UNREPORTED VICTIMS OF AN ECONOMIC DOWNTURN*

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July 13, 2013

Abstract

I document that the recent Great Recession caused large decreases in referral rates for child maltreatment: areas most affected by the recession saw the largest decreases. This fits with some previous work that finds that poor economic conditions are associated with lower reported child maltreatment rates. I argue that this was due not to decreases in actual maltreatment rates, but rather large decreases in the reporting rates of child maltreatment, caused by the economic downturn. I use alternative proxies for actual maltreatment rates, less likely to be affected by reporting rates: rates of child mortality from neglect and Google searches suspecting maltreatment. The proxies comparatively increased in areas more affected by the recent recession. The estimates imply that the recent doubling of the unemployment rate increased actual child maltreatment incidents in the United States by 10.0 to 24.0 percent but decreased reported child maltreatment incidents by 12.7 percent. A likely explanation for the substantial decrease in reporting rates of maltreatment was depleted resources both for organizations likely to report cases and organizations likely to receive and investigate reports.

*I thank Alberto Alesina, Raj Chetty, David Cutler, Ed Glaeser, Lawrence Katz, and Lawrence Summers for helpful conversations. I thank Michael Dineen and Andres Arroyo of of the National Data Archive on Child Abuse and Neglect for help in data collection. All remaining errors are, of course, my own.

I Introduction

How does an economic downturn affect child maltreatment?[1]

We might expect child maltreatment would rise when times are tough. Indeed, sociologists and public health scholars hypothesize that unemployment – and the resulting stress, anger, and low self-esteem – are major risk factors in child maltreatment (Stith et al., 2009; Dooley et al., 1994; Baum et al., 1986; Linn et al., 1985).

Previous research, however, has generally not found a robust positive correlation between community-level unemployment and reported child maltreatment rates (Lindo et al., 2013). Previous research, in fact, has found some evidence for the opposite relationship. Controlling for state and year fixed effects, Paxson and Waldfogel (1999) find that poor economic conditions are associated with fewer reported victims of maltreatment.[2]

This paper begins by extending this puzzle using data from the recent Great Recession. I show that states that were most affected by the recession saw the largest decreases in referral rates for maltreatment. This relationship survives a fairly large set of controls.

How can we reconcile the strong theoretical arguments that poor economic conditions should increase child maltreatment with the area-level, time-series evidence to the contrary?

The paper next suggests and finds evidence for a reconciliation: a recession decreases the reporting rates of child maltreatment. Evidence suggests that the majority of maltreatment cases are not reported to authorities (Finkelhor et al., 2005; Hussey et al., 2006). During the Great Recession, state and local budgets were slashed in hard-hit areas. Budget cuts to agencies likely to deliver and receive reports might lower reporting rates. Individuals have reported long waits at child maltreatment hotlines; many hang up before getting through (Cardona, 2011; Valdez, 2012; Eckholm, 2009).

To test this hypothesis, I use two alternative proxies for area-level maltreatment rates less likely to be biased by reporting rates: rates of child mortality from neglect and the fraction of Google searches that include the phrase "child abuse" or "child neglect." Using an extreme form of an incident with mandatory reporting is a common strategy among economists studying crime (Levitt, 1998; Aizer, 2010). The motivation for the Google proxy is that it can capture community-level suspicion of child maltreatment, including many cases that are never actually reported.

[1]In this paper, when I use the phrase "child maltreatment," I mean child abuse and neglect, as defined by the Federal Government, in CAPTA. This includes one of the following two behaviors: 1) Any recent act or failure to act on the part of a parent or caretaker which results in death, serious physical or emotional harm, sexual abuse or exploitation; or 2) An act or failure to act which presents an imminent risk of serious harm.

[2]Lindo et al. (2013), in addition to an extensive literature review, also present new evidence, using county-level data from California. They find that the male unemployment rate is positively correlated with child maltreatment rates; the female unemployment rate is negatively correlated with child maltreatment rates; and the overall unemployment rate is not correlated with child maltreatment rates. More subtle, heterogenous relationships related to economic conditions and unemployment, such as those found by Lindo et al. (2013), are consistent with the results in this paper. Bitler and Zavodny (2004), Bitler and Zavodny (2002) and Seiglie (2004) find small, and generally insignificant, relationships between economic conditions and reported child maltreatment rates.

Both proxies comparatively increased in hard-hit areas. Each obviously is an imperfect proxy for overall maltreatment, but the likely sources of error are very different. The fact that both showed a comparative rise in recession-hit areas is evidence that the recession caused an increase in actual maltreatment.

I find additional evidence for this explanation: First, recession-hit areas saw an increase in the percent of referred cases that were substantiated. This would make sense if an increase in the cost of reporting cases has a bigger effect on the cases less likely to be substantiated. Second, I study high-frequency, national data for Google search queries likely made by older victims of maltreatment. These searches include "my dad hit me." Such searches rise when weekly unemployment claims are higher, lending further support to the hypothesis that unemployment increases actual maltreatment and any alternative relationship must be due to changes in reporting rates. Third, controlling for the Google proxy for unemployment, areas that spend little money on children have significantly lower referral rates.

The results imply that a one percentage point increase in the unemployment rate increases actual maltreatment by roughly 2.5 percent but decreases referrals by roughly 3.3 percent. In other words, a one percentage point increase in the unemployment rate decreases the percentage of actual maltreatment cases that are referred by 5.8 percent.

This paper shows that great caution should be used in interpreting results relying on reported rates of maltreatment as proxies for actual maltreatment. If the independent variable affects reporting rates, false conclusions might be drawn about the effects of that variable on actual incidents. In addition, the paper suggests an effect of budget cuts during economic downturns. And the paper leads to an unfortunate conclusion: just when children are most in need of assistance, they are least likely to get it. The paper suggests an additional cost of economic downturns.[3]

The paper builds on earlier work suggesting Google data can be useful in social science research (Varian and Choi, 2010; Ginsberg et al., 2009; Scheitle, 2011; Askitas and Zimmermann, 2009). It follows Stephens-Davidowitz (2012) in using Google data to measure a variable complicated by social desirability bias. It is the first paper to suggest using Google to study crime. Reporting issues complicate analysis of both child maltreatment and crime more generally (Levitt, 1998; MacDonald, 2001; MacDonald, 2002). Surveys are often released at too crude a geographic level to be helpful on a particular crime project (Levitt, 1998). Google search data provide an additional data source. In Section III.B.2 and the Conclusion, I discuss the potential of – and some reasons for caution with – using Google data to proxy crime.

It is important to note that the welfare effects of being referred for child maltreatment remain uncertain and limit fully understanding the welfare impacts of these results (Doyle Jr., 2007). Both estimating these impacts, and designing foster care systems that are unambiguously better than abusive households, remain crucial.

[3]Egan et al. (2013) note that the welfare effects of business cycles have to take into account other factors, such as health. Such adjustments can yield meaningful changes.

II Child Maltreatment in the United States

This section briefly reviews some facts about child maltreatment in the United States.

In 2010, more than 3 million (or roughly 1 in 25) children are reported victims of maltreatment. (See Table I.)

Table II show the sources for reported maltreatment cases in 2010. A slight majority (58.6%) came from professionals. The most common professional sources were education personnel (16.4%) legal and law enforcement personnel (16.7%), and social services personnel (11.5%). Almost all the nonprofessional sources (27.7%) were anonymous sources (9.0%), parents (6.8%), other relatives (7.0%), and friends and neighbors (4.4%). Very few reports came from the alleged victim (0.4%) or the alleged perpetrator ($\approx$ 0.0%). The rest of the reports (13.7%) came from other or unknown sources.

Maltreatment cases proceed in three stages.

1. An individual refers a case to child protective services.

2. Child protective services investigates the case.

3. Child protective services substantiates the case.

In 2010, more than 50 percent of referred cases were investigated. Roughly 24 percent of investigated cases were substantiated. Some scholars argue that most unsubstantiated cases should actually classify as maltreatment and even that alleged perpetrators of unsubstantiated cases are just as dangerous as alleged perpetrators of substantiated cases (Kohl et al., 2009; Drake, 1996; Hussey et al., 2005).

Scholars suspect that child maltreatment is significantly underreported to authorities (Finkelhor et al., 2005; Hussey et al., 2006).

The welfare effects of child maltreatment, evidence suggests, are substantial. Compared to demographically similar adults who were not victims, grown-up victims of child maltreatment have higher probability of mental illness (Brown et al., 1999; Mathews et al., 2008), are more likely to engage in criminal behavior (Widom, 1989; Lansford et al., 2007; Currie and Tekin, 2012), and earn substantially less (Currie and Spatz Widom, 2010).

