of living. The national average of the cost of living index or the base of the index number is equal to 100, and the difference between the cost of living index and 100 is used in the regression equation. A positive correlation between the cost of living and APT is shown in Figure 2. The last control variable is the uninsured rate, which is extracted from the US Census Bureau and measured by the number of people without health insurance over the total population in that state. Figure 3 shows that there might be a negative correlation between APT and the uninsured rate: APT decreases as the uninsured rate increases.

The visual analysis of scatter plots is not persuasive and accurate enough to illustrate whether there is a strong structural relationship between the independent variables and APT. In order to further test this relationship, a linear regression must be run. Even though linear regression has a limitation in that it automatically assumes a linear relationship between the independent and dependent variables, while in reality the relationship may not be linear, it is one of the most straightforward tools to test how strong a structural relationship is. This paper will use R Studio to run the regression, and the formulated regression equation is as follows:

$$APT = \alpha + \beta_1 Emp + \beta_2 Eld + \beta_3 Pop + \beta_4 Col + \beta_5 Uir + \varepsilon$$

where Emp, Eld, Pop, Col, and Uir denote the health services employment rate, the percentage of people aged 65 or older, the population size, the cost of living index deviated from the base, and the uninsured rate in each state, respectively. This paper hypothesizes that APT depends on all of the independent variables above. β1 is expected to be negative, because employment can represent the supply in the health service industry, and the more the supply, the lower the compensation rate. β2 and β3 are expected to be positive, because the number of elderly people and total population both increase the demand base for health care. The more the demand, the higher the wage rate. β4 is also expected to be positive, because higher wage rates are offered in states with higher costs of living. β5 is expected to be negative, since people without health insurance are less likely to get a health check because of the higher fees, and thus making hospitals generate less revenue. As a result, hospitals may cut their costs by distributing smaller salaries to employees. An error term is also included to capture the differences between the actual and observed results. The results and conclusions from this test will be reported in the finding and results section.

IV. RESULTS

The control variable population is expressed in millions, and all the data is imported to R Studio to run the regression:

$$APT = \alpha + \beta_1 Emp + \beta_2 Eld + \beta_3 Pop + \beta_4 Col + \beta_5 Uir + \varepsilon$$

The results are shown in Table 2.

From Table 2, the variables ‘Percentage of Elderly People’ and ‘Population’ are not statistically significant. Thus they are dropped in order to improve the precision of the model. The new regression equation is thus:

$$APT = \alpha + \beta_1 Emp + \beta_2 Col + \beta_3 Uir + \varepsilon$$

The output of the new equation is shown in Table 3. Now that all independent variables are statistically significant, the relationship between hourly earnings and employment is negative. The average hourly wage in the health services industry decreases by $0.86 when the percentage of people employ in health services increases by 1%. In addition, the percentage of people without health insurance coverage also negatively contributes to the hourly earnings of health professionals, which declines by $0.16 when the uninsured rate rises by 1%. In this model, only the cost of living index has a positive relationship with the wage rate, which increases by $0.06 with every one-point increase in the index. Among all three variables, the employment rate has the highest absolute magnitude, suggesting that it weighs the most in affecting the wage rate. Conversely, the cost of living index has the smallest coefficient in absolute values, indicating that it does not have a strong causal effect with hourly earnings.

Standard errors are biased if heteroskedasticity exists. To make sure that the model does not have heteroskedasticity, the Breusch-Pagan test is run and the results are presented in Table 4. The p-value of the Breusch-Pagan test is 0.4601, which is much higher than 0.05. Thus, homoscedasticity is not rejected and no further transformation or changes to the model are needed. The whole model has an adjusted R-squared of 0.4133, which means the employment rate, the cost of living index, and the uninsured rate altogether account for 41.33% of the variation in hourly wage rate in 2017. And the model has a very small p-value, 6.97e-06, providing that the coefficients, except the intercept, are not equal to zero. Moreover, the residual standard error is 2.095, so the actual average hourly wage in states may deviate by $2.10 from the predicted wage rate.

V. CONCLUSION

In examining the differences of hourly earnings in the health services industry among states by using 2017 data and regression analysis, I have discovered that the employment rate, cost of living, and the uninsured rate are significant in influencing the wage rate. The employment rate variable has the largest coefficient in absolute values, while the cost of living has the lowest. Thus, changes in the employment rate should contribute more to wage rate fluctuations in 2017. Also, from the findings above, population and the percentage of elderly people are found to not be significant. However, Kantarevic, Kralj, and Weinkauf (2008) suggests a positive relationship between population density and earnings. This inconsistency might have resulted from differences in the data sets. Specifically, this paper only analyzes 2017 data while the existing literature collects time-series data. The finding that the employment rate has a negative relationship with the wage rate aligns with Rizzo and Blumenthal (1994) who discovered that a rise in physician to population ratio negatively contributes to earnings of physicians.

The United States is still dealing with the problem of huge health care expenditures, and nearly half of the disbursements in health services and education were spent on compensation for employees. This research suggests that to alleviate the burden of expensive medical fees, the government should encourage more employment in health services. For example, the government can provide more scholarships to students who attend medical schools or lower the tuition for those programs. Doing this can provide incentives for people to study in the health services field, and thus, increase the supply of health professionals in the future.

