

**Meta-Evaluation of
“Do State TANF Policies Affect Child Abuse and Neglect?”**

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Introduction

In 2016, University of Kansas researchers Donna Ginther and Michelle Johnson-Motoyama (hereinafter, “the authors”) commenced a research project to investigate the effects of state TANF policies on child maltreatment and foster care placements.¹ The authors assert that state TANF restrictions are associated with increases in child maltreatment and foster care placements. Further, they assert that Kansas, in particular, imposed more restrictions on TANF benefits causing caseloads to decline sharply starting in 2011, which resulted in significant increases in child abuse and foster care placements. Even though the authors describe their findings as preliminary, they have received widespread attention.

Given the importance and implications of these findings on the relationship of the safety net and child welfare, the Kansas Department for Children and Families has requested that we assess their study and the degree to which it supports the publicized findings. To do so, we decided to conduct a “meta-evaluation” of the authors’ study. Although the term is sometimes misapplied, a meta-evaluation is generally defined as “the process of delineating, obtaining, and applying descriptive information and judgmental information—about the utility, feasibility, propriety, and accuracy of an evaluation and its systematic nature, competent conduct, integrity/honesty, respectfulness, and social responsibility.”² A number of US government offices prepare meta-evaluations. For example, the Department of Education’s “What Works Clearinghouse” prepares and posts evaluations of education interventions, called “Reviews of Individual Studies.”³

In this report, we use a modified form of the approach laid out by Douglas Besharov, Peter Germanis, and Peter Rossi in their monograph *Evaluating Welfare Reform*, which includes an examination of the program theory, research design, implementation, data collection, measurement instruments, analytical models, and the researchers’ interpretation of findings.⁴ Our analysis addresses each of these areas and is divided into eight sections: (1) the limitations of this

¹US Department of Health and Human Services, National Institutes of Health, “Project Information: Exploring the Causal Impacts of Economic and Social Safety Net Policies on Child Neglect in the US: Implications for Primary Prevention,” https://projectreporter.nih.gov/project_info_description.cfm?aid=9234830&icde=32972365 (accessed November 6, 2018).

²Daniel L. Stufflebeam, “The Methodology of Metaevaluation as Reflected in Metaevaluations by the Western Michigan University Evaluation Center,” *Journal of Personnel Evaluation in Education* 14, no. 1 (2000): 95-125 quoted in Kirsten Olsen and Sheelagh O’Reilly, *Evaluation Methodologies: a Brief Review of Meta-evaluation, Systematic Review and Synthesis Evaluation Methodologies and Their Applicability to Complex Evaluations Within the Context Of International Development*, (UK: IOD PARC, 2011), https://www.iodparc.com/get_resource.html?resource_id=18 (accessed October 25, 2018).

³US Department of Education, Institute for Education Sciences, What Works Clearinghouse, “Reviews of Individual Studies,” <https://ies.ed.gov/ncee/wwc/ReviewedStudies> (accessed November 6, 2018).

⁴Douglas J. Besharov, Peter Germanis, and Peter H. Rossi, *Evaluating Welfare Reform: A Guide for Scholars and Practitioners* (College Park, MD: Welfare Reform Academy, 1997).

meta-evaluation, (2) causal hypothesis based on incomplete data and analysis, (3) research design not sufficiently described for assessment, (4) incomplete and shifting intervention variables concerning TANF and other program changes, (5) changes in child welfare policies and practices apparently not taken into account, (6) growth in substance abuse not sufficiently taken into account, (7) problematic interpretation of results, and (8) overall assessment of study. A review of the literature on key questions follows as Appendix A.

The limitations of this meta-evaluation

Ordinarily, a meta-evaluation would not be conducted until a study is completed and published, and that would be our preference. In this situation, however, it is appropriate to conduct the meta-evaluation now. The authors have shared their work widely so that it has received considerable attention in the media and among policy makers. Moreover, although they often describe their findings as “preliminary,” the context in which they are presented does not suggest that their conclusions will change:

- Presentation and paper at the 2017 APPAM Annual Fall Research Conference, stating: “These preliminary results point out the consequences of federal block grant policies that give state wide discretion in determining the extent of the social safety net. . . . Beginning with the Brownback Administration in 2011, Kansas has imposed more restrictions on TANF benefits and caseloads declined more rapidly than in the US, dropping by almost two-thirds. Our results indicate that these restrictions on the safety net have real consequences for children’s wellbeing.”⁵
- Presentation at a conference at the University of Kansas on “Childhood Poverty and the Kansas Child Welfare Crisis,” stating that: “Restrictions on TANF have a causal effect on the change in abuse victims and foster care placements.” And, that “in Kansas sanctions that remove families from TANF as well as barriers to obtaining TANF appear to increase abuse and foster care placements.”⁶
- Two separate testimonies to committees of the Kansas State Legislature (the Kansas House Standing Committee on Children and Seniors and the Kansas House Social Services Budget Committee) that contain the same text quoted in their KU presentation. “Restrictions on TANF have a causal effect on the change in abuse victims and foster

⁵Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017), 17-18, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

⁶Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (presentation, Childhood Poverty and the Kansas Child Welfare Crisis, Lawrence, KS, December 15, 2017).

care placements.” And, “In Kansas sanctions that remove families from TANF as well as barriers to obtaining TANF appear to increase abuse and foster care placements.”⁷

In addition, the authors have apparently given interviews with various media channels:

