A Deficiency in the Wage and Total Utility Inequalities

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I Introduction

The wage inequality gap between skilled and unskilled workers has been increasing since the 1980s. This is primarily due to the increase in the demand for skilled workers [1]. In this paper a skilled worker will be any individual with a bachelor's degree or higher academic degree. I will often refer to the percentage of bachelor's degrees or higher academic degrees as the PBDH. Using data provided by the Educational Attainment Survey (EAS) and the Case-Shiller Home Price Indices I find that areas with higher concentrations of skilled workers also experience higher costs of living. I discuss the possible causes for this correlation, and the resulting implications on the wage and total utility inequalities.

II Job Concentrations

Over the last several decades the United States has experienced a substantial increase in jobs that require skilled workers. There has been rapid growth in technological and engineering areas, and in the finance and health sectors. The Bureau of Labor and Statistics estimated that there were 5.4 million jobs available in November of 2015, an increase of 32% from 2013 [3]. The National Association of Colleges and Employers (NACE) also has estimated a 11% increase in the number of college graduates demanded for 2016 in comparison with 2015 [4]. However, an increased demand of skilled workers does not correlate to an even distribution of these jobs around the country.

In, "Real Wage Inequality," Enrico Morretti concludes that most of these new jobs will be located in metropolitan and urban areas, such as San Francisco, CA and Manhattan, NY [2]. The imbalance of job locations have affected cities all around the United States. Moretti concludes that under perfectly competitive market conditions where firms have fixed prices, can enter and exit the market freely, and production is in constant returns to scale, the resulting increase in jobs in metropolitan areas is most likely due to demand shocks (a rightward shift of the demand curve) instead of supply shocks [2]. These shocks are not taking place throughout all cities. This entails both positive and negative attributes. The obvious one points to skilled workers becoming more and more in demand, while unskilled workers experience the opposite. This is a classic example of a Pareto efficiency, where the skilled workers are improving their status at the expense of the unskilled workers. It is easy to understand this phenomenon with a simple comparison of large metropolitan cities. Using data from 2014, the EAS shows that 22.8% of Milwaukee, Wisconsin's population of individuals twenty-five years of age and older attained a bachelor's degree or higher academic degree. In that same year, Manhattan had a rate of 59.3%. In section III, I identify a possible implication, being the Housing Price Index (HPI), resulting from this imbalance of demand for individuals with a bachelor's degree or higher academic degree across the United States. In section IV, I provide evidence that the HPI moves according to the PBDH, producing a positive relationship (as one variable increases, the other also increases, and vice versa) between the two.

III Differences in the Housing Price Index

The HPI is a measure of the shift in single-family housing prices. It includes the measurements of changes in the average price of recurring sales and refinances of houses [5]. If a house sells for, or is refinanced, at a higher price or rate than it was a year ago, then there is an increase in the HPI of that individual house. The example is simplified to show the general idea of how HPI is calculated. Overall, the HPI will include many houses and not just one. In the figures below I have plotted the Housing Price Index for a select few "target" cities (Figure 3.1) and those that are not (Figure 3.2). A "target" city will be defined as a city with a high PBDH. The figures are as follows,

Figure 3.1

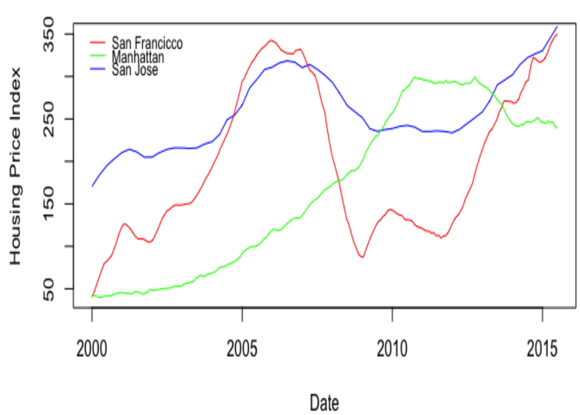
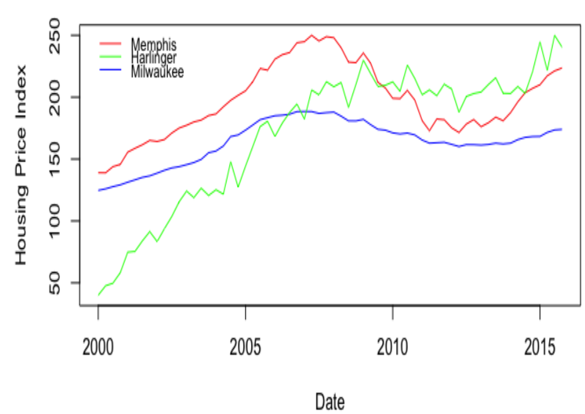


