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Exploring Wage Determination by Education Level: A U.S. MSA Analysis for 2005-2012

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Abstract:

The purpose of this study is to explain urban wage differentials with a special focus on educational levels. We explore whether the share of people with a bachelor's degree or higher in the community matters to the wages of those within specific educational cohorts, accounting for cost of living, human capital externalities, consumer externalities, policy factors and local market conditions. Using data for all U.S. Metropolitan Statistical Areas between 2005-2012, we find that the presence of more highly educated people will result in a higher median wage in the community overall, as do many studies, but that this factor does not significantly increase the wage for any individual education cohort. These results are hidden if we only look at the entire workforce in the aggregate.

Exploring Median Wage Determination by Education Level:
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Introduction

Local leaders across the U.S. strive to create conditions for better employment opportunities, higher incomes and less inequality for their constituents. Research has found evidence that productivity is higher in urban areas which leads to higher wages, after accounting for higher costs of living (Glaeser & Mare, 2001). This urban wage premium has numerous proposed explanations, with concentrations of higher education and skills being key variables. (See a comprehensive review by Heuermann, Halfdanarson and Suedekum, 2010). Cities have been shown to be special in numerous ways. For example, cities “speed the accumulation of human capital” (Glaeser & Mare, 2001), cities have “something in the air” (Krupka & Noonan, 2013); and cities attract “creative” people (Florida, 2012).

Some research has suggested that the benefits of having an educated labor force appear to go beyond the higher incomes earned by knowledge workers concentrated in cities. Moretti (2013), for example, argues in his book, *The New Geography of Jobs*, that there is a positive effect between the share of an area’s population with at least a bachelor’s degree and the average wages earned by less educated workers in a particular geographic area. As he puts it, “Brain hubs pay high average salaries to *unskilled* workers too (p.97).” This type of spillover, if and where it exists, makes the education factor even more valuable to communities.

In this study we examine these knowledge spillovers further by analyzing wage differences across cities using median wages by educational cohorts. Specifically, our study examines the effect of the presence of human capital levels on annual median wages for workers with different education levels across 374 U.S. metropolitan statistical areas (MSA). We also incorporate a substantial time frame covering 2005 to 2012. We explore the relationship between the overall educational attainment of a community and the median wage for different educational attainment groups. The dependent variable is the natural log of the real median annual wage for the working age population 25 and older with earnings by level of educational attainment from the American Community Survey (ACS).

One of the critiques of the numerous studies that have been done to explain wage differentials is that each tends to focus narrowly on one explanation with other factors left out (Hanson, 2000). A strength of our approach in this study is that we explore human capital externalities and their potential spillovers while also considering other variables found to be important in the literature including cost of living, amenities, labor market conditions and policy. We find evidence that the estimated impact of each of these explanations varies by educational cohort. Unlike many studies, we include a measure of labor market conditions to control for business cycle effects across regions, which turns out to be very important in explaining wage variation.

A second contribution of this study is that we use a partial cost of living adjustment, as suggested by Dumond, Hirsch and MacPherson (1999), utilizing newly developed regional price parities (Aten, Figueroa & Vengelen 2015) and data that allows us to separate housing costs from other cost of living factors. This is the first time, to our knowledge, that this has been done for all U.S. MSAs. This approach avoids misleading estimates of real wages as demonstrated in Dumond et al., and suggests that housing should be treated partially as an amenity and not just a cost factor.

A third contribution of this study is to analyze the explanatory power of variables from the literature by educational attainment; in other words, our approach allows us to gain insights by looking at sub-labor markets defined by education levels. Our results suggest that in terms of the aggregate median wage, adjusted properly for cost of living differences, having a better educated population does not significantly increase other people's wages. Contrary to other studies and to what policy makers might hope, our results suggest that the wages of individual education cohorts are not substantively affected simply by the presence of a better educated population.

The Urban Wage Story

The strong linkage between education and wages receives a great deal of attention in the U.S. labor market. By one calculation, the inflation-adjusted wage gap between a family with high school degrees and one with college degrees increased $30,000 between 1979 and 2012 (Porter, 2014). Based on the ACS data, there are large differences in the annual median salaries across groups with different education attainment (Figure 1). The median annual salary for those with a graduate degree in the U.S. was $65,164 in 2012 compared with only $19,404 for those without a high school diploma, and the salary difference between someone with a high school degree and a bachelor's degree increased $825 (in real 2012 dollars) in the seven years between 2005 and 2012. The other trend, however, is that for all education levels, the inflation adjusted U.S. median wage has been falling in recent years. The declines have been larger for the less educated—between 1.6

and 1.9% per year for individuals with some college or an associate degree or less education—compared to an average decline of 0.7% per year for college graduates and 0.5% per year for those with graduate degrees.

(Figure 1 about here)

Underlying these trends are important regional variations. For example, in 2012 the median wage for high school graduates in Milwaukee was $28,708 and only $25,693 in Los Angeles, while the median salary for a person with a graduate degree was $66,024 in Milwaukee and $73,642 in Los Angeles. Most people might simply assume that people living in Los Angeles had higher income than people living in Milwaukee, and for people with graduate degrees that is true, but not for people with only a high school diploma. So while more education is associated with higher incomes in both places, there are other factors that must explain why the median worker with just a high school degree is paid more in Milwaukee than the similarly educated worker in Los Angeles, while the person with a graduate degree earns more in Los Angeles. One explanation could be differences in the cost of living, but cost of living differences cannot explain all of the variance in income between Los Angeles and Milwaukee. Further, in the case of a person with only a high school degree, incorporating those differences would widen Milwaukee's advantage.[1]

A study by the Federal Reserve Bank of Cleveland also found that metro areas with a higher share of workers with a bachelor's degree or more had higher wages and lower unemployment rates, using data for 2011 for the 100 largest metropolitan areas

(Richter & Nelson, 2014). They concluded that these correlations suggest that less educated workers may benefit from working in the same geographical area with a more educated population. This is consistent with Moretti's work based both on individual data (2004a) and average wages (2013).

Using data from the ACS for 2005 to 2012, in comparison with the Cleveland Fed study (Richter & Nelson, 2014), we also find a consistent, positive correlation between the share of the population aged 25 to 64 with a bachelor's degree and the median wage when all education cohorts are put together (Table 1). Table 1 shows the Pearson Correlation coefficient between the share of the population aged 25 to 64 with at least a bachelor's degree and the median wage in a metropolitan area by year. The positive correlation is very strong and highly significant for all workers with a correlation value between .618 and .688. The correlation is also fairly strong for different sub-groups defined by their educational attainment. For the sub-groups the correlation is positive and significant at the 1% level in 37 out of 40 possible year by educational attainment cells, and it is significant at the 5% level in 2 other cells. In 2012, the correlation between the community's educational attainment and the median wage was not significant at the 5% level for individuals who did not complete high school, but even this positive correlation was significant at the 10% level.

These results lend support to the hypothesis that all workers benefit from having a well-educated community; however, as we shall see, this analysis does not hold up under more rigorous tests.

(Table 1 about here)

While aggregate correlations between education and wages are evident, how robust this relationship actually is once local conditions and other factors are considered is a key question (Fontes, Simoes & Hermeto Camilo de Oliveira, 2010). In addition, while evidence of an urban wage premium is fairly well accepted, the explanations for the premium continue to be explored (Heuermann et al., 2010). Most explanations focus on ways that education may increase productivity, through social returns to education (Moretti, 2004b, Rauch, 1993), proximity to college educated workers (Rosenthal & Strange, 2008), or utilization of skills (Combes, Duranton & Gobillon, 2008, Rodriguez-Pose & Vilata-Bufi, 2005), for example, while other studies argue that the nature of cities themselves increase productivity due to scale from density, agglomeration effects, and other local conditions that enhance local resources (Fingleton, 2003, Glaeser & Mare, 2001, Wheaton & Lewis, 2002).

Results from studies looking at more generalized spillovers from the presence of educated workers to wages of less educated workers have been mixed (Bratti & Leombruni, 2014, Schumacher, Dias and Tebaldi, 2014). In his *Journal of Econometrics* article, Moretti (2004a) found that for cities in the U.S., an increase in the supply of college graduates raised the wages of college graduates and of those that did not graduate from high school, and in his book, Moretti (2013) found broader spillovers to non-college workers. A recent study by Schumacher et al., following Acemoglu (1996), found that concentrations of highly educated employees have a positive spillover to all workers in the business services sector in the U.S. and Brazil, with a spillover to other sectors in Brazil but not in the U.S. In contrast, other studies have found small or no spillover effects. For example, Bratti and Leombruni (2014) found a small spillover from the presence of college educated workers to white collar wages but not to blue collar workers in Italian manufacturing. Using U.S. data both Acemoglu and Angrist (2000) and Ciccone and Peri (2006) found insignificant spillovers from education levels to wages.

In this study using the share of the population with a bachelor's degree or more as our measure of human capital stock, we explore possible spillover effects to the wages of five levels of educated workers in U.S. MSAs.

Literature and Variable Choices

Heuermann et al. (2010) outline two sets of literatures focusing on explaining either urban wage premiums and or human capital externalities. The two are closely related. In both approaches two sets of variables are typically used in explaining regional wage differences. The first set is individual characteristics of workers and the second is characteristics of the local economy where the individuals work.

In this study we identify the "median" person by educational attainment in each metro area and attempt to explain what that person is earning by regressing the wages for that median person against community and state variables. Our equation can be represented as follows:

$$\text{Ln } W_{it} = \alpha + \beta X_{it} + \gamma_1 Z_{1it} + \gamma_2 Z_{2it} + \phi_{it} + \varepsilon_{it} \qquad (1)$$

Where Ln W is the log of the real median annual wage for the group of workers with the same educational attainment level;

X is the vector of local human capital characteristics, including the share of the population with a bachelor's degree or more, and the share of young workers as a gauge of experience;

Z_1 is the vector of local community characteristics including metro labor market conditions, the local cost of housing, and the presence of amenities;

Z_2 is the vector of state level policy characteristics including the legally mandated minimum wage adjusted for local area non-housing cost of living differences, and the state-wide tax rate measured by total state and local taxes as a share of personal income;

Φ is the vector of unobservable individual characteristics; and

ε is the error term.