- *Lawrence Journal-World* (November 14, 2017): “During a phone interview Tuesday, Ginther said that states like Kansas that enacted such laws have seen increases in documented abuse cases and foster care case loads ranging from 12 to 23 percent.”⁸
- *KCUR* (December 15, 2017): “It’s remarkable. There is a mirror image. . . . As the Kansas TANF caseloads drop, the number of reports of abuse and neglect go up. And you see a similar relationship for foster care placements.”⁹
- *Rewire.News* (January 11, 2018): “We were interested in investigating harsh sanctions on TANF in particular and what kind of effects they had on foster care and child abuse reports for all forms of maltreatment, but specifically for neglect. . . . And as it turns out, these caseload measures are the mirror image of each other.”¹⁰
- *Kansas Association of School Boards* (January 30, 2018): “Restrictions on access to the safety net appear to have unintended [sic] and consequences with regard to human costs and costs to Kansas taxpayers.”¹¹

⁷Michelle Johnson-Motoyama, “Do Changes to the Social Safety Net Affect Child Maltreatment? A Preliminary Study of TANF” (presentation, Kansas House Standing Committee on Children and Seniors, Topeka, KS, January 30, 2018), http://www.kslegislature.org/li/b2017_18/committees/ctte_h_children_and_seniors_1/documents/testimony/20180130_01.pdf (accessed November 5, 2018).

⁸Peter Hancock, “DCF: No Link Between Welfare Reform, Rising Foster Care Numbers; Researchers Say Otherwise,” *Lawrence Journal-World*, November 14, 2017, <http://www2.ljworld.com/news/2017/nov/14/DCF-no-link-between-welfare-reform-rising-foster-c/> (accessed October 17, 2018).

⁹Madeline Fox, “KU Study Indicates Link Between Kansas Welfare Restrictions, Foster Care Case Increase,” *KCUR*, December 15, 2017, <http://www.kcur.org/post/ku-study-indicates-link-between-kansas-welfare-restrictions-foster-care-case-increase#stream/0> (accessed October 17, 2018).

¹⁰Erin Heger, “When Lawmakers Slash Assistance for Families, Foster Care Cases Increase,” *Rewire.News*, January 11, 2018, <https://rewire.news/article/2018/01/11/lawmakers-slash-assistance-families-foster-care-cases-increase/> (accessed October 17, 2018).

¹¹“Impact of Kansas welfare reforms on children discussed,” *Kansas Association of School Boards*, January 30, 2018, <https://kasb.org/0130-3/> (accessed October 17, 2018).

- *KCUR* (November 2, 2018): “‘We’re talking about children’s lives,’ Ginther said. ‘We have evidence that (Kansas’ welfare) policy is putting children at risk ... so you inform the policymakers who are in a position to make a decision.’”¹²

Similar information was further disseminated via other news outlets, which generally reported on earlier articles such as the *KCUR* story or about one of the author’s testimony without direct comment from the authors.¹³

In addition to these news stories, the authors’ study was cited by the Kansas Child Welfare System Task Force in formulating its recommendations in the Working Groups Report that was submitted in July: “Professor Donna K. Ginther at the University of Kansas reported preliminary findings that restrictive TANF policies in Kansas since 2011 appear to have increased abuse or neglect.” Their study was cited in support of the Task Force’s recommendation that “the State of Kansas and Legislature shall lift restrictions on Temporary Assistance for Needy Families (TANF).”¹⁴

Given the uses to which the authors’ work is being put, even in the absence of a “final” paper, we decided that a meta-evaluation was appropriate. However, respecting the incomplete public record about the study, including the data and analytic methods used, we wrote to the authors requesting any other versions of their paper or analysis.

Unfortunately, they refused, writing that “the document to which you are referring is in draft form. We are currently continuing our analyses as we prepare the manuscript for a peer

¹²Madeline Fox, “Kansas Shops For Second Opinion On Welfare Reform’s Impact On Foster Care Load,” *KCUR*, November 2, 2018, <http://www.kcur.org/post/kansas-shops-second-opinion-welfare-reforms-impact-foster-care-load#stream/0> (accessed November 5, 2018).

¹³See, for example, Shawn Fremstad, “Budget Cuts are Putting More Kids in Foster Care,” *Center for American Progress*, February 23, 2018, <https://talkpoverty.org/2018/02/23/budget-cuts-putting-kids-foster-care/> (accessed November 12, 2018); Sarah K. Burris, “Study Finds After Kansas Cut Funding to Temporary Assistance to Need Families—Child Abuse and Neglect Cases Increased,” *Raw Story Media*, December 15, 2017, <https://www.rawstory.com/2017/12/study-finds-after-kansas-cut-funding-to-temporary-assistance-for-needy-families-child-abuse-and-neglect-cases-increased/> (accessed November 12, 2018); and Joel Mathis, “The Moral Case for Welfare,” *606* (blog), December 18, 2017, <https://sixoh6.com/2017/12/18/the-moral-case-for-welfare/> (accessed November 12, 2018). <https://talkpoverty.org/2018/02/23/budget-cuts-putting-kids-foster-care/>, <https://www.rawstory.com/2017/12/study-finds-after-kansas-cut-funding-to-temporary-assistance-for-needy-families-child-abuse-and-neglect-cases-increased/>, and <https://sixoh6.com/2017/12/18/the-moral-case-for-welfare/>.

¹⁴Kansas Department for Children and Families, Child Welfare Systems Working Group, “Report to the Child Welfare System Task Force,” (Topeka, KS: Kansas Department for Children and Families, 2018) http://www.dcf.ks.gov/Agency/CWSTF/Documents/CWSTF%20Docs/CWSTF_Report_2018.08.01.pdf (accessed October 16, 2018).

review publication.”¹⁵ We wrote a second time asking that they reconsider, but, as of this writing, they have not responded except to tell a reporter that they were “stunned” by our request.¹⁶

Thus, by necessity, this meta-evaluation is based on only those materials that the authors have made public, that is:

- a presentation and a paper at the 2017 APPAM Annual Fall Research Conference;¹⁷
- a presentation at a conference at the University of Kansas on “Childhood Poverty and the Kansas Child Welfare Crisis”,¹⁸
- a presentation to the Kansas House Standing Committee on Children and Seniors;¹⁹ and
- a presentation to the Kansas House Social Services Budget Committee.²⁰

As the following discussion indicates, in many places we have had to deduce what the authors have done because of the sketchy public record. In addition, it appears that they have made various changes in their analysis since they first started sharing their findings, and may be making more. Where appropriate, we have indicated when the lack of assistance from the authors limits our assessment, and that an explanation of why they did something might assuage our concerns.

