

Discrimination in the Restaurant Industry in Ohio

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Abstract

This paper explores the size of discrimination in the restaurant industry in Ohio in 1980 and 2010. I used OLS regressions in order to discover the differences in wages between different groups. From there, I used a set of Oaxaca decompositions to determine how much of the difference, if any, could be attributed to discrimination. I found that African American workers made 14.8% less than their white counterparts. Discrimination may be even worse than this wage gap allows: when comparing African American workers to a counterfactual treated with white coefficients, the African American workers make 17.8% less than the white coefficient counterfactual. This effect seems nonexistent when comparing Hispanic and white workers. When comparing men and women, women make significantly less in almost every case.

1. Introduction

In this paper, I explored the differences in wages between races and genders in the restaurant industry in Ohio. While much research already exists on the topic of wage based discrimination, very little can be found when looking at the restaurant industry in Ohio. In order to explore the levels of discrimination in this sample, I started by using OLS regressions to explore different variables and how they interact with wages for different groups. As with Altonji and Blank in 1999, I chose to use a decomposition method to find which different variables could be used to explain parts of a basic wage gap.

One particular area of interest is how discrimination changes over time. By looking at data in 1980 as well as 2010, I was able to see which groups saw decreases in wage gaps, and which groups seemed to struggle with even more discrimination in more recent years.

I found that discrimination is present for both race and gender in the restaurant industry in Ohio. The effects of gender on wages are especially profound. When studying racial differences, I found that African Americans tend to be paid substantially lower wages than their white counterparts, but Hispanic Americans did not follow the same pattern.

Economic literature based on discrimination reflects many of the same discoveries as I made while researching this topic. For example, Altonji and Blank found that very little wage growth was found for nonwhite races since 1980. They also found that while wage gaps are narrowing on average, they still remain quite large (Altonji, 1999). When looking into discrimination in the restaurant industry, more specifically fast food restaurants, Ihlanfeld and Young found that customers play a large role in discrimination in restaurants. In fact, they found that the only significant discrimination variable was the percentage of white customers that frequented the restaurants (Ihlanfeld, 1994). O'Neill found that the gender wage gap fell by almost half between 1984 and 1994 (O'Neill, 2003). While many of these results are similar to my own, none of them were specific to restaurants in Ohio.

2. Data and Methodology

I pulled data from IPUMS USA in 1980 and 2010 in this study to determine what levels of discrimination may be found in the restaurant industry. I used variables to account for many different characteristics in workers, including race, ethnicity, gender, marital status, occupation, and education. I chose the years 1980 and 2010 because I was interested in exploring discrimination throughout time, as well as seeing if there were any major changes in the wages of different groups in recent years.

I used a data set that included workers in the restaurant industry in Ohio from 1980 to 2013. I further reduced that set by using only the results in the years 1980 and 2010 in order to give a clear comparison of the two different time periods. I also restricted the occupations used in the analysis by cutting out occupations with only a few employees, as well as many occupations that are not industry specific. After combining similar occupations, I used a set of

ten occupational groups in this paper: CEO, manager, chef, food preparation, cashier, waiter, dishwasher, host, baker, and butcher.

The initial regressions were run with six racial groups: white, African American, Hispanic, Asian American, Native American, and other. This frequently resulted in intercept problems where there were not enough data points to get a good representation of Asian American and Native American workers. As a result, those groups were combined into the “other” category.

The dependent variable reflects the income that workers receive, pre-tax, from wages, tips, salaries, and other sources from their workplace. All wage numbers were converted to 2010 dollars for consistency. After looking through the available variables in IPUMS USA data, I decided on variables that I thought could explain the differences in wages between the racial based and gender based groups. I gathered information on education levels, current in-school status, citizenship, metropolitan area status, marital status, and number of children under five.

Using OLS regressions on total income from wages and tips, I discovered which attributes may have effects on wages in the industry. I used two separate sets of regressions in order to compare the results and see whether adding more variables lessened the wage gap. The first model simply regressed race on wages. The second regressed race, gender, education, citizenship, children, in-school status, metropolitan status, and marital status on wages. These two regressions were done for multiple years between 1980 and 2013, but only 1980 and 2010 are used throughout the paper. The goal was to see which variables have statistically significant effects on wages over time.