Our dependent variable is the median wage, W, and is partially adjusted for cost of living differences, measured in U.S. 2012 dollars. We prefer using the median wage over the mean. First, in order to calculate the mean wage by educational attainment one would need to use the micro data sample from the ACS. Two problems with this data set are that the respondent's location is only identified by Public Use Micro Area (PUMA), which does not always correspond to a metropolitan area, and second, the income data is top coded based upon the highest 0.5% in a state. In most states this would imply a top coded value of between $300,000 and $500,000. The wages of individuals whose actual wage exceeds the top code value are assigned a wage value equal to the top code value.

The tabulated data for metropolitan areas published by the U. S. Census Bureau do not have these limitations.

Second, and more importantly, the mean is skewed upwards by the presence of very high wage individuals. Variation in mean and median wages can be seen from data available from the U.S. Census Bureau for all year-round, full-time workers aged 16 and older by gender. For example, for male workers in 2012 the mean wage in the U.S. was $64,650 and the median wage was $47,473, which is a difference of 36%. In 2012 the metropolitan area with the largest difference was Bridgeport-Stamford Connecticut where the mean wage for male workers was $124,784 whereas the median wage was only $70,970, a difference of 76%. In Los Angeles the mean wage for male workers was 45% higher than the median wage, while in Milwaukee the mean was only 28% higher than the median.

Moreover the degree of skewness in the ACS micro data sample varies by level of educational attainment. In Los Angeles the mean wage for someone with only a high school degree in 2012 was 27% higher than the median wage, while in Milwaukee the mean wage for a high school graduate was only 8% higher than the median wage. The disproportionate presence of some high-wage, high school graduates tends to pull up the mean wage much more in Los Angeles than it does in Milwaukee. The mean wage for workers with a graduate degree is 31% higher than the median wage in Los Angeles, while in Milwaukee it is 33% higher. The variance across MSAs in the difference between the mean and the median is much higher for the lower educational attainment categories. To eliminate this distortion we use the ACS data on the median wage published by the U.S. Census Bureau.[2]

We adjust the median wage variable to account for non-housing differences in the cost of living. Our cost of living adjustment is based on regional price parities developed by the Bureau of Economic Analysis (BEA) (Aten, Figueroa, & Vengelen 2015). The adjustment is based upon a weighted average of the goods and non-housing related services cost indices. The housing cost index, which is based upon the median rent data from the ACS, is included as an explanatory variable. Winters (2009) showed that rents were a better measure of housing costs than owner-occupied housing values. Further, regional differences in wages and incomes should only partially adjust for differences in the local cost of living because the local price of housing incorporates some location amenity value (Dumond et al., 1999). The BEA data are also based on direct price measures rather than indirectly using wages (Riefler, 2007). We then extend this measure back in time to derive price parity index values for the period 2005 to 2007, since the BEA estimates start in 2008. (See Appendix A for further discussion of this procedure.)

We study the effect of human capital externalities on the real wage for our whole sample, which is comparable to many previous studies. We also study these relationships for five disaggregated groups distinguished by the standard categories of education attainment: 1) did not graduate from high school; 2) high school diploma or a graduate equivalent degree (GED); 3) associate college degree or some college; 4) bachelor's degree only; and 5) graduate degree. Very few studies have used this type of disaggregated data, and none that we could find use them to analyze urban wage differentials.[3]

In addition to disaggregating by education level as a way to understand the human capital factors, for each education equation we measure the local human capital characteristics with two variables: human capital intensity and experience. We measure human capital intensity by the share of the population aged 25 to 64 that has a bachelor's degree or more. If having more educated people nearby has a knowledge spillover effect on the wages of others, then we would expect to see a positive coefficient on this variable. We measure experience by the share of the working age population that is young. Specifically we define "young" as the share of the working age population that is between 25 and 34 out of the total population aged 25 to 64. This variable is specific to each educational attainment cohort. For example, the population aged 25 to 34 with a graduate degree is divided by the total population aged 25 to 64 with a graduate degree. Younger workers tend to get paid less than older workers, presumably because they are less productive, thus a community where a bigger share of workers are younger, within each educational attainment cohort, we would expect the workers in that cohort to be paid less.

Local labor market conditions are captured with the share of employed individuals (aged 25 to 64) relative to the total prime working age (25 to 64) population. This labor market tightness variable is specific to each educational attainment cohort. For example, the number of employed people who have not completed high school is divided by the total population that has not completed high school. For two of the regression equations, those for the median wage of individuals with a bachelor's degree or a graduate degree, the independent variable used to measure labor market conditions is the number of employed people with a bachelor's degree or more divided by the population with a bachelor's degree or more. The employment data for the population aged 25 to 64 were not available separately for people with only a bachelor's degree or a graduate degree.

If labor markets are tight, where a large proportion of the potential workforce are employed, then we would expect upward pressure on wages. Since labor market conditions in the aggregate tend to be positively correlated with an area's educational attainment (in the aggregate the more educated communities have more people working), it is desirable to include this measure by educational attainment category (instead of simply looking at the aggregate labor market). This will ensure that it is the labor market conditions for a particular type of worker that is determining the wage for that particular type of worker. There is some concern that this variable could be endogenous to this equation as there could be unobserved or unmeasured characteristics of a metro area's industry and employment mix that could lead to both higher wages and a tighter labor market. We examine this issue empirically.

We include two policy variables that vary by state: the legislatively mandated minimum wage adjusted for local non-housing costs of living and expressed in constant 2012 dollars, and a tax rate variable. These are included to capture public policy efforts to directly influence the local wage, or to indirectly influence the local gross wage by reducing or increasing the after tax wage. We would expect that the minimum wage would have a positive effect on the median wage, especially for the less educated cohorts, and that the tax rate would have a positive effect on the median wage if the equilibrium wage rate is determined by after tax income. Note that because the minimum wage variable is adjusted for differences in the local, non-housing cost of living it varies by metro area.

Finally, we include a set of variables to capture various amenities. There are both positive and negative consumption externalities that can affect wages that employees will accept (Dimou, 2012, Gabriel & Rosenthal, 1999, Roback, 1982). For example, Florida's (2012) work on the "creative class" poses the hypothesis that people are attracted to places with an array of activities with opportunities for interaction. In this study we include three desirable amenities: presence of leisure and culture (includes employees at parks, museums, amusement parks, golf course, ski resorts, non-hotel casinos etc.), higher educational institutions and public transportation. The presence of these amenities is measured by the share of employment in each of these industries in the MSA as reported by the Bureau of Labor Statistics.[4] We also include the share of employment in durable manufacturing, expecting that this is a negative amenity in that people may require a higher wage to work in the challenging working conditions in factories or to live near such factories. We expect that the desirable amenities would be negatively related to the median wage for each educational attainment category, while the undesirable amenity would be positively related to wages.

We used a fixed effect estimation technique to account for the metro area factors that do not change over time, and we added year dummies to control for effects that vary by year but not by geography. We also estimate our equations using metro areas larger than 500,000 in 2012 (104 metro areas, thus a sample similar to Richter and Nelson, 2014), less than 500,000, and all MSAs together. (See Appendix B for a list of the 374 MSAs.) This allows us to determine if there are differences in the factors that influence wages in larger and smaller metro areas (Echeverri-Carroll & Ayala, 2011).

Results

The descriptive statistics for each of our variables are reported in Table 2.

(Table 2 about here)

We begin by estimating a base model that includes the human capital variables and the housing price cost of living variable as explanatory variables (Table 3), followed by estimations for our full model shown in Table 4. The results for the year effects are shown in Appendix C. Note that the dependent variable, the housing price variable and the minimum wage variable used in our estimations are in natural logs, and the other variables are measured as shares. The results come from a fixed effects model estimated for all U.S. metropolitan areas over eight years from 2005 through 2012.[5] The standard errors are calculated from a covariance matrix estimator that adjusts for heteroskedasticity and serial correlation at the metropolitan area.[6] The estimated standard errors, clustered at the MSA level, are reported below each coefficient.

(Table 3 about here)

The first column in Table 3 reports results for the whole sample, combining all education levels. Our primary interest is in the impact of human capital intensity measured as the share of the population with a bachelor's degree or more; this variable has a positive and statistically significant coefficient. The more educated the community, the higher the median wage. In our base model, a 10% increase in an area's share of its working age population with at least a bachelor's degree, say from 30 to 33%, would result in almost a 2% increase in the overall real median wage from $35,000 a year to $35,657 a year.

The coefficient on the housing price variable suggests that an area's median wage partially responds to an increase in housing costs (coefficient value of 0.40), indicating that some of the variance in housing prices reflects the amenity value of various communities. A coefficient estimate of 1.0 would imply that workers require a wage rate sufficient to completely offset higher housing costs. A point estimate of 0.0, on the other hand, would imply that the value of the place amenity would completely offset the higher cost of housing.

Our measure of experience is the share of the working age population that is relatively young. This variable is not significant when all education groups are combined, but is significant at the 1% level, as expected, once we control for education attainment, except for high school graduates where it is insignificant.

The more interesting results come from the regressions that consider median wages stratified by educational attainment (Table 3, columns 2-5). Here the base case results show that the impact of a more highly educated workforce is generally quite small and is not statistically significantly different from zero. The higher level of wages in a better educated community appears to reflect each individual's own educational attainment, with no measurable spillovers to the median wages of other workers. This result is inconsistent with the correlations presented in Table 1, and conflicts with the argument that Moretti presents in his book (2013) as well as with the results from the Cleveland Federal Reserve study (Richter & Nelson 2014).