¹⁵Email message from Michelle Johnson-Motoyama to Douglas Besharov, October 10, 2018.

¹⁶Madeline Fox, “Kansas Shops For Second Opinion On Welfare Reform’s Impact On Foster Care Load,” *KCUR*, November 2, 2018, <http://www.kcur.org/post/kansas-shops-second-opinion-welfare-reforms-impact-foster-care-load#stream/0> (accessed November 5, 2018).

¹⁷Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 17-18, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

¹⁸Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (presentation, Childhood Poverty and the Kansas Child Welfare Crisis, Lawrence, KS, December 15, 2017).

¹⁹Michelle Johnson-Motoyama, “Do Changes to the Social Safety Net Affect Child Maltreatment? A Preliminary Study of TANF” (presentation, Kansas House Standing Committee on Children and Seniors, Topeka, KS, January 30, 2018), http://www.kslegislature.org/li/b2017_18/committees/ctte_h_children_and_seniors_1/documents/testimony/20180130_01.pdf (accessed November 5, 2018).

²⁰Michelle Johnson-Motoyama, “Do TANF Policy Changes Affect Child Maltreatment? Findings from Kansas,” (presentation, Kansas House Social Services Budget Committee, Topeka, KS, March 13, 2018).

Although our meta-evaluation is somewhat incomplete in the absence of cooperation from the authors, we hope that our analysis will provide an outside review that will help policy makers to understand their findings. If their preliminary results seem supported by the information they have made public, the field should know that. If, however, it appears that what they have made public does not support those results, then that, too, should be known so that the results are not relied on to make policy or programmatic changes.

Finally, this meta-evaluation only assesses the validity of this project and its findings. It should not be interpreted to apply broadly to the effects of TANF policy changes on child maltreatment and foster care placements.

Causal hypothesis based on incomplete data and analysis.

The authors' causal hypothesis is that changes in state TANF policies concerning work-related activities and behavioral requirements (what they call "restrictions") led to a decline in state TANF caseloads which in turn led to increases in child maltreatment and foster care placement. They base this hypothesis on their observation that although national "rates of child abuse and neglect remained unchanged during the Great Recession. . . several states experienced considerable increases in rates of child abuse and neglect during this time period while others experienced declines."²¹ This variation, they theorize, "may be partly explained by changes that states made in their economic and social safety net policies during this time."²² In fact, the authors state, "The link between social safety net programs and neglect is *direct*: to the extent that social assistance in the form of programs such as the Temporary Assistance to Needy Families (TANF) provide resources for basic needs, reduction in access may result in increased child neglect [emphasis added]."²³

Whatever the validity of this hypothesis, it is missing the crucial intervening factors or changed conditions ("variables") that connect the change in welfare policies to increases in child maltreatment: (1) Did the change in policies, when taken together with other conditions in the states, actually result in a reduction in benefits to the families? and (2) What is it about the size of the actual reduction in benefits that might lead to higher rates of child maltreatment and foster care placements? We think this is a serious lacuna, because the failure to consider these factors

²¹Donna K. Ginther and Michelle Johnson-Motoyama, "Do State TANF Policies Affect Child Abuse and Neglect?" (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 4–5, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

²²Donna K. Ginther and Michelle Johnson-Motoyama, "Do State TANF Policies Affect Child Abuse and Neglect?" (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 5, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

²³Donna K. Ginther and Michelle Johnson-Motoyama, "Do State TANF Policies Affect Child Abuse and Neglect?" (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 4, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

removes an important constraint in the analysis and its interpretation. (We address the first question below; the literature review in the appendix addresses the second question.)

Selective portrayal of different possible correlations of TANF caseloads, and child maltreatment and foster care placements. Based on our review of the authors' paper and presentations, it appears that their hypothesis is at least partly based on Kansas trend lines for the number of families receiving TANF and the number of reports of all forms of child maltreatment²⁴ (hereinafter, "child maltreatment reports") and foster care placements—which suggest a strong inverse relationship.²⁵ In an interview with KCUR, one of the authors called the relationship "remarkable . . . a mirror image."²⁶ "As the Kansas TANF caseloads drop, the number of reports of abuse and neglect go up. And you see a similar relationship for foster care placements."²⁷

After identifying this perceived relationship in Kansas, the authors attempt to apply the relationship to the national level in their APPAM paper. They do so with two figures: Their figure 2 depicts the decline in the number of families receiving TANF between 1990 and 2014 and their figure 3 compares the national trend in the number of families receiving TANF to that

²⁴From our reading of the authors' APPAM paper, they include all "reported incidents of child abuse and neglect" in their definition of child maltreatment reports which, according to the National Child Abuse and Neglect Data System (NCANDS) codebook includes "physical abuse," "neglect or deprivation of necessities," "medical neglect," "sexual abuse," and "psychological or emotional maltreatment." US Department of Health and Human Services, *National Child Abuse and Neglect Data System (NCANDS) Child File Codebook* (Washington, DC: US Department of Health and Human Services, September 2015): A-17, https://www.acf.hhs.gov/sites/default/files/cb/ncands_child_file_codebook.pdf (accessed November 16, 2018).

