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The relationship between unemployment and child maltreatment: A county-level perspective in California

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ABSTRACT

The conventional logic supported by research and statistics suggests that there will be more child maltreatment as the economy becomes worse and less child maltreatment as the economy becomes better. However, in some local jurisdictions in California, statistics indicate the opposite. A closer examination of one county, San Mateo, suggests that this may be due to the fact that the County has a very high Self-Sufficiency Standard in which people get jobs with incomes that do not exceed the Standard, but in fact disqualifies them from the safety net of Federal benefits. Further, children born around the time of the last recession have a higher chance of adverse mental health issues and are now entering schools with issues that may reflect child abuse and neglect.

1. Introduction

On average nationally, there is a report of child maltreatment every 5 s, and child maltreatment is substantiated every 30 s (Children's Bureau, Administration on Children, Youth and Families, 2012). Over 400,000 children are in out-of-home placement in America because of child maltreatment (U.S. Department of Health and Human Services, 2012b). Researchers suggest that child maltreatment has long-term adverse health outcomes or proxy indicators of adverse health outcomes. These adverse health outcomes include poorer gastrointestinal health, poorer gynecologic or reproductive health, more pain, increased cardiopulmonary symptoms (Irish, Kobayashi, & Delahanty, 2010), higher risk for obesity (Irish et al., 2010; Knutson, Taber, Murray, Valles, & Koeppl, 2010), increased hospital visits (Lanier, Jonson-Reid, Stahlschmidt, Drake, & Constantino, 2010), riskier sexual behavior (Houck, Nugent, Lescano, Peters, & Brown, 2010), and increased mental health issues (Oswald, Heil, & Goldbeck, 2010). In fact, "post-traumatic stress disorder (PTSD) rates for [former foster youth] were up to twice as high as for U.S. war veterans" (p. 1, Pecora et al., 2005).

Child maltreatment has had a major impact on the economy conservatively costing the U.S. about $124 billion (Fang, Brown, Florence, & Mercy, 2012), of which only about one-quarter is due to direct child welfare expenditures (Wang & Holton, 2007). In an overview of the literature, researchers noted that although foster children represented less than 4% of all Medicaid enrollees, they account for up to 41% of all Medicaid-funded mental health expenditures for some state Medicaid programs (Rubin, Halfon, Raghavan, & Rosenbaum, 2005). This could be much worse as only about one-third of all foster children who need the services actually receive the services (Rubin et al., 2005).

What, then, is the effect of the economy on child maltreatment? Children are disproportionately represented among the poor, and in turn, are disproportionately affected in a poor economy (Oberg, 2011). Conventional logic, supported by some research, suggests that there is less child maltreatment when the economy becomes better and more child maltreatment when the economy becomes worse. For example, increased hospital administration rates for physical abuse and traumatic brain injury (TBI) were related to increased mortgage delinquency and increased foreclosure rates during the recent recession in 17 of 20 major metropolitan areas (Wood et al., 2012). Increased TBI was also found to be higher during the last recession versus prior to the recession in 74 counties in Ohio, Pennsylvania, and Washington (Berger et al., 2011). Research from the 1970s to the 1990s indicated that child abuse was more likely in the home of a two-parent family in which the father was unemployed (Paxson & Waldfogel, 1999). Another study looked at several economic factors, including the unemployment rate in seven states (Millet, Lanier, & Drake, 2011). They found that there was no relationship in six of seven states, with the exception in California where there was an increase in the unemployment rate correlated with an increase in child maltreatment referrals. Statistics at the national level (Children's Bureau, Administration on Children, Youth and Families, 2012) point to a decline in child abuse maltreatment in the past few years (Oberg, 2011) that is in line with an improving economy. Another recent study suggests that although aggregate

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Table 1
Descriptive statistics of the 58 California counties.

County	Child population	Median income	Self-sufficiency standard	Female	African-American	White	Latino	Asian/Pacific Islander	American Indian	Multi-race	Disproportionality measure for African-American children	Number of allegations per 1000 children	Number of substantiated allegations per 1000 children	Number of entries into foster care per 1000 children	Number of children in foster care per 1000 children	Unemployment rate
Alameda	404,516	$67,295	$61,658	48.6%	12.2%	22.9%	32.0%	25.6%	0.2%	7.0%	4.48	32.7	2.4	1.7	3.8	8.2%
Alpine	270	$46,706	$55,339	53.1%	0.0%	61.0%	11.0%	0.0%	26.4%	1.7%	0.00	139.1	0	0	0	11.6%
Amador	7221	$51,553	$53,687	48.2%	1.9%	68.1%	21.3%	1.2%	1.9%	5.6%	0.00	87	9.3	5	4.8	11.0%
Butte	60,013	$39,208	$47,116	49.0%	1.6%	60.9%	23.3%	6.8%	1.8%	5.7%	5.17	80.3	13	6.2	11.3	11.5%
Calaveras	10,032	$50,599	$48,606	47.8%	1.2%	73.6%	17.7%	1.4%	1.1%	5.0%	5.66	80.2	17.9	7.5	9.9	12.1%
Colusa	7254	$47,469	$46,451	46.9%	0.8%	24.4%	70.5%	1.0%	1.6%	1.6%	0.00	37.6	9.1	3.1	2.9	23.3%
Contra Costa	302,462	$74,241	$60,733	48.8%	9.4%	36.7%	33.7%	13.1%	0.2%	6.9%	4.48	40.5	5.2	2.3	3.7	8.2%
Del Norte	6969	$35,598	$45,399	48.3%	1.5%	53.0%	22.8%	6.0%	10.1%	6.5%	1.83	148	27.7	12.5	13.3	13.2%
El Dorado	46,918	$61,970	$56,021	48.6%	0.8%	69.2%	20.1%	4.2%	0.9%	4.9%	9.01	56.1	10.6	5.1	6.9	9.5%
Fresno	326,056	$42,572	$49,026	48.7%	5.0%	20.5%	61.7%	9.7%	0.6%	2.6%	2.92	69.3	8.2	3.7	6.2	14.9%
Glenn	8916	$40,221	$45,107	48.8%	0.7%	40.0%	52.3%	2.8%	1.8%	2.4%	10.61	81.9	17.1	6.3	8.9	14.2%
Humboldt	33,300	$39,526	$48,052	49.0%	1.2%	62.9%	17.0%	3.6%	7.7%	7.5%	4.89	79.7	7.7	6.3	9.7	9.8%
Imperial	60,280	$36,898	$46,296	48.5%	1.4%	8.0%	88.4%	0.6%	1.0%	0.7%	4.14	39.8	9.4	5	4.7	26.3%
Inyo	4404	$44,928	$46,477	48.0%	0.6%	43.8%	36.7%	1.1%	13.6%	4.2%	0.00	89.6	11.5	2.4	4.8	9.0%
Kern	295,763	$44,903	$44,898	48.7%	5.2%	27.2%	61.4%	3.0%	0.6%	2.6%	2.52	72.9	16.2	3.1	6.9	12.9%
Kings	48,004	$48,319	$45,242	47.8%	4.4%	26.1%	61.8%	2.9%	0.9%	3.9%	2.91	69	10.4	6.7	8.5	14.9%
Lake	15,585	$35,882	$47,238	48.0%	1.4%	58.3%	30.6%	0.9%	3.3%	5.4%	2.38	75.4	6	4	9.2	15.0%
Lassen	7278	$47,938	$46,465	44.7%	2.7%	70.4%	16.4%	1.5%	3.7%	5.4%	0.00	95.2	15.5	8.3	7.9	12.2%
Los Angeles	2,792,610	$52,239	$61,812	48.8%	7.7%	17.4%	62.0%	9.9%	0.2%	2.9%	3.93	59.4	12.2	4.3	7.3	10.2%
Madera	49,461	$44,795	$46,434	48.2%	1.9%	22.6%	71.1%	1.4%	1.0%	2.0%	2.83	70	11.7	5.2	4.8	13.2%
Marin	60,432	$78,470	$82,038	48.4%	2.2%	62.6%	23.5%	5.2%	0.2%	6.3%	19.19	37.2	4.3	1.1	1.5	5.6%
Mariposa	3649	$42,175	$47,330	49.5%	0.4%	74.0%	16.7%	0.9%	2.9%	5.0%	0.00	84.8	33.1	6.9	6.9	11.3%
Mendocino	22,417	$41,236	$50,924	48.2%	0.6%	48.8%	39.0%	1.7%	5.1%	4.7%	2.64	88.4	19.4	7.8	10.1	9.4%
Merced	96,016	$40,016	$43,979	48.4%	2.9%	23.4%	64.5%	6.7%	0.3%	2.3%	4.95	70.7	11	5.4	6.6	16.7%
Modoc	2360	$34,654	$44,986	49.1%	0.5%	67.1%	25.5%	0.4%	3.1%	3.5%	0.00	98.5	23.4	5.5	4.5	13.7%
Mono	3490	$48,758	$58,629	49.2%	0.2%	48.2%	45.9%	0.8%	1.7%	3.2%	0.00	50.8	5	0	0.7	8.8%