Later, I used separate regressions to investigate the differences between the occupational groups that I chose to include in the sample. The models simply regressed race on wages for each occupational group. I decided to do this to see if any occupations had consistently larger wage gaps, and if any of those differences were statistically significant. The occupations that showed a large and statistically significant wage gap were used later in the Blinder-Oaxaca decompositions.

The Blinder-Oaxaca decomposition is an analytical tool used in an attempt to discover the difference in wages between two people who are identical except in the variable where discrimination may be present. This experiment is more robust than a simple OLS regression, as it uses counterfactuals to explore the different returns people get to the same levels of education, number of children, citizenship, and other factors. This adds value to the traditional OLS experiment, as it allows you to break down a standard wage gap by breaking apart pieces that can be explained by difference in education and other attributes, while leaving a residual wage gap that may indicate that discrimination is present.

Using a Blinder-Oaxaca decomposition, I was able to separate the effects on wages from race and chosen attributes including education, citizenship, number of young children, metropolitan status, and marital status. I created estimates for each possible group combination: white workers with white coefficients, nonwhite workers with nonwhite coefficients, white workers with nonwhite coefficients, and nonwhite workers with white coefficients. After taking

the predicted outcomes from this process, I found the total wage gap by finding the difference between the wages of the average white worker and the average nonwhite worker. This shows the real wage gap between the two groups. Then, the explained wage gap was found by looking at the first counterfactual experiment: the difference between the average white worker and the counterfactual: a hypothetical worker with nonwhite X's that receives the returns that a white worker would. Here, the difference shows how much of the wage gap is due to differences that can be explained by differences in Xs in the data. The last experiment finds the residual wage gap, which may be attributed to discrimination. This is found by the difference between the wage of the counterfactual and the average wage of the nonwhite worker.

This was repeated holding certain occupations constant. When looking at the results from the earlier OLS regression based off of the differences in wages between different groups when separated by occupation, some occupations had large and statistically significant differences between groups. These occupations were explored more thoroughly through the Blinder-Oaxaca decomposition.

The entire process was duplicated in part 3.2 using gender as the main variables. While the OLS regression of wages on characteristics remains the same for both race and gender, the occupational regressions were redone by organizing by gender. The Blinder-Oaxaca decompositions were repeated as well, with additional decompositions done for certain occupations that were found significant in the occupational regressions.

Table 1 shows the mean and standard deviation for wages in the restaurant industry in Ohio across time. All amounts are real wages, in 2010 dollars. The chosen occupations for these averages include CEO, management positions, chefs, food preparation workers, cashiers, waiters, dishwashers, hosts, bakers, and butchers. The data is separated by race in order to highlight the differences in race between these two decades.

In 1980, African American workers in the restaurant industry made 15% less than white workers, with an average difference of \$1,437.27. Hispanic workers, on the other hand, only made 4.9% less than their white counterparts. In 2010, the average difference between African American workers and white workers grew to \$3,233.90, with African American workers making 30.8% less than white workers. The wage gap between Hispanic restaurant workers and white restaurant workers reverses in 2010, with Hispanic workers making \$686.69 more than white workers in the restaurant industry in Ohio: a 6.5% increase. In most cases, real wage goes up over time. The only group that saw a wage decrease in this time is African American workers.

Table 2 shows the difference in returns for African American workers versus white workers in the same occupations. Many occupations, especially management and waiting, show African American workers making considerably lower wages. Serving, in particular, is an interesting occupation in that most of the income that waiters make comes from tips. Having a statistically significant difference in average wages for servers suggests the prevalence of consumer discrimination against black workers, which will be explored further in the decomposition section.

When determining which occupations are subjected to racial bias, very few of the results are statistically significant. In fact, many occupations have such small sample sizes that no results can be found. The only occupation that shows statistically significant results in both 1980 and 2010 is waiting, so drawing conclusions from other occupations may be inaccurate.

3. Results

3.1 Racial Discrimination in the Restaurant Industry

Table 3 presents an OLS regression of wages on racial and qualitative characteristics. Here, the data suggests some interesting findings. The return to African American heritage is negative relative to white workers, and gets worse over time. Those with Hispanic American heritage, though, end up making more in 2010 than their white counterparts, despite making a not statistically significant smaller amount in 1980. Without controlling for any characteristics other than race, the OLS regression shows that African American workers make 14.8% less than white restaurant workers. When controlling for specific characteristics, African American workers make 17.6% less. In 2010, the basic regression shows that African Americans make 29.8% less, which shrinks to 26.4% in the more complex model. This suggests that differences in characteristics of the workers do not explain the wage gap. When controlling for characteristics in the Hispanic-American population, the wage gap disappears entirely.