III The Great Recession and Child Maltreatment

III.A The Effects of the Great Recession on Reported Child Maltreatment Rates

I now examine the effects of the recent recession on reported rates of child maltreatment. To do so, I utilize the fact that different parts of the United States were differently affected by the recession. And such differences were largely for idiosyncratic reasons that one would not expect to otherwise be correlated with changes in child maltreatment rates or child maltreatment reporting rates. Following Wolfers and Stevenson (2011) I average two years of data (2006 and 2007) as pre-economic crisis and two years of data (2009 and 2010) as post-economic crisis. I then measure the change in unemployment rates over this time period as a proxy for exposure to the recent crisis. I confirm that all the results in this paper are little affected by using alternative measures of economic performance, such as GDP, or slightly different time periods that similarly capture recession exposure.

In this section, I measure reported cases using both referral rates per child and response/investigation rates per child. I will discuss substantiated cases in Section III.D.1. I study referral rates and response rates now to focus more strongly on reporting pressures and because some scholars argue, due to flaws in the substantiation process, that this is the better measure of maltreatment incidence (Kohl et al., 2009; Drake, 1996; Hussey et al., 2005). Note that many other scholars study only substantiated cases. I hope to clarify the differences between previous results and my results more clearly in Section III.D.1.

There are two factors that influence the referral and investigation rates of maltreatment (reported maltreatment). First is the actual maltreatment and second is the proportion of maltreated cases that are reported.

In other words,

$$\text{reported maltreatment}_{\text{i,t}} \equiv \text{reporting}_{\text{i,t}} + \text{maltreatment}_{\text{i,t}} \tag{1}$$

The economic crisis may have changed the actual maltreatment rate. In other words,

$$\Delta\text{maltreatment}_{\text{i}} = \beta_0 + \beta_1\Delta\text{Unemp}_{\text{i}} + \beta_3\text{X}_{\text{i}} + \epsilon_{\text{i}} \tag{2}$$

It might also have changed the reporting rate of maltreatment. In other words,

$$\Delta\text{reporting}_{\text{i}} = \alpha_0 + \alpha_1\Delta\text{Unemp}_{\text{i}} + \alpha_3\text{X}_{\text{i}} + \text{z}_{\text{i}} \tag{3}$$

Overall, I can test the effects of the economic crisis on the rate of reported maltreatment cases. The empirical specification is:

$$\Delta\text{reported maltreatment}_{\text{i}} = \hat{\beta}_0 + \hat{\beta}_1\Delta\text{Unemp}_{\text{i}} + \hat{\beta}_3\text{X}_{\text{i}} + \text{w}_{\text{i}} \tag{4}$$

where $\hat{\beta}_1 = \beta_1 + \alpha_1$

The results, without any controls, are presented in Figure I. Both referred cases and investigated cases per capita declined in states comparatively affected by the recession. The result is statistically significant for both outcomes.

These correlations, of course, do not mean that the economic crisis caused a decrease in reported child maltreatment cases. One alternative possibility is that demographics changes were correlated with economic conditions in such a way as to affect reported maltreatment rates. This is theoretically unlikely, as demographics would move too slowly to significantly affect reported maltreatment rates. Columns (2) and (4) of Table III shows that the results are little affected by inclusion of changes in the African-American, Hispanic, and very young populations. The change in the percent of the population that is African-American is tiny in all states except District of Columbia. Thus, the coefficient on this variable, which is often statistically significant, can be explained by large changes in District of Columbia. I confirm that results are similar excluding this variable or excluding District of Columbia from the analysis.

Another possibility is that exposure to the economic crisis was correlated with an alternative factor that was also correlated with changes in child maltreatment rates. If there were such a factor, the coefficient should drop upon adding additional controls (Altonji et al., 2005). Columns (3) and (6) of Table III add controls for percent Hispanic, percent African-American, and percent college graduate. These data average data from 2006 and 2007 using the American Community Survey. The coefficient is little affected by adding these controls.

In sum, there is a negative relationship between exposure to the economic crisis and reported cases of maltreatment. And the near-randomness of the crisis and the robustness of the regression results suggest a causal role. There are, by definition, two potential reasons for this: First, the recession caused a drop in actual maltreatment ($\beta_1 < 0$). Second, the recession caused a drop in the reporting rate of maltreatment ($\alpha_1 < 0$). Distinguishing these stories requires alternative proxies for maltreatment that are not likely to be affected by the reporting rates of maltreatment. I now suggest such proxies.

III.B Alternative Proxies for Maltreatment

This section discusses alternative proxies for maltreatment less likely to be affected by reporting bias. The first is child mortality from neglect. The advantage of this proxy is, of course, that it is unlikely that standard reporting pressures will change this rate. The limitation, of course, is that it is an extreme outcome. This means both that it is rare, creating noise in the proxy, and that it may systematically differ from less extreme forms of maltreatment.

Its rareness makes using the natural log of the measure impractical. Large swings from states with few mortalities will create large standard errors. I thus use the change in the fatality rate, which is simply fatalities divided by child population.

In addition, two states note changes in the coding of child fatalities during the time period studied, Mississippi and California. I do not include these states in any regressions with child fatality data, though the main results of this paper are similar including them.

III.B.1 Using Google to Proxy Maltreatment

I supplement the proxy with a new source for crime data: Google search queries. There are two reasons Google search data may have meaningful information on an area's child maltreatment rate. First, victims old enough to use the search engine may look for information. Second, individuals who suspect that a friend, neighbor, or acquaintance is a maltreatment victim may look for information. Many of these suspected cases likely will never be reported to child protective services. Victims rarely report cases themselves. And a large percentage of individuals who suspect maltreatment do not go through with reporting the case. For this to contain information besides official data of referrals, it must be that there are individuals who suspect maltreatment but do not go through with reporting maltreatment. Gunn et al. (2005) found that 28 percent of physicians admitted to suspecting maltreatment but not reporting it, despite being mandated to report it. Flaherty et al. (2008) found that physicians reported 73 % of injuries that they thought were likely or very likely child abuse; and 24 % that they thought were possibly child abuse. Of course, the percent of suspected cases reported is likely substantially higher among this group than the population at large: First, physicians are mandated to do so, whereas many individuals who suspect cases, such as neighbors and relatives are not. Second, the physicians agreed to participate in a survey about how they dealt with child abuse. Third, they are reporting a socially undesirable behavior.

As a constraint on data-mining, following Stephens-Davidowitz (2012), I use the most salient words. The baseline Google proxy is as follows:

$$\text{Google Maltreatment}_{\text{i,t}} \equiv \frac{[\text{searches w/ (“child abuse” | “child neglect”)}]_{\text{i,t}}}{[\text{total searches}]_{\text{i,t}}} \tag{5}$$

Figure III shows the returns for "child abuse." The top returns fit with the idea that a large number of searchers are suspecting child maltreatment. Table IV shows the 'top searches' for the proxy. All of them return results similar to those shown in Figure III.

Prior to the crisis, the proxy positively correlates with an area's child fatality rate, though this relationship is not statistically significant. (Figure IV, Panel (a)). The proxy has a statistically significant correlation with an area's referral rate. (Figure IV Panel (b)).

In January 2011, Google updated its algorithm to improve precision of geographical estimates. Four states – Vermont, Virginia, California, and Delaware – experience patterns of "child abuse" searching that seem to be errors. In particular, they see large increases prior to January 2011 and then dramatic declines from December 2010 to January 2011 when the geographic codes changed. (They do not see such declines in any other January.) I have found that these states are consistently large, and unexplained, outliers when measuring changes through time for most words. The main analysis would be similar with including these states. However, I do not include these four states in any Google-related analysis.[4]

The majority of searches in the previous Google proxy are, evidence suggests, by individuals suspecting maltreatment. Google would seem to offer another way to measure maltreatment: searches by victims after an incident. Of course, very young victims of maltreatment are not going to use Google. But older victims may very well look for help or advice on Google.

Figure III shows a return for the search for "dad hit me." The evidence strongly suggests that individuals making searches are young teenagers who have recently been hit by their fathers.

The second Google maltreatment proxy (Google Maltreatment Victim) combines a few of these types of searches that return similar websites and, evidence suggests, are predominantly

[4] I first noted these anomalies and made identical decisions not to include these states in Stephens-Davidowitz (2013).

by recent maltreatment victims.

$$\text{Google Maltreatment (Victim)}_t \equiv \frac{[\text{searches w/ (“dad hit(s) me”| “dad beat(s) me” | “mom hit(s) me” | “mom beat(s) me”)}]_t}{[\text{total searches}]_t} \quad (6)$$

III.B.2 Caution Using Google Search Data

The Google data might greatly assist researchers trying to understand the causes of maltreatment (as well, of course, as crime more generally). However, there are many reasons the Google proxies might change that do not indicate changes in maltreatment rates. I mention three reasons now; these possibilities motivate many of the data and regression choices in the next section and must always be considered by researchers using the data source for this, or similar, reasons.

First, search rates for “child abuse” or “child neglect” can pick up individuals searching for news stories or research on maltreatment, rather than suspecting an incident. An increase in these searches due to more news coverage should not be interpreted as an increase in actual incidents. In the next section, I suggest some controls for this hypothesis. Even so, these tests might not always be conclusive. And researchers must also use intuition in interpreting the evidence.