²⁵For their analysis, as described below, the authors use national data on child maltreatment reports and substantiated cases of abuse and neglect from the National Child Abuse and Neglect Data System [US Department of Health and Human Services, Administration for Children and Families, Children's Bureau, "About NCANDS," <https://www.acf.hhs.gov/cb/resource/about-ncands> (accessed November 7, 2018)] and national data on foster care placement from the Adoption and Foster Care Analysis and Reporting System [US Department of Health and Human Services, Administration for Children and Families, Children's Bureau, "About AFCARS," <https://www.acf.hhs.gov/cb/resource/about-afcars> (accessed November 7, 2018)]. And, as described below, for TANF caseloads, the authors use data from the Center on Budget and Policy Priorities. Center on Budget and Policy Priorities, "National and State TANF to Poverty Data: 1979 to 2016," <https://www.cbpp.org/sites/default/files/atoms/files/12-13-17tanf.xlsx> (accessed October 30, 2018).

²⁶Madeline Fox, "KU Study Indicates Link Between Kansas Welfare Restrictions, Foster Care Case Increase," *KCUR*, December 15, 2017. Retrieved from <http://www.kcur.org/post/ku-study-indicates-link-between-kansas-welfare-restrictions-foster-care-case-increase#stream/0> (accessed October 17, 2018).

²⁷Madeline Fox, "KU Study Indicates Link Between Kansas Welfare Restrictions, Foster Care Case Increase," *KCUR*, December 15, 2017. Retrieved from <http://www.kcur.org/post/ku-study-indicates-link-between-kansas-welfare-restrictions-foster-care-case-increase#stream/0> (accessed October 17, 2018).

of Kansas between 1994 and 2014. The latter shows what appears to be a similar pattern of decline for both Kansas and the US as a whole.²⁸

In their presentations, the authors include two scissor graphs that depict Kansas data, comparing separately (1) the number of TANF “cases” (that is, families receiving TANF benefits)²⁹ to the number of child maltreatment reports and (2) the number of TANF “cases” to the number of foster care placements between 2000 and 2015.³⁰ Both trend lines indicate an inverse relationship that suggests that when TANF “cases” decline, both the number of child maltreatment reports and foster care placements increase. (As we describe below, there are a number of other variables—such as total cash assistance and type of maltreatment—that, by themselves, would change the shape of the trend lines.)

We tested the strength of the correlation of the authors’ first comparison of TANF families and child maltreatment reports (2000-2015) by calculating the Pearson correlation coefficient (or Pearson’s r), finding that the correlation was, indeed, strong and negative ($r = -0.85$).³¹ When the time frame is limited to the period from 2011 to 2015, corresponding to changes adopted by the Brownback Administration, the correlation is even stronger ($r = -0.96$). Given the widely documented changes to Kansas’s TANF policies that began in 2011, on its face, focusing on this time period might seem justified.

The picture becomes mixed, however, when examining the association between the number of TANF recipients who are children and the number of “substantiated” cases of child

²⁸Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017), <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

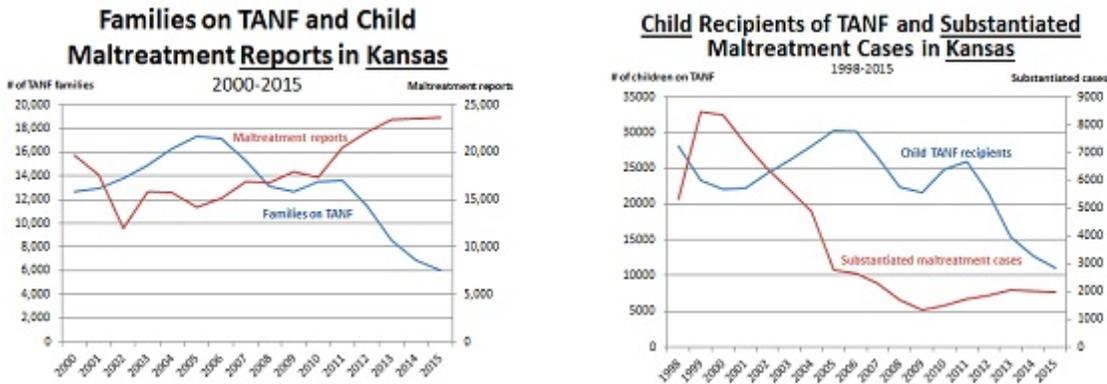
²⁹To estimate the decline in the number of families receiving TANF for both Kansas and the US, the authors use data from the Center on Budget and Policy Priorities (CBPP), not the official data published by the US Department of Health and Human Services (Administration for Children and Families). Presumably, they do so because CBPP adjusts the TANF data to include families that are receiving cash assistance in “solely state-funded programs” which are programs that are not funded through federal TANF funds and are not counted as part of a state’s maintenance-of-effort (MOE) spending requirement.

The national CBPP data, however, do not include two other categories of recipients of assistance under TANF. The first are families that receive small monthly cash grants from state programs that are counted as part of a state’s MOE requirement (and are counted in the calculation of states’ work requirements). The second are families who receive “diversion grants,” lump-sum payments to potential TANF applicants with short-term needs who are then not counted as part of the TANF caseload.

³⁰The authors do not indicate why these dates were selected; we assume that this is because the publicly available data only began in 2000.

