Intimate Partner Violence (IPV) Before, During, and After the Great Recession: Findings from South Carolina

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EXECUTIVE SUMMARY

This report examines the association between intimate partner violence (IPV), specifically counts of reported aggravated assaults, and unemployment figures before, during, and after the Great Recession in South Carolina. While the recession represented economic downturn throughout the early 2000s, its official time period spanned December 2007 through June 2009. Using data supplied by the South Carolina Incident-Based Reporting System (SCIBRS), data on the counts of reported aggravated assaults at the county-level were provided from 2000-2017. Coupling this data with community demographic data from the United States Census Bureau and unemployment data from the Bureau of Labor Statistics, longitudinal county-level snapshots were created, forming the basis of the statistical analyses. Four fixed effects models were employed to examine the association between unemployment and IPV – each model fluctuated time periods and associated variables to provide several perspectives on the topic.

When examining the time period from 2000-2017 across all 46 counties in South Carolina, one of the statistical models revealed there is a positive and statistically significant association between unemployment and aggravated assaults. On average, it is estimated for every one-percent increase in the number of unemployed workers in South Carolina, there is an associated increase in reported aggravated assaults by 0.20 percent. While any increase in IPV is concerning, this increase–while statistically significant–is small. As the time periods were narrowed from 2005-2012, the association between unemployment and reported aggravated assaults dissipates. Of note, reports of aggravated assaults at the county-level in South Carolina were in a steady decline from 2000-2017. While unemployment experienced sharp increases during the recession, there was no interruption to the decline in reported aggravated assaults at this time. This study finds there is not enough evidence to support an association between unemployment and IPV before, during, or after the Great Recession in South Carolina.

While this report does not provide any evidence of a link between unemployment and IPV, it does demonstrate South Carolina's continued commitment to improved understanding of the contributors of IPV. Given the continued decline of IPV within the state, it is possible that these efforts have prevented an increase that may have happened as a result of increased unemployment. Continued monitoring of these metrics as it relates to changes in economic activity within South Carolina along with any changes to public policies that may affect IPV are important steps to preserve public interest and protect well-being of the families of South Carolina.

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The South Carolina Law Enforcement Division (SLED) manages the South Carolina Incident-Based Reporting System (SCIBRS), a system that is National Incident-Based Reporting System (NIBRS)-certified by the Federal Bureau of Investigation (FBI). The South Carolina Governor's Domestic Violence Task Force identified the SCIBRS as the primary source for domestic violence data. This data source provides a rich and important perspective into the lives and families within South Carolina that are impacted by intimate partner violence (IPV). The SCIBRS contains information about crime in South Carolina: it results from South Carolina's approximately 275 law enforcement agencies reporting information about victim, offense, offender, and arrestee (if applicable) for all criminal incidents known to police. The result is a rich set of crime data unparalleled in criminal justice data collection. SLED provides support to law enforcement agencies through auditing, training, and guidance on coding individual incidents. SLED also stores every incident submitted by the law enforcement agencies on a state repository and submits those same incidents to the FBI.

Currently, 14 of the SCIBRS offense categories require reporting the victim-to-offender relationship, which can include the following five intimate relationships: spouse, ex-spouse, common-law spouse, (ex-)boy/girlfriend, and same-sex relationship. Information about offenses coupled with victim-to-offender intimate relationships means that the SCIBRS can be used to study domestic violence. As a NIBRS-certified system, its crimes are categorized by general definitions; thus, the SCIBRS provides a unique opportunity to study domestic violence across jurisdictions—independent of statutory differences.

OBJECTIVE OF THIS WORK

The intent of this work is to examine the association between IPV and unemployment before, during, and after the Great Recession. As unemployment statistics are oftentimes the primary metrics cited when examining economic downturn, unemployment also has spillover effects that negatively impact families – this includes the potential for an increase IPV due to the lack of employment. This project will measure and assess what effect size and statistical association, if any exists, between these two variables.

RELEVANT LITERATURE

Prior research has examined the impact of various factors such as income, employment, economic distress, and financial challenge on IPV. These factors have been broken down in numerous ways to include aggregate level versus individual level, the income differential of the partner and the victim, as well as employment or underemployment. Various contexts of the economic conditions have also been explored

such as the condition of the home versus the conditions of the neighborhood. The findings of the research are as varied as at the contexts in which the research has been conducted and the data explored. [1]

Most central to this research is the effect of unemployment on IPV. Research addressing the relationship between IPV and economic conditions is far from conclusive with no clear association. This has not resulted in a lack of attempts nor a decrease in possible theories. The lack of clear evidence in support of or disagreement with is likely due to many factors, some of which involve limitations in data associated with IPV, as well as an inability to directly link victims and their socioeconomic characteristics.

One such reason that this topic continues to be studied is likely due to the many compelling theories and hypotheses that have strong face validity. Many of these theories are extensions of general strain theory and resource deprivation theories. However, there are three hypotheses that are most relevant to this study.

1. Resource deprivation hypothesis that suggests the unemployment of either partner increases financial stress which strains the relationship.
2. Dependency hypothesis that suggests that partners who are not employed are at an increased risk as they lack the resources to leave an abusive relationship.
3. Backlash hypothesis that posits one partner's employment increases their risk of IPV if the perpetrator is unemployed.