Monterey	133,362	$52,746	$54,926	48.3%	1.6%	17.7%	73.1%	4.2%	0.2%	3.3%	4.55	22.7	3.7	1.7	2.5	13.2%
Napa	37,021	$61,179	$62,612	48.6%	1.7%	38.5%	48.8%	7.0%	0.3%	3.7%	4.02	45.7	6	2.2	2.9	7.7%
Nevada	21,673	$53,833	$58,871	48.6%	0.5%	75.6%	16.8%	1.4%	0.9%	4.8%	4.17	67.6	7.3	3.1	6	8.7%
Orange	864,024	$72,046	$64,932	48.6%	1.4%	31.9%	46.5%	15.8%	0.2%	4.1%	3.24	33.9	7.8	1.6	3.1	6.8%
Placer	100,960	$69,581	$57,797	48.9%	1.2%	64.2%	21.3%	7.0%	0.5%	5.7%	4.94	38.9	8.3	3	2.8	8.6%
Plumas	4033	$44,923	$47,287	49.0%	1.1%	73.3%	14.9%	0.5%	3.6%	6.6%	2.97	62.4	17.2	6.3	17.5	14.6%
Riverside	728,797	$52,491	$53,228	48.9%	6.2%	26.5%	58.2%	5.2%	0.5%	3.5%	2.48	54.7	9.9	3.9	6.2	11.1%
Sacramento	422,981	$52,236	$53,412	48.7%	11.0%	35.9%	29.9%	15.1%	0.5%	7.5%	3.38	58.5	8.1	3.4	6.3	9.8%
San Benito	18,327	$62,618	$59,631	49.1%	0.7%	21.1%	72.6%	2.9%	0.4%	2.2%	2.64	36	4.3	3.8	6.5	13.8%
San Bernardino	686,750	$51,017	$52,513	48.6%	8.6%	22.7%	60.5%	4.8%	0.3%	3.1%	2.63	62.1	7.7	3.7	6.7	10.9%
San Diego	871,665	$59,290	$59,930	48.3%	4.9%	34.3%	45.1%	9.7%	0.5%	5.5%	3.94	66.3	7.6	2.9	4.6	8.2%
San Francisco	140,656	$69,354	$74,239	49.1%	6.6%	30.0%	22.3%	33.7%	0.2%	7.2%	8.49	53.7	6.1	3.4	8.2	6.4%
San Joaquin	234,024	$50,376	$48,821	48.4%	7.5%	24.5%	49.5%	13.2%	0.4%	4.9%	3.58	47.1	6.8	2.6	5.9	14.7%
San Luis Obispo	69,712	$53,877	$55,740	47.9%	1.0%	59.2%	32.0%	3.5%	0.4%	3.9%	4.46	71.4	13.3	4.2	6.9	7.2%
San Mateo	188,890	$81,378	$78,347	48.6%	2.3%	32.2%	35.1%	23.6%	0.1%	6.8%	9.98	33.6	2.3	1.2	1.8	6.0%
Santa Barbara	129,320	$59,494	$58,102	49.0%	1.5%	32.2%	58.5%	4.3%	0.3%	3.2%	4.27	47.6	5.7	2.6	5.2	7.7%
Santa Clara	507,551	$84,741	$75,880	48.5%	2.2%	24.2%	37.0%	30.8%	0.2%	5.6%	5.15	31.3	4.9	1.8	2.2	7.6%
Santa Cruz	73,736	$61,228	$69,369	48.8%	0.9%	42.2%	47.7%	4.3%	0.3%	4.6%	7.02	49.7	7.6	2.6	4.9	11.2%
Shasta	46,376	$41,796	$45,483	48.2%	1.1%	70.8%	15.3%	3.6%	2.9%	6.2%	3.16	92.2	18.2	9	13.5	12.8%
Sierra	579	$45,060	$50,117	47.4%	0.1%	82.9%	13.2%	0.0%	0.9%	2.9%	0.00	118.6	6.2	0	4.2	14.3%
Siskiyou	10,518	$35,175	$44,617	47.6%	1.2%	66.1%	18.9%	1.3%	4.4%	8.1%	3.57	91.4	26.5	8	10.9	16.0%
Solano	116,269	$63,090	$56,368	48.5%	13.3%	29.8%	34.2%	12.5%	0.3%	9.9%	2.87	51.3	5.5	2.5	3.9	9.4%
Sonoma	126,819	$60,792	$59,715	48.6%	1.7%	49.8%	39.3%	3.5%	0.8%	4.9%	3.81	27.2	5.4	2.2	4.8	7.8%
Stanislaus	170,571	$44,287	$47,780	48.5%	2.4%	34.6%	54.7%	4.3%	0.4%	3.6%	5.54	68.3	14.7	2.2	4.1	14.7%
Sutter	29,784	$48,749	$45,452	48.6%	1.7%	39.5%	39.6%	13.3%	1.0%	5.0%	5.20	41	5.4	2.4	6.1	17.5%
Tehama	18,316	$37,297	$44,470	48.7%	0.6%	57.4%	35.4%	0.9%	2.0%	3.7%	1.79	103.4	14.7	11.5	10.1	12.8%
Trinity	2794	$33,163	$44,588	49.4%	0.2%	70.4%	15.7%	2.1%	5.0%	6.6%	0.00	101.9	35.5	20.6	27	14.5%
Tulare	166,777	$40,599	$41,571	48.8%	1.1%	21.6%	72.3%	2.6%	0.7%	1.7%	3.93	76.8	6.2	3.9	6.7	15.9%
Tuolumne	11,187	$43,530	$49,383	47.8%	0.8%	74.1%	17.1%	1.3%	1.8%	4.9%	0.00	86	17.2	7.2	11.2	11.1%
Ventura	245,855	$74,019	$61,465	48.8%	1.3%	35.3%	53.7%	5.6%	0.2%	3.8%	4.44	56.7	6.7	2.7	4.1	8.6%
Yolo	62,220	$50,174	$56,048	51.0%	2.6%	38.1%	39.4%	14.0%	0.5%	5.5%	3.88	42	8.6	3.3	5.3	11.6%
Yuba	23,854	$43,299	$46,311	48.0%	2.9%	46.0%	34.9%	7.5%	1.6%	7.1%	1.53	78.6	9.6	4.6	5.2	15.8%

economic factors in California such as unemployment are not associated with child maltreatment, it is positively associated if the downturn affects men more than women (Lindo, Scaller, & Hansen, 2013).

The conventional logic is concerning because since 1948, there has been 10 recessions in the U.S. (U.S. Bureau of Labor Statistics, 2012a). One economic outcome of a poor economy is unemployment, and there has been a spike in the unemployment rate after each of the 10 recessions in the 50 states (U.S. Bureau of Labor Statistics, 2012b).

I examined the relationship of unemployment and child maltreatment in 58 counties in California. Researchers have noted advantages to looking at data within a state rather than across states. The definition of who is a mandated reporter may differ between states (Paxson & Waldfogel, 1999), as well as the definitions of maltreatment, reporting expectations, and standards for casework (Lindo et al., 2013). In fact, even the standard of what constitutes a substantiated referral may differ from state to state (Paxson & Waldfogel, 1999).

The hypothesis is that as the economy becomes better in the 58 California counties as indicated by lower unemployment, there will be less child maltreatment. Further, in one particular county, the influence of unemployment on child abuse and neglect will have a stronger effect than other economic indicators.

2. Methods

2.1. Sample

California has a state-administered, county-supervised child welfare system. There are 58 counties in California. Each of the counties has a wide range of population, demographics, child maltreatment referral rates, child maltreatment entry rates, and out-of-home (foster care) rates (Table 1). The 58 counties are very different from each other with populations ranging from less than 300 to nearly 2.8 million, with a Latino population that ranges from 8% to nearly 83% (Table 2). The unemployment rate ranges from under 6% to over 26%.

2.2. Period of study and variables for the 58 counties

The period of study was from 2005 to 2012 which encompasses the last major recession from December 2007 to June 2009. Quarterly information is available from March 2005 to December 2012. In essence, there are four months (March, June, September, and December) for each of the eight years from 2005 to 2012, representing data from 32 months.

The dependent variable for the first set of analyses was the rate of out-of-home cases per 1,000 children. Open cases are a better indicator of child maltreatment than just referrals or substantiated referrals, as these cases are a reflection of a risk level high enough to warrant case management by child protective services. The rate of out-of-home cases or foster care cases per 1,000 children in each of the 58 counties was calculated. The rate is the number of out-of-home cases divided by the child population for that county for a given month and both are available from the California Child Welfare Indicators Project (Needell et al., 2013). Quarterly child population estimates were derived based on the difference from one year to the next, and dividing by four (the number of quarters in a year). This provided a more conservative child population denominator than if the number of children was maintained at the same level for the entire year.

