The Effect of the 2008 Great Recession on Child Poverty in California:

A Fixed Effects Model

Economics Honors Thesis Spring 2015

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Abstract

This paper investigates how the 2008 financial crisis affected child poverty in California. Using panel data from 2003 to 2012, this paper evaluates the effect of unemployment and foreclosure rates, as well as exogenous household characteristics, on the likelihood of a child being in poverty in California. Data from both the individual household level and the Metropolitan Statistical Area (MSA) level are used. The main finding is that the recession has had a statistically significant effect on the likelihood of a child being in poverty in terms of unemployment and foreclosure rates, especially when fixed effects are applied. At the same time, household characteristics such as education, race and marital status are also statistically significant in their effects on a child's poverty status. However, changes in exogenous household characteristics can have a larger effect on child's poverty status as compared to the cyclicality of the economy.

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1. Introduction:

The impacts of the 2008 Global Recession remain evident even five years on, and children throughout the United States continue to be negatively impacted. Children have the highest poverty rates in the U.S. (Bitler, Hoynes and Kuka, 2014) and according to the Current Population Reports from the Census, 24.3% of children in California are in poverty as of 2011. This statistic would include another 1.3 million if it were not for safety net resources.

Poverty in the United States is measured with an "absolute" as opposed to a "relative" measurement that is normally championed by other countries in the OECD. U.S. official poverty is determined using total pre-tax family cash income relative to poverty thresholds that vary by family size, the number of children and elderly persons. In 2012, the poverty threshold for a family of four (two parents and two children) was $23.283 (Census Bureau, 2012). Child poverty rate is expressed as the number of children who are in poverty as a percentage of the total number of children.

This research aims to evaluate the impact of the recession on child poverty in California through unemployment rates and foreclosure rates, taking into account existing exogenous demographic factors. This paper analyzes the effects on the likelihood of a child being in poverty given a mix of endogenous variables from the financial crisis, as well as exogenous demographic variables of an individual child's household. The household-level factors in this research are: the head of household's age, marriage status, race and level of educational attainment. The macro factors are the unemployment and foreclosure rates, the latter of which is also used as a proxy to estimate the effect of the housing crisis. Foreclosure and unemployment rates are calculated on a Metropolitan Statistical Area (MSA) level, a geographical region consisting of one or more counties that has a relatively high population density at its core and close economic ties throughout the area. Since this paper makes use of different sources that make use of different MSA groupings, I have regrouped the MSAs to create a new combined list of 14 MSAs. This paper focuses on child poverty status on an individual level, as opposed to the often-used child poverty rates.

However, the conclusion drawn from the poverty measure on a micro scale can also be applied to child poverty on a macro measure, that is, child poverty rates at MSA level, since that is the mean of the individual poverty status across the population. The regressions are weighted by MSA, hence the OLS coefficient will be unbiased when applied to the mean.

The regressions were run on cross-sectional data in California across ten years: the first subset being five years before the crisis (2003-2007), while the second subset would be the five years inclusive of and after the crisis (2008-2012). The data was obtained from the Integrated Public Use Microdata Series – Current Population Survey (IPUMS-CPS), RAND Organization California, as well as the Bureau of Labor Statistics – Local Area Unemployment (BLS-LAU).

The data on a child's poverty status was taken from IPUMS, which is a database from the Census. This is the poverty status of a given child at an individual level. I also calculated child poverty rates from IPUMS, and verified them with the MSA-level weighted data calculated from county-level data taken from the Small Area Income and Poverty Estimates (SAIPE), which is also from the Census. I took unemployment rates directly from the BLS and weighted them by MSAs. Foreclosure rates were calculated using IPUMs and RAND data and were verified with the information on the RealtyTrac and California Office of the Attorney General sites.

This paper reveals several interesting findings. First, as expected, the effects of unemployment and foreclosure rates have been statistically significant in influencing a child's poverty status. Unemployment rates were used to measure the effect of the 2008 recession on child poverty status, while the foreclosure rates were used as proxies for the housing crisis. When unemployment rates rise, the average household income is likely to fall and the rate of child poverty will rise. Foreclosures can also have a significant effect on child poverty, especially in California, since the household may lose a significant portion of their assets, the children may be displaced and the economy could be affected if construction had been a significant economic sector.

Secondly, the exogenous demographic factors are also statistically significant in influencing a child's poverty status on an individual level. Relative to a child whose head of household is white, a child whose head of household is black is more likely to be in poverty, but less so if that person is Asian. I also found that the higher the level of education of the head of household, the older he/she is, and if he/she is married, then the child will be less likely to be in poverty.

When the recession variables were regressed together with the household characteristic variables, the coefficients on both unemployment and foreclosure rates were statistically significant if year-fixed effects were added. When adding MSA-fixed effects, unemployment rates remain statistically significant but foreclosure rates are not. This suggests that the effect of unemployment rates on child poverty are more greatly influenced by time when compared to foreclosure rates. When testing both year and MSA-fixed effects jointly, the F-statistic was statistically significant, meaning that they both have a joint effect on child poverty status.

2. Literature Review

While existing literature acknowledges the severity of the negative impact of the 2008 financial crisis in the US, there is only a modest amount of literature that directly addresses how the crisis affects child poverty relative to the existing demographic characteristics of a household. Instead, researchers have primarily focused on child poverty status in the United States as a whole, overlooking many micro factors, such as the characteristics of the household, as well as geographical inequalities.

A significant quantity of research discusses the severity of child poverty in California, but only a modest number directly addresses the 2008 crisis as a direct cause. Using Census Population data, Fuentes, O'Leary and Barba (2013) reports that currently, 23% of all children in California live at or below the poverty line, and gathers that child poverty increased nearly by nearly 21% from 2006 – 2011. There is also great inequality between different races, counties and household types (e.g. single motherhood versus dual-income families). Similarly, Isaacs (2011) notes that children in the U.S. with unemployed parents suffer more severely than others. Bardhan and Walker (2010) and Bohn (2011) find that single-female households suffer the most, with poverty rates at 35.4% compared to 10.6% for dual income families. While these papers provide a strong foundation to the context of the status of child poverty in the Golden State, they do not address the Great Recession as a cause, which is what this paper seeks to achieve.

Other research papers evaluate the explanatory factors of child poverty in economic crises, but either in a global or national context. Bitler, Hoynes and Kuka (2014) conduct analyses of the impact of the recession on child poverty in the United states and find that child poverty rises in recessions and falls in expansions, as most would expect. They construct two of their own measures of child poverty, the after-tax and transfer income (ATTI), which adds to cash income the cash value of non-cash programs like food stamps, less taxes and private income (PI) poverty which excludes all government tax and transfer benefits. Both measures are constructed at household level. By running a regression on state panel model and data from 1980 to 2012 they estimate the relationship between the business cycle and child poverty. They find that the cyclicality of ATTI child poverty is significantly weakened relative to the cyclicality of PI poverty, which demonstrates how the social safety net insures vulnerable groups, and this has many public policy implications.

In exploring the effect of different household characteristics on child poverty, Litcher and Eggebeen (1994) highlight the central role of parental employment in ameliorating poverty among children, with poverty rates of children in working female-headed families being three times higher than a female head that is unemployed. Race is also a crucial factor. They have also found, in another 1991 paper, that child poverty and racial inequality remain constant even in the context of changing family structures in America. Furthermore, when comparing black and white families of equal income or poverty status, white families tend to have higher assets (Oliver and Shapiro 2006) and will generally live in areas that are usually middle-class.