Macmillan and Gartner (1999) tested each of these hypotheses and found weak support for the resource deprivation hypothesis (male unemployment increased risk of IPV, female unemployment did not). Additional findings supported both the dependence hypothesis and the backlash hypothesis, as women's employment lowered their risk of IPV when the male partner was employed but increased the risk of IPV when the male partner was unemployed. Benson and Fox (2004) found male employment to increase a woman's risk of IPV, supporting the resource deprivation hypothesis. However, Benson and Fox (2004) neglected to consider the comparative effect of women's employment. Riger and Staggs (2004) found that women's employment increased risk of IPV, and that unemployment decreased risk of IPV. However, this finding is flawed on account of the authors' decision to not include an analysis of male partner employment. Resko (2007) conducted an initial analysis that indicated male unemployment increased risk of IPV. Her follow-up analysis of the joint effects of male and female unemployment found nuanced results

dependent on the duration of unemployment. In a meta-analysis, Peterson (2011) found that while controlling for studies that compare the employment status of both male and female partners, "there is support for the resource deprivation hypothesis and the dependency hypothesis, while results for the backlash hypothesis are mixed."

Research by Fox and Benson (2006) suggested the importance of neighborhood context and found that economically vulnerable couples have higher rates of IPV when in disadvantaged neighborhoods. Benson, Fox, DeMaris, and Van Wyk (2003) suggested that neighborhood economic disadvantage, neighborhood residential instability, male employment instability, and subjective financial strain influence the likelihood of violence. Cunradi, Caetano, and Schafer (2002) identified a significant effect of household income on the probability of partner violence. Using American Community Survey data, Cohen (2014) identified a downward spike in divorce rates after 2008 suggesting a negative recession effect despite an increase in divorce odds associated with increased foreclosure rates.

Schneider, Harknett, and McLanahan (2016) examined the effect of the Great Recession on the relationship between adverse labor conditions and mothers' experiences of abusive behavior. Using a combination of longitudinal data from the Fragile Families and Child Wellbeing Study and the U.S. Bureau of Labor Statistics, they found that unemployment and economic hardship were positively related to abusive behavior. Pilkauskas, Currie, and Garfinkel (2012) also found that the unemployment rate is associated with increased material hardship, difficulty paying bills, having utilities disconnected, and increased usage of welfare, food stamps, unemployment insurance, and Medicaid. Aizer (2010) suggested that decreases in the wage gap are associated with reduced violence against women.

Tolman and Wang (2005) used a fixed effects model to explore the relationship between domestic violence and women employment. They found that domestic violence significantly reduced the annual work hours of respondents in their study.

These studies are not limited to the US context, Torrubiano-Domínguez et al. (2015) studied 17 regions of Spain over two time periods (2005-2007 and 2008-2013). Using multi-level linear regression models, they found no evidence to support a relationship between unemployment and IPV.

Analyzing British Crime Survey and disaggregated labor market data from 2004-2011, Anderberg et al. (2015) examined how changes in unemployment affect the incidence of intimate-partner violence in England and Wales. The authors theorized opposite-signed effects:

- An increase in male unemployment would decrease the incidence of IPV

- An increase in female unemployment would increase the incidence of IPV

The findings indicate strong support for both theories: "our empirical results suggest that a 1 percentage point increase in the male unemployment rate causes a decline in the incidence of physical abuse against women of around 3 percent, while a corresponding increase in the female unemployment rate has the opposite effect."[2]

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[2] For additional details concerning economic factors and their association with intimate partner violence, please refer to Matjasko, Niolon, and Valle (2013).

METHODS

This section describes the data sources, the variables from each data source, the methodological approach, and quantitative models employed in this project.

DATA SOURCES

The data in this work stems from three sources. The first source was SCIBRS data, supplied by the South Carolina Statistical Analysis Center. The second data source was unemployment data, obtained from the Bureau of Labor Statistics. The third data source was from the US Census Bureau. Data from the Census Bureau includes variables from the American Community Survey (ACS) along with intercensal population estimates. The relevant years of study for the data included 2000 through 2017, although not all data sources contained all desired variables for all counties throughout the entire time period. Due to this limited variables and timelines, multiple statistical models were incorporated to examine the impact of adjusting the years of study and variables on the topic of interest.

SCIBRS

SCIBRS data included all 46 South Carolina counties with variables related to IPV from 2000 through 2017. Variables included within the data include all violent crimes, which the SC SAC defines as any crime in which the victim recorded in the SCIBRS is an intimate partner of the offender (as defined in the Introduction), and the offense recorded in the SCIBRS is a crime included in the FBI's Violent Crime Index (i.e., murder, sexual battery, robbery, aggravated assault). Variables included counts of murder, sexual battery, robbery and aggravated assault. For purposes of this analysis, aggravated assault was used in the quantitative models. Aggravated assault was of particular interest to the South Carolina SAC and this variable aligned well with some of the prior literature, allowing for comparison of this work's findings to that of previous work. In this study, aggravated assaults are reported counts. Reports of crime are often underreported as compared to their incidence (Fernández-Fontelo, Cabaña, Joe, Puig, & Moriña, 2019).

US CENSUS BUREAU

Data from the US Census Bureau consisted of two major areas – the first included demographic data at the county-level which came from the American Community Survey (ACS). County-level data from the ACS are available in one- and five-year estimates.[3] One-year estimates are only available for geographic areas (e.g.,

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[3] Three-year estimates were recently discontinued.

county-level) with a population greater than 65,000. There are 20 counties in South Carolina with a population less than 65,000 in 2017. As a result, while five-year ACS estimates would encompass all the counties in South Carolina, extreme caution must be taken if including five-year estimates over a longitudinal study, as four of the five years for the reference year could overlap with another reference year.[4] Please refer to Figure 1 for a county-level map referencing which counties are included in the statistical models.

BUREAU OF LABOR STATISTICS

Data on unemployment came from the Bureau of Labor Statistics and encompassed all counties from 2000-2017. In this analysis, unemployment statistics were counts at the county-level each year. Counts of unemployed workers were used in lieu of the unemployment rate. A count rather than a rate was preferred, as other variables in the analysis were also in a count form.