The returns to being male are high, and the returns to education are higher with every level of schooling. What is most interesting is that in 1980, being a citizen results in a statistically insignificant increase in wages, where being a citizen in 2010 brings a significant and substantial increase. Similarly, in 1980, each additional child under the age of five lowers a workers wages by nearly \$3,000, but in 2010, there is a statistically insignificant decrease of \$27.

Table 4 breaks down the wage gap based on how Xs and racial characteristics are assigned. The counterfactual explores workers that have education, location, family status, and citizenship that is consistent with their racial group, yet are given the returns of white workers. The total gap is the difference between the average wages of each group. The explained wage gap compares the average wages for white workers to the counterfactual discussed earlier. This wage gap represents the difference in wages that can be attributed to the differences in Xs across groups. The residual wage gap attempts to explore what part of the wage gap may be attributed to discrimination by comparing the average wages of non-white workers to the counterfactual. This comparison, which can be found by subtracting the explained wage gap from the total wage gap, shows the differences in wages when Xs are being held constant for the non-white group. Workers with non-white Xs and their correct characteristics are compared to hypothetical workers with non-white Xs who are treated with white characteristics.

In 1980, the total wage gap between white workers and African American workers is \$1,452.48 (in 2010 dollars). The explained wage gap in this case, where the white coefficients are held constant, is -\$317.58. In this case, when workers exhibit the average Xs of a white worker and are treated with white coefficients, they make 3.2% less money than workers with

average Xs of African American workers treated the same way. This explained wage gap is interesting, as it suggests that African American Xs have higher returns than their white counterparts, as long as racial coefficients are held constant.

The residual wage gap explores the counterfactual where workers with the average Xs of African American workers are treated with either African American or white coefficients. When a worker in this case is treated with white coefficients, she makes \$1,770.16 more than a worker with the same Xs, yet treated with African American coefficients. In this case, the African American worker treated with African American coefficients makes 17.8% less than one who would be treated with white coefficients. A residual wage gap of any size suggests some degree of discrimination, but having a larger residual wage gap than the total wage gap implies that this effect may be quite large. Because the data shows that African American workers have statistically better Xs, this might itself be evidence of hiring discrimination. It may be that white workers are preferentially hired, while African American workers are hired only if they met higher standards.

When comparing these results to the white-Hispanic wage gap in 1980, the effect nearly disappears. The total wage gap between the two racial groups is only \$54.90. Almost all of that gap can be attributed to the explained wage gap, where workers have Xs consistent with their racial group, but are treated with white coefficients. This explained wage gap is \$48.40, leaving a meager \$6.50 in the residual wage gap.

In 2010, the wage gap between white and African American workers widens to \$3,357.81, which is 131% larger gap than thirty years prior. Here, the explained wage gap is \$459.11, and the residual is \$2,898.71. While the residual wage gap is smaller than the total wage gap in 2010, the numbers indicate that up to 86.3% of the total wage gap could be attributed to discrimination.

The wage gap between white workers and Hispanic workers disappears in 2010, and begins to work in the opposite direction. Hispanic workers made \$828.43 more than white workers on average. \$602 of that difference belongs to the explained wage gap, with just over \$226 residual.

Earlier, in Table 3, it was found that waiters were the only group to have a consistent statistically significant difference in wages between white and African American workers. When a decomposition is run for this demographic, as in Table 4, these differences can be taken apart to determine if any of it may be attributable to customer discrimination through racially biased tipping practices.

In 1980, the total wage gap between white waiters and African American waiters was \$1,967.39. This wage gap is over \$500 larger than the unrestricted wage gap from Table 4. The same effect on the explained wage gap for all of the specified occupations can be seen when the data is restricted to servers, but the effect is relatively larger. This shows that when each racial group keeps their Xs and is treated with white characteristics, the waiters with the average African American Xs make \$555.70 more than the waiters with white Xs. This, again, causes the residual wage gap to reach an outstanding \$2,523.09, which supports our hypothesis that

customer discrimination can have strong negative effects on the incomes of African American workers. Some of this may be explained by hiring bias.