³¹The Pearson correlation coefficient is a commonly used measure of the strength and direction of a relationship between two variables. Its values range from -1 (strong negative relationship) to 1 (strong positive relationship). A coefficient of zero indicates no correlation between the variables.

abuse and neglect (hereinafter, “substantiated cases”).³² (When examining substantiated cases, we use child TANF recipients instead of TANF families in order to compare similar units of analysis.) Again, the correlation is strong and negative when limiting the years observed to 2011 to 2015 ($r = -0.89$). When we do the same for the time frame that the authors use in their scissor graphs (2000 to 2015), however, the correlation weakens and reverses sign ($r = 0.18$); that is, as the number of TANF children declines, so too does the number of substantiated cases. (The results are similar when using the number of TANF families [2011-2015, $r = -0.87$; 2000-2015, $r = 0.23$])



This result would seem to weaken the authors’ hypothesis because, if it is correct, one should expect to find a similar relationship regardless of whether the number of reports or the number of substantiated cases was used, because both should measure, to some extent, the same underlying phenomenon. In fact, the latter comparison is presumably a more accurate (albeit, still imperfect) measure of the prevalence of child maltreatment because it requires that a specified threshold of some evidence be met, and therefore, unlike the number of reports of child maltreatment, is less likely to vary with no relation to the actual incidence or prevalence of child maltreatment.

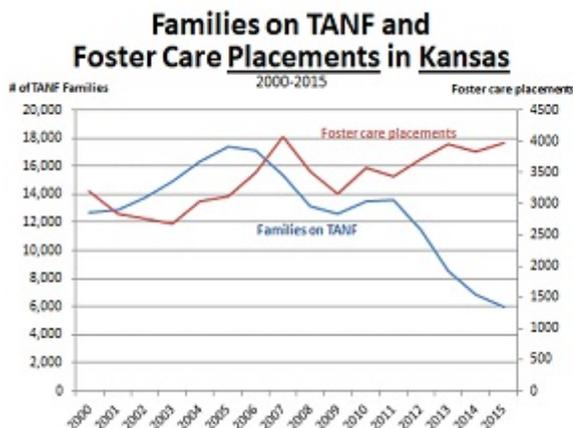
Thus, the number of reports may vary due to changes in administrative practices, reporting laws, and heightened sensitivity of potential reporters as a result of news coverage of

³²According to the US Department of Health and Human Services, a “substantiated case” of child abuse or neglect is “an investigation disposition that concludes the allegation of maltreatment or risk of maltreatment was supported or founded by state law or policy.” US Department of Health and Human Services, *Child Maltreatment: 2016* (Washington, DC: US Department of Health and Human Services, 2018), 15, <https://www.acf.hhs.gov/sites/default/files/cb/cm2016.pdf> (accessed November 16, 2018).

Instead of using this term, in their APPAM paper and their presentations, the authors use the terms “child victims of abuse” and “child victims of neglect.” From our reading of their APPAM paper, it appears the authors include substantiated cases of physical abuse and sexual abuse in “child victims of abuse” and likely also include substantiated cases of “psychological or emotional maltreatment.” (Because they were unwilling to respond to our email requests for more information, we have been unable to confirm if our understanding is correct.) In the definition of “child victims of neglect,” it appears the authors include substantiated cases of neglect and medical neglect.

prominent child abuse cases. Both the Michael Jackson and Jerry Sandusky scandals made national headlines during the years included in the scissor graphs, the former beginning around 2004 and the latter around 2011. The authors seem to be aware of this problem because they mention that researchers Jason Lindo and Jessamyn Schaller “caution against using state variation in child maltreatment reports and victims because of underreporting and measurement error, especially in the case of reports.”³³ (Lindo and Schaller also warn that “focusing on substantiated reports does not necessarily improve our ability to make valid comparisons—and could actually make things worse.”)³⁴ In this context, we do not understand the authors’ comment that “case substantiation may have limited predictive validity in identifying children at greatest risk of harm.”³⁵

Our tests of the second comparison found that, like the correlation between the number of TANF families and the number of child maltreatment reports, the correlation between the number of TANF families and the number of children placed in foster care was sensitive to the years used in the analysis, although to a much lesser degree. From 2000 to 2015, the correlation was moderate and inverse ($r = -0.53$), and was considerably stronger (and still negative) when the analysis was limited to between 2011 and 2015 ($r = -0.90$). Hence, in Kansas, depending on the period chosen, there is a correlation between the number of TANF families and the number of children placed in foster care. Further examination of this relationship, including whether it is causative (or whether some other extraneous factor is responsible), seems to be warranted.



³³Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 17, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

³⁴Jason M. Lindo and Jessamyn Schaller, “Economic Determinants of Child Maltreatment,” unpublished manuscript: 7 (2014), http://people.tamu.edu/~jlindo/EncyclopediaChildAbuse_PrePubVer.pdf (accessed November 19, 2018).

³⁵Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 18, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

Most noteworthy, the trend lines in both figures, show a sharp decline in the number of TANF cases beginning in 2011, presumably as a result of policy and programmatic changes adopted by the Brownback Administration. This, as we will see, gives an incomplete picture because it does not include the increase in total cash-like assistance.

Furthermore, although the intervention variables the authors use are TANF policy changes, there is no evidence-grounded discussion of how, or the degree to which, these changes actually led to a decline in TANF caseloads. It appears that the authors simply assume that the decline in the number of families receiving TANF is a “direct” cause of increased cases of child maltreatment.³⁶

Other states, with equally high caseload declines, do not show the same strong inverse correlation between declining TANF caseloads and rising child maltreatment and foster care placements. The authors do not make similar comparisons for other states, but we did and it appears that the strength and direction of the relationships between TANF reciprocity and the number of child maltreatment reports, substantiated cases, and foster care placements varies widely in different states.³⁷