FIXED EFFECTS MODELS

Four fixed effects models were in this analysis to provide various perspectives on the association between unemployment and IPV before, during, and after the Great Depression. The unit of analysis was county-year. Fixed effects models are popular among econometrics as the models utilize an approach that accounts for variables that cannot be measured. As a result, they reduce omitted variable bias (Fitzmaurice, Laird, & Ware, 2012; Wooldridge, 2013). In order to mitigate omitted variable bias, i.e. cases where key variables exist but are unmeasured (that account for differences across the counties), a fixed effects model holds constant time-invariant, county-level factors. The main assumption in a fixed effects model is the individual fixed effects (the counties in South Carolina) are correlated with the independent variables used in the analysis. A Hausman test was used to determine whether a random effects model or a fixed effects model will be used in this analysis. Under the null hypothesis, the random effects model is the preferred model. Results of the Hausman test indicated use of fixed effects model versus the random effects model (χ^2= 24.144, df = 1, p-value = 8.939e-07).

All model coefficients were evaluated at significance level of α = 0.05. Consequentially, a p-value less than 0.05 is used to reject the null hypothesis of no association between an independent variable and the dependent variable. The alternative hypothesis is that an association between the two variables exists. A key distinction worth noting is the difference between an association and causation. As the data used in

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[4] Please reference Chapter 3 of the ACS General Handbook, "Understanding and Using ACS Single-Year and Multiyear Estimates" for more information.

this analysis are retrospective and counties were not randomly assigned to case and control groups. Therefore, any statistical significance between variables highlights an association (or relationship between two variables), but does not indicate that one variable is the cause for the occurrence of another variable.

The fixed effects models are represented in the following form, $y_{it} = \alpha_{it} + \beta x_{it} + \varepsilon_{it}$, where y_{it} represents the natural log of aggravated assaults, reported for the corresponding county *i* and year *t*. All independent variables in the analysis were transformed with the natural log in order to appropriately scale the differences in magnitude across the variables utilized and to normalize the variables in the models. The y-intercept is represented by α_{it}, independent variables are represented by βx_{it} to include an error term, ε_{it}. Four fixed effects models were employed to examine the association between unemployment and IPV – four models were used to fluctuate the years in the analysis whilst accounting for the availability of variables for the corresponding time periods. A categorical variable indicating the appropriate time period (pre-recession, recession, and post-recession) was also used based upon the time period. The pre-recession time period corresponded to all years before 2008, the recession time period corresponded to 2008 and 2009, and the post-recession time period corresponded to all years after 2009.

Model (1) includes unemployment data for all years from 2000-2017. Model (2) only includes unemployment data for the years 2005-2012, as this provides a basis for comparison in Model (3). Model (3) includes observations from years 2005-2012, but only includes a subset of counties (n = 20). Model (4) includes observations from 2005-2012; it also incorporates variables from the American Community Survey with the same counties represented in Model (3). The beginning time period for models (2) through (4) is 2005 as this corresponds to when one-year estimates were introduced in the ACS. The ending time period was limited to 2012, as several counties had missing ACS data beginning in 2013.

Figure 1 displays a map representing which counties are included in the various models. As population estimates are the main driver for which counties are included in various models (please see the section above describing data from the US Census Bureau), only counties with a population larger than 65,000 residents were included in all four models. Lancaster County had population estimates bordering 65,000 – some years the county had estimates exceeding this amount, and other years it had estimates below this amount. As a result, Lancaster County was excluded from models 3 and 4. Counties represented by a darker shade of purple were included in all four models. Those counties with a lighter shade of purple were only included in Models 1 and 2.

Figure 1: County-Level Map Corresponding to Inclusion in Statistical Models
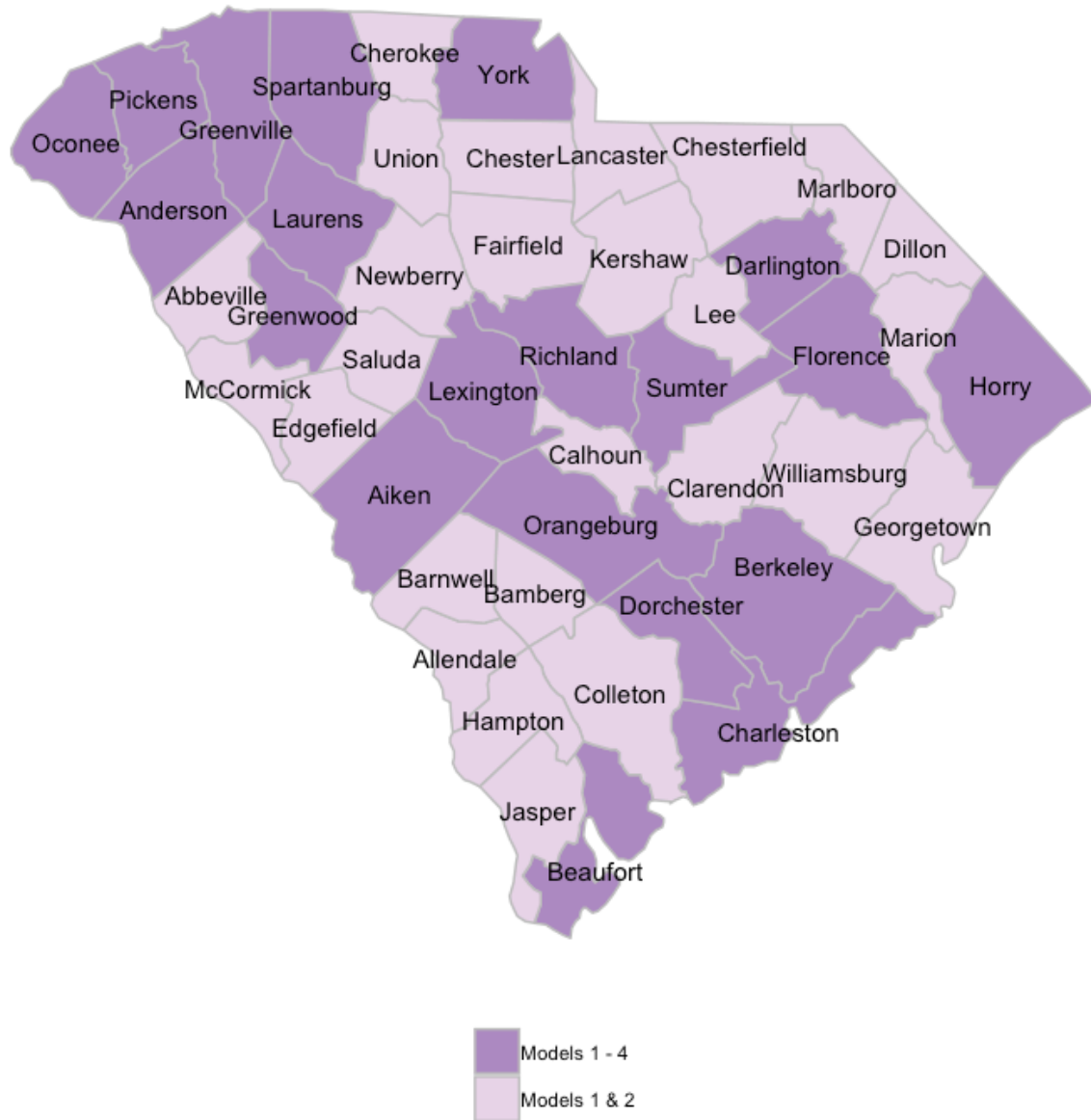
Source: Stonewall Analytics