There has also been literature that attempts to explain the inequities in child poverty through the housing crisis. While children are often overlooked in housing industry statistics, a 2012 report by Isaacs found that 1 in 10 children in the United States was affected by the foreclosure crisis in 2007, and these children had faced greater hardships and growing child poverty. Isaacs also estimates that between 12 to 19 percent of foreclosures in California, between 2004 and 2008, had displaced children, and can directly affect child poverty. Furthermore, Freelon, Betrand and Rogers (2012) have cited particular hard-hit industrial sectors, including construction and housing, which were key areas of California's economic growth and are now particularly vulnerable to the economic meltdown after the mortgage crisis, subsequently adversely affecting child poverty.

When comparing the effects of exogenous, micro-level factors and macro-level economic conditions, there has been literature citing that the impact on child poverty from household characteristics can be more significant. In a study about the effect of low income on child health, Burgess, Propper and Rigg (2004) found that the direct impact of income is small. Rather, the behavior of the household and decision-making, particularly the mother's, is more significant. Blau (1999) found that small impacts of short-term changes in income, as opposed to broader changes from policy and economic conditions have some measurable effect on child development, but household characteristics remain the most significant. Dahl and Lochner (2012) also found that, when studying the relationship between household income and children's test scores, while there can be short term improvements in a child's test scores with an increase in household income, there were negligible long-term effects.

Most of the literature surveyed broadly fall into two categories: either they provide a quantitative background to the child poverty in California, but do not offer a thorough evaluation of the explanatory variables, or they explain causal variables but in a generic national context not in relation to the 2008 Great Recession. This paper seeks to fill in that very gap by evaluating the impact of the financial crisis on child poverty based on a comprehensive set of indicators, from household-level demographic factors to MSA-level unemployment and foreclosure rates.

This paper will thus build on previous literature to create an analysis of child poverty trends before and after the Great Recession that focuses on California. Recognizing the causes, consequences, and welfare programs for child poverty, this paper will not attempt to "solve" the problem, but may provide greater insights into effective policy planning for public agencies in California for those who want to find a possible panacea to the growing problem of child poverty.

3. Data and Sample Description

Integrated Public Use Microdata Series – Current Population Survey (IPUMS-CPS)

I have obtained statistics for child poverty status as well as the exogenous characteristics of the heads of household (race, marriage status, education, age) from the Integrated Public Use Microdata Series – Current Population Survey (IPUMS-CPS), a data source of census microdata for economic and social research. This is an integrated set of annual data from 50 years (1962-2011) of the March Current Population Survey (CPS). The CPS is a monthly U.S. household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics. In this IPUMS data set, the unit of observation is the member of a household per year, over ten years.

However, the one standard sampling caveat in the use of IPUMS-CPS is that the IPUMS-CPS samples are weighted since it involves a relatively smaller sample size as compared to sources of aggregate data. Thus, sample weights need to be applied in order to obtain representative statistics from the samples. In the case of this paper, I am conducting household-level analyses of March data, and I will weight the households using the household-weight supplement variable that automatically adjusts the sample.

Using the IPUMS data, I have also calculated child poverty rates per MSA, which are weighted averages of the child poverty status variable on an MSA level.

RAND Organization

I obtained foreclosure data from RAND organization, which provides publicly available economic data. The foreclosure numbers are sourced from DataQuick News, which ultimately obtains its data from the Census. It has the total number of foreclosures by county, year and Metropolitan Statistical Areas (MSA).

Bureau of Labor Statistics – Local Area Unemployment (BLS LAU)

I obtained the official unemployment rates by county from the BLS, which is taken from the Census. However, since several counties are in non-metropolitan areas, and are hence not part of any MSAs, I dropped them from the regression. For the remaining unemployment rates in the counties, I merged them to fit the combined MSAs used in this paper. By weighting my regressions by the population size of an MSA, I am able to generate coefficients for unemployment rates by MSA, which would theoretically be given by the formula:

$$UR_{MSA} = \frac{\sum_{countiesinMSA} UR_{county} * LF_{county}}{\sum_{countiesinMSA} LF_{county}}$$

Description of Sample Data:

From the IPUMS Dataset, there are 185, 255 observations, one per person per year, over a period of ten years from 2003 – 2012. Among that number, 55,647 are children who are ages 0 to 17, since that is the standard definition of a child in all statistics. I dropped those who are not in any metropolitan areas, and are therefore not part of any MSAs, since they will not be covered in my regression. This is because foreclosure rates from RAND are available only at the MSA level, and the sample size will also be larger for each MSA as opposed to counties.

I obtained the total number of foreclosures in a year from RAND from all available counties that are metropolitan. I construct foreclosure rates in an MSA to be the count of the total number of foreclosures divided by the weighted number of households in the MSA, which in turn is taken from IPUMS. Since the number of households change every year, calculating foreclosure rates with a different denominator every year would not be able to give us an accurate understanding of the relationship between foreclosure rates and child poverty. Hence I used 2003 as the base year to calculate the foreclosure rates as follows:

$$FCR_{MSA} = \frac{\sum_{countiesinMSA} FC}{\sum_{MSA} Households_{2003}}$$

Similarly, I used the given unemployment rates taken from the BLS LAU and merged them with the other two data sets. Another key change I made to the data sets is the recombination of different counties to form new combined MSAs. Please see table 1 in the Description of Variables section for more details.

Description of Dependent Variable:

In this paper, I have only one dependent variable, which is child poverty status.

- CHILDPOV – Child Poverty Status Dummy (1,0). Using the official IPUMS poverty variable, which used by the CPS is the same as that of the U.S. Census Bureau and is based on the 1961 economy food plan. For the relevant years of this project (2003 – 2012), the data on IPUMS-CPS covers all individuals of all ages. I have defined children as those who are under 18 years old, which is generally the convention when defining children.

Description of Independent variables:

- HH EDUC – Educational Attainment Dummy (0,1) of the Head of Household. There are four dummies, each for different levels of educational attainment
    - HHEDUC1 – Less than 12 years of schooling
    - HHEDUC2 – 12 years of schooling/High School Diploma
    - HHEDUC3 – Some college
    - HHEDUC4 – College or more (Tertiary education)
- HH RACE – Race Dummy (0,1) of the head of household. I grouped the races into 4 different categories for ease of understanding the data.

    - HHRACE1 – Whites
    - HHRACE2 – Blacks
    - HHRACE3 – Asian/Pacific Islander
    - HHRACE 4 – Other
- HMARRIED: Marriage dummy. I created a binary variable for those whose head of household are married
- HAGE: Age of the head of household.

MSA: Compared to counties, MSAs have a wider regional coverage and can allow for more accurate analysis. Notably, the RAND data set had different MSAs from the IPUMs data set, and I regrouped the counties based on geographical proximity in order to create the new data set, giving 14 new MSAs. I have also dropped those that are in IPUM's "Not In MSA" group. In my regression, the numbers of the MSAs correspond in the order in which they are presented in Table 2.