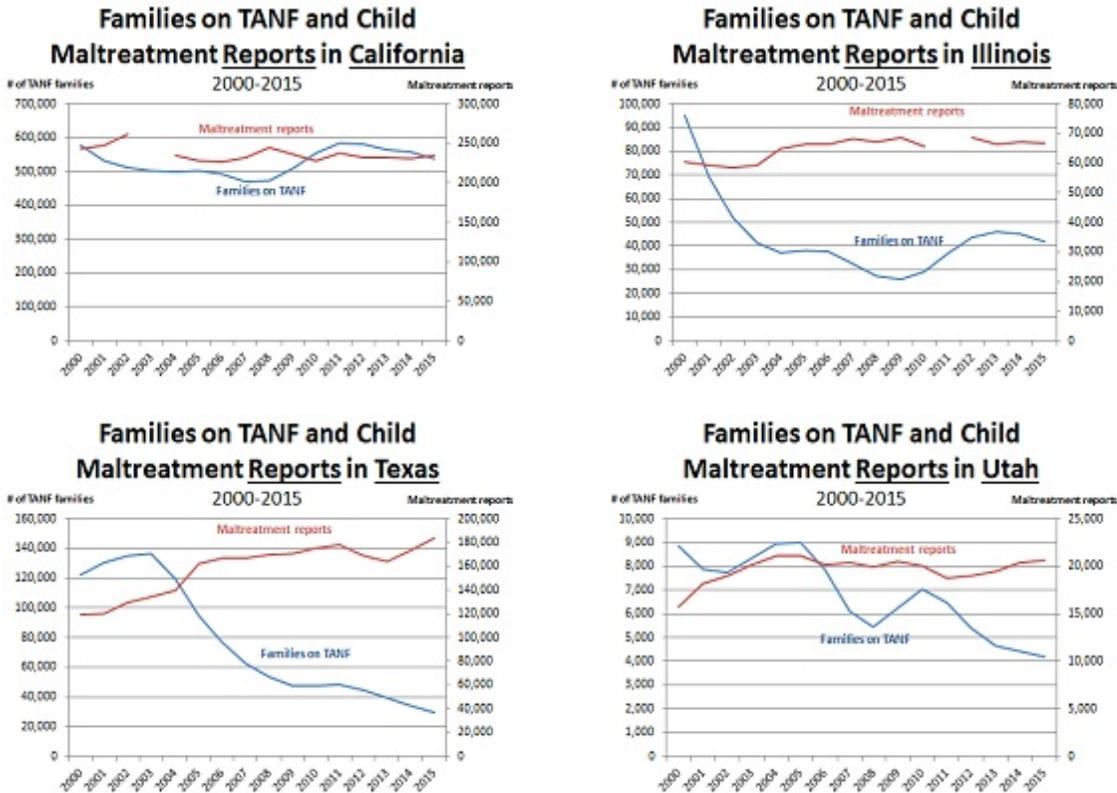
We examined the trend in the number of families receiving TANF and the number of child maltreatment reports in four states between 2000 and 2015: California, Illinois, Texas, and Utah.³⁸ All of the states exhibited different relationships in the trends. For example, in California, between 2000 and 2005, the number of families receiving TANF decreased from about 578,000 to about 504,000 and the number of child maltreatment reports also declined from about 243,000 to about 228,000. Over the next five years, the number of families receiving TANF increased by 50,000 while the number of child maltreatment reports remained roughly the same. In Utah, between 2000 and 2005, the number of child maltreatment reports increased while the number of families receiving TANF remained the same, but over the next ten years, the number of families

³⁶Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 4, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

³⁷The following comparisons are replications of the authors’ analysis, but we do note that these comparisons may be problematic because the TANF estimates are based on the average monthly number of families or child recipients, while child maltreatment reports, substantiated cases, and foster care placements represent unduplicated new cases.

³⁸To replicate the graphs of the authors for California, Illinois, Texas, and Utah, we also use the CBPP TANF data for the number of families receiving TANF.

receiving TANF decreased while the number of child maltreatment reports remained roughly the same.³⁹



In addition to conducting a visual inspection of these trends, we also calculated the Pearson correlation coefficient for each of the four states from 2000 to 2015, finding that the correlations, although consistently negative, vary greatly by state. In California, the relationship was very weak ($r = -0.05$), in Illinois it was moderate ($r = -0.64$), in Texas it was quite strong ($r = -0.93$), and in Utah it was moderate ($r = -0.21$). (As was the case with Kansas, these results were sensitive to both the range of dates included in the analysis and whether the number of child maltreatment reports or the number of substantiated cases were used; see table 1.)

³⁹US Department of Health and Human Services, *Child Maltreatment* (Washington, DC: US Department of Health and Human Services, 2000–2015); and US Department of Health and Human Services, “TANF Caseload Data,” <https://www.acf.hhs.gov/ofa/programs/tanf/data-reports> (accessed November 9, 2018).

Table 1: Strength and direction of associations between the number of abuse and neglect reports, substantiated cases, and foster care placements and TANF reciprocity, by state (Pearson correlation coefficients)

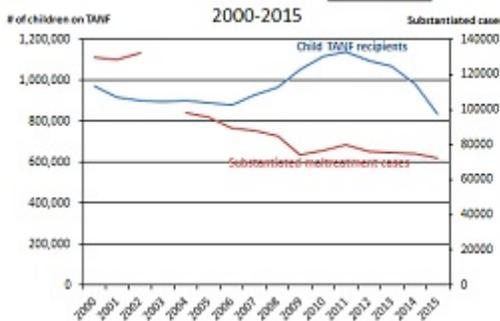
	Child maltreatment reports and TANF families	Substantiated cases and TANF		Foster care placements and TANF families
		children	families	
Kansas				
2000-15	-0.85	0.18	0.23	-0.53
2011-15	-0.96	-0.89	-0.87	-0.90
California				
2000-15	-0.05	-0.41	-0.09	-0.42
2011-15	0.15	0.91	0.88	-0.25
Illinois				
2000-15	-0.64	0.10	0.34	0.57
2011-15	-0.20	-0.96	0.74	0.59
Texas				
2000-15	-0.93	-0.89	-0.85	-0.78
2011-15	-0.35	-0.54	-0.52	-0.82
Utah				
2000-15	-0.21	0.29	0.35	-0.51
2011-15	0.88	0.74	0.69	-0.80

Source: Authors' compilation.