The independent variable for the first set of analyses is the unemployment rate for each of the 58 California Counties. Data on the unemployment rate was attained from the California Employment Development Department (California Employment Development Department, 2013) for each of the 58 counties for the same 32 months.

2.3. Period of study and variables for San Mateo County

For the second set of analyses, monthly information on all open child protective services cases was available from January 2005 to December 2012 for one particular county, San Mateo County. This represented 96 months of information from administrative records. The dependent variable was the rate of all open child protective services cases per 1,000 children (both foster care cases, as well as those cases that were at imminent risk of coming into foster care), and information was obtained from administrative records.

There were five independent variables in which there was available data for each of the 96 months. Data on the unemployment rate for San Mateo County was attained from the California Employment Development Department (California Employment Development Department, 2013) for the 96 months. Labor force information was also attained from the California Employment Development Department, and is a stable measure of economic indicator (Millet et al., 2011). The third economic indicator is median housing prices which is available for San Mateo County (California Association of Realtors, 2013). The fourth indicator is the rate of foreclosures per 10,000 housing units. This indicator is derived by dividing the number of foreclosures for a given month (RAND, 2013) by the number of housing indicated in the American Community Surveys (U.S. Census Bureau, 2013). Monthly housing unit estimates were derived based on the difference from one year to the next, and dividing by 12 (the number of months in a year) based on the number of housing units (U.S. Census Bureau, 2013). This provided a more conservative housing unit denominator than if the number of housing units was maintained at the same level for the entire year. The last indicator was the rate of household Supplemental Nutrition Assistance Program (SNAP) participation per 100 households which was available for San Mateo County. The SNAP program in California is called

Table 2
Summary statistics for some of the demographics for the 58 California counties.

Demographic variable	Mode	Median	Mean	Standard deviation	Minimum	Maximum
Child population	N/A	54,737	23,854	404,310	270	2,792,610
Median income	N/A	$48,754	$43,299	$12,571	$33,163	$84,741
Self-sufficiency standard	N/A	$50,521	$46,311	$9190	$41,571	$82,038
Female	48.60%	48.60%	48.00%	0.97%	44.70%	53.10%
Male	51.40%	51.40%	52.00%	0.97%	46.90%	55.30%
African-American	1.20%	1.50%	2.90%	3.11%	0.00%	13.30%
White	70.40%	39.75%	46.00%	19.59%	8.00%	82.90%
Latino	32.00%	36.05%	34.90%	19.41%	11.00%	88.40%
Asian/Pacific Islander	1.40%	3.90%	7.50%	7.37%	0.00%	33.70%
American Indian	0.20%	0.85%	1.60%	4.05%	0.10%	26.40%
Multi-race	4.90%	4.85%	7.10%	1.87%	0.70%	9.90%
Disproportionality measure for African-American children	0.00	3.58	1.53	3.18	0.00	19.19
Number of allegations per 1000 children	N/A	66.95	78.60	26.38	22.70	148.00
Number of substantiated allegations per 1000 children	7.70	8.45	9.60	7.24	0.00	35.50
Number of entries into foster care per 1000 children	0.00	3.70	4.60	3.35	0.00	20.60
Number of children in foster care per 1000 children	4.80	6.05	5.20	4.25	0.00	27.00
Unemployment rate	8.20%	11.40%	15.80%	3.87%	5.60%	26.30%

CalFresh, and the CalFresh participation rate was calculated by dividing the number of households that participated in CalFresh in San Mateo County (California Department of Social Services, 2013) by the number of households in the County that made less than $25,000 (U.S. Census Bureau, 2013). Monthly household estimates were derived based on the difference from one year to the next, and dividing by 12 (the number of months in a year) based on the information in the American Community Surveys (U.S. Census Bureau, 2013). This provided a more conservative household denominator than if the number of households was maintained at the same level for the entire year.

2.4. Analysis for the 58 California counties

SPSS 21.0 was used for more advanced analyses. For the first set of analyses, linear regressions were conducted for each county whereby the unemployment rate for that county was regressed on out-of-home care cases for the same county. Linear regression models assume that that the residuals are independent of each other (Brower & Jeong, 2007). Autocorrelation is very common and a concern when examining such time-series data (Graddy & Wang, 2007), and out-of-home care and unemployment rates were tracked on a quarterly basis. Autocorrelation is the concept that there is a statistical relationship among values of the same time variable that is measured at different intervals of time (Brower & Jeong, 2007). In essence, data seen in a quarter (or a month) is not entirely independent from the prior quarter (or month) for the same variable which violates the basic premise of independency of linear regression models. These time series data are not made up of randomly selected data points, but rather of data points collected at specific time intervals, which then leads to autocorrelation. If autocorrelated data is not addressed, it can lead to incorrect inferences about regression parameters (James, 2004), thus creating a regression model that is not as accurate as it could be (Brower & Jeong, 2007). The standard errors of coefficients and approximate variances of the regression might be underestimated leading to false findings of statistical significance.

In order to test for autocorrelation, a Durbin–Watson statistic was conducted as a part of the linear regression analysis for each county. The Durbin–Watson statistic is the most common test available for autocorrelation and ranges from 0 to 4 (Graddy & Wang, 2007). A Durbin–Watson statistic of 2 represents no autocorrelation; a statistic closer to 0 may represent positive autocorrelation, and a statistic close to 4 may suggest negative autocorrelation.

If a Durbin–Watson statistic indicates autocorrelation and the linear regression was statistically significant, an autoregressive two-stage model or AR(1) using the Prais–Winsten method was then conducted. The Prais–Winsten method estimates a weighted least-squares regression, then estimates the autocorrelation parameter for an AR(1) process in the error terms, then transforms the data using the autocorrelation parameter and then re-estimates the regression using the transformed data (Bitle & Zavodni, 2002).

2.5. Analysis for San Mateo County

A second set of analyses was conducted with San Mateo County for each of the 96 months from January 1, 2005 to December 31, 2012. Descriptive statistics were generated for the dependent variable of rate of open child protective services cases per 1,000 children, as well as the five independent economic variables (i.e., unemployment rate, median housing price, labor force, foreclosure rate per 10,000 homes, and CalFresh household participation rate per 100 households). The rate of open child protective services cases was calculated by dividing the number of open child protective services cases in a month by the total number of children in San Mateo County for that month.

A linear regression was conducted with the rate of open child protective services cases regressed on the unemployment rate. A Durbin–Watson statistic was also conducted. As before, if the Durbin–Watson statistic indicated autocorrelation and the overall regression was statistically significant, an AR(1) using the Prais–Winsten method was then calculated. If an autoregression model was warranted, then it was calculated and, in turn, if the model was statistically significant, then the linear regression equation was generated.

A multivariate model was conducted in that the rate of open child protective services cases was regressed on the unemployment rate, the median housing price, the labor force, the foreclosure rate per 10,000 homes, and the CalFresh household participation rate per 100 households. A Durbin–Watson statistic was also conducted. As before, if the Durbin–Watson statistic indicated autocorrelation and the overall regression was statistically significant, an AR(1) using the Prais–Winsten method was then calculated.

Like the previous analysis, if autocorrelation was detected, an autoregression with all five independent variables was conducted. If the autoregression model was statistically significant, then the multivariate regression equation was generated. Standardized coefficients were also calculated to identify the relative effect of significant independent variables. The standardized coefficient is a common way to standardize the independent variables (Meltzer-Brody et al., 2007). In essence, changes in the dependent variable in terms of standard deviation units for each of the independent variables are calculated. This statistic measures how much a one-unit standard deviation change in an independent variable affects the dependent variable.

3. Results

3.1. Results for the 58 counties

As can be seen in Table 3, initial linear regressions suggested that there was a statistically significant positive relationship between unemployment and out-of-home care cases in three counties, a statistically significant negative relationship between unemployment and out-of-home care cases in 42 counties, and no relationship between unemployment and out-of-home care case in 13 counties. However, autocorrelation was also detected in 40 of the 42 counties that had statistically significant findings.

As can be seen in Table 4, when autocorrelation is addressed, linear regressions suggested that there was a statistically significant positive relationship between unemployment and out-of-home care cases in two counties, a statistically significant negative relationship between unemployment and out-of-home care cases in 16 counties, and no relationship between unemployment and out-of-home care in 40 counties.

For the two counties with a positive relationship between unemployment and foster care cases, a one percent decrease in unemployment would lead to 1.1 fewer foster care cases in Amador County and 6.1 fewer cases in Stanislaus County. For the 16 counties with a negative relationship, a one percent decrease in unemployment would lead to 65.5 more foster care cases in Alameda County, 72.0 more cases in Contra Costa County, 1.7 more cases in Del Norte County, 3.1 more cases in Lake County, 502.7 more cases in Los Angeles County, 5.8 more cases in Madera County, 6.2 more cases in Mendocino County, 46.7 more cases in Orange County, 11.8 more cases in Placer County, 199.0 more cases in Riverside County, 87.2 more cases in San Bernardino County, 183.1 more cases in San Diego County, 27.1 more cases in San Joaquin County, 21.5 more cases in San Mateo County, 16.0 more cases in Solano County, and 8.3 more in Yuba County.