The full model presented in Table 4 includes several other conditioning variables, as described in the data section above. These variables are the log of the minimum wage, adjusted by metro-area cost of living but not by housing costs, the measure of labor market tightness, a measure of state tax rates, and the amenity variables. The estimated coefficients for the human capital and housing price variables are similar to those obtained in the base case models. The coefficient on the housing price variable varies by educational attainment category but remains significant among all educational levels, except for individuals with a graduate degree. This coefficient was also insignificant in the base regression for people with a graduate degree which suggests that people with a graduate degree are not compensated for higher housing costs with higher wages. Perhaps people with a graduate degree consider that higher housing costs reflect the amenity value of place. People with less education do require higher pay to work in communities with higher housing costs indicating that for them the cost of housing exceeds the amenity value of place and wages partially adjust to compensate.

(Table 4 about here)

Similarly, adding the other explanatory variables does not change the results for the community educational attainment variable. Again, there appears to be no spillover wage benefits for workers because they are living in communities with a relatively large share of educated residents.

Results for the control variables are also interesting. We find, not surprisingly, that metro areas with younger workforces, stratified by the educational attainment of the cohort, have a significant and negative effect on the median wage. For example, an increase in the share of the work-age population with a bachelor's degree that is relatively young (aged 25 to 34) from 25 to 30% would reduce the median wage of that segment of the workforce from about $45,000 to $44,406.

Our measure of labor market conditions is positive and significant except for individuals with a graduate degree. Since the job market for people with a graduate degree tends to be geographically larger than the local metro area it is less surprising that their wages would not be influenced by conditions in the local labor market. However, an increase in the employment to population ratio from 55 to 58% for those with a high school degree would increase the median wage of high school graduates from about $30,000 to $30,379. There is some concern that this variable could be jointly determined along with the median wage, as there are perhaps unobserved factors that increase the tightness of a local labor market and also push up the median wage in that market. To mitigate this concern, we also estimated this model using a lagged measure. The results for all variables were virtually identical, so we present only one set of results.[7]

The minimum wage has a positive effect on median wages for all of the educational attainment groups (and the entire workforce) except for people with a graduate degree. It is significant at the 5% level for all workers without controlling for educational cohort, and at the 5% level for high school dropouts and at the 10% level for high school graduates. So the least educated workers are likely to see an increase in the median wage if there is an increase in the statutory minimum wage in their community.

For individuals who did not complete high school, an increase in the minimum wage from $7.25 an hour to $8.25 an hour would raise the median wage for this group from about $20,000 a year to $20,257 a year.

The state and local tax rate variable tended to be positive across the educational attainment categories but is only significant, at the 10% level, for the all workers category and individuals with a graduate degree. The point estimates indicates that much of an increase in state and local taxes are offset by an increase in the gross wage. For example, if state and local taxes were increased from 10 to 11%, then the typical worker with a graduate degree with a median income of $62,000 would pay an additional $620 per year in taxes. However, our model estimates that their gross income would increase from $62,000 to $62,503, offsetting 81% of those higher taxes.[8]

Among our amenity variables the strongest results were reported for the share of total wage and salary employment in durables manufacturing. This coefficient was positive for all groups and was significant at the 5% level of all educational attainment categories except for people with a bachelor's degree and people with a graduate degree. This indicates that wages for lower educational attainment workers tend to be higher in areas with relatively large share of employment in durables manufacturing. For workers with some college education or an associate degree, an increase in the share of employment in durables manufacturing from 5 to 8% would increase the median annual wage from about $35,000 to $35,638. This result is consistent with an interpretation that the presence of durable manufacturing results in a higher median wage to compensate for the negative amenity. The results could also reflect the fact that durables manufacturing tends to be relatively well paid and employs a disproportionate share of less educated workers. Durables manufacturing, however, represented a very small share of employment in most metropolitan areas and thus this explanation seemed unlikely.[9]

The estimated year effects are also quite interesting (see Appendix C). For example, the dummy variables for the year 2007 were generally insignificant. This year, of course, is the peak year before the great recession and the weak national labor market conditions that followed. In almost every other year the negative effects were significant at the 1% level for every education group except those with a graduate degree. In general, the year dummy variable was not significant or was less significant for those with a graduate degree, suggesting that the downturn had less impact on median wages for this group. There were larger year effects for those with less education and in general they became more negative as we move through the estimation period. For example, the coefficient value for 2012 was -0.087 for individuals who have not completed high school and -0.028 for individuals holding a graduate degree (both results statistically significant at the 1% level). In 2006, the coefficient value for individuals who had not completed high school was -.027 and for people with graduate degrees it was -.010. The fall in real wages over time, even controlling for local labor market conditions and other factors, is a matter of socio-economic concern as it has primarily affected the less educated.

Robustness Checks

We examined the robustness of our results in several ways. First, we estimated several models that varied in how the cost of living was incorporated into the estimation procedure, including using nominal wages and including all price variables as independent variables. The coefficient estimates on the other independent variables were remarkably similar in all of these alternative models.

Second, we estimated a random effects model, which was soundly rejected in favor of fixed effects, for both the base model and the full model. Interestingly the random effects model was the only estimation that resulted in a positive and significant effect of the community education attainment variable on the median wage for people with a bachelor's degree and people with a graduate degree.

Third, to examine the importance of city size, we divided our data set into MSAs greater than 500,000 people and those with fewer. The parameter estimates between these and our estimates on the full data set were very similar. The standard errors increased in the MSA subsets as one would expect and this reduced the statistical significance of the variables and in couple of instances made the coefficient estimates insignificantly different from zero at the 5% level. One exception to these overall results was that the housing price variable for the population with a graduate degree in the larger MSAs became significantly positive. Further, the coefficient on the community education attainment variable was not statistically significant for any of the educational attainment cohorts even when we restrict our sample to the larger MSAs.

As mentioned in the results section, we also examined the sensitivity of our results to our choice of the labor market tightness variable. Our measure was the share of the adult population that was employed. We found no qualitative differences in the parameter estimates when either a lagged version, or a lead version, of our variable was used.

Finally, we estimated a Hierarchical Linear Model (HLM) type specification that used the two levels of the metro area and the state (Fontes et al., 2010). Our state level variable was the tax rate variable. This specification differs slightly from a fully specified HLM model in that our error structure allowed for non-parametric correlation within each metro area, rather than metro and state level random effects. Again, this specification did not produce parameter estimates that were qualitatively different from the simpler specifications. We found no evidence to support the existence of positive spillovers from an educated workforce to the wages of less educated workers.

Discussion

These results suggest two overall scenarios, defined by educational group—those who are relatively educated and those who are not. For those with a graduate degree, local factors do not seem to matter much, and instead wages in this cohort are probably determined more by national and international opportunities. Only the share of young people with graduate degrees was significant, indicating that a more youthful and less experienced community will have lower wages once education is accounted for. Interestingly, even the cost of housing did not matter for this group, i.e., people with a graduate degree did not need to be compensated for higher urban housing costs, suggesting that living in an expensive community includes an amenity value to them that almost completely offsets higher housing costs. For those with a bachelor's degree, in addition to the share of young workers, the median wage was affected by the local labor market—the tighter the market for those with bachelor's degrees, the higher the wage. For this group, higher housing costs must be partially compensated with higher wages, indicating that living in a higher cost area has benefits of its own for these workers as well.

At the other end of educational attainment, the wages of workers who did not graduate from high school appear quite sensitive to local factors. Their wages are lower the younger the population, influenced by labor market tightness, and need to be paid more than those with more education to compensate for housing costs. In addition, the wages in this group benefit from a mandated minimum wage. The minimum wage was not statistically significant for any other group, although it was almost significant for those individuals with just a high school diploma. The wages for people who did not complete high school are also higher the larger the share of durable manufacturing. The wages of those that graduated with a high school degree and those with some college or an associate's degree are affected similarly.

Hence clear differences between those with a bachelor's degree and graduate degree, and those with less education, are suggested by these results. Further, as indicated throughout this paper, we do not find statistically significant evidence that the presence of a relatively educated group in the aggregate has any effect on the wages of others.

Finally, anecdotal evidence indicates that real wages generally have been on the decline over time (Figure 1, Irwin, 2015). Our results are consistent with this observation, with less educated workers losing more than educated workers. The unexplained decline in the median wage is a topic for future research.

One implication of these results is that they do not point to any policy short-cuts to raising workers' wages. On the other hand, importantly, metro areas where employment opportunities are better have been able to sustain higher wages than metro areas where employment opportunities are more limited. Hence, one possible way to increase wages would be to increase the demand for labor with the relevant educational skills (see also Groen, 2011 and Nolan, Morrison, Kumar, Galloway & Cordes, 2011) as well as to find ways to teach the skills needed by businesses (see for example Holzer, 2012). From an individual's point of view, moving to an area with more demand for his or her particular skill level might be necessary. Moretti (2013) suggests a national program of vouchers to help low income people around the country move to places that better match their skills. From a city's point of view, this means that a strategy targeting diversification might make more sense than one of specialization. A diversified economy would more likely accommodate a range of education and skill levels. In our results, adding durables manufacturing jobs, for example, increased wages for people with a high school degree and some college or an associate's degree. This approach is quite different than trying to replicate the Silicon Valley phenomenon.

Conclusion

In contrast to anecdotal evidence using simple correlations and some more formal studies that have been done to date, using a representative individual we were not able to find significant human capital spillovers to wages due to having an educated community. These results were consistent across several different estimations and robustness checks. Standard variables from the literature performed mostly as expected, especially when all workers were estimated together, and gave us added insight as a result of using the labor market segments defined by educational attainment. Looking at the aggregate population with all education groups together, we find, as do many others, that the presence of a larger share of educated workers has a positive effect on wages. However, explaining wage levels across metro areas reveals new insights when we disaggregate the analysis by educational cohort and correct appropriately for cost of living differences. First, local market conditions matter especially to less educated workers. Second, and most importantly, the wages of each educational cohort are determined primarily by their own characteristics and are not significantly influenced by the educational level of the community at large.