Second, Google has gained users through time. And the composition of searchers has changed. Long-term trends in search rates may be due to changing composition of searchers. For example, the percent of Google searches that include “science” has consistently dropped through time in the United States. This does not mean, though, that interest in “science” has dropped through time. Rather, early Google users were likely among the demographics most interested in “science.” Over time, they have contributed a smaller share of total Google searches. Note that this problem is likely substantially smaller when comparing changes across different areas. Many of the changing demographics are likely to show up, similarly, across different areas. For example, if people uninterested in science were late to use Google, we would expect this pattern would, to some degree, hold in different areas. Thus, all areas would see, on average, decreases in search rates for “science.” However, the magnitude of the decrease might depend, in large part, on changes in actual science interest.[5] Note, also, that this problem is likely substantially smaller when comparing high-frequency changes. The

[5] This is very clear in examining health-related searches that include the word “depression.” These searches have consistent declined, as a share of Google searches, through time, even through the Great Recession. However, the decline was smallest in areas that were most affected by the Great Recession, consistent with other research on the effects of economic hardship on mental health (Luo et al., 2011; Reeves et al., 2012; Tefft, 2011). The interpretation of Google data on depression would suggest that despite a consistent national trend downwards in the rate at which depression searches are made in Google, the recession increased depression. This is how I am interpreting the Google child maltreatment data, as well.

composition of searches changes slowly. A big increase in a search on a particular week or day is unlikely due to changing composition of searchers. Having spent many years studying Google data, I have found that comparing the size of changes in different areas and studying high-frequency changes usually lead to meaningful conclusions, whereas studying long-term national trends very often do not. This motivates many of the econometric choices used in this paper; that said, demographics changes driving results are still possible, and I try to test for them as best I can.

Third, the second Google proxy ($Google\ Maltreatment\ (Victim)$), includes rare searches. Particularly in the early years of Google data, the data are very noisy. Using different combinations of searches can lead to different results. And there is not an obvious constraint on data-mining. Due to this, I limit the use of this data to a high-frequency study of national search data, where each of the different searches tends to follow the same pattern and similar results obtain using different choices of searches. This proxy, though, may have broader use in future studies, relying on more recent data, since the data have become less noisy as the Google user population has grown.

III.C The Effects of the Great Recession on Actual Child Maltreatment Rates

The goal now is to use the alternative proxies for maltreatment to test whether the recession decreased actual maltreatment, or whether the decrease in reported maltreatment is instead due to decreased maltreatment rates.

Assume that both $\mathrm{fatalities_{i,t}}$ and $\mathrm{google\ maltreatment_{i,t}}$ are noisy proxies of maltreatment.

$$\mathrm{fatalities_{i,t}} = \alpha_0 + \alpha_1 \mathrm{maltreatment_{i,t}} + \gamma_\mathrm{i} + \psi_\mathrm{t} + \epsilon_\mathrm{i,t} \tag{7}$$

$$\mathrm{google\ maltreatment_{i,t}} = \lambda_0 + \lambda_1 \mathrm{maltreatment_{i,t}} + \zeta_\mathrm{i} + \eta_\mathrm{t} + \mu_\mathrm{i,t} \tag{8}$$

Now I test

$$\Delta \mathrm{fatalities_i} = \grave{\beta}_0 + \grave{\beta}_1 \Delta \mathrm{Unemp_i} + \grave{\beta}_3 \mathrm{X_i} + \mathrm{z_i} \tag{9}$$

and

$$\Delta \mathrm{google\ maltreatment_i} = \check{\beta}_0 + \check{\beta}_1 \Delta \mathrm{Unemp_i} + \check{\beta}_3 \mathrm{X_i} + \mathrm{q_i} \tag{10}$$

The results are shown in Figure V and Table V. A comparatively large exposure to the economic crisis is associated with comparative *increases* in child maltreatment, using both proxies.

There are two explanations for the different results in Sections III.A and III.C. Either $\alpha_1 < 0$ (i.e. the reporting rates of maltreatment declined due to the recession) or $\beta_1 < 0$, $Cov(\Delta Unemp_i, z_i) > 0$, and $Cov(Unemp, q_i) > 0$. In other words, the recession lowered overall maltreatment cases while increasing both child fatality rates and Google searches for "child abuse" or "child neglect."

There is little evidence for the second possibility, though. Overall, there is little reason to suspect that error in the child fatality proxy is positively correlated with error in the Google proxy ($Cov(z_i, q_i) > 0$). The reasons for high fatality rates, controlling for total child maltreatment incidents, and high Google search rates, controlling for total child maltreatment incidents, are likely very different.

In addition, I did not find evidence for alternative explanations for either $Cov(\Delta Unemp_i, z_i) > 0$ and $Cov(Unemp, q_i) > 0$.

One important issue in interpreting the Google data is Google does not report absolute search volumes, only searches normalized as in Equation 5. Since the major analysis of interest is how maltreatment is affected by an economic crisis, the proxy could be problematic if the denominator – total Google searches – is affected by economic conditions. It is not obvious which way such bias would work – whether an economic crisis leads to more or less total searches. As evidence against a large change in total Google searches caused by the economic crisis, I find that comparative exposure to the crisis is not correlated with changes in normalized search volume for common words, including "weather," "the," and "a." In results not shown, I divide the Google proxy by normalized search volume for "weather." With this normalization, the proxy is the ratio of child abuse related searches compared to searches that include "weather" instead of compared to total Google searches. The results are little affected by this normalization.

A source of error in the Google proxy is undoubtedly interest in maltreatment, independent of suspected cases. Perhaps in bad economic times individuals are more curious in this topic. However, in results not shown, I do not find a statistically significant correlation between exposure to recession and change in percentage of Google searches that include the phrases "child abuse" or "child neglect" and are in Google's news category.[6] In addition, this would not explain the effects on child mortality.

In sum, I do not find evidence for either $Cov(\Delta Unemp_i, z_i) > 0$ or $Cov(Unemp, q_i) > 0$. And it is unlikely for there to be some missing factor that positively correlates with *both* q_i and z_i. The child maltreatment proxies are very different, with very different sources of error; yet, they yield similar results.[7]

Figure VI shows the relationships between changes in the various child maltreatment

[6]There is a small relationship between changes in news stories that include these terms. However, news stories might partly be capturing the actual increases in maltreatment, consistent with this paper's story. In addition, the relationships in Table V are unaffected including changes in news stories with the terms as an independent variable.

[7]Wood et al. (2012) also explores the relationship between child abuse and economic conditions, using hospital data, which is also unlikely to suffer from reporting bias. Their results are consistent with the results using infant mortality data and the Google data: bad economic conditions increase child maltreatment. There is still, I claim, new evidence using the data sources of this paper. Hospital data is only available for 35 areas. In addition, it is a rare outcome, and Lindo et al. (2013) question whether the results would be statistically significant if standard errors were clustered. And the hospital data, like the mortality data, represent an extreme outcome. The use of the Google data is still helpful in capturing a different part of the maltreatment severity distribution. Hospital and mortality data, the usual sources that can best deal with reporting biases, are, in many ways, similar to each other. But the Google proxies are very different from both.

proxies over the time periods used. Panel (a) shows a small, though not statistically significant, positive correlation between changes in fatality rates and changes in Google maltreatment searches. The lack of statistical significance is likely explained, in large part, due to the noise in the fatality rate measure. Panel (b) of Figure VI shows no relationship between changes in Google searches suspecting maltreatment and referral rates. This is in strong contrast to the results prior to the recession, shown in Figure IV. Prior to the recession, Google search rates suspecting maltreatment were significantly positively related to maltreatment referral rates. The lack of relationship between the changes in these variables, during this time of economic hardship, supports the interpretation that the change in referral rates was largely unrelated to actual changes in maltreatment.

III.D Additional Evidence

III.D.1 Composition of Reported Cases

Section III.A finds that the recent economic downturn led to a significant decrease in reports and investigations for child maltreatment. Section III.C finds that two proxies unlikely to be affected by reporting rates point to the opposite story: an economic downturn increases actual maltreatment.

The suggested reconciliation is that an economic downturn decreases the reporting rates of maltreatment.

Some additional evidence from official data can better test this hypothesis.

We might expect that, if a recession increased the cost of reporting – perhaps by increasing the wait to report – reporting pressures would be most sensitive among individuals least sure about their case.

Section III.A used data on reported cases of maltreatment. However, we can also use data on the percent of reported cases that are substantiated by authorities. While there is certainly error in this rate, we would expect that true cases of maltreatment are more likely to be substantiated. Thus, if the cost of reporting went up in the recession and reporting pressures were most sensitive to individuals least sure about their case, we would expect that the cases that were actually reported in recession-harmed areas were more likely to be substantiated.

There is indeed evidence for this, as shown in Figure VII, panel (a), and Table VI, Columns (1) through (3). The dependent variable is the percent of investigated cases that are substantiated. The greater the recession, the higher probability of investigated cases being substantiated. This suggests that the recession decreased the rates of reporting cases more for cases that were less likely to be substantiated.