When repeating the process for Hispanic waiters in 1980, Hispanic waiters actually make more than their white counterparts, which was not the case for the group of selected occupations. Hispanic waiters made \$507 more than white workers, with an explained wage gap of \$122.96 in the Hispanic workers' favor. That leaves a residual wage gap of \$384.04, where workers with average Hispanic Xs make more if they are treated with Hispanic coefficients than if they were treated with white coefficients.

In 2010, there is still a quantifiable wage gap between African American and white waiters, but the effect is smaller than that of the group as a whole. On average, African American waiters make \$2,486.41 less than white waiters in the same year. The total wage gap for servers is about 26% smaller than that of the unrestricted group. When workers with African American Xs are treated with white coefficients, they make \$286 less than workers with white Xs treated similarly. This leaves a residual wage gap of \$2,200.41, which may be able to be attributed to customer discrimination.

Using the same tactics to find the wage gap for Hispanic waiters in 2010, the wage gap actually appears where it did not exist for all occupations. Instead of having a wage gap that benefits Hispanic workers, Hispanic waiters get paid on average \$271.49 less than white waiters. When treating both Hispanic and white workers with white coefficients, the explained wage gap more than covers the total wage gap, with Hispanic workers making \$792.20 less than those with white Xs. The residual wage gap, on the other hand, shows that workers with Hispanic Xs get paid \$520.71 less if they are treated with white coefficients than if they were treated as Hispanics.

3.2 Gender-Based Discrimination in the Restaurant Industry

Table 5 shows the average wages for male and female workers in the restaurant industry in Ohio, in 2010 dollars. According to the data, women make 49% less than men in the restaurant industry in 1980. In 2010, women only make 32.1% less than men on average.

When breaking wage differences down by occupation, the data in Table 6 suggests that men consistently make more than women in every occupation except food preparation. It also shows that the difference in real wages between men and women in the restaurant industry goes down over time. For example, where male waiters made \$4,224.05 more than women in 1980, they only made \$1,292.87 more in 2010. There are many cases in which this difference is statistically significant, but the consistently significant results are only found in management and serving.

In 1980, women made 48.9% less than men in the restaurant industry on average, with a total wage gap of \$7,137.98. In 2010, the total wage gap between the two went down to 32.2%, with women making \$4,122.01 less than men on average. When comparing male and female Xs holding male coefficients constant, we find an explained wage gap of -\$3,960.92 in 1980, and an explained wage gap of -\$909.56 in 2010. To put it into perspective, male restaurant workers

would make 21.4% less than female workers in 1980 if everyone was treated with male coefficients. Men would make 6.6% less if this were the case in 2010. Just like in the comparison between white and African American workers in Table 4, this negative explained wage gap shows that when coefficients are held constant, women get paid significantly more than men. This effect can still be seen in 2010, but to a much lesser degree.

The residual wage gap explores the difference between male and female coefficients when female Xs are held constant. In this case, the residual wage gap in 1980 between men and women is \$11,098.90. This means that females treated with female coefficients make 59.8% less than females treated with male coefficients in 1980. In 2010, female restaurant industry workers with female coefficients make 36.7% less than female workers with male coefficients. The total residual wage gap in this case is \$5,031.52. While this is much smaller than in 1980, it still shows a large possibility for gender based discrimination in the restaurant industry.

Table 6 showed that female servers consistently made less than male servers, with statistically significant results in both 1980 and 2010. Because most servers in Ohio are paid through tips from customers, this may be an indication of discrimination from customers based on the gender of their servers. After further exploration shown in Table 9, we find that waitresses make 37.7% less than waiters in Ohio in 1980, with a total wage gap of \$4,012.90. In 2010, the total wage gap shrinks dramatically to \$1,373.28, with female servers only making 14.96% less than their male counterparts.

When looking into the explained wage gap, the same pattern of data is found for waiters that was found in the general population of restaurant workers, where holding male coefficients constant results in females making higher wages. In 1980, waitresses would make \$1,819.63 more than waiters if the male coefficients were held constant. In 2010, waitresses would make \$40.50 more than waiters if the same conditions were true. Here, men would make 14.6% less than women in 1980, and 0.4% less in 2010.

The residual wage gap suggests that gender-based discrimination may be present in the restaurant industry in Ohio. Holding female Xs constant, waitresses treated with female coefficients in 1980 would make \$5,832.53 less than waitresses treated with male coefficients. In 2010, waitresses with female coefficients would make \$1,413.78 less than those treated with male coefficients. While the residual wage gap went from 46.8% in 1980 down to 15.3% in 2010, both are indicative of possible gender based discrimination from restaurant customers.