Figure 3.2



From the year 2000 to 2015, the figures show that cities that are considered "targets" experience a higher HPI in comparison with those that are not. Recall the comparison between Milwaukee and Manhattan in section II. Milwaukee had a low PBDH in comparison with a high PBDH in Manhattan. From Figure 3.1 and Figure 3.2, we see that Milwaukee has a low HPI and Manhattan has a high HPI. A hypothesis has presented itself, the PBDH dictates whether the HPI will be high or low. I now present a definitive analysis of the relationship between the PBDH and the HPI.

IV Evidence of a Connection

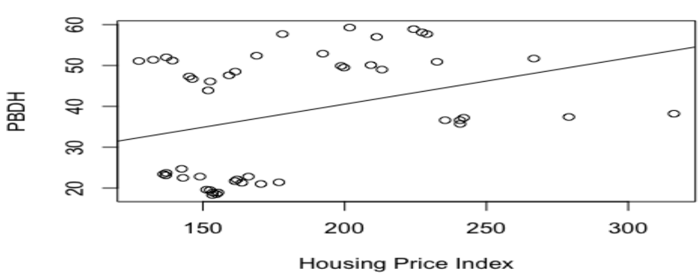
There are two variables in question: the PBDH and the HPI. To test the hypothesis of whether the PBDH dictates whether the HPI will be high or low, I constructed a null hypothesis (a hypothesis stating that a statistical correlation fails to exist): the PBDH does not dictate, on any level, whether the HPI will be high or low. To test the null hypothesis a simple linear regression was used of the form,

$$Y \approx \beta_0 + \beta_1 X, \tag{4.1}$$

where Y (response variable) represents the PBDH and X (predictor variable) the HPI. In 4.1, β_0 and β_1 are two unknown coefficients that will represent the intercept and slope terms in our regression. They define the least squares coefficient estimates,

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \tag{4.2}$$
$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}.^*$$

In addition to the cities plotted in the previous figures, the regression also included Fremont and San Jose, CA (targets), and Harlingen, TX and Fayetteville, AK (non-targets) to give a greater amount of data for comparison. A plot of the regression is below, along with the associated R-squared and p-value:



R-squared	0.1176
p-value	.01704

To keep the mathematical nature of this paper simple, the R-squared variable is a measure of how

*The least squared coefficient estimates are found by letting $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$. Then the ith residual is given by $e_i = y_i - \hat{y}_i$. We can then find the residual sum of squares (RSS) as $RSS = e_1^2 + e_2^2 + \cdots + e_n^2$ or $RSS = (y_1 - \hat{\beta}_0 - \hat{\beta}_1 x_1)^2 + (y_2 - \hat{\beta}_0 - \hat{\beta}_1 x_2)^2 + \cdots + (y_n - \hat{\beta}_0 - \hat{\beta}_1 x_n)^2$. Solving for $\hat{\beta}_1$ and $\hat{\beta}_0$ produces the least squares equations above.

well the data fits the regression line. The plot shows that much of the data is on either extrema (high Bachelor's and high HPI or vice versa), with little data in the middle. Thus, it is expected to have a low R-squared value, though a high one would be more preferred. The p-value measures the relationship between the response variable, Y, and the predictor value, X. A high p-value means that the null hypothesis is most likely true; there is not any evidence of a statistical significance between the PBDH and the HPI. A low p-value means that the null hypothesis is likely to be false; there is evidence of a statistical significance between the PBDH and the HPI. What is considered to be a low enough p-value to reject the null hypothesis varies. In this model we will set a low p-value that is acceptable enough to reject a null hypothesis at 0.05.[†] Thus, the p-value is lower than the acceptable one. This constitutes a rejection of the null hypothesis, meaning there does seem to be a relationship between the PBDH and the HPI.