All statistical analyses were performed using R. The syntax used to organize the data, produce the figures, and employ the statistical models are contained within the Appendix. All data and syntax files for this project are posted on the Stonewall Analytics website, www.stonewallanalytics.com/southcarolina (please refer to Phase 3).

RESULTS

This section is organized by summary and descriptive statistics for the variables included in the model, along with figures of the variables of main interest. Following these components, the results of the four fixed effects models are presented.

Key variables of interest presented in Table 1 identify the summary statistics which are stratified by the fixed effects model numbers. As Models 1 and 2 utilize observations from all 46 counties in South Carolina, it is evident that there are counties with lower observations of aggravated assault, unemployment, and population as compared to the subset of counties used in Models 1-4. A wide distribution in the statistics at the county-level; this is evident in both the standard deviations and the interquartile ranges for all statistics.

Table 1: County-Level Summary Statistics on Variables of Interest Stratified by Models

|	Counties in Models 1 & 2 (N = 46)		Counties in Models 1 – 4 (n =20)	
	Median (IQR)	Mean (SD)	Median (IQR)	Mean (SD)
Aggravated Assault	68 (119)	120 (140)	180 (205)	224 (159)
Unemployment	2,367 (4,153)	3,953 (4,075)	7,084 (5,542)	5,756 (4,447)
Population	55,822 (111,706)	98,130 (104,467)	153,850 (155,158)	184,465 (107,668)
Total Households	-	-	58,617 (66,024)	70,792 (42,183)
Population 18-24 < HS diploma	-	-	2,779 (2,431)	3,177 (1,757)

Note: Statistics were rounded to the whole number; some county-level statistics are not presented (represented by '-') as counties with a population less than 65,000 do not have estimates available; IQR = interquartile range; SD = standard deviation.
Source: Stonewall Analytics

Figure 2 displays the mean (average) count of aggravated assaults at the county-level along with the mean count of unemployed workers at the county-level in South Carolina from 2000 through 2017. The y-axis is presented in the natural logarithm (or natural log). The natural log scale is a nonlinear representation of the data – it is best used in scenarios where there is a large range of positive values. In this case, the natural log scale visually supports both the counts of aggravated assaults and the counts of unemployed workers in one visual. The recession time period is captured by the vertical, dotted lines at years 2008 and 2009. All time periods prior to 2008 incorporate the pre-recession, whereas all time periods after 2009 correspond to the post-recession (the time between 2008 and 2009 corresponds to the recession). The mean number of unemployed workers at the county-level was in a steady increase until reaching the recession, where the mean number of unemployed sharply increased. Following the recession, the mean number of unemployed

workers began to steadily decrease. For the mean count of reported aggravated assaults at the county-level, this value was in steady decline from the onset of 2000, irrespective of the impact of the recession period. Between 2012 and 2013, the mean count of aggravated assaults experienced a sharper downturn, where after in time the value leveled off. Visually, no association or relationship is evident between the mean count of unemployed workers at the county-level and the mean count of aggravated assaults at the county-level before, during, or after the recession.