IPUMS MSAs	RAND MSAs	Combined MSAs
Bakersfield	Bakersfield	Bakersfield
Fresno-Madera	Fresno	Fresno-Madera-Merced
Merced		
Los Angeles-Long Beach	Los Angeles-Long Beach	Los Angeles-Long Beach
	Orange County	
Modesto	Modesto	Modesto
San Francisco-Oakland-Vallejo	Oakland	San Francisco-Oakland-Vallejo
	San Francisco	
	Vallejo-Fairfield-Napa	
Riverside-San Bernardino	Riverside-San Bernardino	Riverside-San Bernardino
San Luis Obispo-Atascadero-Paso	Salinas	Salinas-Monterey
Salinas-Monterey		
San Diego-Carlsband-San Marcos	San Diego	San Diego-Carlsband-San Marcos-El Centro
Santa Cruz - Watsonville	San Jose	San Jose
San Jose		
Santa Barbara-Santa Maria - Lomp	Santa Barbara	Santa Barbara-Santa Maria-Lompoc
Santa Rosa-Petaluma	Santa Rosa	Santa Rosa-Petaluma
Stockton	Stockton-Lodi	Stockton
Ventura-Oxnard-Thousand Oaks	Ventura	Ventura-Oxnard-Thousand Oaks
Visalia-Tulare-Porterville	Sutter-Yuba	Sacramento-Yolo-Yuba City
Chico	Yolo-Sacramento region	
Sacramento-Yolo-Yuba City	Sacramento	

Table 1 Combining different MSAs from IPUMS and RAND

1	Bakersfield
2	Fresno-Madera-Merced
3	LosAngeles-LongBeach
4	Modesto
5	Sacramento-Yolo-Yuba City
6	Salinas-Monterey-SanLuisObispo
7	San Diego-Carlsband-San Marcos-ElCentro
8	San Francisco-Oakland-Vallejo
9	San Jose-Santa Cruz
10	Santa Barbara-Santa Maria-Lompoc
11	Santa Rosa-Petaluma
12	Stockton
13	Ventura-Oxnard-ThousandOaks
14	Riverside-San Bernardino

Table 2 Combined MSAs and corresponding numbers

- Foreclosure Rates: Calculated as the total number of foreclosures divided by the total weighted number of households in each MSA.
- Unemployment Rate: Calculated as the total number of unemployed individuals divided by the labor force.

4. Model Description

There are a total of 11 regressions performed in this paper. The first four will focus on the effect of endogenous recession variables on child poverty, while the next will estimate the effects of exogenous household characteristics, and finally all the variables will be regressed together. All of the models look only at the child population, and hence will have only 55,647 observations.

Models (1) to (4): Regression of child poverty status on recession variables

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 UR_{m,t} + \varepsilon_{i,t} \text{ -----}(1)$$

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 FCR_{m,t} + \varepsilon_{i,t} \text{ -----}(2)$$

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 UR_{m,t} + \beta_2 FCR_{m,t} + \varepsilon_{i,t} \text{ -----}(3)$$

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 UR_{m,t} + \beta_2 FCR_{m,t} + \beta_{11} MSA_2 + \ldots + \beta_{24} MSA_{14} + \beta_{25} YEAR_{2004} + \ldots + \beta_{34} YEAR_{2012} + \varepsilon_{i,t} \text{ -----}(4)$$

Since this research aims to evaluate the effect of the financial crisis on child poverty, I have regressed the endogenous recession variables, one at a time, and then together and with fixed effects. Each of the first four models is intended to give us an idea of the effect that each recession variable, i.e. unemployment and foreclosure rates, has on child poverty, and how the variations in geography and time affect the results.

Models (5) to (11): Regression of child poverty status on household and recession variables

Model 5: Regression on head of household's exogenous characteristics

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 HHRACE2_{i,t} + \beta_2 HHRACE3_{i,t} + \beta_3 HHRACE4_{i,t} + \beta_4 HHMARRIED_{i,t} + \beta_5 HHEDUC1_{i,t} + \beta_6 HHEDUC2_{i,t} + \beta_7 HHEDUC3_{i,t} + \beta_8 HHAGE_{i,t} + \varepsilon_{i,t} \text{ -----(5)}$$

This model estimates the probability of a child being in poverty given his/her head of household's exogenous characteristics, which are race, highest level of education and age. I dropped the white dummy as well as the '12 years of school' education dummy variables to prevent multicollinearity.

Ex Ante, I would expect that if a head of household is black or other, the child would be more likely to be in poverty, while the reverse is true if the head of household is Asian. Since I dropped the 'college' dummy, this means that all the other variables should have positive coefficients, since fewer years of education for the head of household would mean that the child is more likely to be in poverty.

Model (6): Estimating the effects of unemployment rates on child poverty

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 HHRACE2_{i,t} + \beta_2 HHRACE3_{i,t} + \beta_3 HHRACE4_{i,t} + \beta_4 HHMARRIED_{i,t} + \beta_5 HHEDUC1_{i,t} + \beta_6 HHEDUC2_{i,t} + \beta_7 HHEDUC3_{i,t} + \beta_8 HHAGE_{i,t} + \beta_9 UR_{m,t} + \varepsilon_{i,t} \text{ -----(6)}$$

This model builds on model 1, and therefore also includes the original exogenous characteristics of the head of household. Using a panel data set of unemployment rates across different MSAs over the decade, I regressed child poverty rates in the MSAs over the years on the unemployment rates. To prevent multicollinearity, I dropped the White, high school degree, MSA1 (Bakersfield) and Year 2003 dummies. I also clustered the standard errors by MSA.

I would expect the unemployment rate to be positively correlated with the child poverty rate, and for that coefficient to be statistically significant. This allows us to estimate and compare between the effects of unemployment rates relative to existing household characteristics.

Model (7): Estimating the effects of foreclosure rates on child poverty (no unemployment)

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 HHRACE2_{i,t} + \beta_2 HHRACE3_{i,t} + \beta_3 HHRACE4_{i,t} + \beta_4 HHMARRIED_{i,t} + \beta_5 HHEDUC1_{i,t} + \beta_6 HHEDUC2_{i,t} + \beta_7 HHEDUC3_{i,t} + \beta_8 HHAGE_{i,t} + \beta_9 FCR_{m,t} + \varepsilon_{i,t} \text{-----}(7)$$

This is a modification of the previous model. I ran the regression on foreclosure rates, and dropped the same dummies to prevent multicollinearity. This model allows us to isolate the effect of foreclosure rates in different MSAs on child poverty rates relative to household factors.

Model (8): Regression on both household-level and MSA-level factors

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 RHHRACE2_{i,t} + \beta_2 HHRACE3_{i,t} + \beta_{3HH} RACE4_{i,t} + \beta_4 HHMARRIED_{i,t} + \beta_5 HHEDUC1_{i,t} + \beta_6 HHEDUC2_{i,t} + \beta_7 HHEDUC3_{i,t} + \beta_8 HHAGE_{i,t} + \beta_9 UR_{m,t} + \beta_{10} FCR_{m,t} + \varepsilon_{i,t} \text{-----}(8)$$

This model combines the previous two models, allowing us to see the combined effect of both unemployment and foreclosure rates, as well as household characteristics, on child poverty rates. From the literature, we might expect the effect of recession variables to be either less statistically significant, or to be of a smaller magnitude, hence having less of an effect on child poverty relative to household characteristics.