3.2. Results for San Mateo County

Descriptive statistics for the rate of open child protective services cases (OCPS), unemployment rate (UR), labor force (LF), median housing prices (MHP), foreclosure rate (FR), and CalFresh participation rate (CPR) can be seen in Table 5. During the 96 months, the

Table 3
The rate of out-of-home care per 1000 children regressed on the unemployment percentage for each of the 58 counties.

County	R	Adj R^2	Regression equation	df	F	p-Value	Number of out-of-home care change for every 1% increase in unemployment based on current population	Durbin–Watson statistic (1.160)
Alameda	−0.818	0.658	OHC = −0.335[UR] + 7.797	1,30	60.594	<.001	−135.508	0.166
Alpine	−0.382	0.118	OHC = −0.389[UR] + 6.479	1,30	5.139	<.05	−0.105	0.799
Amador	0.797	0.623	OHC = 0.152[UR] + 2.591	1,30	52.192	<.001	1.099	1.418
Butte	−0.617	0.36	OHC = −0.193[UR] + 12.563	1,30	18.435	<.001	−11.596	0.248
Calaveras	−0.529	0.256	OHC = −0.141[UR] + 9.356	1,30	11.677	<.01	−1.417	0.339
Colusa	−0.576	0.309	OHC = −0.177[UR] + 7.944	1,30	14.869	<.001	−1.282	0.735
Contra Costa	−0.914	0.83	OHC = −0.366[UR] + 7.213	1,30	152.472	<.001	−110.699	0.257
Del Norte	−0.516	0.242	OHC = −0.243[UR] + 15.672	1,30	10.888	<.01	−1.694	1.339
El Dorado	0.313	0.068	OHC = 0.045[UR] + 5.134	1,30	3.25	n.s.	n.s.	0.356
Fresno	−0.651	0.405	OHC = −0.161[UR] + 9.233	1,30	22.065	<.001	−52.338	0.248
Glenn	−0.533	0.261	OHC = −0.154[UR] + 10.990	1,30	11.927	<.01	−1.374	0.655
Humboldt	−0.13	−0.016	OHC = −0.039[UR] + 7.624	1,30	0.514	n.s.	n.s.	0.304
Imperial	−0.651	0.404	OHC = −0.138[UR] + 8.535	1,30	22.052	<.001	−8.307	0.270
Inyo	0.231	0.022	OHC = 0.074[UR] + 2.316	1,30	1.693	n.s.	n.s.	0.844
Kern	−0.745	0.54	OHC = −0.264[UR] + 10.653	1,30	37.404	<.001	−78.02	0.456
Kings	−0.501	0.226	OHC = −0.101[UR] + 7.648	1,30	10.073	<.01	−4.822	0.416
Lake	−0.804	0.635	OHC = −0.376[UR] + 15.659	1,30	54.871	<.001	−5.854	0.575
Lassen	−0.487	0.212	OHC = −0.205[UR] + 9.049	1,30	9.336	< .01	−1.491	0.627
Los Angeles	−0.924	0.849	OHC = −0.226[UR] + 9.355	1,30	175.915	< .001	−631.494	1.051
Madera	−0.843	0.7	OHC = −0.259[UR] + 8.089	1,30	73.474	< .001	−12.828	1.118
Marin	−0.556	0.286	OHC = −0.060[UR] + 1.633	1,30	13.418	< .001	−3.619	0.528
Mariposa	−0.658	0.415	OHC = −0.529[UR] + 13.702	1,30	22.949	< .001	−1.932	1.220
Mendocino	−0.816	0.655	OHC = −0.454[UR] + 14.725	1,30	59.789	<.001	−10.181	1.174
Merced	−0.177	−0.001	OHC = −0.025[UR] + 7.120	1,30	0.975	n.s.	n.s.	0.350
Modoc	−0.572	0.304	OHC = −0.312[UR] + 7.432	1,30	14.553	<.001	−0.737	1.015
Mono	−0.548	0.277	OHC = −0.017[UR] + 2.920	1,30	12.875	<.01	−0.592	0.364
Monterey	−0.656	0.411	OHC = −0.112[UR] + 3.962	1,30	22.604	< .001	−14.904	0.740
Napa	−0.052	−0.031	OHC = −0.010[UR] + 2.901	1,30	0.081	n.s.	n.s.	0.245
Nevada	0.324	0.075	OHC = 0.087[UR] + 3.128	1,30	3.511	n.s.	n.s.	0.233
Orange	−0.816	0.654	OHC = −0.095[UR] + 3.712	1,30	59.723	<.001	−81.725	0.138
Placer	−0.858	0.728	OHC = −0.134[UR] + 4.001	1,30	83.896	<.001	−13.54	0.484
Plumas	0.354	0.096	OHC = 0.174[UR] + 9.286	1,30	4.298	<.05	0.7	0.513
Riverside	−0.954	0.907	OHC = −0.306[UR] + 9.628	1,30	304.458	< .001	−222.7	0.600
Sacramento	−0.755	0.555	OHC = −0.391[UR] + 11.970	1,30	39.676	<.001	−165.327	0.114
San Benito	−0.02	−0.033	OHC = −0.003[UR] + 4.453	1,30	0.012	n.s.	n.s.	0.606
San Bernardino	−0.892	0.788	OHC = −0.168[UR] + 7.814	1,30	116.482	<.001	−115.449	0.286
San Diego	−0.908	0.819	OHC = −0.340[UR] + 7.694	1,30	141.489	<.001	−296.524	0.171
San Francisco	−0.697	0.468	OHC = −0.740[UR] + 15.965	1,30	28.307	<.001	−104.024	0.118
San Joaquin	−0.907	0.818	OHC = −0.216[UR] + 8.791	1,30	139.865	<.001	−50.503	0.552
San Luis Obispo	−0.145	−0.012	OHC = −1.772[UR] + 4.922	1,30	0.643	n.s.	n.s.	0.443
San Mateo	−0.936	0.873	OHC = −0.186[UR] + 3.217	1,30	213.206	<.001	−35.197	0.441
Santa Barbara	0.32	0.073	OHC = 0.046[UR] + 3.965	1,30	3.428	n.s.	n.s.	0.311
Santa Clara	−0.839	0.695	OHC = −0.281[UR] + 5.243	1,30	71.533	<.001	−142.508	0.257
Santa Cruz	−0.557	0.288	OHC = −0.082[UR] + 4.609	1,30	13.525	<.001	−6.078	0.546
Shasta	−0.515	0.241	OHC = −0.117[UR] + 13.312	1,30	10.834	<.01	−5.448	0.374
Sierra	−0.429	0.157	OHC = −0.654[UR] + 19.791	1,30	6.777	<.05	−0.379	0.437
Siskiyou	−0.745	0.54	OHC = −0.369[UR] + 16.129	1,30	37.434	<.001	−3.885	0.754
Solano	−0.88	0.767	OHC = −0.172[UR] + 5.174	1,30	102.88	<.001	−20.034	0.283
Sonoma	−0.335	0.083	OHC = −0.022[UR] + 4.270	1,30	3.803	n.s.	n.s.	0.663
Stanislaus	0.744	0.539	OHC = 0.047[UR] + 2.858	1,30	37.263	<.001	8.083	0.574
Sutter	−0.368	0.106	OHC = −0.058[UR] + 6.336	1,30	4.692	<.05	−1.714	0.328
Tehama	−0.587	0.323	OHC = −0.177[UR] + 12.746	1,30	15.785	<.001	−3.246	0.425
Trinity	0.309	0.066	OHC = 0.287[UR] + 9.895	1,30	3.177	n.s.	n.s.	0.295
Tulare	−0.805	0.636	OHC = −0.195[UR] + 8.570	1,30	55.21	<.001	−32.601	0.636
Tuolumne	0.211	0.013	OHC = −0.093[UR] + 9.794	1,30	1.403	n.s.	n.s.	0.351
Ventura	0.248	0.03	OHC = 0.033[UR] + 2.511	1,30	1.973	n.s.	n.s.	0.086
Yolo	−0.826	0.672	OHC = −0.285[UR] + 7.995	1,30	64.434	<.001	−17.761	0.809
Yuba	−0.921	0.843	OHC = −0.399[UR] + 12.272	1,30	167.435	<.001	−9.521	1.039

range of the rate of open child protective services cases was from 2.77 per 1,000 children to 4.58 per 1,000 children (M = 3.56 per 1,000, SD = 0.58 per 1,000). The unemployment percentage in San Mateo County for the same period ranged from 3.3% to 9.3% (M = 6.1%, SD = 2.1%).