Figure 2: Unemployment and Aggravated Assaults in South Carolina
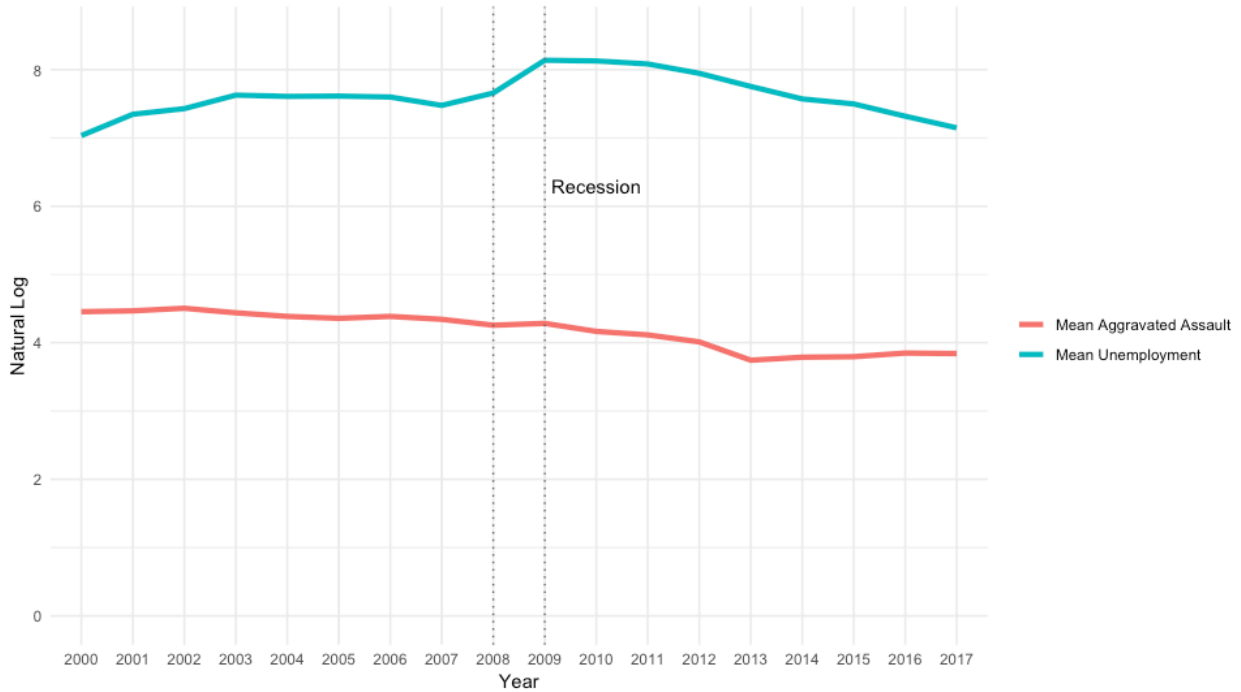
Source: Stonewall Analytics

Table 2 presents results for the fixed effects models. Model numbers are displayed by numerical value in parentheses along the top row of the table. Values reported in each cell for the corresponding variable are coefficient estimates, and values reported in parentheses are standard errors.

Table 2: Model Results for County-Level Reported Aggravated Assaults in South Carolina

	Model (1)	Model (2)	Model (3)	Model (4)
Coefficients				
Recession	-0.243 ***	-0.108 *	-0.075	-0.079
	(0.444)	(0.050)	(0.062)	(0.063)
Post-recession	-0.561 ***	-0.288 ***	-0.143	-0.145
	(0.029)	(0.059)	(0.079)	(0.079)
Unemployment (ln)	0.204 ***	0.041	-0.040	-0.044
	(0.042)	(0.098)	(0.116)	(0.117)
Total population (ln)	0.224	0.100	-0.012	0.783
	(0.207)	(0.534)	(0.646)	(0.942)
Total households (ln)				-0.817
				(0.714)
Population 18-24 years < HS diploma (ln)				-0.038
				(0.081)
Fixed Effects				
All counties (N = 46)	X	X		
ACS counties (n = 20)[1]			X	X

Note: X indicates fixed effects were included in the model; * = p-value < 0.05, ** = p-value < 0.01, *** = p-value < 0.001; ln = natural log; HS = high school; ACS = American Community Survey; [1] = refer to the Appendix for a listing of included counties.

Source: Stonewall Analytics

When examining Model 1 (all counties in South Carolina from 2000-2017), unemployment is statistically significant (it has a corresponding p-value less than 0.001), and its magnitude is positive (indicating that as the independent variable increases, so does the dependent variable). The recession, as compared to the pre-recession is also statistically significant, although its magnitude is negative (indicating that the recession experienced lower counts of aggravated assaults as compared to the pre-recession). This finding is also similar with the post-recession, where the magnitude was negative and statistically significant (this estimate is also compared to the pre-recession). The population estimate is not associated with aggravated assaults.

In Model 2 (all counties in South Carolina from 2005-2012), the recession and post-recession time periods are also statistically significant. Similar to Model 1, both are of a negative magnitude. Furthermore, neither unemployment nor population is associated with aggravated assaults in Model 2. In Model 3 (20 counties from 2005-2012), none of the variables are statistically significant. Similar to Model 3, Model 4 (20 counties from 2005-2012 with additional variables) does not have any statistically significant findings. Comparing the trends from Models 1-4, we find that as the time periods are limited (less years present) and more variables are added to the models, variables that were statistically significant in previous models are no longer

statistically significant. With the exception of the categorical variables representing the recession and post-recession, the magnitudes (i.e., positive or negative values) do not hold constant across all four models when examining variables individually. For instance, unemployment is positively associated with aggravated assaults in Model 1, positively associated in Model 2 (not statistically significant), but then has a negative association in Model 3 and Model 4 (and not statistically significant in both of these models).

As both the dependent variable and the independent variables in the fixed effects models were log transformed, interpretation of the coefficients is not as straightforward. In cases where both the dependent variable and independent variables are transformed, the model coefficients are interpreted as follows: a one-percent increase in [insert name of independent variable here] results in a corresponding increase (or decrease if the coefficient estimate is negative) by [insert coefficient estimate value here] percent for [insert dependent variable here], holding all other variables constant. In the case of unemployment in Model 1, a one-percent increase in the number of unemployed workers at the county-level in South Carolina results in a corresponding increase by 0.20 percent for the number of reported aggravated assaults, holding all other variables constant. Since the recession variable is not transformed (but the dependent variable is transformed), the interpretation is different. The interpretation for the recession and post-recession variables are essentially a comparison to the pre-recession variable. The interpretation for these variables is as follows: holding all other variables constant, the average difference between [insert name of dependent variable here] as compared to [insert categorical reference variable here] is [insert coefficient estimate value here] percent. In the case of the recession variable in Model 1, holding all other variables constant, the average difference between reported aggravated assaults at the county-level during the recession, as compared to the pre-recession is -24.3 percent.