References

Acemoglu, D. (1996). A microfoundation for social increasing returns in human capital accumulation. *The Quarterly Journal of Economics*, *111*, 779-804. doi:10.2307/2946672

Acemoglu, G. & Angrist, J. (2001). How large are human-capital externalities? Evidence from compulsory-schooling laws. In Bernanke, B. S. and Rogoff, K. (Eds.), *NBER Macroeconomics Annal 2000*, Vol. 15 (pp.9-74). Cambridge, MA: MIT Press.

American Consumer Survey (ACS), Table S2001; Table B20004; Table B23006 Table B15001; retrieved using the American Factfinder data retrieval program http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml.

Angrist, J. D. & Pischke, J.-S. (2009). *Mostly Harmless Econometrics*. Princeton, N.J.: Princeton University Press.

Aten, B. H., Figueroa, E. B. & Vengelen, B. M. (2015). Real Personal Income and Regional Price Parities for States and Metropolitan Areas, 2008-2012. Available at http://www.bea.gov/scb/pdf/2015/07%20July/0715_real_personal_income_and_regional_price_parities.pdf. Accessed 21 August 2015.

Bratti, M. & Leombruni, R. (2014). Local human capital externalities and wages at the firm level: The case of Italian manufacturing. *Economics of Education Review*, *41*, 161-175.

Bureau of Labor Statistics Quarterly Census of Employment and Wages, http://www.bls.gov/cew/

Ciccone, A. & Peri, G. (2006). Identifying human capital externalities: Theory with applications. *Review of Economic Studies*, 73(2), 381-412.

Combes, P.-P., Duranton, G. & Gobillon, L. (2008.) Spatial wage disparities: Sorting matters! *Journal of urban economics 63*, 723-742.

Díaz, A. M. (2013). The employment advantages of skilled urban municipalities in Colombia. *Ensayos sobre POLÍTICA ECONÓMICA*,*31*(SPE70), 315-366.

Dimou, M. (2012). Do local amenities affect urban wage premium? Some evidence from the Greek case. *Sustainable Cities and Society*, *2*, 63-69.

Dumond, J. M., Hirsch, B. T., & MacPherson, D. A. (1999). Wage differentials across labor markets and workers: Does cost of living matter? *Economic Inquiry*, *37*(4), 577-598.

Echeverri-Carroll, E. L. & Ayala, S. G. (2011). Urban Wages: Does City Size Matter. *Urban Studies 48*(2), 253-271. DOI: 10.1177/0042098010369393.

Fingleton, B. (2003). Increasing returns: Evidence from local wage rates in Great Britain. *Oxford Economic Papers*, *55*, 716-739.

Florida, R. L. (2012). *The rise of the creative class: revisited*. New York: Basic books.

Fontes, G. G., Simoes, R. F. & Hermeto Camilo de Oliveira, A. M. (2010.) Urban attributes and wage disparities in Brazil: A multilevel hierarchical model. *Regional Studies*, *44*(5), 595-607.

Gabriel, S. & Rosenthal, S. (1999). Location and the effect of demographic traits on earnings. *Regional Science and Urban Economics*, *29*,445-461.

Glaeser, E. L., & Maré, D. C. (2001). Cities and Skills. *Journal of Labor Economics*, *19*(2), 316-342.

Groen, J. A. (2011). Building knowledge stocks locally: Consequences of geographic mobility for the effectiveness of state higher education policies. *Economic Development Quarterly*, *25*(4), 316-329.

Hanson, G. H. (2000). Firms, workers, and the geographic concentration of economic activity. *Handbook of Economic Geography*. New York: Oxford University Press.

Heuermann, D., Halfdanarson, B. & Suedekum, J. (2010). Human Capital Externalities and the Urban Wage Premium: Two Literatures and their Interrelations. *Urban Studies 47*(4),749-767. DOI: 10.1177/0042098009352363.

Holzer, H. J. (2012). Good workers for good jobs: Improving education and workforce systems in the U.S. *IZA Journal of Labor Policy*, *1*(5). Retrieved from http://izajolp.com/content/1/1/5. doi:10.1186/2193-9004-1-5

Irwin, N. (2015, April 23). Why less educated workers are losing ground on wages. *The New York Times*, p. A3.

Krupka, D. J. & Noonan, D. S. (2013). City air and city markets: Worker productivity gains across city size. *International Regional Science Review*, *36*(2), 183-206.

Moretti, E. (2004a). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of econometrics*, *121*(1), 175-212.

Moretti, E. (2004b). Human capital externalities in cities. *Handbook of regional and urban economics, 4*, 2243-2291.

Moretti, E. (2013). *The new geography of jobs*. Boston, MA: Mariner Books, Houghton Mifflin Harcourt.

Nolan, C., Morrison, E., Kumar, I., Galloway, H., & Cordes, S. (2011). Linking industry and occupation clusters in regional economic development. *Economic Development Quarterly*, *25*(1), 26-35.

Porter, E. (2014, September 11). Equation is simple: Education = Income. *The New York Times*, p. B1, B5.

Rauch, J. E. (1993). Productivity gains from geographic concentration of human capital: Evidence from cities. *Journal of Urban Economics*, *34,* 380-400.

Richter, F. G. C. & Nelson, L. (2014, February 10). The prospects of non-college bound workers in the Fourth District. Federal Reserve Bank of Cleveland. Retrieved July 29, 2015 from https://www.clevelandfed.org/en/Newsroom%20and%20Events/Publications/A%20Look%20Behind%20The%20Numbers.aspx

Riefler, R. F. (2007). State patterns of occupational earnings: Implications for long-term growth. *Economic Development Quarterly*, *21*(1), 34-48. DOI: 10.1177/0891242406294927.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, *90*(6), 1257-1278.

Rodriguez-Pose, A. & Vilata-Bufi, M. (2005). Education, migration, and job satisfaction: the regional returns of human capital in the EU. *Journal of Economic Geography, 5*, 545-566.

Rosenthal, S. S. & Strange, W. C. (2008). The attenuation of human capital spillovers. *Journal of Urban Economics*, *64*, 373-389.

Ruggles, S., Alexander, J. T., Genadek, K., Goeken, R., Schroeder, M. B., & Sobek, M. (2010). *Integrated Public Use Microdata Series: Version 5.0* [Machine-readable database] (IPUMS). Minneapolis: University of Minnesota.

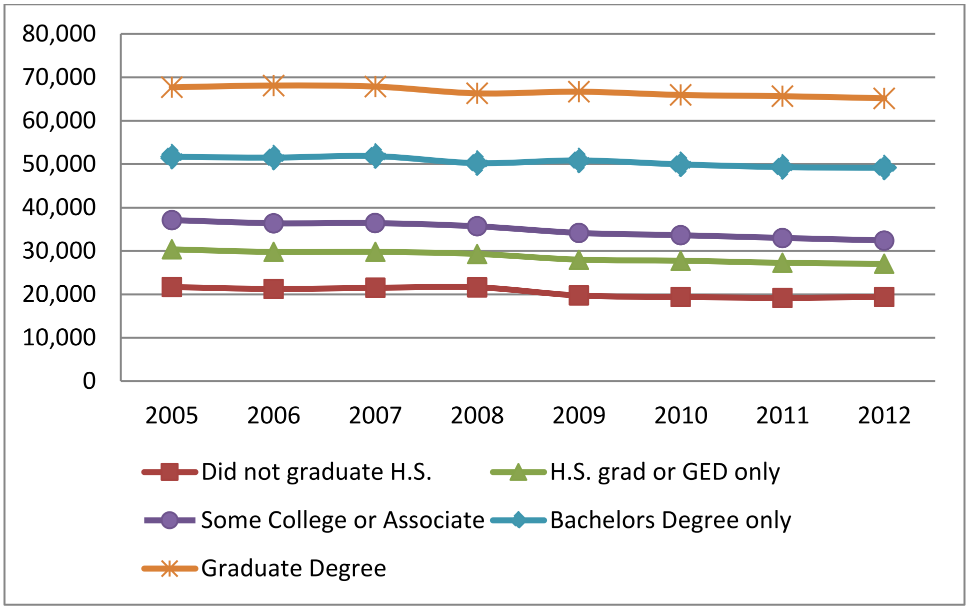
Schumacher, F. I., Dias, J. & Tebaldi, E. (2014). Two tales on human capital and knowledge spillovers: The case of US and Brazil. *Applied Economics*, *46*(23), 2733-2743.

Wheaton W. C. & Lewis M. J. (2002). Urban wages and labor market agglomeration. *Journal of Urban Economics*, *51*, 542-562.

Winters, J. V. (2009). Wages and prices: Are workers fully compensated for cost of living differences? *Regional Science and Urban Economics*, *39*(5), 632-643.

Yankow, J. (2006). Why do cities pay more? An empirical examination of some competing theories of the urban wage premium. *Journal of Urban Economics, 60*(2), 139-161.

Figure 1: U.S. Median Annual Salaries by Education Level, adjusted for inflation (Constant 2012 dollars): 2005-2012



Source: Calculated from the American Community Survey.

Table 1: Pearson Correlation Coefficients between nominal median wage by education attainment with the share of the population aged 25 to 64 with a bachelor's degree or more: 2005-2012.

	2005	2006	2007	2008	2009	2010	2011	2012
Nominal Median Wage N =	374	374	374	374	374	374	374	374
All education levels	.618***	.648***	.618***	.659***	.675***	.659***	.688***	.672***
Did not graduate HS	.206***	.253***	.108**	.145***	.159***	.159***	.250***	.101*
HS Grad or GED	.359***	.377***	.313***	.360***	.360***	.286***	.299***	.300***
Some College or Associate	.326***	.320***	.295***	.362***	.347***	.359***	.388***	.338***
Bachelor's only	.123**	.192***	.165***	.301***	.280***	.231***	.204***	.272***
Graduate Degree	.260***	.236***	.234***	.309***	.264***	.258***	.291***	.334***

Note: ***, **, * coefficients are significant at the 1% level, 5% level, and 10% level, respectively.