Model (9) to (11): Regression of all independent variables and fixed effects

$$CHILDPOV_{i,t} = \beta_0 + \beta_1 RHHRACE2_{i,t} + \beta_2 RACE3_{i,t} + \beta_3 RACE4_{i,t} + \beta_4 MAR_{i,t} + \beta_5 HEADEDUC1_{i,t} + \beta_6 HEADEDUC2_{i,t} + \beta_7 HEADEDUC3_{i,t} + \beta_8 HEADAGE_{i,t} + \beta_9 UR_{m,t} + \beta_{10} FCR_{m,t} + \beta_{11} MSA_2$$

$$+ \ldots + \beta_{24}MSA_{14} + \beta_{25}YEAR_{2004} + \ldots + \beta_{34}YEAR_{2012} + \varepsilon_{i,t} \text{ -----}(11)$$

These models add year and MSA fixed effects one at a time, then both together, to model (8), allowing us to see how periodic and geographic variations can have effects on child poverty status in California.

5. Results:

Trends:

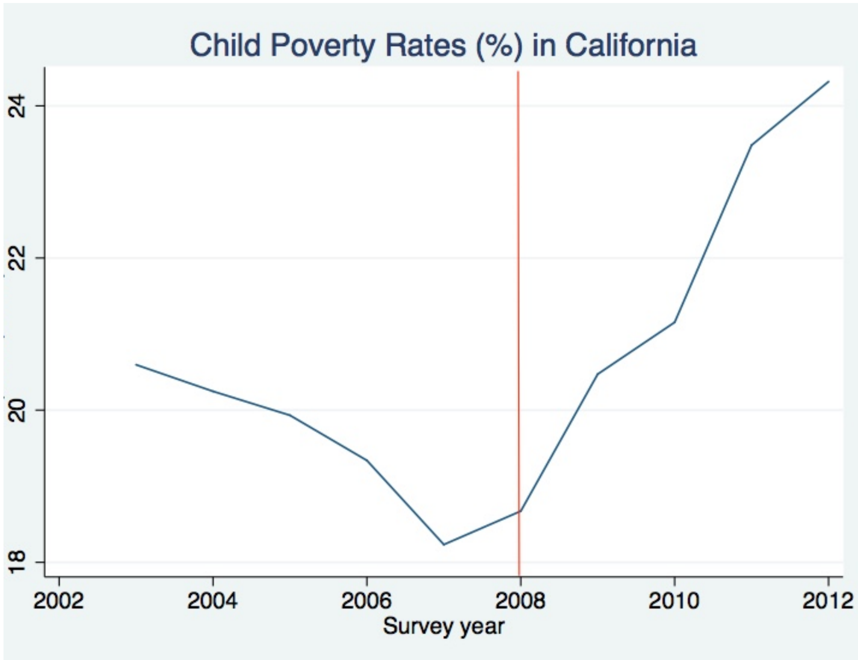

Figure 1 Child Poverty Rates in California. Source: Author's calculations from IPUMS-CPS

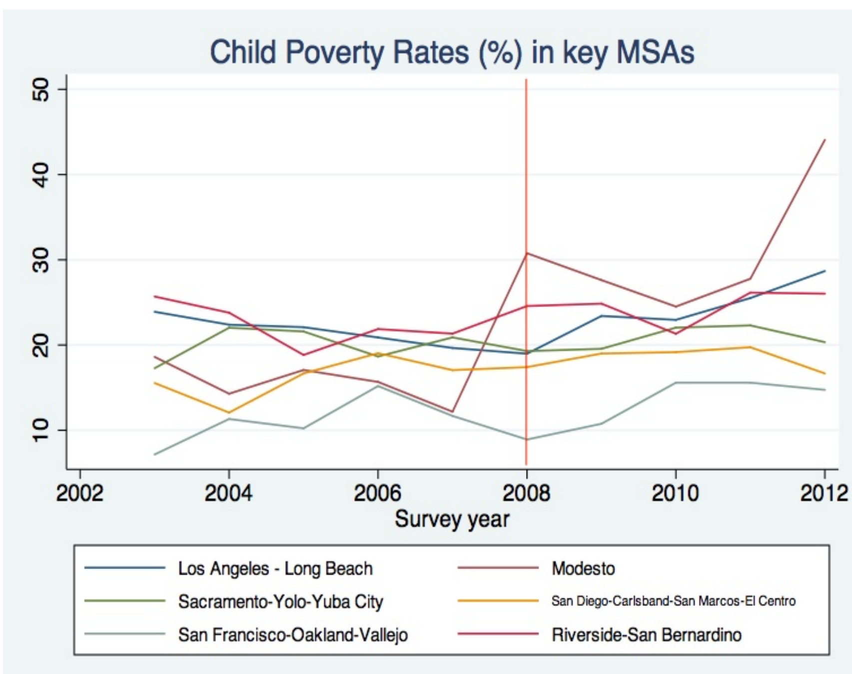

Figure 2 Child Poverty Rates in key MSAs. Source: Author's calculations from IPUMS-CPS

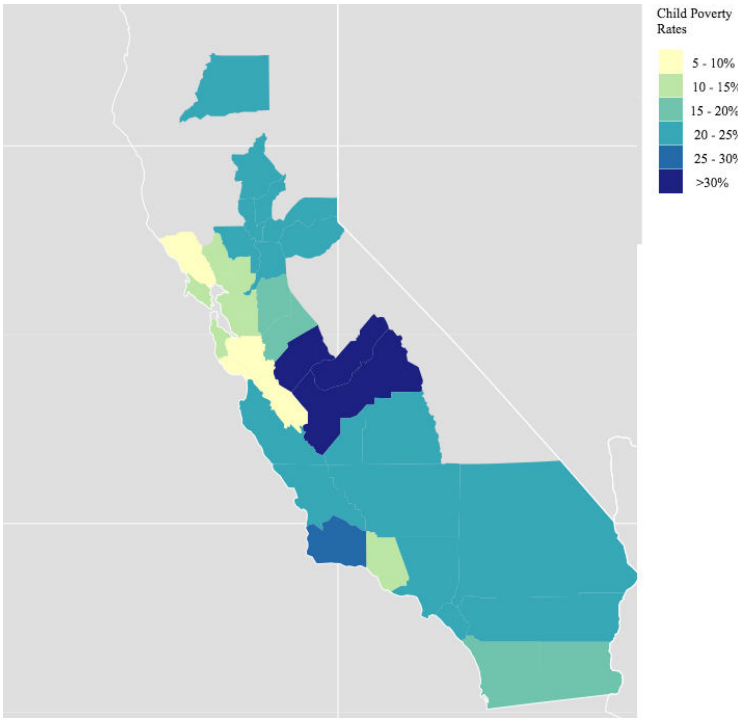

Figure 3 Child Poverty Rates 2003-2007 Source: Author's calculations from IPUMS-CPS