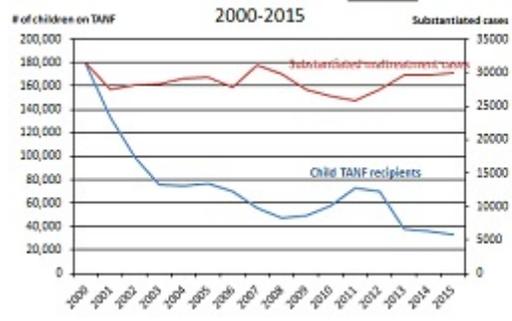
The relationship between the number of children receiving TANF benefits and the number of substantiated cases is also mixed. For example, in California, the number of child TANF recipients increased from 972,116 in 2000 to 1,140,452 in 2011 and then decreased to 838,090 in 2015 while the number of substantiated cases experienced a relatively steady decline from 129,678 in 2000 to 72,000 in 2015. In contrast, in Texas, the number of child TANF recipients decreased nearly each year between 2000 and 2015 from 255,492 to 60,483 and the number of substantiated cases increased overall during the same period from 45,800 to 63,781.

When examining the Pearson correlation coefficients for each state, there is substantial variation in the both the direction and strength of the association. In California, the correlation was moderate and inverse ($r = -0.41$), in Illinois it was weak and direct ($r = 0.10$), in Texas it was quite strong and inverse ($r = -0.89$), and in Utah it was moderate and direct ($r = 0.29$). In general, these results were fairly consistent whether the number of TANF families or child recipients was used (the exception being California, where the weakening was substantial, $r = 0.09$) but, like Kansas, there is considerable variation when the time period is narrowed to 2011 to 2015. For example, in California and Illinois, the direction of the relationship not just reverses but also becomes quite strong when the time period is adjusted ($r = 0.91$ and -0.96 , respectively).⁴⁰

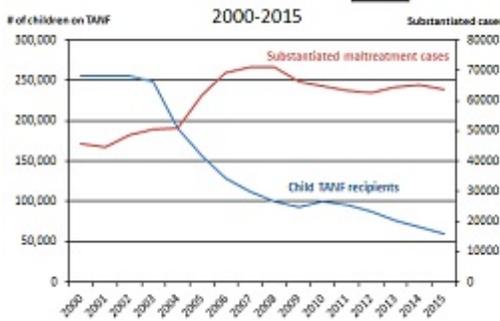
Child Recipients of TANF and Substantiated Maltreatment Cases in California



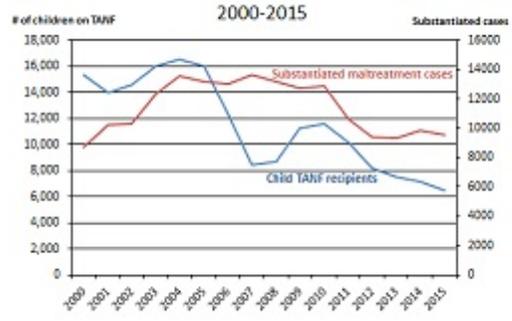
Child Recipients of TANF and Substantiated Maltreatment Cases in Illinois



Child Recipients of TANF and Substantiated Maltreatment Cases in Texas



Child Recipients of TANF and Substantiated Maltreatment Cases in Utah

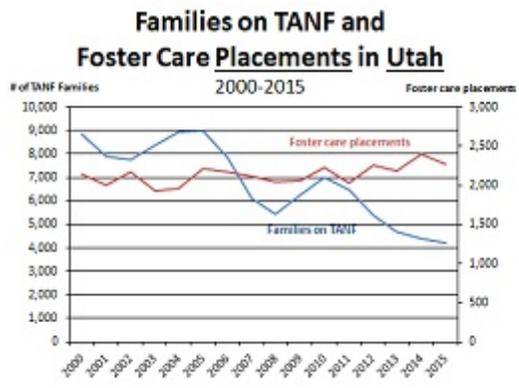
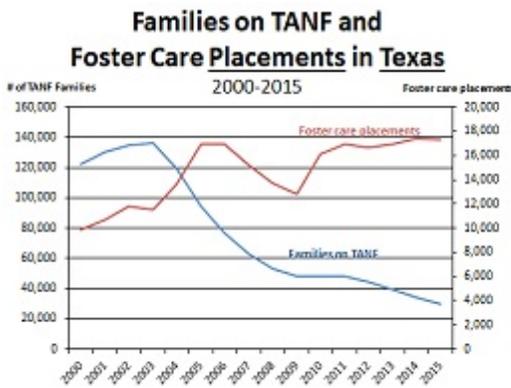
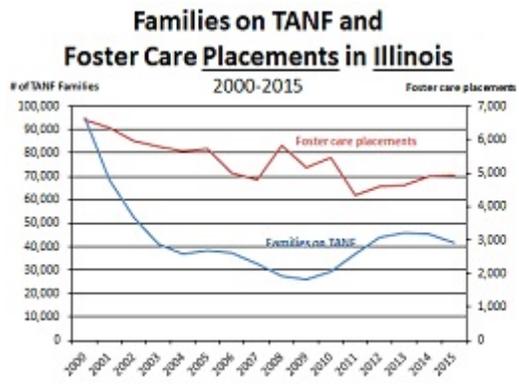
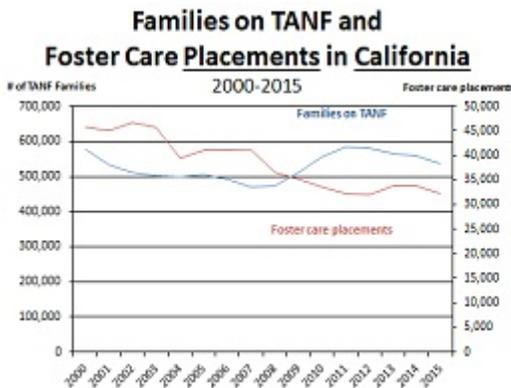