Table 2. Descriptive statistics

	Minimum	Maximum	Mean	Standard Deviation
Median Wage all, 2012$, adjusted for non-housing cost of living	20,457	61,419	35,054	4,365
Median Wage Did Not Graduate from High School, 2012$ adjusted for non-housing cost of living	5,865	58,169	20,732	3,888
Median Wage High School Graduate or GED, 2012$ adjusted for non-housing cost of living	17,924	52,682	28,986	3,350
Median Wage Some College or Associate’s Degree, 2012$ adjusted for non-housing cost of living	19,486	60,061	34,561	3,873
Median Wage Bachelor's Degree, 2012$ adjusted for non-housing cost of living	22,773	80,990	47,525	5,950
Median Wage Graduate Degree, 2012$ adjusted for non-housing cost of living	6,053	114,106	62,020	8,361
Price Parity Index Housing	48.0	195.5	88.8	24.9
Share of Population 25 to 64 with Bachelor’s or more	10.0	62.0	26.7	8.3
Share of Population 25 to 64 who are 25 to 34, All	13.1	43.8	25.4	3.4
Share of Population 25 to 64 who are 25 to 34, Did not graduate from high school	2.7	66.6	26.3	6.5
Share of Population 25 to 64 who are 25 to 34, High school graduate or GED	10.5	46.4	23.5	4.8
Share of Population 25 to 64 who are 25 to 34, Some College or Associate’s	10.8	50.0	26.8	4.4
Share of Population 25 to 64 who are 25 to 34, Bachelor’s	5.8	51.9	28.4	6.0
Share of Population 25 to 64 who are 25 to 34, Graduate Degree	0.4	39.5	19.0	5.9
Share of Population 25 to 64 who are employed, All	50.6	86.7	72.3	5.4
Share of Population 25 to 64 who are employed, Did not graduate from high school	14.8	84.4	52.1	9.8
Share of Population 25 to 64 who are employed, High school graduate or GED	43.5	90.0	68.6	6.0

Table 3: Results for Base Model

Dependent variable: Natural log of Median Wage in 2012 U.S. dollars, partially adjusted for metro area cost of living differences						
	1	2	3	4	5	6
Variable	All	Did not graduate from High School	High School graduate or GED	Some College or Associates	Bachelor's only	Graduate degree
Constant	8.53075***	7.98410***	8.25544***	8.73598***	9.49874***	10.57434***
	(.17516)	(.50944)	(.22652)	(.24029)	(.22266)	(.29897)
Ln (price parity index, housing)	0.40250***	0.45736***	0.46494***	0.41212***	0.30555***	0.10956
	(.03959)	(.11550)	(.05050)	(.05420)	(.05017)	(.07113)
Share of Population (25-64) with bachelor’s or more	0.00626***	0.00152	0.00024	-0.00056	0.00009	0.00192
	(.00061)	(.00217)	(.00107)	(.00083)	(.00104)	(.00169)
Population (25-34)/Population (25-64), education specific	-0.00004	-0.0026***	-0.00084	-0.0026***	-0.00250***	-0.00401***
	(.00069)	(.00078)	(.00057)	(.00055)	(.00045)	(.00044)
R-squared overall	0.3785	0.0803	0.1529	0.2517	0.1067	0.1164

Note: ***, **, * coefficients are significant at the 1% level, 5% level, and 10% level, respectively.

Table 4: Results for Full Model

Dependent variable: Natural Log of Median Wage in 2012 U.S. dollars, partially adjusted for metro area cost of living differences						
	1	2	3	4	5	6
Variable	All	Did not graduate from High School	High School graduate or GED	Some College or Associate’s	Bachelor's only	Graduate degree
Constant	8.39161***	8.16493***	8.14249***	8.65223***	9.3965***	10.49469***
	(.17225)	(.50593)	(.22372)	(.23316)	(.23353)	(.33875)
Ln (price parity index, housing)	0.34186***	0.32311***	0.40306***	0.34866***	0.27899***	0.09612
	(.03853)	(.11384)	(.04758)	(.05300)	(.05090)	(.07140)
Share of Population (25-64) with bachelor’s or more	0.00546***	0.00173	-0.00013	-0.00052	0.00005	0.00184
	(.00056)	(.00215)	(.00103)	(.00084)	(.00105)	(.00170)
Population (25-34)/Population (25-64), education specific	-0.00104	-0.0030***	-0.00117**	-0.00279***	-0.00265***	-0.00401***
	(.00066)	(.00079)	(.00056)	(.00054)	(.00045)	(.00044)
Employment (25-64)/Population (25-64), education specific	0.00454***	0.00340***	0.00418***	0.00392***	0.00223***	0.00081
	(.00056)	(.00075)	(.00049)	(.00052)	(.00085)	(.00088)
Ln (minimum wage)	0.03569**	0.09864**	0.04251*	0.01126	0.00898	-0.00967
	(.01653)	(.04633)	(.02280)	(.02099)	(.02284)	(.02977)
State & local taxes/personal income	0.00429*	0.00456	0.00324	0.00413	0.00076	0.00808*
	(.00260)	(.00898)	(.00360)	(.00386)	(.00434)	(.00490)
Employment share, durables manufacturing	0.00461***	0.01411***	0.00412**	0.00598***	0.00395	0.00104
	(.00142)	(.00451)	(.00190)	(.00209)	(.00246)	(.00238)
Employment share, arts & recreational services	-0.01120**	-0.0485***	-0.00929	-0.01645**	-0.00765	0.00027
	(.00527)	(.01723)	(.00645)	(.00725)	(.00761)	(.00956)
Employment share, 4-year colleges	-0.00110	-0.00633	-0.00920*	-0.00114	0.00044	0.00504
	(.00385)	(.01148)	(.00530)	(.00438)	(.00472)	(.00464)

Employment share, public transit	-0.00409	-0.12374	0.06329	-0.05902	0.01246	-0.06766
	(.04328)	(.11831)	(.05623)	(.06645)	(.09181)	(.08069)
R-squared overall	0.4829	0.1304	0.2304	0.3477	0.1466	0.0826

Note: ***, **, * coefficients are significant at the 1% level, 5% level, and 10% level, respectively.

Appendix A: Extending the Regional Price Parities back in time

In order to extend the Bureau of Economic Analysis (BEA) regional price parities back to 2005, we applied the difference in the regional change in prices as measured by the CPI to the national CPI. The Price Parity Index for Housing Costs was extended using the Shelter Component of the regional CPI and the Price Parity Index for Non-Housing Costs was extended using the CPI less Shelter regional index. For example, shelter price inflation between 2005 and 2008 as measured by the Atlanta CPI was 0.7% less than the U.S. CPI (9.2% compared to 9.9%), which we then applied to the 2008 BEA Price Parity Index for Atlanta. Table A1 presents the housing cost price parity values used in our analysis. These extensions tended to have a relatively small effect on the price parity indices, i.e., the 2005 values tended to be very close to the 2008 values.

What these data show is that the cost of housing in Atlanta was slightly higher than it was in the U.S. in 2005 (index value of 101.6), but that by 2012 the cost of housing in Atlanta was 7.2% less than in the U.S. (index value of 92.8). The non-housing cost of living in Atlanta was 3.8% less than in the U.S. overall (index value of 96.2) in 2012, and 0.6% less than in the U.S. overall (index value of 99.4) in 2005. Adjusting for the non-housing cost of living raised the median wage in the Atlanta MSA by 3.8% in 2012, and by 0.6% in 2005. The real median wage in Atlanta declined sharply between 2005 and 2012, but this adjustment for non-housing cost of living costs moderated that decline.

Table A1: Price Parity Housing Cost Indices for Atlanta

Year	Price Parity Index
2005	101.6
2006	100.8
2007	101.8
2008	100.9
2009	100.5
2010	97.0
2011	94.70
2012	92.8

Appendix B: Metropolitan Statistical Areas Included in the Analysis

FIPS code	Name
10180	Abilene, TX (Metropolitan Statistical Area)
10420	Akron, OH (Metropolitan Statistical Area)
10500	Albany, GA (Metropolitan Statistical Area)
10540	Albany, OR (Metropolitan Statistical Area)
10580	Albany-Schenectady-Troy, NY (Metropolitan Statistical Area)
10740	Albuquerque, NM (Metropolitan Statistical Area)
10780	Alexandria, LA (Metropolitan Statistical Area)
10900	Allentown-Bethlehem-Easton, PA-NJ (Metropolitan Statistical Area)
11020	Altoona, PA (Metropolitan Statistical Area)
11100	Amarillo, TX (Metropolitan Statistical Area)
11180	Ames, IA (Metropolitan Statistical Area)
11260	Anchorage, AK (Metropolitan Statistical Area)
11460	Ann Arbor, MI (Metropolitan Statistical Area)
11500	Anniston-Oxford-Jacksonville, AL (Metropolitan Statistical Area)
11540	Appleton, WI (Metropolitan Statistical Area)
11700	Asheville, NC (Metropolitan Statistical Area)
12020	Athens-Clarke County, GA (Metropolitan Statistical Area)
12060	Atlanta-Sandy Springs-Roswell, GA (Metropolitan Statistical Area)
12100	Atlantic City-Hammonton, NJ (Metropolitan Statistical Area)
12220	Auburn-Opelika, AL (Metropolitan Statistical Area)
12260	Augusta-Richmond County, GA-SC (Metropolitan Statistical Area)
12420	Austin-Round Rock, TX (Metropolitan Statistical Area)
12540	Bakersfield, CA (Metropolitan Statistical Area)
12580	Baltimore-Columbia-Towson, MD (Metropolitan Statistical Area)
12620	Bangor, ME (Metropolitan Statistical Area)
12700	Barnstable Town, MA (Metropolitan Statistical Area)
12940	Baton Rouge, LA (Metropolitan Statistical Area)
12980	Battle Creek, MI (Metropolitan Statistical Area)
13020	Bay City, MI (Metropolitan Statistical Area)
13140	Beaumont-Port Arthur, TX (Metropolitan Statistical Area)
13380	Bellingham, WA (Metropolitan Statistical Area)
13460	Bend-Redmond, OR (Metropolitan Statistical Area)
13740	Billings, MT (Metropolitan Statistical Area)
13780	Binghamton, NY (Metropolitan Statistical Area)
13820	Birmingham-Hoover, AL (Metropolitan Statistical Area)
13900	Bismarck, ND (Metropolitan Statistical Area)
13980	Blacksburg-Christiansburg-Radford, VA (Metropolitan Statistical Area)
14010	Bloomington, IL (Metropolitan Statistical Area)