V The Effect on Wage Inequality and Total Utility

As mentioned in section I, the wage inequality gap has been increasing since the 1980s [1]. However, the positive relationship between the PBDH and the HPI leads to differences in nominal and real wage differences. Nominal wage is the amount of money you earn an hour performing a specific job or task, and it is not a good indicator of purchasing power (amount of goods and services bought with a unit of currency), due to the omission of inflation as a considerable factor. In contrast, real wage is essentially nominal wage with adjustments from inflation. The real and nominal wage inequality gap has increased overall in both a nominal and real sense. This can mostly be attributed to a decreased growth in skilled workers and the depletion of labor market institutions that help defend the rights of unskilled workers [1]. The nominal wage inequality fails to take into consideration the added inflation. An increase in inflation results in an increase in prices, and a decrease in purchasing power. Housing prices are not immune to inflation. The nominal wage inequality does not take this into account, only comparing the relative differences in wage over time. In section IV a positive relationship was found between the PBDH and with the HPI. When cities with the highest HPI also consist of the largest amount of skilled workers. These workers are feeling the impact of higher inflation rates in comparison with unskilled workers. Hence, the nominal wage inequality is larger in comparison with the real wage inequality. This difference expands beyond wage inequality to affect the total utility inequality.

[†]In, "Calibration of p-Values for Testing Precise Null Hypothesis" (2001), by Thomas Sellke, M.J. Bayarri, and James Berger, a p-value at or lower than 0.5 correlated to a 23% chance of incorrectly rejecting the null hypothesis, and a p-value at or lower than 0.1 correlated to a 7% chance of incorrectly rejecting the null hypothesis.

Total utility can be defined as the total satisfaction an individual receives from consuming the total amount of goods and services. It is acceptable to say that a skilled worker would have a higher total utility level in comparison with an unskilled worker due to a higher salary. The ability to buy more goods and services and a higher satisfaction level of their work leads to a higher total utility [2]. A higher HPI decreases the benefit of an increased wage rate in skilled workers, which carries over to an erosion in the gain in total utility [2]. According to the Council for Community and Economic Research, the cost of living in Manhattan, New York is about 68.8% above the national average [6]. As an example, based on the average salary calculated in New York, let a skilled worker have an income on average of $70,000. The average national cost of living is $28,474 for a single adult with no children [6]. Now, 68.8% more than that is $41,386. Subtracting that amount from our estimated income gives only $28,614 left of the original $70,000 salary (note that housing costs make up most of the cost of living calculation). Therefore, just as Moretti concluded, total utility is not as high in skilled workers as once predicted [2]. [‡]

VI Conclusions

In this paper I have showed that cities that have a higher PBDH also have a higher HPI. Through linear regression a positive relationship between these two variables was found, though the relationship was not as strong as I would have preferred due to a R-squared value that was quite low. This was most likely caused by an insufficient amount of data, and an outlier in the group of data, Fayetteville, AK (high PBDG and low HPI). From this positive relationship I arrived at the first conclusion; a lower real wage inequality versus the nominal wage inequality of skilled and unskilled workers. The conclusion is shown to exist through the analysis provided, but the question remains as to why areas with a higher PBDG also have a higher HPI. In II I accepted that this was due to demand shocks in those specific cities, but Moretti also states in, "Real Wage Inequality," that supply shocks could play a contributing role [2].

A second conclusion; the total utility inequality between skilled and unskilled workers was not as large as once suspected. This was proven by identifying changes in the HPI that have an effect on wages, which in turn affected wealth, and then carrying over to effect total utility. However, the exact measurement of the gap of total utility between skilled and unskilled workers is not definitive, meaning there is not a unit

[‡] In more detail this means that the slope of the marginal utility of consumption, defined as,

$$MU_y = \frac{\Delta U}{\Delta y},$$

where ΔU is the change in total utility and Δy is the change in consumption (includes living expenses), is not as steep.

or exact measurement to gauge utility. Among other factors that may explain the relation of a small total utility inequality are job risks, preference of job location, health benefits, and amount of leisure time. A more detailed analysis of this conclusion is needed to make any definitive claims. This paper leaves many questions unanswered in a relatively new area of research. Nonetheless, it provides a brief analysis into two variables that present a base level cause for differences in real and nominal wage inequality and total utility inequality.

References

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[5] Federal Housing and Finance Agency. "House Price Index." `https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx`.

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