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The Gender Wage Gap and Child Poverty: A Statistical Analysis

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Introduction

Child poverty is an immense societal problem because of the unnecessary hardship it creates for the children who experience it, and the ways in which it negatively impacts others as well. Poor children experience malnutrition, lower academic performance, and higher death rates than children not in poverty. In addition, poverty continues to follow them throughout their life time. There are additional negative results for society as well. Higher healthcare costs and lower productivity can harm the economy. Communities with high child poverty levels also experience additional education and interaction challenges (Griggs and Walker 2008). Reducing child poverty would not only help the specific people who experience it, but all of society as well. This is specifically important for the United States. Despite the high income levels in the US, it also has one of the highest child poverty levels in the developed world. It is in society's best interest to do everything possible to identify why our child poverty rates are higher than in other countries, and work to bring them down. While many papers have worked to determine the cause of child poverty, none of the empirical literature examines the role of the gender wage gap.

The gender-wage gap is an important issue on the political agenda in the United States, and in addition it may be contributing to child poverty. Not only does the gender wage gap seem unreasonable and unfair, but political theory commonly agrees that the gender wage gap between males and females negatively affects society in a variety of ways. The two biggest societal problems that have a hypothesized relationship with the gender wage gap in political science are domestic violence and child poverty. *The Great Divergence* by Timothy Noah is a political science text that addresses the reasons for the growing inequality in the US. Noah suggests that although the gender wage gap is not contributing to the growing inequality in the US, the gender wage gap possibly contributes to violence against women as well as child poverty (Noah 2012).

Due to the recent rise in single-parent homes headed by women, the gender wage gap may be having an independent effect on child poverty levels in the US. The objective of this paper is to test if the gender wage gap does have a positive relationship with child poverty levels.

Literature Review

There have been a number of studies done on the determinants of child poverty. It is generally accepted that there are both individual and large-scale factors involved in child poverty. Individual factors include family structure, demographics, and social and cultural aspects. Large-scale factors include the overall condition of the economy and location. Something that has recently surfaced in these studies is the necessity of including spatial characteristics in the model. A number of empirical studies have shown the importance of place in determining child poverty. Although there is a large body of literature, a problem that has been identified in previous studies is a lack of complete modelling. For this reason, only the papers that have the most complete models to date are reviewed and considered in this paper.

Friedman and Lichter (1998) developed the most commonly used model today. Using data from the 1990 deceniel census they found that the determinants of child poverty in the US include race, lack of education beyond high school, unemployment, location of employment, if the county was in the South or not, the composition of the county's economic industry, the percent of female headed households in the county, and whether the area is considered to be metro or non-metro. The regression methodology they utilize is a logit regression model (Friedman & Lichter 1998). Their paper started the discussion of a relationship between place and poverty that is still a large portion of interest when examining child poverty today. Child poverty is shown to be clustered in the South as well as in urban areas, which is why these variables were included in their model. This is the model that all the newer existing literature is still based on, and inspired the spatial dependence inquiries on the subject. Their specification of child poverty determinants remains relevant.

Voss, Long, Hammer and Friedman (2006) updated the model offered by Friedman and Lichter by using spatial regression analysis on the same model to see if spatial dependence existed, and if correcting it altered the results. If spatial autocorrelation exists, and is ignored, it can result in inaccurate inferences about predictor variables. This is why they re-examine the Friedman and Lichter data and results for this kind of autocorrelation. Their re-analysis finds that child poverty rates are not randomly distributed at the county level, indicating that spatial autocorrelation does exist. Because of these findings, spatial dependence must be accounted for.