Figure VII, panel (b), and Table VI, Column (4) through (6) show the overall effect of the recession on substantiated cases. The dependent variable is substantiated cases per child. There is not a statistically significant relationship between substantiated cases per child and the economic downturn. In other words, the recession caused a significant decrease in referred and investigated cases of maltreatment. However, since the unreported cases were less likely to be substantiated, it did not cause as large a decrease in substantiated cases of maltreatment.

Even if the substantiation process were perfect, comparing the results on substantiated cases to the results on Google searches and mortality still suggests that the recession decreased the percentage of actual maltreatment cases that were substantiated. The effect of the recession on substantiated cases is slightly negative, while the effects of the recession on child mortality and Google fatalities is always positive. Also note that calculating the welfare effects of the recession on child maltreatment would have to consider changes in referral and investigation rates, not just changes in substantiation rates. Unsubstantiated cases still received an investigation and may also be given resources.

In sum, the substantiated rate lends further support to the economic downturn decreasing reported rates of maltreatment. The substantiated rate fails to accurately pick up the positive relationship between economic distress and increased maltreatment.

III.D.2 High-Frequency Google and Unemployment Claims Data

Section III.C uses Google data to argue that bad economic conditions during the Great Recession increased child maltreatment. I show that states most affected by the downturn saw the largest increases in searches suspecting child maltreatment.

However, this methodology appears to not fully take advantage of the Google data in understanding the relationship between unemployment and child maltreatment. The Google data can be obtained over a high frequency. They deliver potentially the only meaningful weekly measure of maltreatment incidents.

This allows for an additional test of the effects of unemployment on maltreatment. We can compare the maltreatment proxy to weekly unemployment claims data.[8]

Figure VIII shows the second Google maltreatment proxy, $Google\ Maltreatment\ (Victim)$, through time, for the United States. On the same graph are total weekly unemployment claims in the United States. Both measured are in natural logs and normalized to lie between 0 and 1, for comparison.

Visually inspecting the graph seems to show a relationship. Both were decreasing in the beginning of this time period. However, they both change direction at roughly the same time.

Table IV tries to test for a relationship at a high-frequency level. The dependent variable in each regression is the change, compared to the previous week, in $ln(Google\ Maltreatment\ (Victim))$, in the United States. The independent variable is the change, compared to the previous week, in the natural log of total unemployment claims in the United States.

All regressions also include a once-lagged value of both the dependent and independent variable. Column (1) shows a positive correlation. Column (2) and (3) show that the relationship increases upon increasing more lags of the dependent and independent variables.

[8] As mentioned in Section III.B.2, I could not think of an obvious salient search for these searches that are likely by victims, which is the usual constraint on data-mining. It does not seem that the particular choices are driving the results. Visually inspecting individual searches almost always yields similar changes in trends around the time the Great Recession started.

Columns (4), (5), and (6) show that the relationship stays roughly the same, or is slightly larger, including fixed effects for month of year, week of year, and year. These variables are calculated using the Sunday of a given week.

As mentioned in , while I did have discretion

The evidence of Table IV does suggest that the more people collecting unemployment claims in a given week, the more victims of child maltreatment.[9]

Since the variables of the Table IV are in natural logs, the coefficients are not immediately comparable to those from previous regressions. However, back-of-the-envelope comparisons can be obtained. The coefficients mean that a 100% increase in unemployment claims (doubling) unemployment is associated with between a 114% and 181% increase in child maltreatment searches, which I assume is a proxy for victims.

I estimated earlier that a doubling of the unemployment rate during the Great Recession increased maltreatment incidents by 10% to 24% percent during the Great Recession.

Thus, the estimates from the high-frequency analysis using the victim-specific Google proxy are substantially higher. One possibility is that the effects of unemployment are more concentrated around changes in unemployment. Children might be particularly vulnerable when individuals have just lost their job and particularly safe when an individual has just obtained a new job. This explanation would also explain why the coefficient seems to rise including more lagged variables in the analysis. Even so, the estimates with the high-frequency analysis do appear unreasonably large. The size of this relationship warrants further exploration and understanding.

III.E The Effects of State and Local Spending on the Reporting Rate of Maltreatment

A reason for the decreased reporting rates of maltreatment may be decreases in resources for government agencies brought about by the recession. Figure IX shows, not surprisingly, that areas most exposed to the recent economic downturn saw relative cuts in government spending. The relationship was particularly strong in education.

Unfortunately, it was difficult to test the effects of government cuts on reporting rates using the same empirical strategy earlier. This is due to the combination of the limited number of observations and high collinearity between exposure to the downturn and budget cuts. Including both change in unemployment rate and change in spending, the coefficients on both depend upon specification choice and do not prove robust.

Table VIII offers some suggestive evidence, from before the recession, that both of the channels discussed influence reporting rates. As shown in Table II and discussed earlier, Roughly 16 percent of total reports of maltreatment come from educators. Columns (1) compares the percent of total maltreatment reports that originate from educators to a state's spending per pupil on education. The more resources devoted to education, the higher the

[9]Interestingly, and somewhat surprisingly, when dividing total claims into initial unemployment claims and continued claims, there it not a statistically significant relationship with initial claims. The relationship is entirely driven by continued claims.

fraction of maltreatment reports that originate from educators. Column (2) shows that the effect is, if anything, slightly larger upon adding controls, including for overall state and local spending per capita. In other words, spending more money on educators leads to more referrals from educators.[10] Thus, we might expect that cutting funds from educators – as was done in areas most affected by the recession – would lead to fewer referrals.

Column (3) compares a state's referral rate to its public spending per capita, controlling for its Google maltreatment proxy. Public spending per capita, here, is a rough proxy for resources to a number of organizations related to children. Controlling for the Google searches – a proxy for actual maltreatment – the more a state spends on public welfare, the more referrals. The implied elasticity is large, with each additional 1 % of spending on public welfare leading to .35% additional referrals. Columns (4) shows that the effect is higher with a broad set of controls, including overall government spending, suggesting that omitted variables may bias the effect towards zero. The estimated reductions in reporting rates from the recession are greater than would be predicted by the cross-sectional correlations between spending and reporting rates.

IV Conclusion

This paper tests what happens in a large recession to child maltreatment and child maltreatment reporting. The evidence suggests that actual child maltreatment goes up; reports of maltreatment go sharply down; and overall assistance to maltreated children (substantiated cases) stays about the same.

The paper also suggests that official data on reported maltreatment can lead to misleading conclusions on the effects of the recent recession on actual maltreatment.

Some of the evidence in this paper uses Google searches to proxy child maltreatment. Google data should be considered by scholars studying this very important topic. Using Google searches to proxy domestic violence and crime more generally also seems promising.

When using Google search data to study crime, scholars should test for alternative explanations for changing search trends, such as changing media attention. And Google data can most fruitfully be used when combined with other data sources. If both Google searches and an extreme, always reported outcome show similar trends, this is more convincing evidence than either data point alone can provide.

Ultimately, all data related to crimes may be biased; some uncertainty will always remain; and the more sources that can be gathered – including Google searches – the better the chance of understanding potentially complex stories of how crime and crime reporting change.

[10] Of course, this does not test for any general equilibrium effect. It is not known whether the additional referrals from educators were for cases that would have been referred by others, had they not been referred by educators.

Table I
Child Maltreatment

Maltreatment	*Annual Incidents*
Google Searches for “child abuse” or “child neglect”	$\approx$ 8.4 million
Referrals to agencies	$\approx$ 3.3 million
Responses by agencies	$\approx$ 2 million
Substantiated incidents	436,321
Child mortalities from neglect	1,560

Notes: According to Google AdWords, on 3/22/12, there were an average of 673,000 monthly searches in the United States, on desktops and laptops, including the phrase “child abuse.” There were 27,100 including ”child neglect.” Multiplying by 12 and adding yields the estimate. Other estimates are from Child Maltreatment 2010.

Table II
Sources of Maltreatment Reports, 2010

Report Source	*Percent*
PROFESSIONAL	**58.6**
Child Daycare Providers	0.7
Educational Personnel	16.4
Foster Care Providers	0.5
Legal and Law Enforcement Personnel	16.7
Medical Personnel	8.2
Mental Health Personnel	4.6
Social Services Personnel	11.5
NONPROFESSIONAL	**27.7**
Alleged Perpetrators	0.0
Alleged Victims	0.4
Anonymous Sources	9.0
Friends and Neighbors	4.4
Other Relatives	7.0
Parents	6.8
OTHER AND UNKNOWN	**13.7**
Other	7.9
Unknown	5.8

Notes: Source: *Child Maltreatment 2010 (2011).*

Table III
Reported Cases of Child Maltreatment and Severity of Recession

	Δ ln(Referral Rate)			Δ ln(Response Rate)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Unemployment Rate	-0.033**	-0.022*	-0.034**	-0.032**	-0.033*	-0.027*
	(0.014)	(0.012)	(0.014)	(0.015)	(0.017)	(0.015)
Δ % Hispanic		-0.022			-0.041	
		(0.054)			(0.071)	
Δ % Black		-0.076**			-0.107**	
		(0.030)			(0.040)	
Δ % Age 0-4		0.097			-0.148	
		(0.247)			(0.223)	
% Hispanic			0.000			-0.002
			(0.002)			(0.002)
% Black			0.001			0.000
			(0.003)			(0.003)
% College			0.004			0.009*
			(0.003)			(0.005)
Adjusted R-squared	0.07	0.08	0.01	0.04	0.09	0.05
Observations	36	36	36	46	46	46

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Robust standard errors are in parentheses. Δ variables represent the average, for 2010 and 2009, minus the average, for 2006 and 2007. Referral Rate and Response Rate are from the Children's Bureau Child Maltreatment Annual Reports. Unemployment Rate is from the Bureau of Labor Statistics. Demographics variables are from the Current Population Survey.