14020	Bloomington, IN (Metropolitan Statistical Area)
14100	Bloomsburg-Berwick, PA (Metropolitan Statistical Area)
14260	Boise City, ID (Metropolitan Statistical Area)
14460	Boston-Cambridge-Newton, MA-NH (Metropolitan Statistical Area)
14500	Boulder, CO (Metropolitan Statistical Area)
14540	Bowling Green, KY (Metropolitan Statistical Area)
14740	Bremerton-Silverdale, WA (Metropolitan Statistical Area)
14860	Bridgeport-Stamford-Norwalk, CT (Metropolitan Statistical Area)
15180	Brownsville-Harlingen, TX (Metropolitan Statistical Area)
15260	Brunswick, GA (Metropolitan Statistical Area)
15380	Buffalo-Cheektowaga-Niagara Falls, NY (Metropolitan Statistical Area)
15500	Burlington, NC (Metropolitan Statistical Area)
15540	Burlington-South Burlington, VT (Metropolitan Statistical Area)
15680	California-Lexington Park, MD (Metropolitan Statistical Area)
15940	Canton-Massillon, OH (Metropolitan Statistical Area)
15980	Cape Coral-Fort Myers, FL (Metropolitan Statistical Area)
16020	Cape Girardeau, MO-IL (Metropolitan Statistical Area)
16220	Casper, WY (Metropolitan Statistical Area)
16300	Cedar Rapids, IA (Metropolitan Statistical Area)
16540	Chambersburg-Waynesboro, PA (Metropolitan Statistical Area)
16580	Champaign-Urbana, IL (Metropolitan Statistical Area)
16620	Charleston, WV (Metropolitan Statistical Area)
16700	Charleston-North Charleston, SC (Metropolitan Statistical Area)
16740	Charlotte-Concord-Gastonia, NC-SC (Metropolitan Statistical Area)
16820	Charlottesville, VA (Metropolitan Statistical Area)
16860	Chattanooga, TN-GA (Metropolitan Statistical Area)
16940	Cheyenne, WY (Metropolitan Statistical Area)
16980	Chicago-Naperville-Elgin, IL-IN-WI (Metropolitan Statistical Area)
17020	Chico, CA (Metropolitan Statistical Area)
17140	Cincinnati, OH-KY-IN (Metropolitan Statistical Area)
17300	Clarksville, TN-KY (Metropolitan Statistical Area)
17420	Cleveland, TN (Metropolitan Statistical Area)
17460	Cleveland-Elyria, OH (Metropolitan Statistical Area)
17660	Coeur d'Alene, ID (Metropolitan Statistical Area)
17780	College Station-Bryan, TX (Metropolitan Statistical Area)
17820	Colorado Springs, CO (Metropolitan Statistical Area)
17860	Columbia, MO (Metropolitan Statistical Area)
17900	Columbia, SC (Metropolitan Statistical Area)
17980	Columbus, GA-AL (Metropolitan Statistical Area)
18020	Columbus, IN (Metropolitan Statistical Area)
18140	Columbus, OH (Metropolitan Statistical Area)

18580	Corpus Christi, TX (Metropolitan Statistical Area)
18700	Corvallis, OR (Metropolitan Statistical Area)
18880	Crestview-Fort Walton Beach-Destin, FL (Metropolitan Statistical Area)
19060	Cumberland, MD-WV (Metropolitan Statistical Area)
19100	Dallas-Fort Worth-Arlington, TX (Metropolitan Statistical Area)
19140	Dalton, GA (Metropolitan Statistical Area)
19180	Danville, IL (Metropolitan Statistical Area)
19300	Daphne-Fairhope-Foley, AL (Metropolitan Statistical Area)
19340	Davenport-Moline-Rock Island, IA-IL (Metropolitan Statistical Area)
19380	Dayton, OH (Metropolitan Statistical Area)
19460	Decatur, AL (Metropolitan Statistical Area)
19500	Decatur, IL (Metropolitan Statistical Area)
19660	Deltona-Daytona Beach-Ormond Beach, FL (Metropolitan Statistical Area)
19740	Denver-Aurora-Lakewood, CO (Metropolitan Statistical Area)
19780	Des Moines-West Des Moines, IA (Metropolitan Statistical Area)
19820	Detroit-Warren-Dearborn, MI (Metropolitan Statistical Area)
20020	Dothan, AL (Metropolitan Statistical Area)
20100	Dover, DE (Metropolitan Statistical Area)
20220	Dubuque, IA (Metropolitan Statistical Area)
20260	Duluth, MN-WI (Metropolitan Statistical Area)
20500	Durham-Chapel Hill, NC (Metropolitan Statistical Area)
20700	East Stroudsburg, PA (Metropolitan Statistical Area)
20740	Eau Claire, WI (Metropolitan Statistical Area)
20940	El Centro, CA (Metropolitan Statistical Area)
21060	Elizabethtown-Fort Knox, KY (Metropolitan Statistical Area)
21140	Elkhart-Goshen, IN (Metropolitan Statistical Area)
21300	Elmira, NY (Metropolitan Statistical Area)
21340	El Paso, TX (Metropolitan Statistical Area)
21500	Erie, PA (Metropolitan Statistical Area)
21660	Eugene, OR (Metropolitan Statistical Area)
21780	Evansville, IN-KY (Metropolitan Statistical Area)
21820	Fairbanks, AK (Metropolitan Statistical Area)
22020	Fargo, ND-MN (Metropolitan Statistical Area)
22140	Farmington, NM (Metropolitan Statistical Area)
22180	Fayetteville, NC (Metropolitan Statistical Area)
22220	Fayetteville-Springdale-Rogers, AR-MO (Metropolitan Statistical Area)
22380	Flagstaff, AZ (Metropolitan Statistical Area)
22420	Flint, MI (Metropolitan Statistical Area)
22500	Florence, SC (Metropolitan Statistical Area)
22520	Florence-Muscle Shoals, AL (Metropolitan Statistical Area)
22540	Fond du Lac, WI (Metropolitan Statistical Area)

22660	Fort Collins, CO (Metropolitan Statistical Area)
22900	Fort Smith, AR-OK (Metropolitan Statistical Area)
23060	Fort Wayne, IN (Metropolitan Statistical Area)
23420	Fresno, CA (Metropolitan Statistical Area)
23460	Gadsden, AL (Metropolitan Statistical Area)
23540	Gainesville, FL (Metropolitan Statistical Area)
23580	Gainesville, GA (Metropolitan Statistical Area)
23900	Gettysburg, PA (Metropolitan Statistical Area)
24020	Glens Falls, NY (Metropolitan Statistical Area)
24140	Goldsboro, NC (Metropolitan Statistical Area)
24220	Grand Forks, ND-MN (Metropolitan Statistical Area)
24260	Grand Island, NE (Metropolitan Statistical Area)
24300	Grand Junction, CO (Metropolitan Statistical Area)
24340	Grand Rapids-Wyoming, MI (Metropolitan Statistical Area)
24420	Grants Pass, OR (Metropolitan Statistical Area)
24500	Great Falls, MT (Metropolitan Statistical Area)
24540	Greeley, CO (Metropolitan Statistical Area)
24580	Green Bay, WI (Metropolitan Statistical Area)
24660	Greensboro-High Point, NC (Metropolitan Statistical Area)
24780	Greenville, NC (Metropolitan Statistical Area)
24860	Greenville-Anderson-Mauldin, SC (Metropolitan Statistical Area)
25060	Gulfport-Biloxi-Pascagoula, MS (Metropolitan Statistical Area)
25180	Hagerstown-Martinsburg, MD-WV (Metropolitan Statistical Area)
25220	Hammond, LA (Metropolitan Statistical Area)
25260	Hanford-Corcoran, CA (Metropolitan Statistical Area)
25420	Harrisburg-Carlisle, PA (Metropolitan Statistical Area)
25500	Harrisonburg, VA (Metropolitan Statistical Area)
25540	Hartford-West Hartford-East Hartford, CT (Metropolitan Statistical Area)
25620	Hattiesburg, MS (Metropolitan Statistical Area)
25860	Hickory-Lenoir-Morganton, NC (Metropolitan Statistical Area)
25940	Hilton Head Island-Bluffton-Beaufort, SC (Metropolitan Statistical Area)
26140	Homosassa Springs, FL (Metropolitan Statistical Area)
26300	Hot Springs, AR (Metropolitan Statistical Area)
26380	Houma-Thibodaux, LA (Metropolitan Statistical Area)
26420	Houston-The Woodlands-Sugar Land, TX (Metropolitan Statistical Area)
26580	Huntington-Ashland, WV-KY-OH (Metropolitan Statistical Area)
26620	Huntsville, AL (Metropolitan Statistical Area)
26820	Idaho Falls, ID (Metropolitan Statistical Area)
26900	Indianapolis-Carmel-Anderson, IN (Metropolitan Statistical Area)
26980	Iowa City, IA (Metropolitan Statistical Area)
27060	Ithaca, NY (Metropolitan Statistical Area)