There are four reasons they identify that could potentially explain the non-random distribution of child poverty; identifying the most likely is important to then choosing the correct regression technique. First, feedback could cause non-random grouping because as people interact, they influence one another, thus increasing the feedback result (child poverty in this case). This suggests the need for a spatial lag model. Given that poverty is an economic condition not likely increased by feedback, they conclude this is not the correct explanation. The second explanation for the non-random distribution could be grouping forces. Individuals and households with shared characteristics sometimes are found located close together either by choice or because they are pushed to locate their by other forces. These forces could be social, economic, or political. People in poverty could be forced to locate close to one another by factors such as housing prices or societal choices. Grouping forces would create spatial autocorrelation in a dependent variable, and it may be possible to identify the variable or variables involved in the process and then include them in the model. If the variable cannot be identified then the source of the autocorrelation will remain in the error term. This would indicate a need for the spatial error model. Grouping responses are the third possible explanation. Individuals or households that share a common attribute or a set of common characteristics may respond in similar ways to outside pressure. Different groups of people will possess varying capacities to overcome obstacles and challenges. Voss et al. suspect that county-level child poverty is spatially autocorrelated because of the combined disposition of such contextual influences. This indicates the need for a spatial error model. The final potential explanation is nuisance autocorrelation. This occurs when the underlying spatial process creates regions of attribute clustering that are much larger than the units of observation. When units of analysis are much smaller than the regions of high or low attribute values, spatial autocorrelation in the observations is inevitable. Nuisance autocorrelation must somehow be recognized and eventually brought into the formal analysis (Voss et al., 2006).

Voss et al. then ran both spatial error and spatial lag models to see how these alter the original Friedman and Lichter results. Although the spatial lag model is run, they conclude that based on both theory and statistical tests that the spatial error model is the best alternative to the weighted least squares model originally utilized by Friedman and Lichter. The spatial-weighted matrix they use to run the spatial models is a first-order queen matrix, meaning that it only weights immediate neighbors. They also justify their choice through theory: "We choose this convention because there is evidence when using county economic data that neighborhood influences extend out approximately 40-50 miles and then dampen appreciably (Wheeler, 2001) - quite unlike a smooth inverse distance decay. This distance (40-50 miles) will certainly include immediate neighbors for most counties in the US" (Voss et al., pg 15, 2006).

The improvements made by the spatial error model include "(1) the shifting of "wrong sign" parameters in the direction originally hypothesized by the authors, (2) a reduction of residual squared error, and (3) the elimination of any substantive residual spatial autocorrelation" (Voss et al., pg 1, 2006). Their main conclusion is that it is necessary for other social scientists to account for spatial autocorrelation, specifically when examining child poverty. This is of major importance to my paper, as it provides support for the implementation of the spatial error model over a spatial lag model on my data set.

Sri Ranjith and Anil Rupasingha (2012) update the literature further by including social and cultural factors not previously identified before. They utilize Friedman and Lichter's model, but then add in social capital and religious adherence as determinants of child poverty. The child poverty rate by county is their dependent variable. Their independent variables include the percentage of female headed households**,** black, Hispanic, high school only completion**,** unemployment rates**,** unemployment rate for males**,** percent labor of the work force that works in the county of residence, percent agriculture, forestry, fishing and hunting, percent manufacturing, percent service industry, percent professional services, urban county, southern county**,** social capital index, percent religious adherence, percent of mainland protestants, percent of evangelical protestants, and percent of Catholics. The independent variables are all from 2000, while the child poverty rate is from 2007. This lag is included because conditions of previous years are more likely to be causing current child poverty, and to avoid endogeneity. All the data are also county level and cross-sectional. The authors mention that they are utilizing spatial regression estimation methods to account for spatial dependence in both the dependent variable and the error term, but fail to mention with what regression model or technique.

Most of their findings are consistent with the existing literature. They find that the percentage of female headed households is statistically significant and has a positive relationship with child poverty levels. Out of the race variables, only the percentage of African Americans is found to be statistically significant and negative, which conflicts with findings in previous papers. However, results in previous work have been greatly mixed. Both measures of unemployment are found to be statistically significant and have a positive relationship with child poverty. All of the variables measuring industrial composition have a negative relationship with child poverty, except extractive industries which has a positive relationship. Employment in any other industry lowers child poverty, but employment in the extractive industry raises it. The spatial variables are all statistically significant and show the expected results. Child poverty is higher in the South, in rural areas, and in counties where more individuals work in their county of residence. Their new additions to existing literature include finding that both social capital and religious adherence are statistically significant and have negative relationships with child poverty. These are the results they report from their OLS regression that has not been corrected for spatial dependency. They also find that their major findings regarding social capital and religion are consistent after accounting for both kinds of spatial dependence.