There is a statistically significant inverse relationship between the rate of open child protective services cases per 1,000 children and unemployment rate, $R = -0.956$, Adj. $R^2 = 0.912$, $F(1,94) = 984.161$, $p < .001$. However, the Durbin–Watson statistic was 0.360, suggesting that the model of regressing the rate of open child protective services cases per 1,000 children on unemployment rate was autocorrelated. As seen in Fig. 1, the autoregression model was still statistically significant, $R = -0.424$, Adj. $R^2 = 0.162$, $F(1,94) = 20.174$, $p < .001$:

$$\mathrm{OCPS} = 4.218 - 0.111 * \mathrm{UR}.$$

This suggested that for every one percent increase in the unemployment, there is a decrease of 0.11 open child protective services

Table 4
The rate of out-of-home care per 1,000 children regressed on unemployment percentage for each of the 58 counties including some counties that warranted the use of autoregression to address autocorrelation.

County	R	Adj R^2	Regression equation	df	F	p-Value	Number of out-of-home care change for every 1% increase in unemployment based on current population
Alameda	−0.430	0.129	OHC = −0.162[UR] + 6.484	1,29	6.611	<.05	−65.532
Alpine	−0.027	−0.068	OHC = −0.023[UR] + 2.392	1,29	0.022	n.s.	n.s.
Amador	0.797	0.623	OHC = 0.152[UR] + 2.591	1,30	52.192	<.001	1.099
Butte	−0.239	−0.008	OHC = −0.087[UR] + 11.394	1,29	1.769	n.s.	n.s.
Calaveras	−0.097	−0.059	OHC = −0.039[UR] + 8.581	1,29	0.276	n.s.	n.s.
Colusa	−0.057	−0.066	OHC = −0.005[UR] + 4.923	1,29	0.094	n.s.	n.s.
Contra Costa	−0.643	0.372	OHC = −0.238[UR] + 6.303	1,29	20.220	<.001	−71.986
Del Norte	−0.516	0.242	OHC = −0.243[UR] + 15.672	1,30	10.888	<.01	−1.694
El Dorado	0.313	0.068	OHC = 0.045[UR] + 5.134	1,30	3.25	n.s.	n.s.
Fresno	−0.067	−0.064	OHC = −0.010[UR] + 7.330	1,29	0.136	n.s.	n.s.
Glenn	−0.169	−0.039	OHC = −0.055[UR] + 9.748	1,29	0.848	n.s.	n.s.
Humboldt	−0.130	−0.016	OHC = −0.039[UR] + 7.624	1,30	0.514	n.s.	n.s.
Imperial	0.015	−0.069	OHC = 0.002[UR] + 5.154	1,29	0.008	n.s.	n.s.
Inyo	0.231	0.022	OHC = 0.074[UR] + 2.316	1,30	1.693	n.s.	n.s.
Kern	−0.164	−0.040	OHC = −0.042[UR] + 8.132	1,29	0.796	n.s.	n.s.
Kings	0.000	−0.069	OHC = −0.000[UR] + 6.471	1,29	0.000	n.s.	n.s.
Lake	−0.427	0.126	OHC = −0.203[UR] + 13.438	1,29	6.456	<.05	−3.164
Lassen	−0.179	−0.035	OHC = −0.069[UR] + 7.750	1,29	0.961	n.s.	n.s.
Los Angeles	−0.799	0.614	OHC = −0.180[UR] + 8.973	1,29	51.267	<.001	−502.670
Madera	−0.465	0.162	OHC = −0.117[UR] + 6.554	1,29	7.975	<.01	−5.787
Marin	−0.233	−0.011	OHC = −0.038[UR] + 1.530	1,29	1.714	n.s.	n.s.
Mariposa	−0.333	0.049	OHC = −0.249[UR] + 11.338	1,29	3.608	n.s.	n.s.
Mendocino	−0.513	0.213	OHC = −0.278[UR] + 13.321	1,29	10.383	<.01	−6.232
Merced	−0.177	−0.001	OHC = −0.025[UR] + 7.120	1,30	0.975	n.s.	n.s.
Modoc	−0.161	−0.041	OHC = −0.081[UR] + 4.986	1,29	0.773	n.s.	n.s.
Mono	−0.277	0.013	OHC = −0.070[UR] + 2.056	1,29	2.396	n.s.	n.s.
Monterey	−0.292	0.022	OHC = −0.011[UR] + 2.980	1,29	2.722	n.s.	n.s.
Napa	−0.052	−0.031	OHC = −0.010[UR] + 2.901	1,30	0.081	n.s.	n.s.
Nevada	0.324	0.075	OHC = 0.087[UR] + 3.128	1,30	3.511	n.s.	n.s.
Orange	−0.468	0.165	OHC = −0.054[UR] + 3.395	1,29	9.333	<.01	−46.657
Placer	−0.585	0.297	OHC = −0.117[UR] + 3.8867	1,29	15.192	<.01	−11.812
Plumas	0.005	−0.069	OHC = 0..002[UR] + 10.872	1,29	0.001	n.s.	n.s.
Riverside	−0.829	0.666	OHC = −0.273[UR] + 9.271	1,29	64.273	<.001	−198.962
Sacramento	−0.205	−0.024	OHC = −0.105[UR] + 9.254	1,29	1.273	n.s.	n.s.
San Benito	−0.020	−0.033	OHC = −0.003[UR] + 4.453	1,30	0.012	n.s.	n.s.
San Bernardino	−0.598	0.313	OHC = −0.127[UR] + 7.543	1,29	16.129	<.001	−87.217
San Diego	−0.210	0.368	OHC = −0.210[UR] + 6.704	1,29	19.724	<.001	−183.050
San Francisco	−0.118	0.054	OHC = −0.092[UR] + 11.737	1,29	0.413	n.s.	n.s.
San Joaquin	−0.558	0.264	OHC = −0.116[UR] + 7.636	1,29	13.014	<.01	−27.147
San Luis Obispo	−0.145	−0.012	OHC = −1.772[UR] + 4.922	1,30	0.643	n.s.	n.s.
San Mateo	−0.444	0.406	OHC = −0.114[UR] + 2.789	1,29	23.571	<.001	−21.533
Santa Barbara	0.320	0.073	OHC = 0.046[UR] + 3.965	1,30	3.428	n.s.	n.s.
Santa Clara	−0.220	−0.017	OHC = −0.039[UR] + 3.458	1,29	1.500	n.s.	n.s.
Santa Cruz	0.003	−0.069	OHC = 0.000[UR] + 3.969	1,29	0.000	n.s.	n.s.
Shasta	0.050	−0.066	OHC = 0.014[UR] + 11.861	1,29	0.072	n.s.	n.s.
Sierra	−0.217	−0.019	OHC = −0.223[UR] + 14.155	1,29	1.436	n.s.	n.s.
Siskiyou	−0.251	−0.001	OHC = −0.072[UR] + 12.483	1,29	1.955	n.s.	n.s.
Solano	−0.625	0.348	OHC = −0.138[UR] + 4.984	1,29	18.565	<.001	−16.045
Sonoma	−0.335	0.083	OHC = −0.022[UR] + 4.270	1,30	3.803	n.s.	n.s.
Stanislaus	0.487	0.185	OHC = 0.036[UR] + 3.039	1,29	8.765	<.01	6.141
Sutter	−0.065	−0.064	OHC = −0.009[UR] + 5.713	1,29	0.122	n.s.	n.s.
Tehama	−0.191	−0.030	OHC = −0.074[UR] + 11.536	1,29	1.098	n.s.	n.s.
Trinity	0.309	0.066	OHC = 0.287[UR] + 9.895	1,30	3.177	n.s.	n.s.
Tulare	−0.340	0.054	OHC = −0.056[UR] + 6.912	1,29	3.779	n.s.	n.s.
Tuolumne	0.211	0.013	OHC = −0.093[UR] + 9.794	1,30	1.403	n.s.	n.s.
Ventura	0.248	0.030	OHC = 0.033[UR] + 2.511	1,30	1.973	n.s.	n.s.
Yolo	−0.303	0.029	OHC = −0.083[UR] + 6.195	1,29	2.929	n.s.	n.s.
Yuba	−0.800	0.616	OHC = −0.348[UR] + 11.602	1,29	51.616	<.001	−8.301

cases per 1,000 children or a decrease of 21.0 open child protective services cases.

The multivariate regression model was statistically significant (Adj. $R^2 = 0.964$, $F[5,95] = 505.543$, $p < .001$) for unemployment rate (UR), labor force (LF), median housing prices (MHP), foreclosure rate per 10,000 homes (FR), and CalFresh participation rate 100 households (CPR). However, the Durbin–Watson statistic was 0.703 indicating some positive autocorrelation. An autoregression was calculated and was statistically significant (Adj. $R^2 = 0.763$, $F[5,90] = 59.429$, $p < 0.001$) for unemployment rate (UR), median housing prices per \$100,000 (MHP), and CalFresh participation rate per 100 households (CPR). The regression equation was:

$$\mathrm{OCPS} = 1.986 - 0.141 * \mathrm{UR} + 0.053 * \mathrm{MHP} - 0.024 * \mathrm{CPR}.$$

This suggested that for every one percent increase in unemployment there is a decrease of 0.141 open child protective services cases per 1,000 children or a decrease of 26.6 open child protective services cases. For every \$100,000 increase in median home prices, there is an increase of 0.053 open child protective services cases per

Table 5
Summary statistics of the dependent and five independent variables used in the San Mateo County analyses.