Table 6 also showed possible discrimination in the restaurant industry between male and female managers. The statistically significant results showed that female managers were given consistently lower wages than male managers of restaurants in Ohio. In Table 7, we see that there is a total wage gap of \$20,827.31 in 1980, with female managers making 58.7% less than male managers in that year. In 2010, the gap closed a bit, but still shows women making 39.3% less than men. Here, a total wage gap of \$13,710.10 can be observed.

Unlike the explained gap for servers, male and female managers do not seem to follow the same pattern where women would actually make more than men if everyone were treated with male coefficients. In 1980, female managers would have made 15.8% less than male

managers if the male coefficients were held constant between the two groups. This means that the explained wage gap for male and female managers in 1980 was \$5,600.19. In 2010, the explained wage gap goes down to \$2,049.41 for restaurant managers, with female managers making 5.9% less than males if both were treated with male coefficients.

Unfortunately, the residual wage gap is quite large in both 1980 and 2010 between managers of different genders. In 1980, there was a residual wage gap of \$15,227.12 where female managers got paid 51% less when they were treated with female coefficients than if they were treated with male coefficients. The gap was only \$11,660.69 in 2010, with female servers making 35.5% less when they are treated with female coefficients.

4. Conclusion

In order to find the extent of discrimination in the restaurant industry in Ohio, I used OLS regressions and Blinder-Oaxaca decompositions to determine how much of the difference in wages between groups can be attributed to chosen characteristics.

Using these methods, I found that racial discrimination not only exists between white and African American workers, but that the wage gap widens even further when attempting to explain the differences. This problem seems to get worse over time, as the residual wage gap in 2010 is 63.8% larger than it was in 1980. When investigating the difference in wages between white and Hispanic restaurant workers, almost no discrimination can be found. When looking at the difference in wages for servers, the residual wage gap is a higher percentage of the average incomes of workers than when looking at the original group of workers, which suggests that customer based discrimination may play a key role in the difference in average wages. This, once again, does not appear to exist when looking at Hispanic workers.

In Ohio restaurants, gender based discrimination appears to be more severe than racially based discrimination. But, unlike its racial counterparts, gender based discrimination seems to be shrinking rapidly. The residual wage gap was 45.3% lower in 2010 than in 1980, which suggests improvement in equality between genders. While a large wage gap exists when focusing on servers of different genders, it is important to note that the wage gap is much smaller than it is on average for all of the specified occupations. This may suggest that women face most of the discrimination from employers, while it remains less severe from customers. Decompositions regarding gender discrimination for managers shows just the opposite: the wage gap is 37.2% higher for managers than for the entire occupational group.

These discoveries are interesting because they show surprising differences between reality and the perceived norm of discrimination in Ohio restaurants. For example, one would not assume that discrimination between white and African American workers appears even worse once Xs are controlled for. It also seems surprising that the effect of discrimination against Hispanic workers appears nonexistent. While many of the results are not totally different from existing information in different locations and industries, it bolsters previous knowledge on discrimination.

References

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Table 1. Average Wages for Selected Occupations in the Restaurant Industry, by Race

	1980		2010	
	Mean	Standard Deviation	Mean	Standard Deviation
White	9547.82	15342.07	10506.52	17981.92
African American	8110.55	13468.52	7272.62	10823.95
Hispanic American	9081.56	12138.41	11193.21	10342.73
Other	13465.82	14268.3	11004.33	18054.69

Note: Data collected from IPUMS USA: 1980, 2010
All values are in 2010 dollars

Table 2. Average Wages of White Workers minus Average Wages of African American Workers, by Occupation

	1980	2010
All Occupations	1432.1***	3189.5***
CEO	N/A	N/A
Manager	2082.3	11394**
Chef	-1411.57**	10.103
Food Preparation	102.05	384
Cashier	739.87	1511.5*
Waiter	1937.6**	2390.2*
Dishwasher	N/A	-1227.26
Host	N/A	2385.2
Baker	N/A	N/A
Butcher	-7447.25	N/A