The importance of this paper to my work is their use of the same Friedman and Lichter model that was developed in 1998. This demonstrates the relevance of the model all the way up to current research being done today.

The major hole in the existing literature that I seek to remedy throughout the course of this paper is the fact that the gender wage gap is not included. I also use a more current data set than was utilized in any current paper on child poverty.

Data

All of the data for this study came from the American Community Survey from the US Census Bureau website. The American Community Survey is an ongoing survey that provides data every year. It specifically collects data on age, sex, race, family and relationships, income and benefits, health insurance, education, veteran status, disabilities, where you work and how you get there, where you live, and how much you pay for some essentials. Data are offered in one year, three year, and five year estimates. The five year estimates include 60 months of collected data, include data for all of the areas, has the largest sample size, and is the most reliable. The one downside to using the five year estimate data over the one year or three year is that it is the least current of the three kinds of estimates. This one downside is far outweighed by the fact that the data are available for all areas[1] and that they are more reliable.

American Community Survey (ACS) data were chosen over the Decennial survey data for two main reasons. One is that the ACS data are slightly more current. The second reason is that the ACS asks questions that are not asked by the Census. If the census data had been used in this paper, I would have been forced to exclude certain variables as the data were not available from the 2010 census.

The data were all downloaded using American Fact finder, a data tool offered by the US Census Bureau. The portions of the survey that the data were acquired from include the tables of selected housing characteristics, selected economic characteristics, commuting characteristics by sex, black or African American alone or in combination with one or more other races, race, and employment status. All the variables were acquired from these data sets offered under the American Fact Finder download center.

All data for this paper came from the 2010 ACS 5-year estimates and is county level data. This means that the data were collected for the years 2008 through 2012. Counties in Alaska and

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[1] Areas refers to counties in this instance

Hawaii are excluded as their spatial effects are likely to be different than for the mainland. Their determinants of child poverty may have been different as well. Any counties that had a zero value for any of the variables were also removed. This left us with 3,096 counties, compared to the full 3,143 that were originally downloaded.

Methodology

The model being utilized in this paper is based on the three papers previously discussed. Friedman and Lichter developed the model in 1998, but it has proven to still be relevant today. The additional variables included by Ranjith and Rupasingha are not included even though they found them to be statistically significant. Social capital and religious adherence were their included variables, and although they were found to be statistically significant their theoretical backing for their inclusion was not compelling enough for them to be considered necessary additions to the original model. Social capital was thought to decrease poverty because it decreases transaction costs in the economy and society. Religion is also thought to play a role in the economy through the social capital affect, as well as an increase in adherence to moral values that deter poverty (Ranjith & Rupasingha 2012). Given that the economic factors thought to influence child poverty are already included in the model, including these other variables does not make theoretical sense. Their impact should already be captured in the economic factors that are included.

The first model is specified as follows. The dependent variable is the percentage of children in poverty. As in the other three papers discussed in the literature review, the independent variables include the percent of female headed households, percent of the population that is black, percent of the population that is Hispanic, percent of the population with high school only completion, unemployment rates, percent labor of the work force that works in the county of residence, percent agriculture, forestry, fishing and hunting, percent manufacturing, percent service industry, percent professional services, urban county, and southern county. This model varies slightly from the previous model as the unemployment rate for males is excluded. Unemployment is already included to measure the state of the local economy, so there is not enough theoretical backing to also include the unemployment of men specifically. Extra variables I introduce to the model listed above that are not utilized in the previous literature are dummy variables for the other two regions; the West and the Midwest. This makes the base region the Northeast. Dummy variables for all regions allow us to determine if any of the other regions besides the South have different intercepts as well. I also include the ratio of fulltime working females' median incomes to the median incomes of fulltime working males.