	Mode	Median	Mean	SD	Min	Max
Open child protective services cases per 1,000 children	4.004	3.395	3.561	0.580	2.771	4.585
Unemployment percentage	3.90%	6.10%	6.10%	2.10%	3.30%	9.30%
Labor force	362,200	373,800	374,565	10,362	358,200	398,900
Median housing price	$850,000	$793,750	$785,486	$110,347	$551,000	$1,020,000
CalFresh participation per 100 households	N/A	17.061	21.638	11.804	8.61	45.682
Foreclosure per 10,000 homes	N/A	4.521	4.291	2.92	0.058	10.631

1,000 children or an increase of 10.0 open child protective services cases. For every 1.0 per 100 households that participates in CalFresh, there is a decrease of .024 open child protective services cases per 1,000 children or a decrease of 4.5 open child protective services cases.

Further, a one standard deviation change in unemployment rate would cause a −0.502 standard deviation change in open child protective services cases. A one standard deviation change in the median housing prices would cause a 0.168 standard deviation change in open child protective services cases. A one standard deviation change in the CalFresh household participation rate would cause a −0.473 standard deviation change in open child protective services cases. These standardized coefficients suggest that the unemployment rate has a stronger relative effect on open child protective services cases than CalFresh household participation rate, which in turn has a stronger effect than median housing prices.

4. Discussion

4.1. Inverse relationship of unemployment and child maltreatment in some counties

What was surprising was the fact that 16 of the California counties had a significant negative relationship between unemployment and child maltreatment and only two California counties had a significant positive relationship between unemployment and child maltreatment. Table 6 provides some comparisons between the 18 counties to see if there are any similarities between the 16 counties with negative relationships and two counties with positive relationships. Unfortunately, at a descriptive level, there seems to be many more differences than similarities. Negative relationship counties included the most populous in California, Los Angeles County, and one of the least populous, Del Norte County. Del Norte had the highest rate of allegations, and one of the highest rates of substantiated allegations, entries, and out-of-home care cases. Del Norte County also had one of the lowest median incomes in the California as opposed to San Mateo County which seemed opposite in every aspect to Del Norte.

4.2. Findings in San Mateo County

With such stark differences between the 58 counties, there was an opportunity to more closely examine the relationship unemployment and child maltreatment in San Mateo County for each of the 96 months, and not just the 32 quarters of many of the counties. In terms of the simple relationship between rate of open child protective services cases and unemployment rate, there was an inverse relationship between the two variables, even after accounting for potential autocorrelation. In essence, as the economy strengthens (indicated by falling unemployment), the rate of open child protective services cases rises in San Mateo County. As the economy weakens (indicated by a rise in unemployment), the rate of open child protective services cases drops in the County.

In looking at a multivariate model, two measures of a better economy (increased unemployment rate and increased median housing price) suggested a significant decrease in child maltreatment. Further, increased CalFresh household participation also suggested a significant decrease in child maltreatment. A closer examination of the findings in San Mateo County suggest that there are two potential factors that may partially explain this paradox of a better economy and worse child maltreatment, and both factors may play upon each other. The first relates to job gains and the Self-Sufficiency Standard, and the second relates to the impact of the economy on mental health.

Table 6
The most recent rankings for the two counties that had statistically significant positive relationships and the 16 counties that had had statistically significant negative relationships between the unemployment percentage and the rate of out-of-home care per 1000 children. A rank of “1” indicates the highest or most of that particular category.

County	Relationship between unemployment and foster care cases	Child population rank	Median income rank among 58 counties in California	Median income rank among 3143 counties in the U.S.	Self-sufficiency rank	Number of allegations per 1000 children rank	Number of substantiated allegations per 1000 children rank	Number of entries into foster care per 1000 children rank	Number of children in foster care per 1000 children rank
Alameda	Negative	8	9	127	9	55	56	51	47
Amador	Positive	49	24	575	25	12	27	20	36
Contra Costa	Negative	10	4	71	11	47	50	46	48
Del Norte	Negative	50	55	2464	49	1	3	2	4
Lake	Negative	42	54	2430	39	21	44	25	12
Los Angeles	Negative	1	22	525	8	33	18	23	17
Madera	Negative	30	39	1215	44	25	19	18	36
Mendocino	Negative	38	46	1683	29	11	6	7	8
Orange	Negative	3	6	82	6	53	33	53	49
Placer	Negative	22	7	104	18	49	30	37	52
Riverside	Negative	4	21	502	27	37	24	26	28
San Bernardino	Negative	5	25	610	28	32	35	29	22
San Diego	Negative	2	17	254	12	30	36	38	41
San Joaquin	Negative	13	27	668	33	43	39	40	31
San Mateo	Negative	14	2	38	2	54	57	54	55
Solano	Negative	21	10	179	19	39	47	43	46
Stanislaus	Positive	15	40	1279	36	28	14	47	44
Yuba	Negative	37	42	1403	45	19	25	22	34

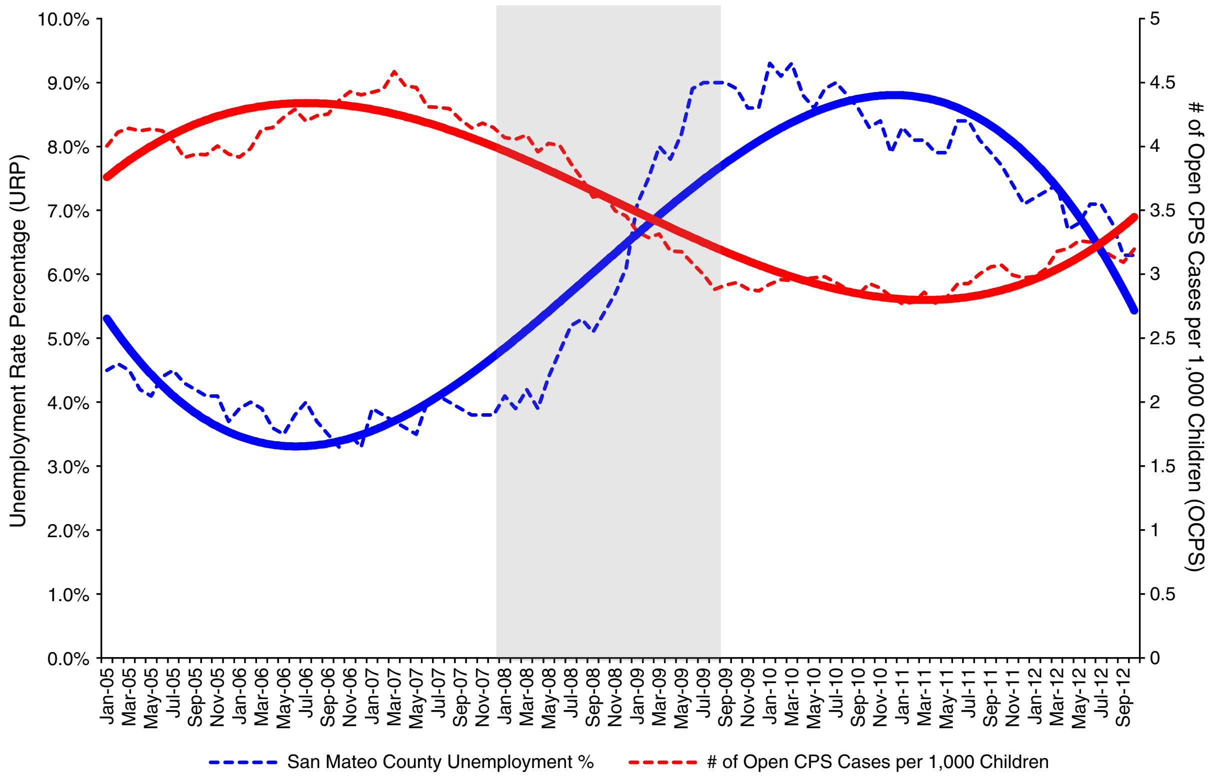

Fig. 1. In San Mateo County, CA from 2005 to 2012, there is a significant relationship in that for every one percent increase in the unemployment, there is a decrease of 0.11 open child protective services cases per 1,000 children or a decrease of 21.0 open child protective services cases, $R = -0.424$, Adj. $R^2 = 0.162$, $F(1,94) = 20.174$, $p < .001$.

4.2.1. Job gains and self-sufficiency standard

San Mateo County has seen a decline in the unemployment rate since 2009 following the last recession. However, as more people acquire jobs in San Mateo County, they may end up getting jobs with incomes that disqualify them from the safety net of Federal benefits, but do not make enough to meet or exceed the Self-Sufficiency Standard.