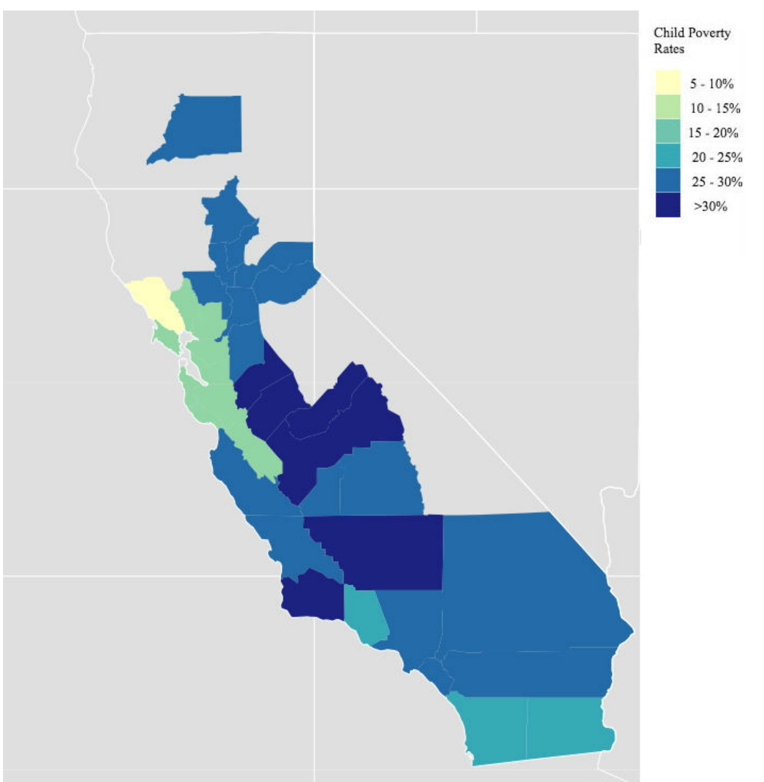

Figure 4 Child Poverty Rates 2008-2012 Source: Author's calculations from IPUMS-CPS

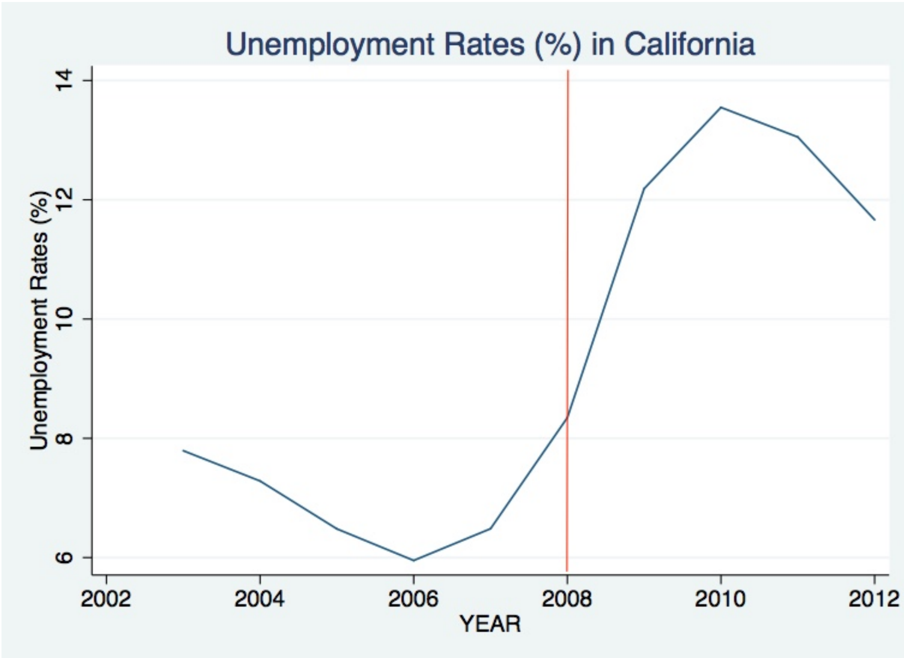

Figure 5 Unemployment Rates in California. Source: BLS LAU

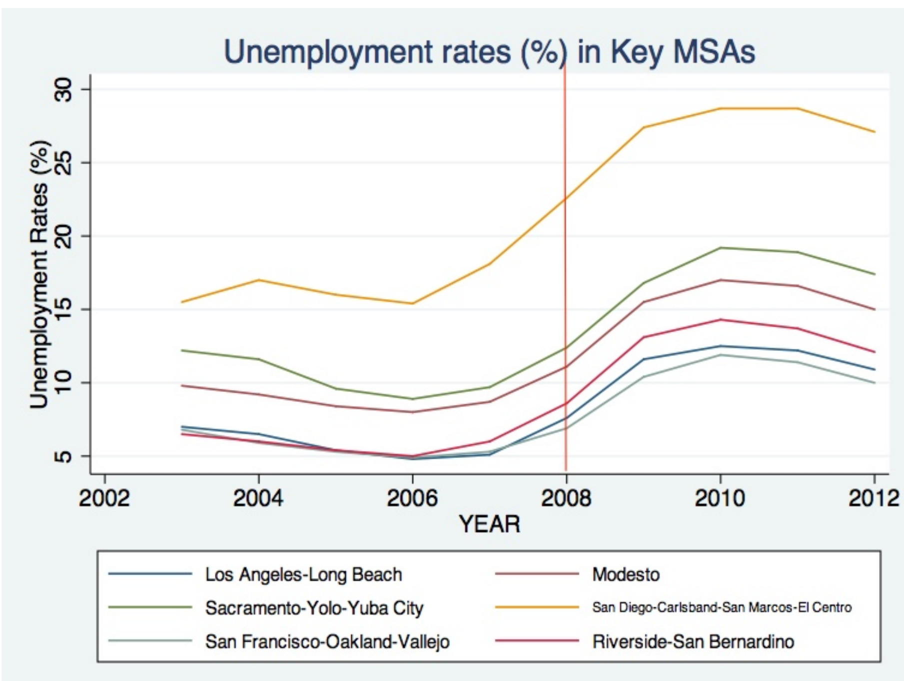

Figure 6 Unemployment Rates in key MSAs. Source: Author's calculations from BLS LAU

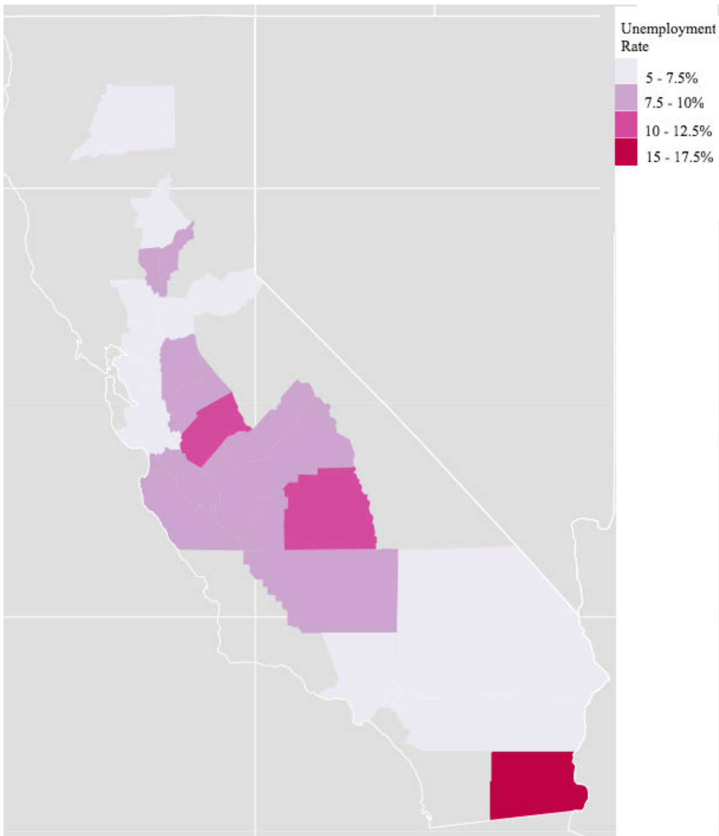

Figure 7 Unemployment Rates 2003-2007. Source: Author's calculations from BLS LAU