A second model is also run where the impact of female wages on child poverty is examined. Instead of including the wage ratio, the median female and male incomes are included in the model. This is done to test the impact of an increase in male and female wages on child poverty.

The ways in which these variables are measured is included below. The gender wage ratio is determined by dividing the income of full-time working females by the income of full-time working males. Percent female headed households is measured by the number of female headed-households with related children under the age of 18, divided by the total number of households in the county. Percent of the population that is black is measured by the total number of African Americans and blacks that identified as at least partially being black (could include other races), divided by the total county population. Percent of the population that is Hispanic is measured the same way as the black population. Percent of the population with high school only completion is measured by taking the number of people who only held a high school degree and dividing it by the total adult population. The unemployment rate is measured as the percent unemployed divided by the number of people in the labor force (currently looking for work). The percent of the work force that works in the county of residence is calculated by taking the number of people who work inside their county and dividing it by the total number of people working. The percent agriculture, forestry, fishing and hunting, percent manufacturing, percent service industry and percent professional services are measured by the amount of economic activity in their given sector, divided by the total amount of economic activity. Percent of urban county is measured by taking the number of households considered to be in urban areas and dividing them by the total number of households. The gender wage gap is measured by taking the income of all fulltime working women and dividing it by the income of all fulltime working men. Female median income is measured as the median income of head of household women without families. The male median incomes are measured in the same manner. The reason for including the incomes of only householders, is to get an accurate representation of the median wage of individuals working to support themselves. All the regions are measured by dummy variables which are 1 if the county is in that region, and 0 if not.

Estimation Methodology

A spatial error model is the main regression analysis of interest. Ordinary least squares (OLS) is also run for comparison purposes only[2]. The spatial error specification is chosen over spatial lags for two reasons. The first reason is that it is supported by the existing literature, making it the best choice in trying to contribute new findings to the literature. Second is the fact that I agree with the theoretical backing that supports the error correction over the lag correction.

[2] The use of OLS is not meant to imply that it is the correct estimation technique. OLS was run and the results were included only to compare them to the spatial error results to determine if there was a major difference between the two.

A spatial lag model should only be utilized if feedback is supported by theory (Drukker, 2008). It is highly unlikely that people in poverty interacting with others causes those individuals to become poor as well. Poverty is more likely distributed unequally because of grouping forces or grouping responses, which indicate a need for a spatial error model. In addition to the reasons provided by Voss et al., history also supports the theory that poverty is a result of grouping forces and responses. One example is white flight out of urban areas in history. A more recent example is the opposite effect of gentrification. As it has become more popular to live in downtown urban areas, the poor have been pushed out by a number of factors. These two trends and their impact on impoverished areas support using a spatial error model.

The spatial matrix being used in the spatial error model is an inverse weight matrix, with a limit. The matrix assigns a 0 value if it is outside our specified range, indicating that the value has no impact on the poverty in that county. If the counties are within the specified area, an inverse weight is assigned that shows a larger impact on counties that are closer to one another. A band of 100 miles was chosen, as there is proof that regarding poverty, there is no spatial affect beyond 40-50 miles (Voss et al., 2008). We chose to use a band larger than 50 miles, as the distance data we obtained were the latitude and longitude center points of each county. If all counties beyond 50 miles of the center point had been assigned a value of 0 in the matrix, then areas on the edges of the county would not have had all the surrounding counties that may have impacted them included. By extending the range to 100 miles we hope to have eliminated this issue.

Three regression sets were run and reported. First are the OLS and spatial error models for all the counties in the US excluding Alaska and Hawaii. Second are the OLS and spatial error models for the same area, but with male and female incomes included instead of the wage ratio.

The third set of regressions include separate regressions by US regions. These were included to determine if child poverty's intercept not only varied by region, but if the slopes varied by region as well.