27100	Jackson, MI (Metropolitan Statistical Area)
27140	Jackson, MS (Metropolitan Statistical Area)
27180	Jackson, TN (Metropolitan Statistical Area)
27260	Jacksonville, FL (Metropolitan Statistical Area)
27340	Jacksonville, NC (Metropolitan Statistical Area)
27500	Janesville-Beloit, WI (Metropolitan Statistical Area)
27620	Jefferson City, MO (Metropolitan Statistical Area)
27740	Johnson City, TN (Metropolitan Statistical Area)
27780	Johnstown, PA (Metropolitan Statistical Area)
27860	Jonesboro, AR (Metropolitan Statistical Area)
27900	Joplin, MO (Metropolitan Statistical Area)
27980	Kahului-Wailuku-Lahaina, HI (Metropolitan Statistical Area)
28020	Kalamazoo-Portage, MI (Metropolitan Statistical Area)
28100	Kankakee, IL (Metropolitan Statistical Area)
28140	Kansas City, MO-KS (Metropolitan Statistical Area)
28420	Kennewick-Richland, WA (Metropolitan Statistical Area)
28660	Killeen-Temple, TX (Metropolitan Statistical Area)
28700	Kingsport-Bristol-Bristol, TN-VA (Metropolitan Statistical Area)
28740	Kingston, NY (Metropolitan Statistical Area)
28940	Knoxville, TN (Metropolitan Statistical Area)
29020	Kokomo, IN (Metropolitan Statistical Area)
29100	La Crosse-Onalaska, WI-MN (Metropolitan Statistical Area)
29180	Lafayette, LA (Metropolitan Statistical Area)
29200	Lafayette-West Lafayette, IN (Metropolitan Statistical Area)
29340	Lake Charles, LA (Metropolitan Statistical Area)
29420	Lake Havasu City-Kingman, AZ (Metropolitan Statistical Area)
29460	Lakeland-Winter Haven, FL (Metropolitan Statistical Area)
29540	Lancaster, PA (Metropolitan Statistical Area)
29620	Lansing-East Lansing, MI (Metropolitan Statistical Area)
29700	Laredo, TX (Metropolitan Statistical Area)
29740	Las Cruces, NM (Metropolitan Statistical Area)
29820	Las Vegas-Henderson-Paradise, NV (Metropolitan Statistical Area)
29940	Lawrence, KS (Metropolitan Statistical Area)
30020	Lawton, OK (Metropolitan Statistical Area)
30140	Lebanon, PA (Metropolitan Statistical Area)
30340	Lewiston-Auburn, ME (Metropolitan Statistical Area)
30460	Lexington-Fayette, KY (Metropolitan Statistical Area)
30620	Lima, OH (Metropolitan Statistical Area)
30700	Lincoln, NE (Metropolitan Statistical Area)
30780	Little Rock-North Little Rock-Conway, AR (Metropolitan Statistical Area)
30860	Logan, UT-ID (Metropolitan Statistical Area)

30980	Longview, TX (Metropolitan Statistical Area)
31020	Longview, WA (Metropolitan Statistical Area)
31080	Los Angeles-Long Beach-Anaheim, CA (Metropolitan Statistical Area)
31140	Louisville/Jefferson County, KY-IN (Metropolitan Statistical Area)
31180	Lubbock, TX (Metropolitan Statistical Area)
31340	Lynchburg, VA (Metropolitan Statistical Area)
31420	Macon, GA (Metropolitan Statistical Area)
31460	Madera, CA (Metropolitan Statistical Area)
31540	Madison, WI (Metropolitan Statistical Area)
31700	Manchester-Nashua, NH (Metropolitan Statistical Area)
31740	Manhattan, KS (Metropolitan Statistical Area)
31860	Mankato-North Mankato, MN (Metropolitan Statistical Area)
31900	Mansfield, OH (Metropolitan Statistical Area)
32580	McAllen-Edinburg-Mission, TX (Metropolitan Statistical Area)
32780	Medford, OR (Metropolitan Statistical Area)
32820	Memphis, TN-MS-AR (Metropolitan Statistical Area)
32900	Merced, CA (Metropolitan Statistical Area)
33100	Miami-Fort Lauderdale-West Palm Beach, FL (Metropolitan Statistical Area)
33140	Michigan City-La Porte, IN (Metropolitan Statistical Area)
33220	Midland, MI (Metropolitan Statistical Area)
33260	Midland, TX (Metropolitan Statistical Area)
33340	Milwaukee-Waukesha-West Allis, WI (Metropolitan Statistical Area)
33460	Minneapolis-St. Paul-Bloomington, MN-WI (Metropolitan Statistical Area)
33540	Missoula, MT (Metropolitan Statistical Area)
33660	Mobile, AL (Metropolitan Statistical Area)
33700	Modesto, CA (Metropolitan Statistical Area)
33740	Monroe, LA (Metropolitan Statistical Area)
33780	Monroe, MI (Metropolitan Statistical Area)
33860	Montgomery, AL (Metropolitan Statistical Area)
34060	Morgantown, WV (Metropolitan Statistical Area)
34100	Morristown, TN (Metropolitan Statistical Area)
34580	Mount Vernon-Anacortes, WA (Metropolitan Statistical Area)
34620	Muncie, IN (Metropolitan Statistical Area)
34740	Muskegon, MI (Metropolitan Statistical Area)
34820	Myrtle Beach-Conway-North Myrtle Beach, SC-NC (Metropolitan Statistical Area)
34900	Napa, CA (Metropolitan Statistical Area)
34940	Naples-Immokalee-Marco Island, FL (Metropolitan Statistical Area)
34980	Nashville-Davidson--Murfreesboro--Franklin, TN (Metropolitan Statistical Area)
35100	New Bern, NC (Metropolitan Statistical Area)
35300	New Haven-Milford, CT (Metropolitan Statistical Area)
35380	New Orleans-Metairie, LA (Metropolitan Statistical Area)

35620	New York-Newark-Jersey City, NY-NJ-PA (Metropolitan Statistical Area)
35660	Niles-Benton Harbor, MI (Metropolitan Statistical Area)
35840	North Port-Sarasota-Bradenton, FL (Metropolitan Statistical Area)
35980	Norwich-New London, CT (Metropolitan Statistical Area)
36100	Ocala, FL (Metropolitan Statistical Area)
36140	Ocean City, NJ (Metropolitan Statistical Area)
36220	Odessa, TX (Metropolitan Statistical Area)
36260	Ogden-Clearfield, UT (Metropolitan Statistical Area)
36420	Oklahoma City, OK (Metropolitan Statistical Area)
36500	Olympia-Tumwater, WA (Metropolitan Statistical Area)
36540	Omaha-Council Bluffs, NE-IA (Metropolitan Statistical Area)
36740	Orlando-Kissimmee-Sanford, FL (Metropolitan Statistical Area)
36780	Oshkosh-Neenah, WI (Metropolitan Statistical Area)
36980	Owensboro, KY (Metropolitan Statistical Area)
37100	Oxnard-Thousand Oaks-Ventura, CA (Metropolitan Statistical Area)
37340	Palm Bay-Melbourne-Titusville, FL (Metropolitan Statistical Area)
37460	Panama City, FL (Metropolitan Statistical Area)
37620	Parkersburg-Vienna, WV (Metropolitan Statistical Area)
37860	Pensacola-Ferry Pass-Brent, FL (Metropolitan Statistical Area)
37900	Peoria, IL (Metropolitan Statistical Area)
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD (Metropolitan Statistical Area)
38060	Phoenix-Mesa-Scottsdale, AZ (Metropolitan Statistical Area)
38220	Pine Bluff, AR (Metropolitan Statistical Area)
38300	Pittsburgh, PA (Metropolitan Statistical Area)
38340	Pittsfield, MA (Metropolitan Statistical Area)
38540	Pocatello, ID (Metropolitan Statistical Area)
38860	Portland-South Portland, ME (Metropolitan Statistical Area)
38900	Portland-Vancouver-Hillsboro, OR-WA (Metropolitan Statistical Area)
38940	Port St. Lucie, FL (Metropolitan Statistical Area)
39140	Prescott, AZ (Metropolitan Statistical Area)
39300	Providence-Warwick, RI-MA (Metropolitan Statistical Area)
39340	Provo-Orem, UT (Metropolitan Statistical Area)
39380	Pueblo, CO (Metropolitan Statistical Area)
39460	Punta Gorda, FL (Metropolitan Statistical Area)
39540	Racine, WI (Metropolitan Statistical Area)
39580	Raleigh, NC (Metropolitan Statistical Area)
39660	Rapid City, SD (Metropolitan Statistical Area)
39740	Reading, PA (Metropolitan Statistical Area)
39820	Redding, CA (Metropolitan Statistical Area)
39900	Reno, NV (Metropolitan Statistical Area)
40060	Richmond, VA (Metropolitan Statistical Area)