Table IV
Top Searches for Google Proxy

Top searches for 'child abuse+child neglect'
child abuse neglect
child abuse statistics
child abuse prevention
about child abuse
child abuse report
child abuse reporting
child services
child sexual abuse
sexual abuse
child abuse services

Notes: These show the 'top searches' for "child abuse+child neglect," 2004-present. It is downloaded on 11/27/2012. Results would be similar regardless of time period selected. Depending on the draw, the 'top searches' might be slightly different. Top searches, according to Google, 'are related to the term,' as determined 'by examining searches that have been conducted by a large group of users preceding the search term you've entered, as well as after,' as well as by automatic categorization.

Table V
Child Maltreatment and Severity of Recession

	Δ (Fatality Rate)			Δ ln(Google Maltreatment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Unemployment Rate	0.121*	0.110	0.111	0.025***	0.035***	0.022**
	(0.070)	(0.104)	(0.075)	(0.008)	(0.008)	(0.008)
Δ % Hispanic		0.034			0.030	
		(0.399)			(0.027)	
Δ % Black		-0.401***			-0.039***	
		(0.145)			(0.014)	
Δ % Age 0-4		-0.256			0.187**	
		(0.921)			(0.078)	
% Hispanic			0.003			0.000
			(0.008)			(0.001)
% Black			0.010			0.002*
			(0.009)			(0.001)
% College			0.057**			-0.001
			(0.023)			(0.002)
Adjusted R-squared	0.03	0.06	0.20	0.17	0.26	0.16
Observations	43	43	43	47	47	47

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Robust standard errors are in parentheses. Δ variables represent the average, for 2010 and 2009, minus the average, for 2006 and 2007. Fatality Rate is from the Children's Bureau Child Maltreatment Annual Reports. Unemployment Rate is from the Bureau of Labor Statistics. Demographics variables are from the Current Population Survey.

Table VI

Substantiated Cases and Severity of Recession

	Δ % Substantiate			Δ ln(Substantiated Rate)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Unemployment Rate	0.599**	0.139	0.336	0.001	-0.023	-0.010
	(0.254)	(0.317)	(0.254)	(0.017)	(0.022)	(0.021)
Δ % Hispanic		1.824			0.019	
		(1.362)			(0.085)	
Δ % Black		0.488			-0.084***	
		(0.403)			(0.028)	
Δ % Age 0-4		-3.381			-0.392*	
		(3.963)			(0.207)	
% Hispanic			0.084*			0.004*
			(0.043)			(0.002)
% Black			0.035			0.002
			(0.045)			(0.003)
% College			-0.038			0.008
			(0.100)			(0.006)
Adjusted R-squared	0.05	0.06	0.04	-0.02	0.00	-0.01
Observations	46	46	46	46	46	46

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Robust standard errors are in parentheses. Δ variables represent the average, for 2010 and 2009, minus the average, for 2006 and 2007. Percent Substantiated and Substantiated Rate are from the Children's Bureau Child Maltreatment Annual Reports. Unemployment Rate is from the Bureau of Labor Statistics. Demographics variables are from the Current Population Survey.

Table VII
Weekly Google Maltreatment (Victim) and Unemployment Claims

		Δ ln(Google Maltreatment (Victim))				
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ln(Unemployment Claims)	1.135*	1.280**	1.421**	1.392	1.672*	1.809**
	(0.610)	(0.552)	(0.558)	(1.023)	(0.952)	(0.915)
Adjusted R-squared	0.24	0.32	0.34	0.26	0.33	0.36
Observations	469	465	461	469	465	461
Lags	1	3	5	1	3	5
Year FE	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	Yes	Yes	Yes
Week FE	No	No	No	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Data are weekly, for the United States, beginning in 2004 through the week of March 10, 2013. The Google weekly data is from Sunday through Saturday. Unemployment claims data are from Monday through Friday. Δ variables represent changes compared to the previous week. Google Maltreatment (Victims) is as defined in Equation 6. It is the percent of Google searches that include "dad hit(s) me", "dad beat(s) me", "mom hit(s) me", or "mom beat(s) me." Unemployment Claims are total unemployment claims – continuing plus initial – for the United States, downloaded at FRED. Lags represent number of lagged variables included in the regressions. Lagged values of both the independent and dependent variable are included. Year, month, and week-of-the-year fixed effects are all based on the Sunday of a given week.

Table VIII

Government Spending and Reports of Maltreatment, Pre-Recession

	Pct Referrals from Educators		ln(Referral Rate)	
	(1)	(2)	(3)	(4)
ln(Education Spending Per Pupil)	0.061**	0.096***		
	(0.026)	(0.034)		
Expenditure Per Capita		-0.068*		-0.150
		(0.036)		(0.272)
% Hispanic		0.000		-0.005
		(0.000)		(0.005)
% Black		-0.000		-0.015***
		(0.000)		(0.004)
% College		0.001		0.014
		(0.001)		(0.010)
ln(Google Maltreatment)			0.689***	0.641**
			(0.221)	(0.273)
ln(Public Spending Per Capita)			0.370**	0.447**
			(0.142)	(0.194)
Adjusted R-squared	0.10	0.09	0.19	0.39
Observations	47	47	36	36

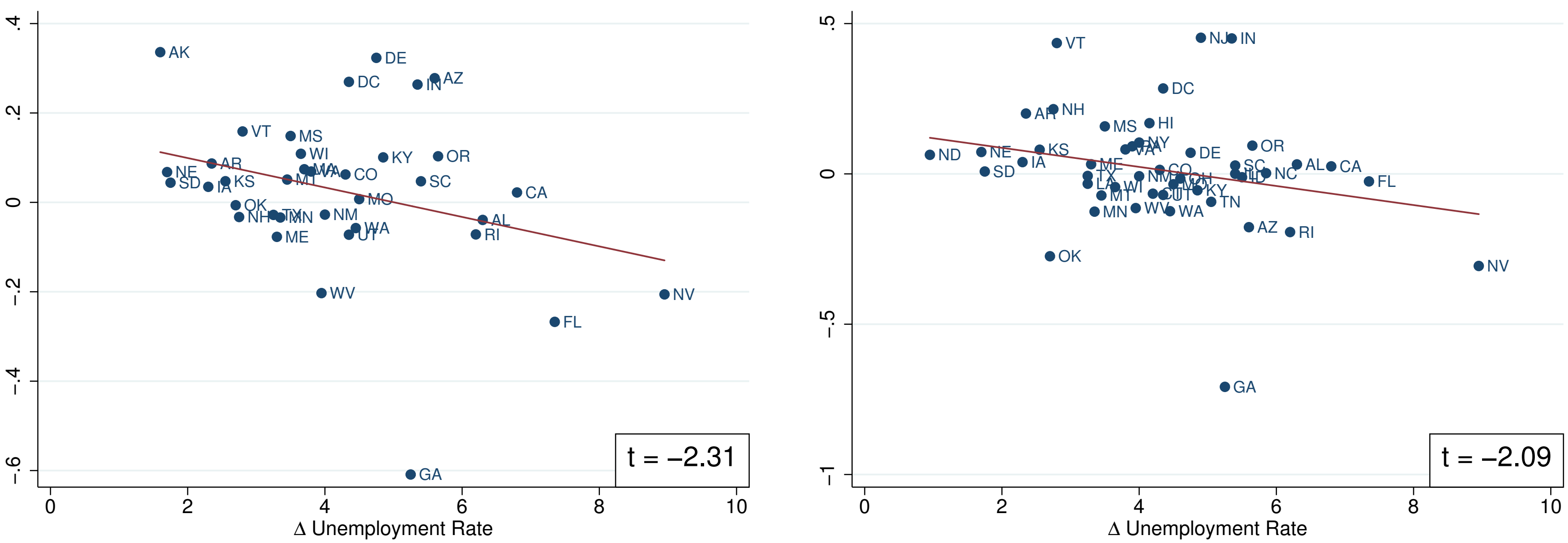
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Robust standard errors are in parentheses. All variables are averages, for the years 2006 and 2007. The dependent variables in Columns (1) and (2) is the average percent referrals that come from educators, from the National Data Archive on Child Abuse and Neglect. The dependent variable in Columns (3) and (4) is the natural log of maltreatment referrals per child, from the Children's Bureau annual child maltreatment reports. Education spending per pupil is from the Census Bureau's Public Education Finances. Child welfare spending is from the Casey Child Welfare Financing Survey. Demographics variables are from the Current Population Survey. Google Maltreatment is as defined in Equation 5, from Google Trends.