Logistic regression analysis was also utilized in all three regression sets to normalize the dependent variable, complying with the existing literature. Heteroskedasticity was not corrected for, as it was not indicated that the correction was necessary. When the correction was included, the results were almost identical to when it was not included.

Results

The results of the OLS and Spatial Error Auto Regression (SAR) models are reported in Table 1. The model in which the median income of male and female householders replaces the wage ratio is reported in Table 2. The separate results of the SAR model by region are reported in Table 3.

Unemployment has a coefficient of .04 and is statistically significant, indicating that an increase in unemployment makes child poverty more likely. This was the hypothesized relationship and supports the existing literature. The percent of female headed households has a coefficient of .055 and is also statistically significant. As the percent of female headed households increases in a county, it is more likely that child poverty will exist as well. The percent of the population that is black as well as the percent of the population that is Hispanic are also statistically significant and have coefficients of .0028 and .003 respectively. The percent of the population that has only completed a high school degree is also statistically significant and has a coefficient of .015; an increase in the portion of the population that only holds a high school degree increases the likelihood of child poverty. The percent of the county that is classified as urban is also statistically significant. It has a coefficient of -.003, indicating that an increase in the urban portion of the county actually decreases the log odds of child poverty. The percentage individuals in the work force that work in the county has a coefficient of .0059, an increase in the percentage of those working inside the county increases the likelihood of child poverty in the county as well. Of the economy composition variables, only the percentages of agriculture, professional, and service industries were statistically significant. Percent agriculture and service increase the likelihood of child poverty, while professional services decrease the log odds of child poverty. The final statistically significant variable was the South, indicating that holding all other variables constant, child poverty is more likely in the South.

Most of these findings support the existing literature, but there are some conflicting findings as well. All of my results support the findings of Voss, Long, Hammer and Friedman when they utilized a spatial error model. The only difference was that I found the percent of professional services that makes up a counties industry to be statistically significant, and make child poverty less likely. This continues to support the model created by Friedman and Lichter, as this is what they initially expected. In comparing my findings to those of Ranjith and Ruspingha I find larger differences. They found that the percent of the population that is black actually makes child poverty less likely. This finding conflicts with both mine and those of Voss et al.; they found the percent of the population that is Hispanic to be insignificant, while I found it significant. The other conflicting results are all regarding industry composition. Voss et al. found percent manufacturing in the county to be significant and to decrease the likelihood of child poverty, while I found it to be insignificant. I also found that more participation in the service industry increases the likelihood of child poverty, while they found the relationship between these two variables to be negative. Race and industry variables are the only areas in which my findings differ from the existing literature.

The main variable of interest in this study is the wage ratio. It was the only other additional variable found to be statistically significant besides the ones listed above. The coefficient on this variable is .0022, showing that as female wages rise in relation to male wages, the likelihood of child poverty in the region increases. This not only proves the original hypothesis wrong, but provides evidence in the opposite direction. Reasons behind this result will be reviewed in the following section. While there is no currently published literature on the topic, this conflicts greatly with my initial findings from my first paper written on this topic. In that paper, using only the wage ratio, the number of single parent homes, unemployment, and the Gini coefficient, I found a negative relationship between the increase in the portion women make compared to men and child poverty (Farwell 2013).

(Table 1 on following page)