CONCLUSION

Our findings suggest there is not enough evidence to indicate an association exists between reported aggravated assaults and unemployment before, during, and after the Great Recession. The general findings of this study seem somewhat counterintuitive based upon one's perception of the recession and the negative impact it had on employment. Model 1 seems to capture one's perceived notion of unemployment and aggravated assaults – in this case the finding, the finding was statistically significant and had a positive association between unemployment and aggravated assaults (as one value increased, so did the other). As time periods were limited and more variables were added to the models, however, the statistical significance dissipated, and no patterns emerged. Figure 2 does an important job of visually representing the trends and lack of association between these variables of interest. Reports of aggravated assaults were in a decline from 2000-2017. Unemployment was increasing during the recession and then began to decrease after the recession. Since there is no visual association between the two variables of interest in this study, there is no statistical association in the fixed effects models either. The possibility of a washout effect, however, exists as the data were aggregated at the county-level. In some geographic units in South Carolina, associations between aggravated assaults and unemployment could exist. Only when encompassing a wider timeframe, in this case from 2000-2017, do we see a statistical significance between unemployment and aggravated assaults. While statistically significant, we find that this estimate is not practically significant (in this case we estimated that a one percent increase in the number of unemployed workers in South Carolina is associated with a 0.20 percent increase in reports of aggravated assaults). While any increase in unemployment or aggravated assaults represents devastating effects for the families in South Carolina, these statistical results must always be balanced in the context of practicality and interpretation.

Comparing these findings to the published literature, only our first model which encompassed reports of aggravated assaults as the dependent variable with population and unemployment as the independent variables contained statistically significant findings. In light of findings found by Anderberg et al. (2015) studying a population in England and Wales, their previous findings were not in line with this project's findings – both in effect size and magnitude.

One of the limitations in this study is the inability to capture all variables of interest across all counties. This was limited by the availability of estimates in the American Community Survey using one- and five-year estimates. Introducing multiple models and adjusting time periods to bridge these limitations mitigated any potential negative impact. A second limitation is the inability to adequately capture the detailed time

periods of the recession – from December 2007 through June 2009. As the data were only available at the annual level, our analysis captured the recession from 2008 through 2009. All years prior to 2008 were considered the pre-recession, whereas all years after 2009 were considered the post-recession. A third limitation in this study is on the SCIBRS data for aggravated assaults. This variable represents reported aggravated assaults, which is quite different from actual aggravated assaults. As IPV is often underreported, it is likely that the reported numbers of aggravated assaults differ significant from actual aggravated assaults. Additionally, more than 275 agencies report IPV across South Carolina. There is also the likelihood that differences in reporting mechanisms and available resources contribute to variation in numbers reported across the state throughout this time period.

Future research should examine IPV and unemployment in South Carolina with a unit of analysis that extends beyond the county-year level. While demographic characteristics were provided for each county, this aggregate level may washout any noticeable effect. Furthermore, this study examined unemployment but not the loss of a job (i.e., the point in time one has employment and then loses employment) nor underemployment. Future studies should vary the dependent variable of interest to determine what impact these may have on IPV.

While this report does not provide any evidence of a link between unemployment and IPV, it does demonstrate South Carolina's continued commitment to improved understanding of the contributors of IPV. Given the continued decline of IPV within the state, it is possible that these efforts have prevented an increase that may have happened as a result of increased unemployment. Continued monitoring of these metrics as it relates to changes in economic activity within South Carolina along with any changes to public policies that may affect IPV are important steps to preserve public interest and protect well-being of the families of South Carolina.

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R Syntax for Project Analysis and Related Figures[5]

Set up the working directory as appropriate. The following code will evaluate the current working directory. One could place the data files in this default location, or set the working directory with the 'setwd()' command. Please type 'help(setwd)' within R for more information.

```r
library(plm)
library(ggplot2)
library(dplyr)
library(tidyr)
library(magrittr)

setwd('INSERT PATH HERE FOR YOUR DIRECTORY')

scibrs <- read.csv('phase3_data_19may19.csv', header = TRUE, stringsAsFactors =
FALSE)

names(scibrs) <- c('county_name', 'county', 'fips', 'year', 'agg_assault',
'all_scibrs', 'intimidation', 'simple_assault', 'violent_crimes', 'employment',
'labor_force', 'unemployment', 'unemployment_rate', 'recession', 'population',
'male_population', 'female_population', 'total_households',
'married_households', 'female_householder_no_husband', 'population_over_15',
'married_population', 'widowed_population', 'divorced_population',
'separated_population', 'population_18_24', 'male_population_18_24',
'female_population_18_24', 'population_18_24_less_hs_diploma',
'male_population_18_24_less_hs_diploma',
'female_population_18_24_less_hs_diploma')


scibrs$year <- as.character(scibrs$year)

## adding in the population data from census
population <- read.csv(file = 'pop2000to2017.csv', header = TRUE,
stringsAsFactors = FALSE)

## making the data long
pop_long <- population %>% gather(key = year_hold, population, pop00:pop17)
names(pop_long) <- c('county', 'fips', 'year_hold', 'population')

## custom function like excel's right formula
right = function(text, num_char) {
  substr(text, nchar(text) - (num_char-1), nchar(text))
}
```