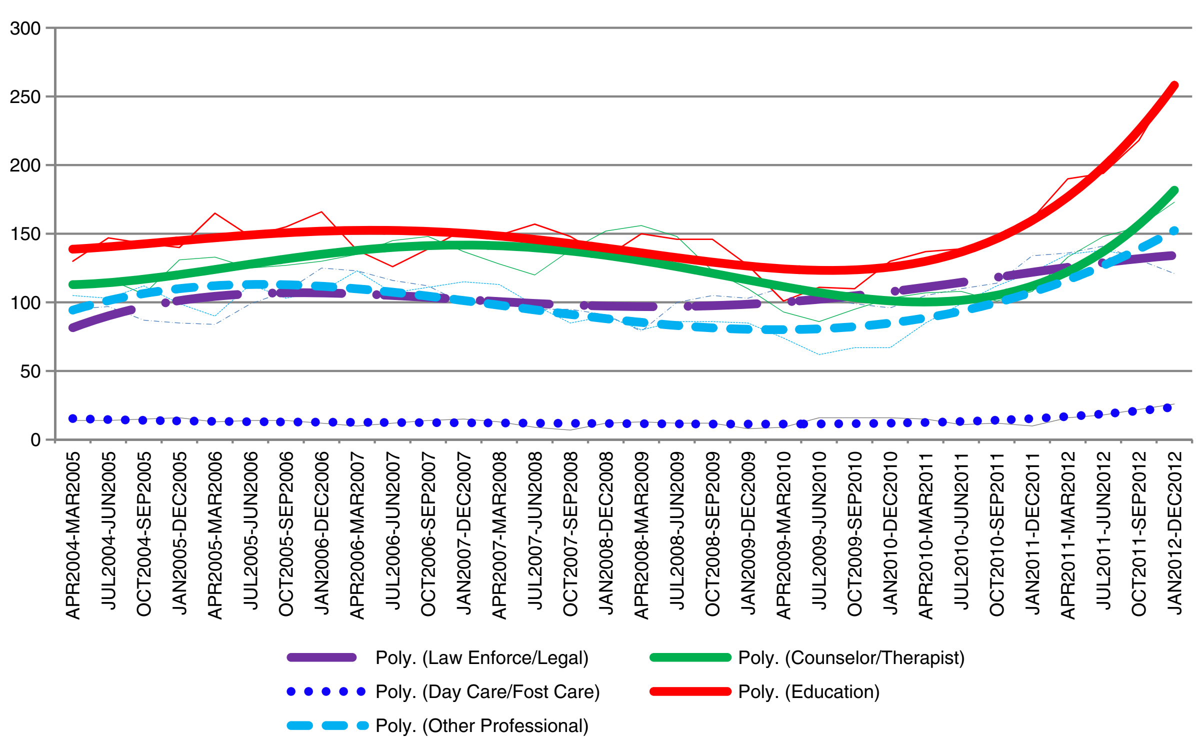

Fig. 2. Examination of some of the number of referrals for child maltreatment among four year olds to six year olds in San Mateo County among some mandated reporters.

To understand the Self-Sufficiency Standard, one has to first look at the Federal Poverty Level (FPL). The FPL was developed to identify whether or not a family made enough income to buy food; if they were below the FPL they were poor and if they were above the FPL, they were not poor (Pearce, 2011). Based on the FPL, the U.S. Department of Agriculture administers a number of programs that offers benefits to families (Hanson & Oliveira, 2012). If a family is within a certain percentage of the FPL (i.e., an income eligibility limit), then they would be eligible for benefits from these programs. These programs include: 1) the Supplemental Nutrition Assistance Program (SNAP) which targets households that are within 130% of the FPL; 2) the Special Supplemental Nutrition Program for Women, Infants, an Children (WIC) with households that are within 185% of the FPL; 3) the National School Lunch Program (NSLP) that targets primary and secondary students with households that are within 130% of the FPL for free meals and 185% of the FPL for reduced-cost meals; and 4) the School Breakfast Program (SBP) that targets primary and secondary students with households that are within 130% of the FPL for free meals and 185% of the FPL for reduced-cost meals.

In California, the median income is $57,287 with an average of 3.0 individuals in a household (U.S. Census Bureau, 2013). In San Mateo County, the median income is $81,378 with an average of 3.4 individuals. The FPL for three individuals is $19,090 (U.S. Department of Health and Human Services, 2012a, 2012b). A family of three will be eligible for certain services if they have no more than $24,817 at 130% of the FPL and no more than $35,316 at 185% of the FPL.

The Self-Sufficiency Standard ("Standard") was developed in the 1990s to provide a more modern measure of a minimum family income adequate to provide for the basic needs (Pearce, 2009). This Standard addressed at least five conceptual limits of the FPL (Pearce, 2011). First, the FPL was based on a single metric of income, more specifically the income available to purchase the cost of food. Second, any adjustments to the FPL could not keep up with inflation. Third, the FPL is tied to the concept of either a two-parent family with one parent not employed, or a single parent family in which that parent is not employed. Fourth, there is no geographic difference of the FPL for the 48 contiguous states (U.S. Department of Health and Human Services, 2012a); in essence, it is the same level from state to state. And finally, the FPL does not account for how changes to the above costs would individually affect the FPL.

The Standard attempts to address some of the limitations of the FPL (Pearce, 2011). In addition to looking at the cost of food, the Standard takes into account the different number of types of individuals in a family (e.g., up to four adults, and up to eight children who can either be infants, preschooler, school-aged, or teenagers), the cost of housing, the cost of child care, the various costs of transportation (e.g., insurance, car maintenance, distance to work), the cost of health care, and the various different impacts of taxes that affect the family (e.g., income and property).

In the context of the Standard, the average family composition in San Mateo County is one adult with a pre-school child and a school-aged child. The San Mateo County Standard is approximately $78,945 for this family of three (Insight Center for Community Economic Development, 2012). This family would need to have at least $78,945 in order to survive economically and provide for the basic needs of the family. For those that make above 185% of the FPL (i.e., $35,316) and below $78,945, they would be in the Self-Sufficiency Gap or those who make enough to disqualify them from the safety net of Federal and other benefits, but not enough to economically survive and provide for their basic needs. In comparison, the California Standard is $50,885 or only about two-thirds of the San Mateo County Standard.

The American Community Survey provides estimates of households that are at certain income levels, including those between $35,000 and $74,999 (U.S. Census Bureau, 2013) which is a conservative estimate of those in the Self-Sufficiency Gap in San Mateo County. Approximately 45,182 (25.7%) of the 175,804 households in the County are in this income range. If each household has an average of at least 3.4 individuals, this would be 153,619 individuals who are in the Self-Sufficiency Gap. This is a 17.3% increase from the 38,519 households (130,965 individuals) in 2008 and three times the California increase during the same period. In essence, from 2008 to 2011, 6663 more households (representing 22,654 more individuals) in San Mateo County had incomes that disqualify them from the safety net of Federal benefits, but not enough to survive economically.

Further, these incomes may not be enough to be able to afford the rising housing costs in the County. The findings of this study indicate that as median housing prices go up, there seems to be more child maltreatment. Median housing prices have increased 40.6% from a low of $551,000 during the recession to $775,000 in December 2012 (California Association of Realtors, 2013). Wood et al. (2012) noted found evidence to suggest that housing concerns were a significant stressor in the community that led to more child maltreatment.

4.2.2. Impact of economy on mental health

Researchers have found that an increase in economic adversity is associated with poorer self-reported physical and mental health that was independent of demographics and socio-economic status (Kruger, Turbeville, Greenberg, & Zimmerman, 2012). People who are unemployed, poor, are facing family disruptions have a much greater risk of mental health problems (W.H.O. Regional Office for Europe, 2011). Increased mortgage delinquency rates have also led to elevated depressive symptoms, increased food insecurity, and increased cost-related prescription non-adherence (Alley et al., 2011). In fact, the adverse impact of a poorer economy on mental health has been evidenced on a global scale (W.H.O. Regional Office for Europe, 2011).

There is little research on the effect of the economy on children's mental health, but what there is shows an adverse effect on mental health (Solantaus, Leinonen, & Punamaki, 2004). Solantaus et al. (2004) noted that higher social status and higher education of parents did not protect these families from the stress that led to these adverse outcomes.

One element of the economy and mental health relates to food insecurity which is defined as the lack of food or the lack of nutritious food (U.S. Department of Agriculture, 2013a). The Great Recession of 2007 to 2009 has led to a tremendous amount of food insecurity (Chaparro, Langellier, Birnback, Sharp, & Harrison, 2012), which in turn was associated with a higher chance of mood, anxiety, behavioral, and substance disorders, and was a stronger factor than poverty (McLaughlin et al., 2012).