For health services workers, if they want to receive higher compensations, they are recommended to go to a state with a low employment rate in health services and education industry. In addition, states with high costs of living might not be a good choice. Although the hourly earnings increase as the cost of living index rises, the $0.06 rise can never catch up with the surge in the cost of living. A location with a close-to-median cost of living is certainly a better choice. Moreover, a state with a large uninsured rate may fail to provide workers with a high wage rate. As a result, states with a low employment rate, close-to-median cost of living, and high insurance coverage rates are where health professionals should consider moving to.

This study could be extended in a number of ways. If feasible, including more variables can increase the precision of the analysis and decrease the possibility of omitted variable bias. Also, if two or three more recent years are included in the regression, it would be able to further test the relationship between population and wages for the instances where inconsistencies are found between this paper and the research conducted by Kantarevic, Kralj, and Weinkauf (2008).

APPENDIX

Figure 1: Wage Rate and Percentage of Elderly People (aged 65+)

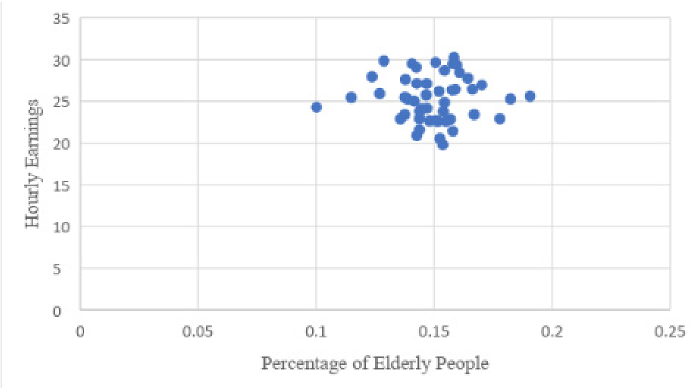

Figure 2: Wage Rate and Cost of Living Index

Figure 3: Wage Rate and Uninsured Rate

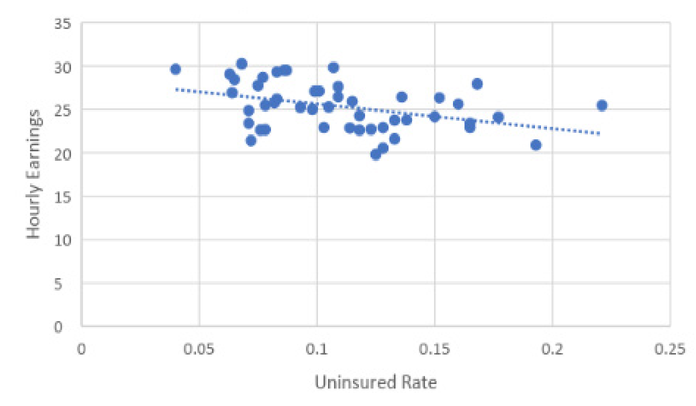

Table 1: Descriptive Statistics

data series	mean	maximum	minimum
average weekly earning ($)	841.26	Washington 1014.46	Missouri 652.74
average weekly hours	33.2	Utah 38.8	Idaho 30.4
average productivity ($/hr)	25.35	Rhode Island 30.23	Missouri 19.78
Health Care Employment as a Percent of Total Employment	9.39%	West Virginia 11.9%	California 7.3%
percentage of population age 65 or over	14.94%	Florida 19.06%	Utah 10.02%
population	6,693,487	California 39,536,653	Wyoming 579,315
cost of living index deviate from 100	3.99	Hawaii 87.7	Mississippi -15
uninsured rate	11.05%	Texas 22.1%	Massachusetts 4%

APPENDIX

Table 2:

General Estimation Results of Linear Regression Model of Hourly Earnings in the Field of Health Services and Education by State in 2017

Dependent Variable: Hourly Earnings in Dollars, N=48

Observations: N = 48

(State Alaska and Nevada are not included)

Constant	34.0081***
	(7.998)
Employment Rate	-0.8347*
	(-2.009)
Percentage of Elderly people	0.0417
	(0.173)
Population	0.0498
	(1.122)
Cost of Living Index Deviated from the Mean (100)	0.0608***
	(2.929)
Uninsured Rate	-0.1851*
	(-1.85)
Adjusted R-Square	0.4033
s.e equation	2.113
Residual diagnostics tests	
Heteroskedasticity	0.4601[a]

Significance at the 1% (***), 5% (**), and 10% (*) levels (t-values in parenthesis)

[a] p-values of Breusch-Pagan-Godfrey' s statistical test for Heteroskedasticity

Table 3:

Final Estimation Results of Linear Regression Model of Hourly Earnings in the Field of Health Services and Education by State in 2017

Dependent Variable: Hourly Earnings in Dollars, N=48

Observations: N = 48

(State Alaska and Nevada are not included)

Constant	34.9820***
	(9.201)
Employment Rate	-0.8642 **
	(-2.467)
Cost of Living Index Deviated from the Mean (100)	0.0655***
	(3.306)
Uninsured Rate	-0.1633*
	(-1.689)
Adjusted R-Square	0.4133
s.e equation	2.095
Residual diagnostics tests	
Heteroskedasticity	0.4601[a]

Significance at the 1% (***), 5% (**), and 10% (*) levels (t-values in parenthesis)

[a] p-values of Breusch-Pagan-Godfrey' s statistical test for Heteroskedasticity

Table 4:

Breusch-Pagan test

BP = 4.6496	df = 5	p-value = 0.4601

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