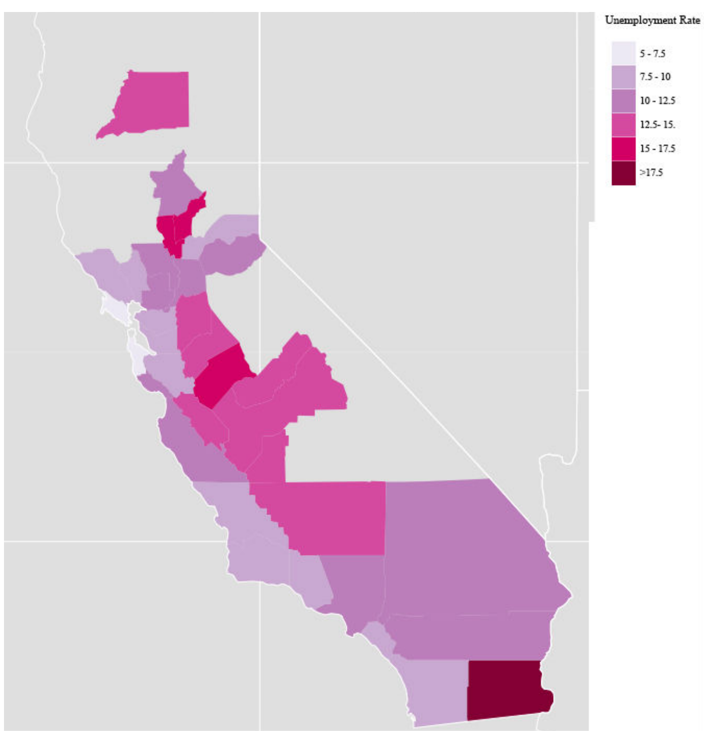

Figure 8 Unemployment Rates 2008-2012 Source: Author's calculations from BLS LAU

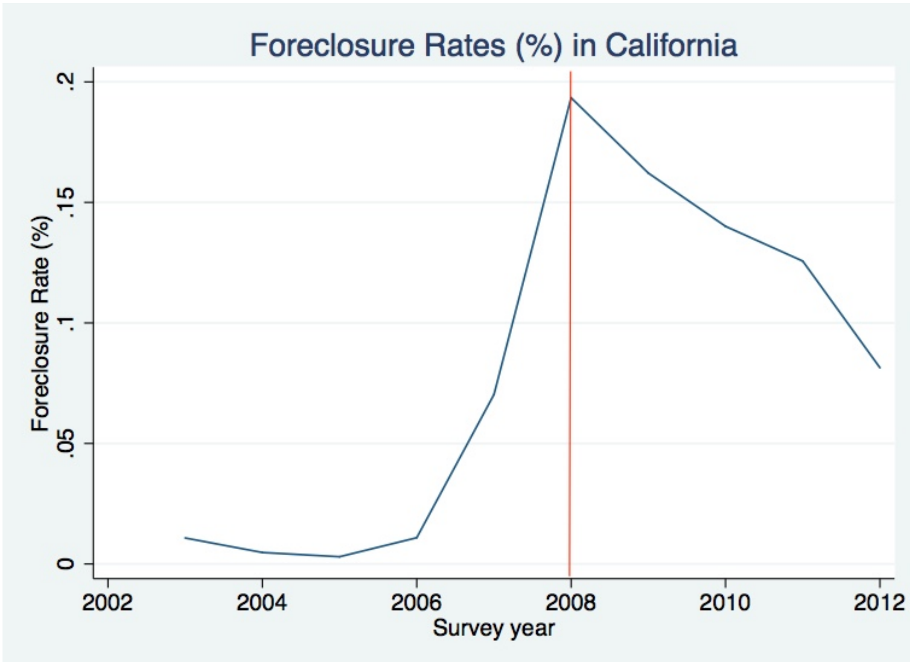

Figure 9 Foreclosure Rates in California. Source: Author's calculations from RAND and IPUMS

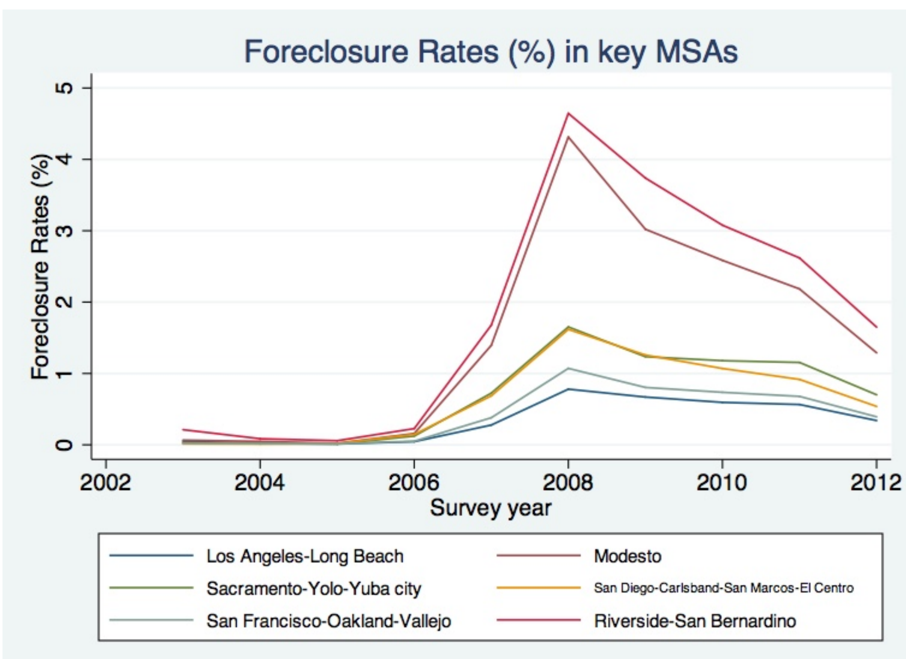

Figure 10 Foreclosure Rates in California. Source: Author's calculations from RAND and IPUMS