---

[5] This portion of the appendix contains code for the project that was conducted in R. A number of external packages were used in this analysis, so in cases where syntax containing 'library' is displayed, it may be required to first install the package using the install.packages() command. For more information, please type the command, 'help(install.packages)' within R. It is recommended that the syntax from this section not be directly copy and pasted into R, as this code is no longer in a plain text format. On occasion, error messages may occur with code copied and pasted directly from a word processing document directly in R. It is advisable to type the syntax above in lieu of copying and pasting.

```r
pop_long$year <- paste0('20', right(pop_long$year_hold, num_char = 2))
str(pop_long)
pop_long <- pop_long[ , -3]
str(pop_long)

## merging
dta <- merge(x = scibrs, y = pop_long, by = c('fips', 'year'), all.x = TRUE)

## setting up dummy variables
dta$pre_recession_dummy <- ifelse(test = dta$recession == 'pre_recession', yes =
1, no = 0)
dta$recession_dummy <- ifelse(test = dta$recession == 'recession', yes = 1, no =
0)
dta$post_recession_dummy <- ifelse(test = dta$recession == 'post_recession', yes
= 1, no = 0)

## fixing the population with commas
dta$population2 <- gsub(',', '', dta$population.y)
dta$population2 <- as.numeric(dta$population2)
dta$population.y <- NULL
dta$population.x <- NULL
dta$population <- dta$population2
dta$population2 <- NULL

## converting year to factor
dta2 <- dta[dta$year >= 2005 & dta$year <= 2012 , ]

## there are observations that have 'N' and also '' in them - going to remove
those
dta2[dta2 == 'N'] <- NA
dta2[dta2 == ''] <- NA

## subsetting to just the variables we need with acs
names(dta2)
dta3 <- dta2[ , c(1, 2, 3, 4, 5, 12, 17, 18, 25, 28, 32, 33, 34, 35) ]
dta3 <- dta3[complete.cases(dta3) , ]
names(dta3)[4] <- 'county'

## dropping Lancaster
dta4 <- dta3[(dta3$county != 'Lancaster') , ]

table(dta4$county, dta4$year)
length(unique(dta4$county))

## summary statistics
summary(dta4)

## creating actual variable for population 18-24 < hs diploma
dta4$population_18_24_less_hs_diploma_est <- dta4$population_18_24 *
(dta4$population_18_24_less_hs_diploma / 100)

fe_model1 <- lm(formula = log(agg_assault) ~ log(unemployment) + log(population)
+ recession_dummy + post_recession_dummy +
                                        factor(county.x),
              data = dta)
summary(fe_model1)

## controlling for county and only presents years 2005-2012
fe_model2 <- lm(formula = log(agg_assault) ~ log(unemployment) + log(population)
```

```r
+ recession_dummy + post_recession_dummy +
            factor(county.x),
            data = dta2)
summary(fe_model2)

## subset to counties that have acs variables and from years 2005-2012
fe_model3 <- lm(formula = log(agg_assault) ~ log(unemployment) + log(population)
+ recession_dummy + post_recession_dummy +
            factor(county),
            data = dta4)
summary(fe_model3)

# # ## years 2005-2012 with acs
fe_model4 <- lm(formula = log(agg_assault) ~ log(unemployment) + log(population)
+ recession_dummy +
                                    post_recession_dummy +
log(total_households) +

log(population_18_24_less_hs_diploma_est) + factor(county),
            data = dta4)
summary(fe_model4)




## grouping data to generate plots
dta_assault <- data.frame(dta %>% group_by(year) %>% summarise(n =
length(county.x),
                                                    mean_log_assault
= mean(log(agg_assault)),
                                                    sd_log_assault =
sd(log(agg_assault))))

i <- ggplot(data = dta_assault, aes(x = year, y = mean_log, group = 1))
i <- i + geom_ribbon(aes(ymin = lower, ymax = upper), fill = '#f0f0f0')
i <- i + geom_line(color = 'blue', size = 1) + geom_point(color = 'blue', size =
3)
i <- i + theme_minimal()
i <- i + labs(x = '',
            y = 'Log Aggravated Assault')
i <- i + geom_vline(xintercept = 2008, color = '#636363', linetype = 'dotted')
i <- i + geom_vline(xintercept = 2009, color = '#636363', linetype = 'dotted')
i <- i + annotate(geom = 'text', label = 'Standard Deviation', x = 2013, y =
4.25)
i <- i + annotate(geom = 'text', label = 'Recession', x = 2010.25, y = 3.65)
i <- i + theme(axis.text = element_text(size = 11), axis.title =
element_text(size = 13))
i

## unemployment
dta_unemp <- data.frame(dta %>% group_by(year) %>% summarise(n =
length(county.x),
                                                    mean_log_unemp =
mean(log(unemployment)),
                                                    sd_log_unemp =
sd(log(unemployment))))

j <- ggplot(data = dta_unemp, aes(x = year, y = mean_log, group = 1))
#j <- j + geom_ribbon(aes(ymin = lower, ymax = upper), fill = '#f0f0f0')
```

```
j <- j + geom_line(color = 'blue', size = 1) + geom_point(color = 'blue', size =
3)
j <- j + theme_minimal()
j <- j + labs(x = '',
              y = 'Log Unemployed')
j <- j + geom_vline(xintercept = 2008, color = '#636363', linetype = 'dotted')
j <- j + geom_vline(xintercept = 2009, color = '#636363', linetype = 'dotted')
j <- j + annotate(geom = 'text', label = 'Standard Error', x = 2015, y = 7.8)
j <- j + annotate(geom = 'text', label = 'Recession', x = 2010.25, y = 7.3)
j <- j + theme(axis.text = element_text(size = 11), axis.title =
element_text(size = 13))
j

## going to group all the data together
dta_combined <- merge(x = dta_assault, y = dta_unemp, by = 'year')
dta_combined2 <- dta_combined[ , c(1, 3, 6)]
dta_combined_long <- dta_combined2 %>% gather(key = 'attribute', value =
'measurement', - year)

## one combined plot
k <- ggplot(data = dta_combined_long, aes(x = year,