Figure I

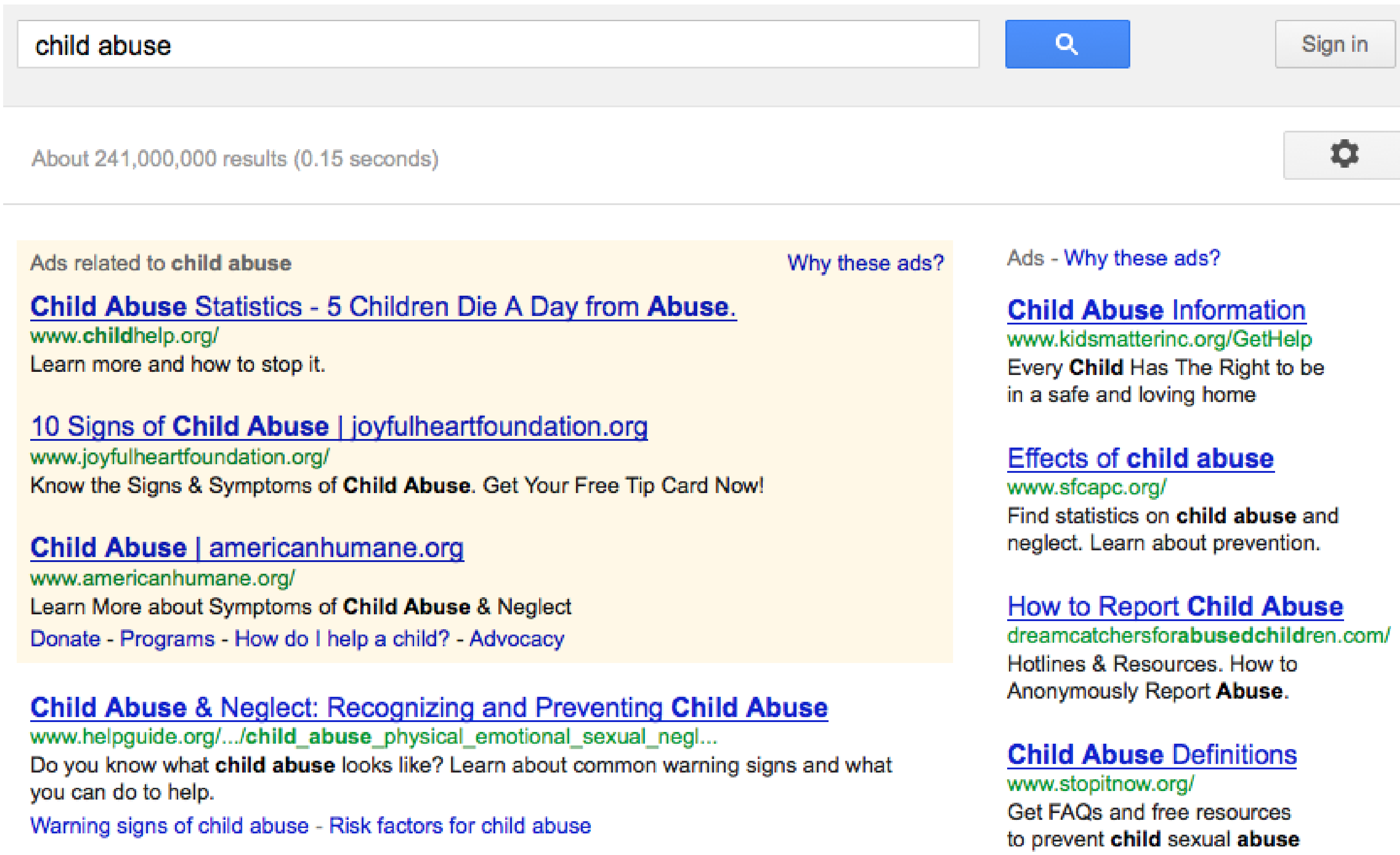
Severity of Recession and Change in Reported Maltreatment

(a) Δ ln(Referral Rate) *(b) Δ ln(Response Rate)*



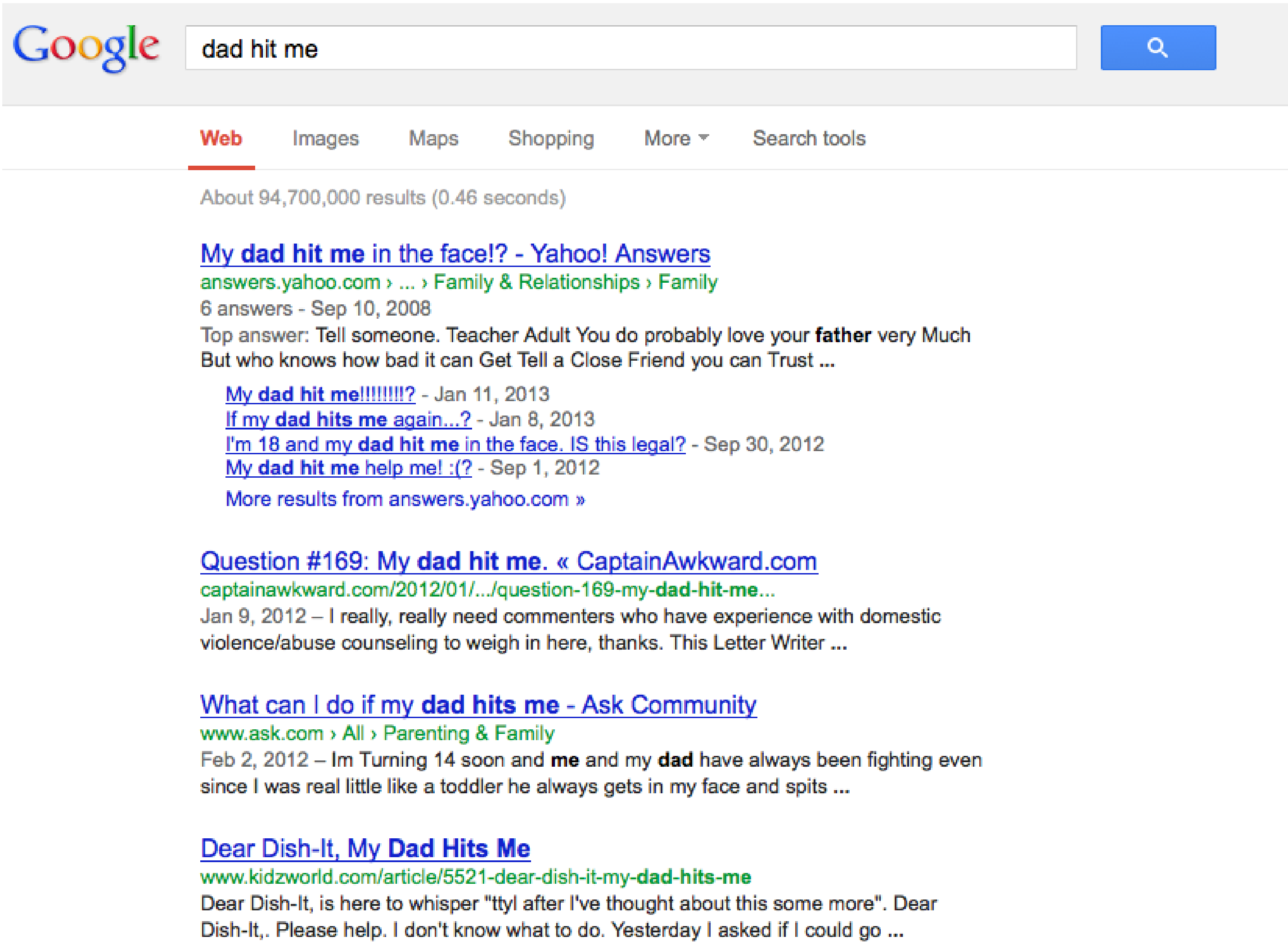
Notes: This figure shows the relationship between change in unemployment and change in two proxies for child maltreatment. Changes for all variables are the difference between the 2009-2010 average value and the 2006-2007 average value. The referral rate is referrals per child, from *Child Maltreatment*. The response rate is responses per child, from *Child Maltreatment*.