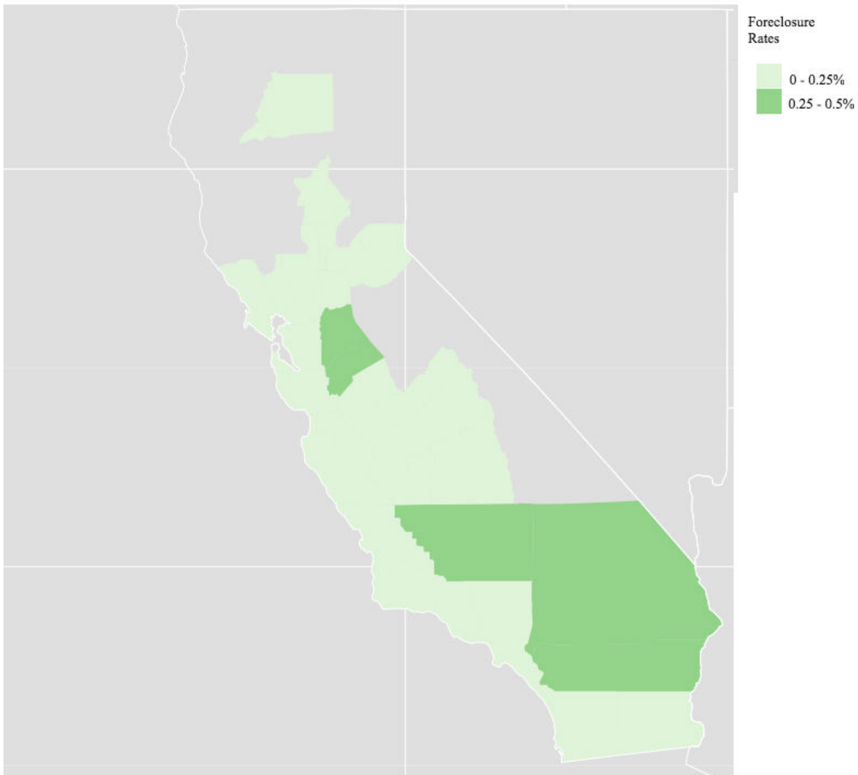

Figure 11 Foreclosure Rates 2003-2007. Source: Author's calculations from RAND and IPUMS

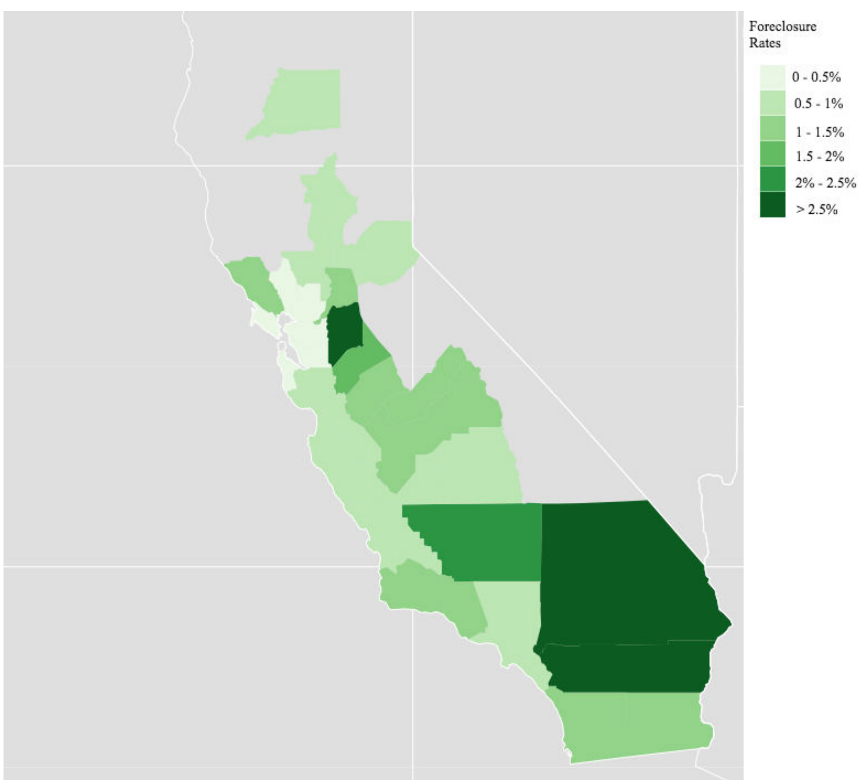

Figure 12 Foreclosure Rates 2008-2012. Source: Author's calculations from RAND and IPUMS

Child poverty rates in California have been on the rise since its low point in 2007, at a rate of over 18%. Since then, child poverty has increased to a height of over 24% in 2012, with the sharpest rate of increase between 2010 and 2011. However, when we look at the child poverty rates in different MSAs, the trend is less clear. In fact, many of the larger MSAs, such as Los Angeles-Long Beach or Riverside-San Bernardino have seen relatively stable trends, or a slight increase towards 2012. On the other hand, poorer MSAs in the Central Valley, such as Modesto, have seen sharp increases in child poverty, with a sharp rise leading up to the crisis in 2007-2008. The increases in child poverty rates are highly unequal within the state of California, suggesting that the average rate in California was pulled up because of poorer regions like Modesto. When mapping out the average poverty rates, we can see that poverty rates are indeed highly uneven. On the legends for the maps in Figures 3 and 4, we can see that overall, poverty rates have risen, especially in key areas.

Unlike the trends in child poverty rates, weighted unemployment rates in different MSAs share the same trend as that of California as a whole. Unemployment had dipped to a low of about 6% in 2006, but rose to a peak in 2010 to over 13%, before dropping slightly to under 12% by the end of 2012. There are similar but less pronounced trends in the different MSAs, but the trend is less erratic as compared to that of child poverty rates. We also see, from the choropleth maps, that there is a high level of unemployment in central California, but unemployment has risen across the board.

Foreclosure rates rose to a peak of about 0.19% in 2008, before settling to about 0.09% in 2012. Like unemployment rate trends, there are similar trends between foreclosure rates at a state level and at the MSA level. Southern California areas, including Riverside-San Bernardino and Los Angeles-Long Beach have the highest rates of foreclosure rates since the recession. Notably, these areas with highest levels of foreclosure rates have rates that are much higher than that of California as a whole (4.7% compared to 0.09%). We can also see the variation in the choropleth map.

Regression results:

	(1) Child Poverty Status	(2) Child Poverty Status	(3) Child Poverty Status	(4) Child Poverty Status
UR (%)	0.003** (0.001)		0.003 (0.002)	-0.008* (0.004)
FCR		0.015*** (0.004)	0.002 (0.05)	0.016*** (0.03)
Standard Errors	Clustered	Clustered	Clustered	Clustered
Year FEs	No	No	No	Yes
MSA FEs	No	No	No	Yes
Mean of Dependent Var	0.206	0.206	0.206	0.206
Constant	0.195*** (0.011)	0.197*** (0.008)	0.196*** (0.011)	0.320*** (0.048)
R^2	0.00	0.00	0.00	0.01
N	55,647	55,647	55,647	55,647

Table 3. Results of the four regressions of Child Poverty Status on unemployment and foreclosure rates with fixed effects. Standard errors in parentheses. Clusters at the MSA level and by year. Mean of Dependent Variable is weighted by MSA. *p <0.10, * * p <0.05, * * * p < 0.01

Models (1) and (2) follow in line with my original expectations. When regressing child poverty status against unemployment and foreclosure rates, we see that they are both statistically significant and have a positive correlation with child poverty. A rise in unemployment rate corresponds to a rise in 0.3 percentage points in the likelihood of a child being in poverty. Similarly, from (2), we see that an increase in foreclosure rate leads to an increase of 1.5 percentage points in the likelihood of a child being in poverty. Interestingly, when you combine the two variables together, they are both statistically insignificant unless fixed effects are added, in which case both are statistically significant. This could mean that the geographical and periodical variation affects how the MSA-level unemployment and foreclosure rates affect child poverty status in these regions.