Table 3. OLS Regression of Wages on Characteristics

	1980	1980	2010	2010
African American	-1432.05*** (460.82)	-1697.58*** (432.34)	-3189.47*** (924.41)	-2827.43*** (890.82)
Hispanic American	-556.91 (1681.38)	-7.10 (1724.23)	679.63 (1672.97)	612.64 (1598.61)
Other Race/Ethnicity	3930.45*** (1229.89)	-1022.39 (1162.33)	510.16 (1164.08)	-2380.91** (1176.85)
Male		7854.86*** (257.98)		4278.83*** (521.60)
High School Degree		3149.26*** (263.06)		3070.47*** (686.04)
Some College		7211.45*** (365.70)		6748.19*** (754.76)
College Degree		19311.00*** (664.87)		16921.00*** (1096.89)
Citizen		920.36 (786.73)		4538.82*** (1475.61)
Children Under 5 (Per Child)		-2967.11*** (245.14)		-27.42 (589.60)
In School		-7616.18*** (288.38)		-6017.30*** (593.08)
In a Metropolitan Area		1717.86*** (314.12)		1991.31*** (648.85)
Married		1903.50*** (285.41)		5820.08*** (657.43)

Note: Data collected from IPUMS USA: 1980, 2010

*Denotes 10% statistical significance

**Denotes 5% statistical significance

***Denotes 1% statistical significance

All values are in 2010 dollars

Table 4. Racial Wage Decompositions, 1980 and 2010

	Average Wages White $(\bar{X}_w \hat{\beta}_w)$ (i)	Average Wages Non- white $(\bar{X}_N \hat{\beta}_N)$ (ii)	Counterfactual $(\bar{X}_N \hat{\beta}_w)$ (iii)	Total Gap (i)-(ii) (iv)	Explained Gap (i)-(iii) (v)	Residual Gap (iii)-(ii) (vi)
White and Black, All Occupations						
1980	9651.08	8198.50	9968.66	1452.58	-317.58	1770.16
2010	10715.00	7357.19	10255.89	3357.81	459.11	2898.70
White and Hispanic, All Occupations						
1980	9651.08	9596.18	9602.68	54.90	48.40	6.50
2010	10715.00	11543.43	11317.00	-828.43	-602	-226.43
White and Black, Servers						
1980	6907.89	4940.50	7463.59	1967.39	-555.70	2523.09
2010	8061.99	5575.58	7775.99	2486.41	286.00	2200.41
White and Hispanic, Servers						
1980	6907.89	7414.89	7030.85	-507.00	-122.96	-384.04
2010	8061.99	7790.500	7269.79	271.49	792.20	-520.71

Table 5. Average Wages for Selected Occupations in the Restaurant Industry, by Gender

	1980		2010	
	Mean	Standard Deviation	Mean	Standard Deviation
Male	14498.35	22699.24	12573.5	22354.3
Female	7392.48	9910.89	8536.97	12078.7

Note: Data collected from IPUMS USA: 1980, 2010
All values are in 2010 dollars

Table 6. Average Wages of Male Workers minus Average Wages of Female Workers, by Occupation

	1980	2010
All Occupations	7105.87***	4036.50***
CEO	N/A	N/A
Manager	20462***	14062***
Chef	1750.74***	1278.05
Food Preparation	-381.79	-468.81
Cashier	1836.76***	549.01
Waiter	4224.05***	1292.87*
Dishwasher	N/A	558.52
Host	N/A	645.24
Baker	11916	2381.43
Butcher	12784	N/A

Table 7. Gender Based Wage Decompositions, 1980 and 2010

	Average Wages Male ($\bar{X}_M \hat{\beta}_M$)	Average Wages Female ($\bar{X}_F \hat{\beta}_F$)	Counterfactual ($\bar{X}_F \hat{\beta}_M$)	Total Gap (i)-(ii)	Explained Gap (i)-(iii)	Residual Gap (iii)-(ii)
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
All Occupations						
1980	14588.5	7450.52	18549.42	7137.98	-3960.92	11098.90
2010	12792.61	8670.60	13702.17	4122.01	-909.56	5031.57
Servers						
1980	10655.96	6643.06	12475.59	4012.90	-1819.63	5832.53
2010	9181.01	7807.73	9221.51	1373.28	-40.50	1413.78
Managers						
1980	35485.52	14658.21	29885.33	20827.31	5600.19	15227.12
2010	34883.19	21173.09	32833.78	13710.10	2049.41	11660.69