Table 1
Dependent Variable: Logit of PCTCHILDPOV

VARIABLES	(1) OLS	(2) SAR
unemployment	0.0522***	0.0407***
	(0.00250)	(0.00269)
wageratio	0.00248***	0.00224***
	(0.000613)	(0.000623)
pctfemalehouse	0.0587***	0.0550***
	(0.00394)	(0.00379)
pctblack	-0.00111*	0.00282***
	(0.000637)	(0.000804)
pcthisp	0.00115*	0.00308***
	(0.000619)	(0.000929)
pcths	0.0154***	0.0146***
	(0.00135)	(0.00148)
pcturban	-0.00377***	-0.00313***
	(0.000305)	(0.000312)
pctworkinco	0.00671***	0.00590***
	(0.000438)	(0.000432)
pctag	0.00635***	0.00838***
	(0.00161)	(0.00167)
pctmfg	0.00196	0.00234
	(0.00139)	(0.00151)
pctprof	-0.0185***	-0.0162***
	(0.00333)	(0.00332)
pctserv	0.0150***	0.0134***
	(0.00164)	(0.00159)
west	0.162***	0.0915
	(0.0322)	(0.0727)
midwest	0.0568**	0.0545
	(0.0273)	(0.0616)
south	0.420***	0.302***
	(0.0273)	(0.0598)
Constant	-4.445***	-4.232***
	(0.125)	(0.135)
rho		0.689***
		(0.0246)
Observations	3,096	3,096
R-squared	0.595	

Note: *** {**} [*] represent statistical significance at the 1% {5%} [10%] level.

Below in Table 2, the results for the model in which male and female incomes replace the wage ratio are included. The main differences in this specification are that the percent black population no longer has any relationship with child poverty. The second difference is that the percent of professional services now makes child poverty more likely, rather than less likely. This indicates that the original findings regarding race and industry composition are not robust.

The main coefficients of interest are those of male median income and female median income. Male median income has a coefficient of -.000147, showing that an increase in income makes child poverty less likely. Female median income has a coefficient of -.0000155, which indicates that an increase in women's income decreases the likelihood of child poverty as well. It is also important to note that a one dollar increase in the median female income, makes child poverty even less likely than a one dollar increase in the median male income.

(Table 2 on following page)

Table 2

Dependent Variable: Logit of PCTCHILDPOV

	(1)	(2)
VARIABLES	OLS	lpctcp
unemployment	0.0407***	0.0333***
	(0.00232)	(0.00252)
nonhhincmale	-1.63e-05***	-.00001465***
	(1.11e-06)	(1.10e-06)
nonhhincfemale	-1.73e-05***	-.000015505***
	(1.64e-06)	(1.63e-06)
pctfemale	0.0536***	0.0534***
	(0.00358)	(0.00357)
pctblack	-0.00129**	0.00103
	(0.000577)	(0.000712)
pcthisp	0.000685	0.00211***
	(0.000559)	(0.000785)
pcths	0.00571***	0.00618***
	(0.00128)	(0.00142)
pcturban	-0.00198***	-0.00191***
	(0.000285)	(0.000296)
pctworkinco	0.00427***	0.00431***
	(0.000409)	(0.000411)
pctag	0.00539***	0.00682***
	(0.00145)	(0.00154)
pctmfg	-0.000284	0.000502
	(0.00127)	(0.00139)
pctprof	0.0131***	0.00655**
	(0.00327)	(0.00328)
pctserv	0.00674***	0.00714***
	(0.00152)	(0.00152)
west	0.0647**	0.0525
	(0.0294)	(0.0533)
midwest	-0.0159	-0.00702
	(0.0249)	(0.0455)
south	0.225***	0.199***
	(0.0259)	(0.0449)
Constant	-2.635***	-2.704***
	(0.124)	(0.133)
		0.552***
rho		(0.0304)
Observations	3,096	3,096
R-squared	0.666	

Note: *** {**} [*] represent statistical significance at the 1% {5%} [10%] level.

Shown below in Table 3 are the different regression results across regions. While there is nothing extremely noteworthy about these results, it does bring to light that perhaps the impact on child poverty of race and industry composition are not consistent across regions. This illustrates another avenue that should possibly be considered for further research.