	(5) Child Poverty Status	(6) Child Poverty Status	(7) Child Poverty Status	(8) Child Poverty Status	(9) Child Poverty Status	(10) Child Poverty Status	(11) Child Poverty Status
Black	0.027***	0.009	0.009	0.009	0.009	0.012	0.013
	(0.008)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Asian	-0.074***	-0.089***	-0.089***	-0.089***	-0.089***	-0.080***	-0.080***
	(0.005)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Other	-0.007	0.006	0.007	0.006	0.004*	0.011	0.009
	(0.010)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
<12 years	0.048***	0.048	0.048***	0.048***	0.048***	0.046***	0.046***
	(0.006)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)
Some Coll.	-0.009**	-0.013***	-0.013	-0.013	-0.012	-0.011	-0.010
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
More than Coll.	-0.022***	-0.020	-0.020	-0.020	-0.019	-0.017	-0.017
	(0.004)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	-0.000***	-0.001	-0.001**	-0.001**	-0.000*	-0.001***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.220***	-0.206***	-0.206***	-0.206***	-0.205***	-0.205***	-0.204***
	(0.004)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
UR (%)		0.003**		0.003	-0.004***	0.006***	-0.010**
		(0.001)		(0.001)	(0.001)	(0.002)	(0.004)
FCR (%)			0.006	-0.000	0.015***	-0.011	0.014***
			(0.003)	(0.005)	(0.004)	(0.008)	(0.004)
Standard Errors	Not Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Year FEs	No	No	No	No	Yes	No	Yes
MSA FEs	No	No	No	No	No	Yes	Yes
Mean of Dependent Variable	0.206	0.206	0.206	0.206	0.206	0.206	0.206
Constant	0.399***	0.383***	0.402***	0.383***	0.435***	0.367***	0.503***
	(0.007)	(0.018)	(0.017)	(0.018)	(0.019)	(0.031)	(0.050)
R^2	0.07	0.06	0.06	0.06	0.06	0.06	0.07
N	55,647	55,647	55,647	55,647	55,647	55,647	55,647

Table 4. Results of the seven regressions of child poverty status on household and recession variables. All household independent variables are characteristics of the head of household of the child. Total number of observations is the total number of children across the 14 MSAs and 10 years. Standard errors in parentheses. Clusters at the MSA level and by year. Dependent variable is weighted by MSA. *p <0.10, * * p <0.05, * * * p < 0.01

The results of Model (5) are also as expected. In comparison to children whose heads of households are whites (since the white dummy was dropped), those whose heads of households are black are 3 percentage points more likely to be in poverty, but 7 percentage points less likely to be in poverty. In all seven regressions, the ‘other’ race variable is statistically insignificant while the ‘Asian’ variable is always statistically significant.

In terms of the educational attainment of the head of household, we see that, as predicted, a child is less likely to be in poverty if the head of household has had more years of education. Compared to a head of household with a high school degree, someone with less than 12 years of education would have a child who is about 5 percentage points more likely to be poor, but someone with some college education would have a child who is about 1 percentage point less likely to be poor. Notably, however, only the ‘<12 years’ education variable is statistically significant across all seven regressions. This means that the effect of not completing a high school degree compared to having a high school degree is has a more significant effect relative to having pursued higher education compared to having a high school degree.

The older the head of household is in general, the less likely the child is to be in poverty. This is expected, since the older the head of household, the more likely the person is employed or has an income, and the less likely the household, including the child, will be poor.

In terms of marriage, if a head of household is married, the child will be about 20 percentage points less likely to be in poverty. This could be because the head of household married another income earner and could pool their financial resources. Another reason could be that a person who wants to marry is already financially stable.

When we factor in unemployment rates and foreclosure rates on a MSA level in models (6) through (7), we see that some of the demographic factors of the head of household remain statistically significant in influencing a child’s poverty status at an individual level, such as the Asian race, a ‘<12 years’ of education, age and marriage status. This makes sense, since we are estimating child poverty at an individual level, which is highly influenced by the head of household's existing characteristics, which can affect a child's resistance to poverty and the cyclicality of the economy.

When we regress the recession variables together with the exogenous household characteristics, we see that unemployment rates remain statistically significant except when year fixed effects are not added. Otherwise, it remains highly significant at the 1% level and the magnitude of the coefficient is not too different from models (1) – (4) when household variables were not regressed. The effect of unemployment rates on child poverty is hence also influenced by the year. This suggests that the crisis did indeed have a statistically significant impact on the likelihood of a child being in poverty, since the year fixed effects are also proxies for cyclicality.

Foreclosure rates are also statistically significant once year fixed effects are regressed, possibly because the foreclosure crisis led to a sharp increase in foreclosure rates relative to the pre-crisis period. Similar to the coefficient on unemployment rates, the coefficient of foreclosure rates does not alter very much when head of household characteristics are added. The fact that the addition of year fixed effects can affect the statistical significance of both recession variables suggest that there is a strong macro trend for California in terms of child poverty.

In order to see the significance of both the two fixed effects, I jointly tested them and found that the F-statistic was statistically significant. Using model (11) which regresses all the different macro and micro variables, I first jointly tested the year dummies to find that there was a statistically significant effect of time on child poverty status ($F(9, 139) = 13.97$, $P = 0.000$). Next, I jointly tested the MSA dummies to find a statistically significant effect of geographical variation on child poverty status ($F(13, 139) = 28.32$, $P = 0.000$). Finally, I jointly tested all time and geographical fixed effects, finding a statistically significant effect of both on child poverty status ($F(22, 139) = 27.12$, $P = 0.000$).

From the regressions, we find that both recession and exogenous variables have statistically significant influences on a child's poverty status. Notably, however, some head of household characteristics are always statistically significant, and the magnitude of their coefficients is also larger when compared to that of unemployment and foreclosure rates. For example, if the head of household is married, the effect is a 20 percentage point deduction in the likelihood of a child being in poverty, as opposed to a 0.3 percentage point difference from the impact of MSA level unemployment rate. This means that changing certain demographic characteristics of a head of household has a greater impact on a child's poverty status than macro, financial crisis factors.

6. Conclusion

The analysis of factors associated with childhood poverty in California and the recession are complex, involving social issues, educational and economic achievement. This paper aimed to show the effect of the 2008 Great Recession on child poverty in California, and measures the effect of the external crisis on children relative to the existing exogenous characteristics of the head of household. In particular, I found that on an individual level, while both economic and household characteristics are statistically significant in affecting a child's poverty status, the effect of a change in demographic factors can have a much greater impact on the poverty status.

This can have several policy implications. Firstly, it means that improving the demographic conditions of a household, such as a head of household's education, can have significant effects on a child's poverty rate. This means that investing in a child's education now can have significant impacts on the family in future when, in turn, the child becomes an adult. Secondly, it also means that inequality is also a significant factor in influencing California's overall child poverty rates, hence targeted policies in specific counties and MSAs would be most effective.

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