                                          y = measurement,
                                          color = attribute,
                                          group = attribute)) + geom_line(size =
1.5)
k <- k + labs(x = 'Year', y = 'Natural Log')
k <- k + theme(axis.text = element_text(size = 11), axis.title =
element_text(size = 13))
k <- k + theme_minimal()
k <- k + geom_vline(xintercept = which(dta_combined_long$year == '2008'),
                    color = '#636363',
                    linetype = 'dotted')
k <- k + geom_vline(xintercept = which(dta_combined_long$year == '2009'),
                    color = '#636363',
                    linetype = 'dotted')
k <- k + annotate(geom = 'text', label = 'Recession', x = 11, y = 6.3)
k <- k + scale_color_discrete(name = '',
                              breaks = c('mean_log_assault',
                                         'mean_log_unemp'),
                              labels = c('Mean Aggravated Assault', 'Mean
Unemployment'))
k <- k + ylim(c(0,8.5))
k
####################

## log variables
dta$agg_assault_log <- log(dta$agg_assault)
dta$unemployment_log <- log(dta$unemployment)

##
## testing for individual and time effects
dp <- plm(log(agg_assault) ~ log(unemployment),
          data = d_panel,
          model = 'pooling')
di <- plm(log(agg_assault) ~ log(unemployment),
          data = d_panel,
          effect = 'individual',
          model = 'within')
dt <- plm(log(agg_assault) ~ log(unemployment),
```

```r
          data = d_panel,
          effect = 'time',
          model = 'within')
dd <- plm(log(agg_assault) ~ log(unemployment),
          data = d_panel,
          effect = 'twoways',
          model = 'within')
pFtest(di, dp)
pFtest(dt, dp)
pFtest(dd, dp)
pFtest(log(agg_assault) ~ log(unemployment),
        data = d_panel,
        effect = "twoways")

d_panel = pdata.frame(x = dta, index = c('year', 'county'))

plotmeans(log(agg_assault) ~ year, data = d_panel)
plotmeans(log(unemployment) ~ year, data = d_panel)

## hausman test
form <- agg_assault_log ~ unemployment_log + recession_dummy +
post_recession_dummy
phtest(form, data = d_panel, method = "aux", vcov = vcovHC)


## a random effects model
re_model1 <- plm(formula = log(agg_assault) ~ log(unemployment) +
recession_dummy + post_recession_dummy,
                data = dta,
                index = c('year', 'county'),
                model = 'random',
                effect = 'twoways')
summary(re_model1)

## removing comma from the field and converting to numeric
dta$all_scibrs <- as.numeric(gsub(',', '', dta$all_scibrs))

## format the axes
ditch_the_axes <- theme(
  axis.text = element_blank(),
  axis.line = element_blank(),
  axis.ticks = element_blank(),
  panel.border = element_blank(),
  panel.grid = element_blank(),
  axis.title = element_blank() )

## get proper capitalization for the county names in order to use them with
labels
library(tools)
sc$county <- toTitleCase(sc$subregion)
sc$county[sc$subregion == 'mccormick'] <- 'McCormick' ## one fix needed that
wouldn't else be taken care of

## get the centroid of the county
county_df <- map_data('county')
sc <- subset(county_df, region == "south carolina")
sc$county <- sc$subregion
cnames <- aggregate(cbind(long, lat) ~ subregion, data = sc, FUN = mean)
```

```r
county_poly <- map("county", "south carolina", plot = FALSE, fill = TRUE)
county_centroids <- maps:::apply.polygon(county_poly, maps:::centroid.polygon)

county_centroids <- county_centroids[!is.na(names(county_centroids))]
centroid_array <- Reduce(rbind, county_centroids)
dimnames(centroid_array) <- list(gsub("[^,]*,", "", names(county_centroids)),
                                 c("long", "lat"))
label_df <- as.data.frame(centroid_array)
label_df$county <- unique(toTitleCase(sc$subregion))
label_df$county[33] <- 'McCormick'

## a few nudges of the data
label_df$lat[label_df$county == 'Greenville'] <- label_df$lat[label_df$county ==
'Greenville'] - 0.10
label_df$lat[label_df$county == 'Chesterfield'] <- label_df$lat[label_df$county
== 'Chesterfield'] + 0.10
label_df$lat[label_df$county == 'Clarendon'] <- label_df$lat[label_df$county ==
'Clarendon'] - 0.10
label_df$lat[label_df$county == 'Dorchester'] <- label_df$lat[label_df$county ==
'Dorchester'] + 0.10
label_df$lat[label_df$county == 'Beaufort'] <- label_df$lat[label_df$county ==
'Beaufort'] - 0.10
label_df$lat[label_df$county == 'Charleston'] <- label_df$lat[label_df$county ==
'Charleston'] - 0.10
label_df$lat[label_df$county == 'Berkeley'] <- label_df$lat[label_df$county ==
'Berkeley'] + 0.10


## 915 x 679 for saving the image
library(maps)
sc <- map_data(map = 'county', region = 'south carolina')

## getting data value for whether in all 4 models, or just models 1-2
sc$all_models <- 1
sc$all_models[sc$subregion %in% tolower(dta4$county)] <- 0

m <- ggplot()
m <- m + geom_polygon(data = sc, aes(x = long, y = lat, group = group, fill =
factor(all_models)),
                      color = 'gray')
m <- m + coord_fixed(ratio = 1.3)
m <- m + theme_bw() + ditch_the_axes
m <- m + geom_text(data = label_df, aes(x = long, y = lat,
                                        label = county,
                                        group = county), size = 4, color =
'black')
m <- m + scale_fill_manual(values = c('#af8dc3', '#e7d4e8'),
                           labels = c('Models 1 - 4', 'Models 1 & 2'))
m <- m + theme(legend.position = 'bottom',
               legend.direction = 'vertical',
               legend.title = element_blank(),
               legend.key = element_rect(size = 6, fill = 'white', color = NA),
               legend.key.size = unit(0.75, "cm"))
m
```