Children who were born around the time of the Great Recession and may have mental health symptoms are now entering the school systems. In 2011, there were 9.2 million children nationally, 1.1 million children in California, and over 25,000 children in San Mateo County enrolled in preschool and kindergarten (U.S. Census Bureau, 2013). Schools have become one of the largest providers of mental health services to children (U.C.L.A. Center for Mental Health in Schools, 2008). Further, school officials are also mandated reporters, so are now more likely to have to report alleged child maltreatment relating to all the stressors families faced during and since the Great Recession. In fact, there is some evidence to suggest that school officials and mental health providers were reporting more cases of suspected child maltreatment in San Mateo County. As seen in Fig. 2, school officials and mental health clinicians reported the most suspected child abuse referrals for four year olds to six year olds in San Mateo County, with a noticeable spike starting the beginning of the school year in the Fall of 2011 (Needell et al., 2013). One might posit that as more parents are working, that they would put a child in daycare, and that the number of child maltreatment reports from daycare would rise. This is not, however, the case (Fig. 2).

There are protective factors that may moderate the adverse effects of a poor economy on mental health. One study did not find a relationship between increase unemployment and child maltreatment and the researchers opined that this may be due to the availability of unemployment benefits and other social services which might have mitigated against the worst shocks of unemployment for families (Wood et al., 2012). At the height of the recession, 40.4% (3.8 million) of all Californian households were food insecure and the rise in food insecurity was most significant among those who were low income, unless they were in the SNAP program (Chaparro et al., 2012). Further, schools enrolling at least 40% of children from low-income families (as indicated by NSLP participation rates) are eligible for Federal funding for school-wide programs designed to improve educational achievement for all students, particularly the lowest-achieving students (U.S. Department of Education, 2012) and may help to further mitigate the impact of mental health issues.

Ironically, although San Mateo County is the 38th richest county in the U.S. out of 3141 counties and the second richest county in California (U.S. Department of Agriculture, 2013c), it has the 57th lowest SNAP participation rate among 58 counties in California (California Food Policy Advocates, 2012), which in turn has the lowest SNAP participation rate of the 50 states (U.S. Department of Agriculture, 2013b). This means that San Mateo County cannot leverage $49.8 million in Federal funding in relation to SNAP (California Food Policy Advocates, 2012) and could lose even more funding in relation to educational funding for schools for not meeting NSLP participation levels (U.S. Department of Education, 2012). This may explain the finding that increased SNAP participation in the County would lead to decreased child maltreatment.

4.3. Increased financial impact on local jurisdictions

Regardless of the impact of the economy on children, local jurisdictions should be in a better position to address child maltreatment because of a better economy. However, this is not true in San Mateo County because of two factors. The first relates to the Look-Back provision and the second is due to the realignment of state funds in California.

4.3.1. Look-Back provision

Child welfare expenditures are funded by three sources: Federal, state, and local funding. In California, when there is an open child protective services (CPS) case, the child is assessed for eligibility (i.e., whether or not the case qualifies for Federal or state funding). In terms of the Federal determination, the determination was locked into 60.0% of the FPL on July 16, 1996 which has become known as the Look-Back provision (Child Welfare League of America, 2006). Based on the 1996 FPL table (U.S. Department of Health and Human Services, 2010), 60.0% of the FPL for a family of three is $7,788. Thus, for a CPS case to be eligible for Federal funding today, a family of three can make no more than the 1996 standard of $7,788. This means that San Mateo County will have to cover more CPS cases with local funding as there are likely fewer children that qualify for Federal funding in future years.

4.3.2. Realignment of state funding

In California from 1991 to 2011, there were prescribed formulas for how much of an eligible case is covered by State funds for the non-Federal portion of the funding. For example, Schwartz, Kniffin, Lemley, and Matthews (2012) noted that federal funding would have covered 50% of an eligible case in terms of child welfare expenditures, California would have covered 35%, and San Mateo County would have covered 15% (known as net county costs or NCC). In 2011, the Governor of California shifted responsibility for child welfare programs from the State to the counties, along with a specified funding source (Schwartz et al., 2012). This realignment meant that as of 2011, the formula for an eligible case was 50% Federal funding, 0% State funding, and 50% County funding. Further, the funding levels were locked into the Fiscal Year (FY) 2009–2010. About 70.0% of the current open CPS cases are in California counties that have seen a caseload reduction since FY 2009–2010 (Needell et al., 2013). Unfortunately, there has been an increase in CPS cases in San Mateo County, so the County has had to rely more on NCC.

5. Limitations

5.1. Limitations of the findings for the 58 counties

There are several limitations of the findings for the 58 counties. First, the finding that 40 of the 58 counties had no significant outcomes may be due to the fact that the study period was not long enough. Second, the unemployment rate as the single economic indicator may either not be sufficient or the wrong economic indicator to be looking at. Both of these limitations were noted by Millet et al. (2011) who found that in some states where there was no relationship between the economy and child maltreatment. The aspect of unemployment as an insufficient indicator of physical abuse was also posited by other researchers (Wood et al., 2012).

Another limitation is that only quarterly data is readily available at the county-level in California. There is a significant challenge for researchers to have access to monthly child welfare agency data, including monthly information on referrals, entries, and open cases. Finally, the limitation of the determinant of child maltreatment may impede the ability to compare this to other studies. This paper defined child maltreatment as out-of-home care cases while others have examined other definitions such as child abuse referrals (Millet et al., 2011) or traumatic brain injury (Berger et al., 2011; Wood et al., 2012).

5.2. Limitations of the findings for San Mateo County

There were several limitations of the findings for San Mateo County. Some of the limitations are the same for that of the findings for the 58 counties, such as the time period not being long enough and the definition of child maltreatment (in the case of San Mateo, the definition was the rate of open child protective services cases). The one advantage of the findings of San Mateo County was monthly data that was available, especially for open child protective services cases. Another limitation could be spurious relationships of other administrative factors. For example, there may have been an increase in cases because there was more staff hired which in turn created more capacity to address a larger number of cases. However, this may be unlikely, as there was a steady 36.8% decrease (238 to 150) in staffing from 2005 to 2011. Although there was a slight increase of nine staff in 2012, none were line social workers.

The biggest limitation is that even if monthly information was available for both independent and dependent variables, there is no system in place for a public child welfare agency anywhere to consistently use research methodologies to analyze real-time data for decision-making purposes. Human services professionals, including those in child welfare, have been long aware of the gap between practice and research (Osterling & Austin, 2008). Child welfare practitioners heavily rely on descriptive statistics to make multi-million dollar decisions that affect outcomes of hundreds of thousands of children on a day-to-day basis, often without the critical perspective of researchers. There were 27 California counties in this study that had significant relationships between unemployment and child maltreatment, until autocorrelation was taken into account. However, while concepts such as autocorrelation and autoregression are common among economists studying econometrics, there are few child welfare researchers who have this knowledge, let alone child welfare practitioners. On the other hand, researchers heavily rely on inferential statistics based on long-term data and studies that can reduce the randomness of outcomes, often without practitioners being able to understand or apply the research at the local level in a timely basis.

Several have proposed the development of a child welfare informatics system and discipline of study (Naccarato, 2010; Nguyen, 2007). There are, however, few knowledgeable analysts in a public child welfare agency who can process data from such a system quickly, and even fewer who are able to translate this information to an understandable form for agency staff (Webster, Needell, & Wildfire, 2002). Osterling and Austin (2008) note that the divide between practice and research is detrimental to both the quality of the social services practice as well as the quality of the social services research. This particular limitation must be addressed for future studies.

Wood et al. (2012) note that further studies relating to macroeconomics and child maltreatment are needed. They also note that studies such as this one provide an opportunity to examine macroeconomic indicators as proxy risk factors for child maltreatment. They suggest that tracking macroeconomic factors would help identify local jurisdictions with heightened risk for child maltreatment and help such communities develop prevention programs and allocate necessary resources.

6. Conclusion

There is no relationship between the unemployment and child maltreatment in many California counties. However, in certain jurisdictions, there seems to be more child maltreatment as the economy is getting better. An examination in one particular county suggests two aspects which partly help to explain the paradox. First, in San Mateo County with a very high Self-Sufficiency Standard, people are getting jobs with incomes that are disqualifying them from the safety net of most benefits, which in turn may lead to more child maltreatment. Second, as they lose their safety net, these families may face more food insecurity which leads to others issues, including heightened mental health issues among both parents and children. Children who were born around the time of the recession are just starting school where their behaviors or other child welfare concerns are now coming to the attention of mandated reporters. Even then, jurisdictions like San Mateo County have to offset more child welfare costs with local funding because of the Look-Back provision and realignment of state funds.

San Mateo County will continue to provide high quality services for children who are maltreated. However, the County and other similar jurisdictions have to be even more vigilant about potential child maltreatment issues in an improving economy. Further, child welfare practitioners in such counties must form stronger collaborative relationships with researchers in order to make more timely use of the rich amount of information that is available in child welfare.

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