Figure II
Search for “child abuse”



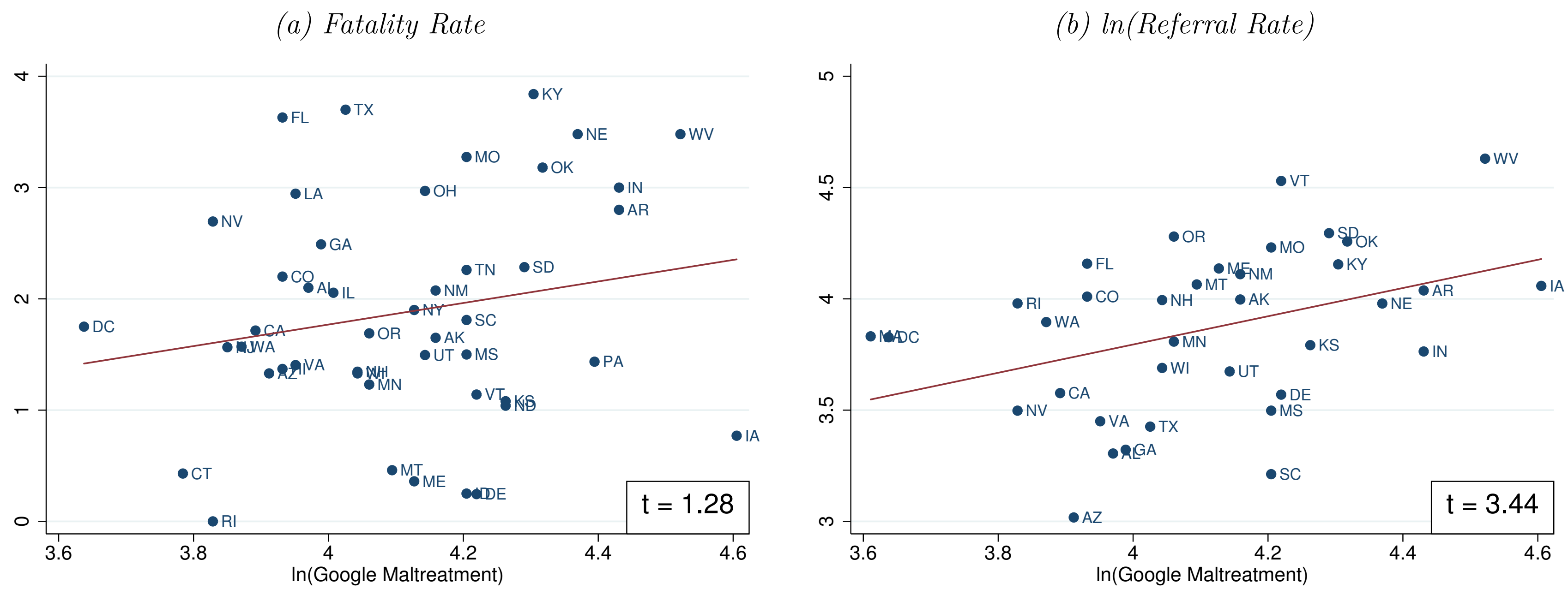
Notes: This shows the returns for a search of “child abuse” on 9/3/2012.

Figure III
Search for "dad hit me"



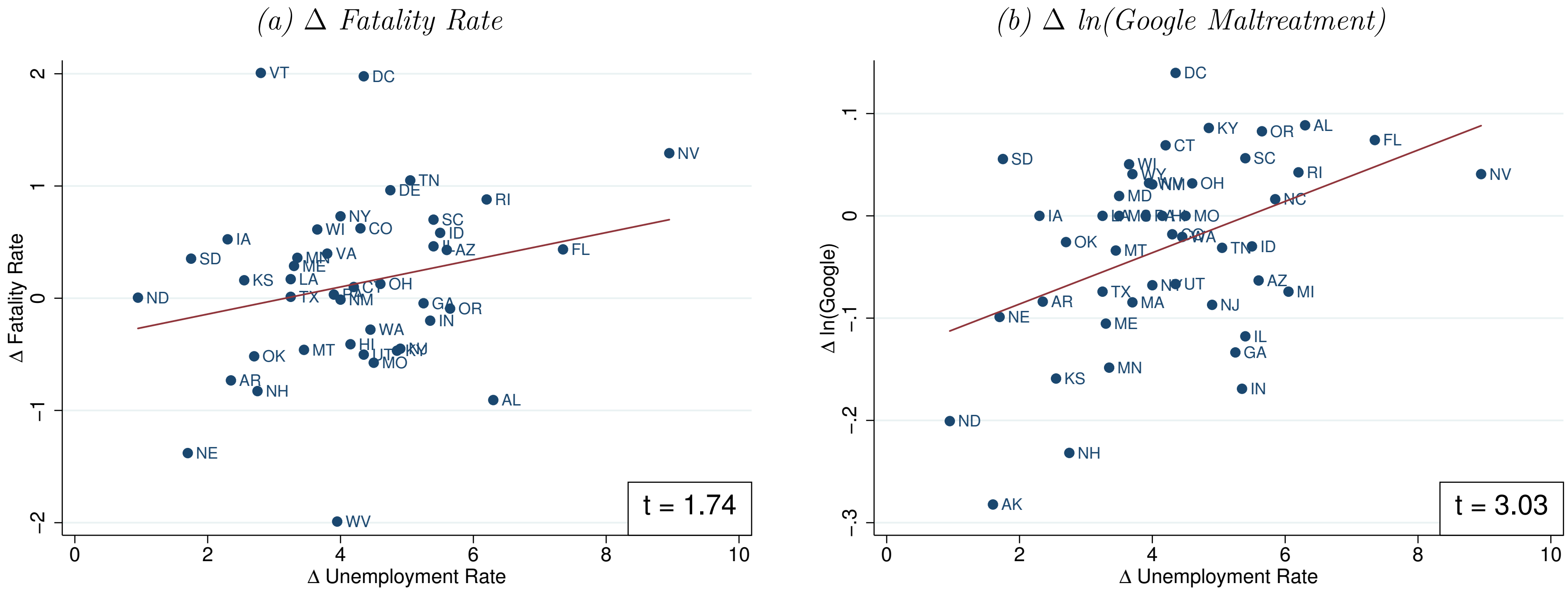
Notes: This shows the returns for a search of "dad hit me" on 1/11/2013.

Figure IV
Google Maltreatment and Other Proxies, Pre-Recession



Notes: All variables are averaged for 2006 and 2007. Fatality rate is fatalities per 100,000 children, from *Child Maltreatment*. Referral rate is referrals per child, from *Child Maltreatment*. Google Maltreatment is the percent of Google that searches include "child abuse" or "child neglect," from Google Trends.

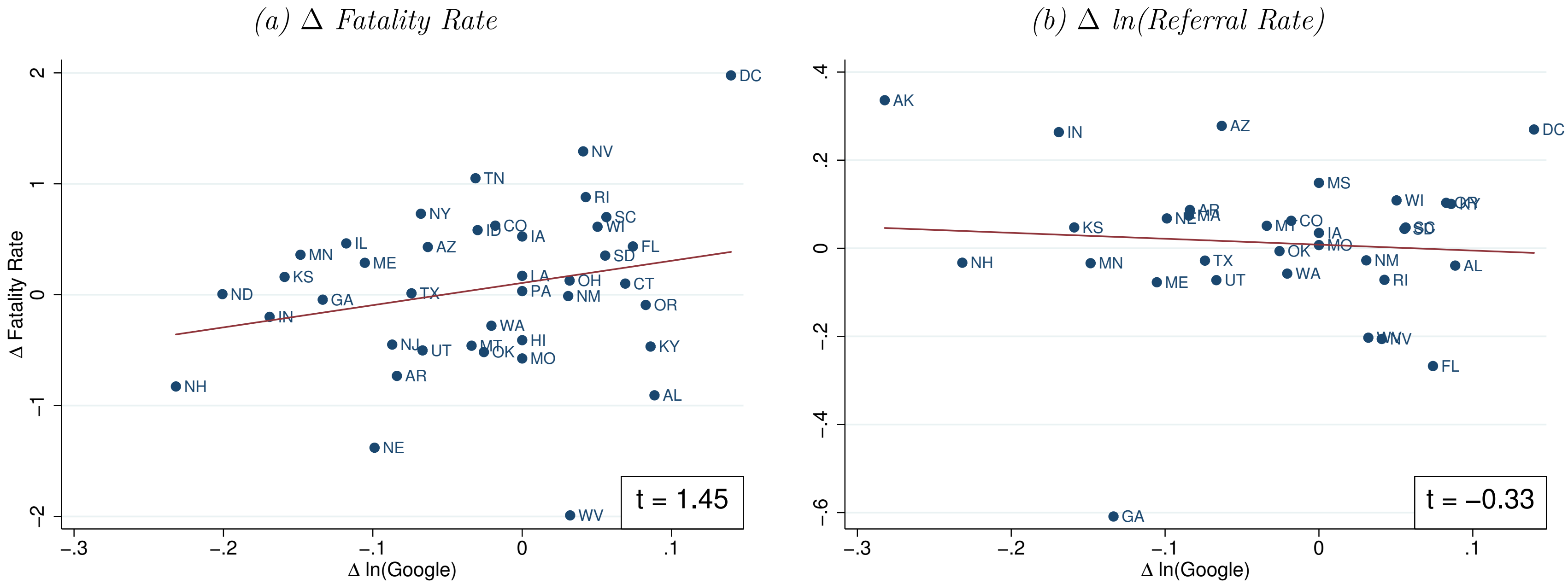
Figure V
Severity of Recession and Change in Actual Maltreatment



Notes: Δ variables represent the average, for 2010 and 2009, minus the average, for 2006 and 2007. Unemployment Rate is from the Bureau of Labor Statistics. Fatality Rate is from the Children's Bureau Child Maltreatment Annual Reports. Google Maltreatment is as defined in Equation 5, from Google Trends.