40140	Riverside-San Bernardino-Ontario, CA (Metropolitan Statistical Area)
40220	Roanoke, VA (Metropolitan Statistical Area)
40340	Rochester, MN (Metropolitan Statistical Area)
40380	Rochester, NY (Metropolitan Statistical Area)
40420	Rockford, IL (Metropolitan Statistical Area)
40580	Rocky Mount, NC (Metropolitan Statistical Area)
40660	Rome, GA (Metropolitan Statistical Area)
40900	Sacramento--Roseville--Arden-Arcade, CA (Metropolitan Statistical Area)
40980	Saginaw, MI (Metropolitan Statistical Area)
41060	St. Cloud, MN (Metropolitan Statistical Area)
41100	St. George, UT (Metropolitan Statistical Area)
41140	St. Joseph, MO-KS (Metropolitan Statistical Area)
41180	St. Louis, MO-IL (Metropolitan Statistical Area)
41420	Salem, OR (Metropolitan Statistical Area)
41500	Salinas, CA (Metropolitan Statistical Area)
41540	Salisbury, MD-DE (Metropolitan Statistical Area)
41620	Salt Lake City, UT (Metropolitan Statistical Area)
41660	San Angelo, TX (Metropolitan Statistical Area)
41700	San Antonio-New Braunfels, TX (Metropolitan Statistical Area)
41740	San Diego-Carlsbad, CA (Metropolitan Statistical Area)
41860	San Francisco-Oakland-Hayward, CA (Metropolitan Statistical Area)
41940	San Jose-Sunnyvale-Santa Clara, CA (Metropolitan Statistical Area)
42020	San Luis Obispo-Paso Robles-Arroyo Grande, CA (Metropolitan Statistical Area)
42100	Santa Cruz-Watsonville, CA (Metropolitan Statistical Area)
42140	Santa Fe, NM (Metropolitan Statistical Area)
42200	Santa Maria-Santa Barbara, CA (Metropolitan Statistical Area)
42220	Santa Rosa, CA (Metropolitan Statistical Area)
42340	Savannah, GA (Metropolitan Statistical Area)
42540	Scranton--Wilkes-Barre--Hazleton, PA (Metropolitan Statistical Area)
42660	Seattle-Tacoma-Bellevue, WA (Metropolitan Statistical Area)
42680	Sebastian-Vero Beach, FL (Metropolitan Statistical Area)
42700	Sebring, FL (Metropolitan Statistical Area)
43100	Sheboygan, WI (Metropolitan Statistical Area)
43300	Sherman-Denison, TX (Metropolitan Statistical Area)
43340	Shreveport-Bossier City, LA (Metropolitan Statistical Area)
43420	Sierra Vista-Douglas, AZ (Metropolitan Statistical Area)
43580	Sioux City, IA-NE-SD (Metropolitan Statistical Area)
43620	Sioux Falls, SD (Metropolitan Statistical Area)
43780	South Bend-Mishawaka, IN-MI (Metropolitan Statistical Area)
43900	Spartanburg, SC (Metropolitan Statistical Area)
44060	Spokane-Spokane Valley, WA (Metropolitan Statistical Area)

44100	Springfield, IL (Metropolitan Statistical Area)
44140	Springfield, MA (Metropolitan Statistical Area)
44180	Springfield, MO (Metropolitan Statistical Area)
44220	Springfield, OH (Metropolitan Statistical Area)
44300	State College, PA (Metropolitan Statistical Area)
44420	Staunton-Waynesboro, VA (Metropolitan Statistical Area)
44700	Stockton-Lodi, CA (Metropolitan Statistical Area)
44940	Sumter, SC (Metropolitan Statistical Area)
45060	Syracuse, NY (Metropolitan Statistical Area)
45220	Tallahassee, FL (Metropolitan Statistical Area)
45300	Tampa-St. Petersburg-Clearwater, FL (Metropolitan Statistical Area)
45460	Terre Haute, IN (Metropolitan Statistical Area)
45500	Texarkana, TX-AR (Metropolitan Statistical Area)
45780	Toledo, OH (Metropolitan Statistical Area)
45820	Topeka, KS (Metropolitan Statistical Area)
45940	Trenton, NJ (Metropolitan Statistical Area)
46060	Tucson, AZ (Metropolitan Statistical Area)
46140	Tulsa, OK (Metropolitan Statistical Area)
46220	Tuscaloosa, AL (Metropolitan Statistical Area)
46340	Tyler, TX (Metropolitan Statistical Area)
46520	Urban Honolulu, HI (Metropolitan Statistical Area)
46540	Utica-Rome, NY (Metropolitan Statistical Area)
46660	Valdosta, GA (Metropolitan Statistical Area)
46700	Vallejo-Fairfield, CA (Metropolitan Statistical Area)
47020	Victoria, TX (Metropolitan Statistical Area)
47220	Vineland-Bridgeton, NJ (Metropolitan Statistical Area)
47260	Virginia Beach-Norfolk-Newport News, VA-NC (Metropolitan Statistical Area)
47300	Visalia-Porterville, CA (Metropolitan Statistical Area)
47380	Waco, TX (Metropolitan Statistical Area)
47580	Warner Robins, GA (Metropolitan Statistical Area)
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV (Metropolitan Statistical Area)
47940	Waterloo-Cedar Falls, IA (Metropolitan Statistical Area)
48060	Watertown-Fort Drum, NY (Metropolitan Statistical Area)
48140	Wausau, WI (Metropolitan Statistical Area)
48260	Weirton-Steubenville, WV-OH (Metropolitan Statistical Area)
48300	Wenatchee, WA (Metropolitan Statistical Area)
48540	Wheeling, WV-OH (Metropolitan Statistical Area)
48620	Wichita, KS (Metropolitan Statistical Area)
48660	Wichita Falls, TX (Metropolitan Statistical Area)
48700	Williamsport, PA (Metropolitan Statistical Area)
48900	Wilmington, NC (Metropolitan Statistical Area)

49020	Winchester, VA-WV (Metropolitan Statistical Area)
49180	Winston-Salem, NC (Metropolitan Statistical Area)
49340	Worcester, MA-CT (Metropolitan Statistical Area)
49420	Yakima, WA (Metropolitan Statistical Area)
49620	York-Hanover, PA (Metropolitan Statistical Area)
49660	Youngstown-Warren-Boardman, OH-PA (Metropolitan Statistical Area)
49700	Yuba City, CA (Metropolitan Statistical Area)
49740	Yuma, AZ (Metropolitan Statistical Area)

Appendix C: Results for Dummy Variables: Base and Full Model

	All Education Levels	Did not Graduate from High School	High School Graduate or GED	Some College or Associate's Degree	Bachelor's only	Graduate degree
Base Model						
Dummy 2006	-0.0102***	-0.0327***	-0.0122***	-0.00650*	-0.0164***	-0.00746
	(.00232)	(.00984)	(.00422)	(.00355)	(.00471)	(.00556)
Dummy 2007	-0.00375	-0.0334***	-0.00723*	-0.00472	-0.00522	-0.00698
	(.00275)	(.01036)	(.00427)	(.00406)	(.00491)	(.00820)
Dummy 2008	-0.0169***	-0.0270**	-0.0240***	-0.0285***	-0.0343***	-0.0150***
	(.00301)	(.01116)	(.00480)	(.00406)	(.00500)	(.00563)
Dummy 2009	-0.0532***	-0.1112***	-0.0732***	-0.0697***	-0.0348***	-0.00476
	(.00317)	(.01092)	(.00467)	(.00432)	(.00535)	(.00553)
Dummy 2010	-0.0436***	-0.1156***	-0.0654***	-0.0614***	-0.0355***	-0.00143
	(.00334)	(.01188)	(.00518)	(.00478)	(.00601)	(.00547)
Dummy 2011	-0.0625***	-0.1291***	-0.0870***	-0.0812***	-0.0526***	-0.0191***
	(.00363)	(.01171)	(.00552)	(.00482)	(.00554)	(.00669)
Dummy 2012	-0.0669***	-0.1139***	-0.0859***	-0.0987***	-0.0574***	-0.0338***
	(.00384)	(.01171)	(.00527)	(.00502)	(.00537)	(.00598)
Full Model						
Dummy 2006	-0.0106***	-0.0266**	-0.0117***	-0.0082***	-0.0179***	-0.01048*
	(.00248)	(.01030)	(.00426)	(.00372)	(.00474)	(.00592)
Dummy 2007	-0.0041	-0.02773**	-0.00595	-0.00480	-0.00668	-0.00900
	(.00298)	(.01107)	(.00454)	(.00449)	(.00535)	(.00730)
Dummy 2008	-0.0238***	-0.0268***	-0.0282***	-0.0317***	-0.0378***	-0.01635**
	(.00353)	(.01228)	(.00531)	(.00460)	(.00555)	(.00656)
Dummy 2009	-0.0437***	-0.0868***	-0.0597***	-0.0544***	-0.0316***	-0.00133
	(.00462)	(.01388)	(.00635)	(.00590)	(.00710)	(.00791)
Dummy 2010	-0.0294***	-0.0887***	-0.0457***	-0.0404***	-0.0311***	0.00303
	(.00515)	(.01535)	(.00750)	(.00673)	(.00805)	(.00858)

Dummy 2011	-0.0473***	-0.1020***	-0.0676***	-0.0586***	-0.0478***	-0.01486*
	(.00519)	(.01417)	(.00735)	(.00644)	(.00709)	(.00860)
Dummy 2012	-0.0522***	-0.0870***	-0.0654***	-0.0771***	-0.0538***	-0.0284***
	(.00516)	(.01390)	(.00690)	(.00646)	(.00683)	(.00736)

Note: ***, **, * denotes coefficients significant at the 1%, 5%, and 10% level respectively.

Endnotes

[1] In 2012 the price parity index values were 118.4 for Los Angeles and 95.3 for Milwaukee, meaning that Los Angeles was 18.4% more expensive than the national average and the cost of living was 4.7% less expensive than the national average in Milwaukee. A big part of the difference in the cost of living between Milwaukee and Los Angeles is the cost of housing, but even when housing costs are ignored, other costs are 5.9% higher than the national average in Los Angeles and 5.2% lower in Milwaukee. When adjusted for non-housing cost of living differences the median person with a high school education earns $30,293 in Milwaukee and $24,265 in Los Angeles, while the person with a graduate degree earns $69,669 in Milwaukee and $69,557 in Los Angeles.

[2] The mean income values were obtained from the IPUMS (Ruggles et al., 2010).

[3] Diaz (2013) also disaggregates her sample for Colombia into different education groups, although her dependent variable is employment rather than wage. In some studies different educational levels are included as independent variables (e.g., Dimou, 2012).

[4] Bureau of Labor Statistics Quarterly Census of Employment and Wages, www.bls.gov/cew/

[5] We also estimated a random effects model, which was rejected in favor of fixed effects. See the section on robustness checks.

[6] This estimator is discussed in Angrist and Pischke (chapter 8, 2009).

[7] We would like to thank an anonymous referee for pointing this out.

[8] The worker would presumably have to pay federal income taxes on their higher gross income, thereby reducing some of the net benefit from the boost in pay indicated by the model.

[9] On average durable manufacturing only accounts for 6.6% of total employment. It is difficult to see how mathematically it could directly account for the higher median wage in all three of the relatively low educational attainment categories. Another explanation could be that the relatively high unionization rate in durable manufacturing raises wages in other industries, thereby indirectly increasing the median wage (Yankow 2006).