Table 3
Dependent Variable: Logit of PCTCHILDPOV - Spatial Autocorrelation

	(1)	(2)	(3)	(4)
VARIABLES	West	Midwest	South	Northeast
unemployment	0.0297***	0.0454***	0.0398***	0.0619***
	(0.00922)	(0.00463)	(0.00356)	(0.0135)
Wageratio	0.00516***	-0.000319	0.00153*	0.0106***
	(0.00180)	(0.00112)	(0.000826)	(0.00340)
pctfemalehouse	0.0476***	0.0570***	0.0560***	0.0805***
	(0.0137)	(0.00661)	(0.00492)	(0.0146)
pctblack	0.00899	0.0110***	0.00172*	-0.00113
	(0.0109)	(0.00256)	(0.000939)	(0.00399)
pcthisp	0.00454**	0.00287	0.00211	0.00708*
	(0.00190)	(0.00271)	(0.00139)	(0.00407)
pcths	0.0203***	0.0171***	0.00909***	0.0287***
	(0.00488)	(0.00243)	(0.00208)	(0.00537)
pcturban	-0.00257**	-0.00215***	-0.00392***	-0.00198*
	(0.00103)	(0.000579)	(0.000418)	(0.00102)
pctworkinco	0.00772***	0.00528***	0.00563***	0.00608***
	(0.00163)	(0.000769)	(0.000563)	(0.00115)
pctag	0.00649	0.0145***	0.00851***	0.0258**
	(0.00434)	(0.00295)	(0.00247)	(0.0125)
pctmfg	0.00460	-0.00232	0.00741***	0.000266
	(0.00741)	(0.00256)	(0.00202)	(0.00487)
pctprof	-0.0123	-0.0133*	-0.0202***	0.0135
	(0.00815)	(0.00749)	(0.00449)	(0.0137)
pctserv	0.0220***	0.00913***	0.0126***	0.0178***
	(0.00528)	(0.00276)	(0.00211)	(0.00514)
Constant	-4.881***	-4.056***	-3.597***	-6.123***
	(0.374)	(0.210)	(0.169)	(0.473)
Rho	0.300***	0.773***	0.837***	0.764***
	(0.0819)	(0.0467)	(0.0409)	(0.166)
Observations	412	1,051	1,416	217

Note: *** {**} [*] represent statistical significance at the 1% {5%} [10%] level.

Discussion and Conclusions

Given the reported results above, the data show that the gender wage gap between men and women does not cause child poverty to increase. In fact, the results show that as the ratio of female wages to male wages gets smaller, child poverty is more likely to occur. This tells us that as the gender wage gap increases, child poverty becomes less likely, contradicting the original hypothesis. A possible reason for this result is that the wage ratio is actually measuring something else that is going on in the county. While the state of the economy, industry composition, and family structure have all been accounted for, perhaps there is another factor that the wage gap is measuring. An example may be cost of living. In the counties in which the biggest wage gap occurs, perhaps women don't need to work to support the family. The only women working are those who need to in order to support their families, while most of the other families live comfortably off the male wages. This could explain why a bigger wage gap is shown to result in less child poverty. The only major conclusion that can be drawn from this result is that as female income increases compared to male income; child poverty does not become less likely. More research in this area should be pursued.

While an increase in female purchasing power compared to male purchasing power was not shown to decrease child poverty; the results do indicate that a rise in female income does make child poverty less likely than does a rise in male income. Both female and male incomes were shown to decrease the likelihood of child poverty; but the decreasing effect of female income is stronger. This demonstrates that comparable purchasing power between men and women does not decrease child poverty chances. However, increasing both gender's income does, and the effect of increases in women's income has a stronger negative impact on the likelihood of child poverty.

Overall, my findings support the existing literature, except regarding the race and industry variables. My results conflict with previous findings for the race and industry composition variables, but these are also the variables that the existing literature do not agree upon either. My results of the different regressions run across regions also show that the only variables (besides the wage ratio) that are not consistent in statistical significance and sign are the race variables and industry variables. All of these findings raise a need to continue to study the impact of race and industry on child poverty further in the United States. Perhaps it is these regional differences that are causing the variation in the different papers.

As far as policy implications are concerned, reducing the wage gap between the genders will not reduce child poverty. If any action were to be taken regarding income, a policy should target an increase in female income in order to yield the best results.

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