Figure VI

Changes in Google Maltreatment and Changes in Other Proxies

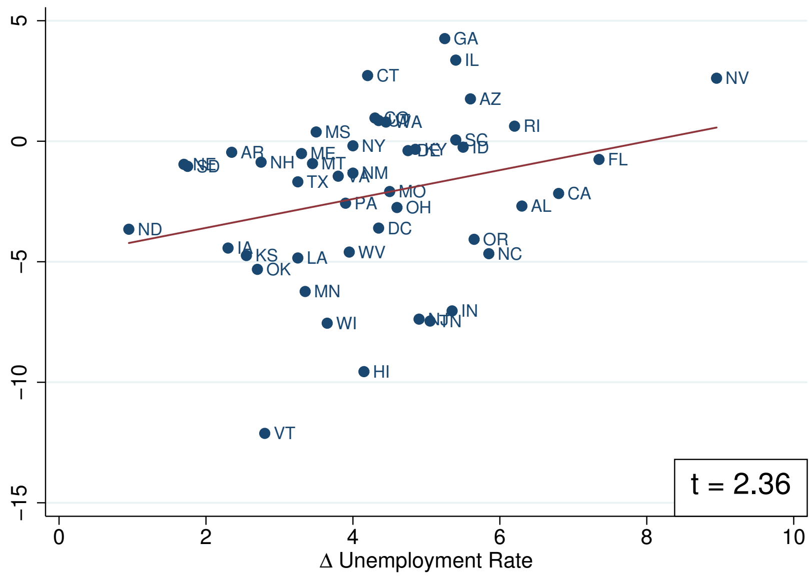


Notes: Robust standard errors are in parentheses. Δ variables represent the average, for 2010 and 2009, minus the average, for 2006 and 2007. Fatality Rate, Referral Rate, and Response Rate are from the Children's Bureau Child Maltreatment Annual Reports. Google Maltreatment is as defined in Equation 5, from Google Trends.

Figure VII

Severity of Recession and Change in Substantiated Cases

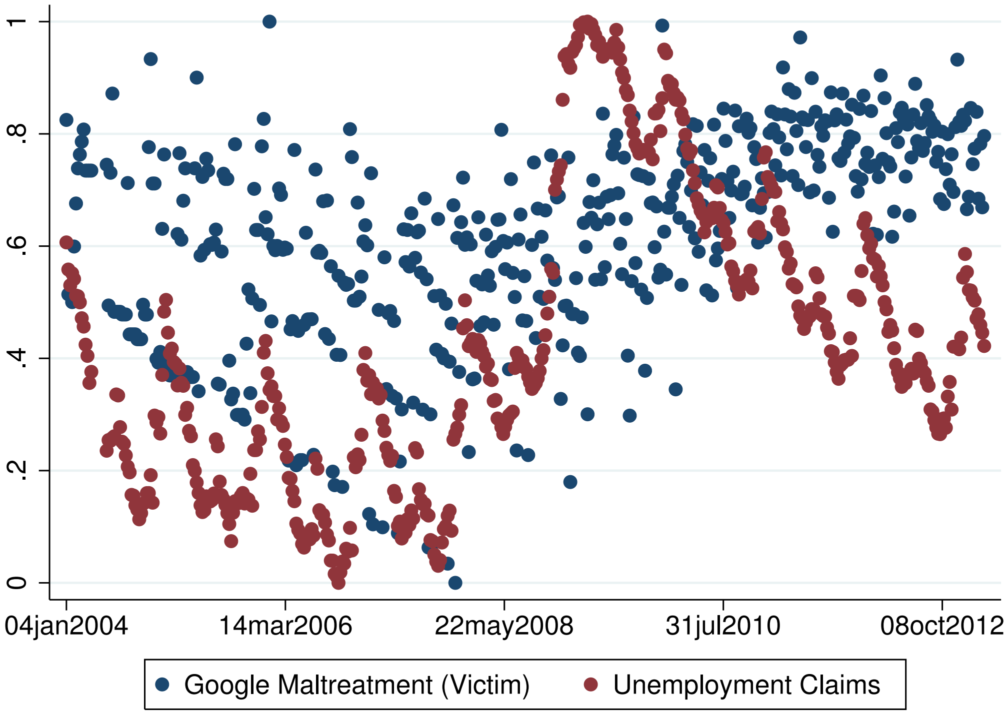
(a) Δ % Substantiated



(b) Δ ln(Substantiated Rate)

Notes: Δ variables represent the average, for 2010 and 2009, minus the average, for 2006 and 2007. Unemployment Rate is from the Bureau of Labor Statistics. Percent Substantiated and Substantiated Rate are from the Children's Bureau Child Maltreatment Annual Reports.

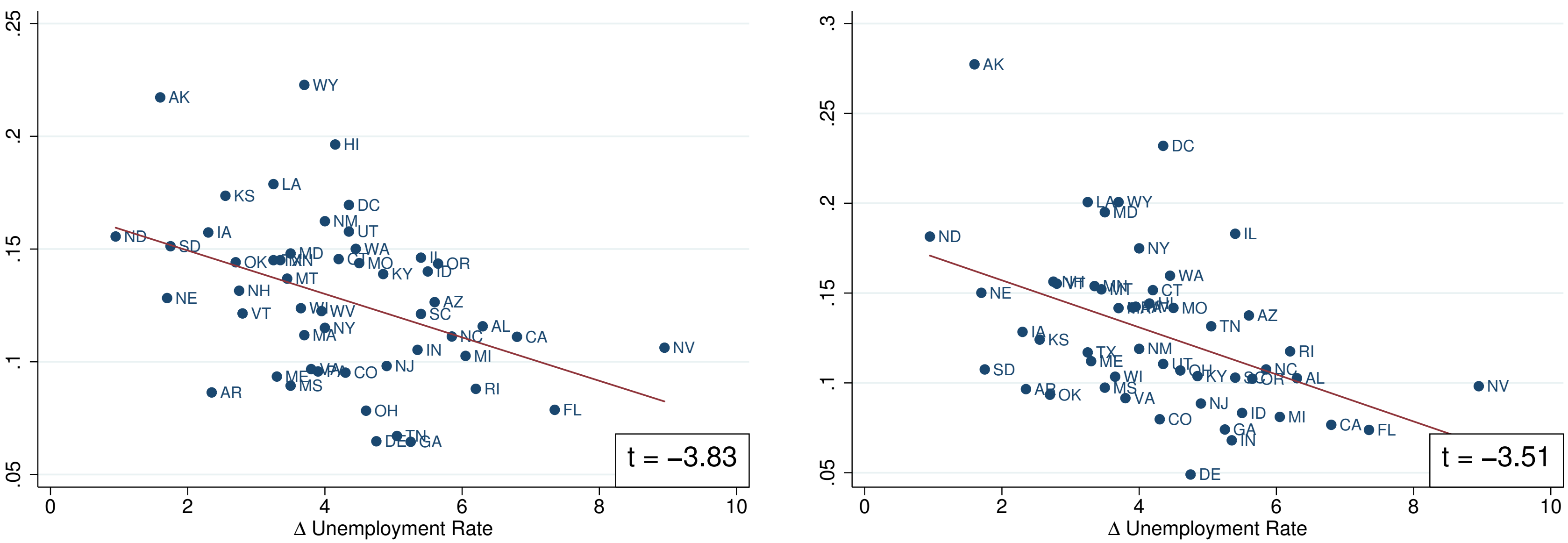
Figure VIII
Unemployment Claims and Google Maltreatment (Victim), Weekly in United States



Notes: Data are weekly, for the United States, beginning in 2004 through the week of March 10, 2013. The Google weekly data is from Sunday through Saturday. Unemployment claims data are from Monday through Friday. Google Maltreatment (Victims) is as defined in Equation 6. It is the percent of Google searches that include "dad hit(s) me", "dad beat(s) me", "mom hit(s) me", or "mom beat(s) me." Unemployment Claims are total unemployment claims – continuing plus initial – for the United States, downloaded at FRED. Both variables are shown, after taking the natural log, and scaling to lie between 0 and 1.

Figure IX
Severity of Recession and Budget Cuts

(a) Δ ln(Government Spending per Capita) *(b) Δ ln(Education Spending per Pupil)*



Notes: Changes for all variables are the difference between the 2009-2010 average value and the 2006-2007 average value. Government Spending Per Capita and Education Spending per Pupil are from Census Survey of State and Local Governments.

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