This variation in trends is also true for foster care placements. For example, in Illinois, between 2000 and 2015, the number of families receiving TANF declined from about 95,000 to about 42,000, but the number of children placed in foster care each year also declined from about 6,600 to about 4,900. In California, as the number of families receiving TANF fluctuated over this fifteen-year period, the number of children placed in foster care each year declined

⁴⁰Also noteworthy is a large variation between the correlation coefficient for Illinois between 2011 and 2015 when using TANF families versus child recipients. One possible explanation is that the TANF families data, from the CBPP, includes family recipients of state funded programs, whereas the number of child recipients may not.

consistently from about 46,000 in 2000 to about 32,000 in 2015.⁴¹ In examining the Pearson correlation coefficients for each state, there appears to be slightly more consistency: three states, like Kansas, showed a moderate inverse relationship between the number of TANF families and the number of foster care placements (California, $r = -0.42$; Texas, $r = -0.78$; and Utah, $r = -0.51$). The exception (Illinois), showed a moderate direct correlation ($r = 0.57$).

These simple checks suggest that some other extraneous forces might be causing the changes in child maltreatment and foster care placements—and, as we will see, raise additional questions about the appropriateness of the authors’ use of the difference-in-differences methodology.



Including all cash-like benefits all but eradicating the correlation in Kansas. The authors limit their comparisons to TANF reciprocity, but welfare leavers (and those who do not apply for TANF) who are without sufficient income can also receive benefits from the Supplemental Nutrition Assistance Program (SNAP). The addition of SNAP recipients

⁴¹Annie E. Casey Foundation, “Kids Count Data Center,” <https://datacenter.kidscount.org/> (accessed November 9, 2018); and US Department of Health and Human Services, “TANF Caseload Data,” <https://www.acf.hhs.gov/ofa/programs/tanf/data-reports> (accessed November 9, 2018).

substantially changes the perception that the number of children receiving cash or cash-like benefits has declined considerably. For example, in Kansas, between 1998 and 2015, the number of children receiving SNAP benefits increased by about 77,000 (from about 53,000 to about 130,000, an increase of about 145 percent).⁴² That's about 50,000 more families than the decline in TANF families.⁴³

Of course, SNAP benefits are not the equivalent of TANF benefits, but they are large enough that they *must* be considered in any analysis of welfare policy. (Although SNAP benefits increase when a family loses income from leaving TANF, the increase often does not equal the amount of benefits lost. For example, in Kansas, a family of three with no income would be eligible to receive about \$800 a month in TANF and SNAP benefits. After leaving TANF, the SNAP benefits would increase, but only to about \$500 a month, for a loss of roughly \$300 a month in overall benefits.)⁴⁴

On a smaller scale, welfare leavers (and those who do not apply for TANF) may also receive Supplemental Security Income (SSI) if their children have a disability. (In many states, solely state-funded programs consist of families who are waiting for approval for SSI benefits for their children.) In Kansas, between 1998 and 2015, the number of children receiving SSI benefits increased by about 2,500 (from about 6,500 to about 9,000, or about 38 percent higher).⁴⁵ Thus, the originally striking correlations cited by the authors all but disappear in Kansas after recognizing the increased number of children receiving benefits under these programs.⁴⁶ Between

⁴²US Department of Agriculture, *Characteristics of Supplemental Nutrition Assistance Program Households: Fiscal Years 2000-2015* (Washington, DC: US Department of Agriculture, 2002–2017).

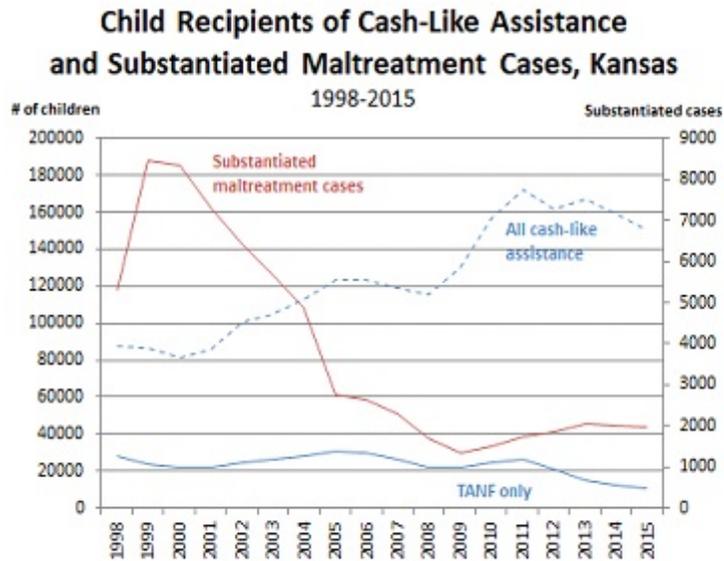
⁴³The number of children receiving TANF benefits declined by only about 17,000 (from about 28,000 to about 11,000, a decline of about 60 percent). US Department of Health and Human Services, “TANF Caseload Data,” <https://www.acf.hhs.gov/ofa/programs/tanf/data-reports> (accessed November 9, 2018).

⁴⁴This is a stylized analysis. In practice, some recipients may not receive an increase in their SNAP benefits when leaving TANF because of SNAP's standard deduction or the excess shelter deduction. US Department of Agriculture, “Supplemental Nutrition Assistance Program (SNAP): Frequently Asked Questions,” <https://www.fns.usda.gov/snap/eligibility> (accessed November 9, 2018); and Urban Institute, *Welfare Rules Databook: State TANF Policies as of July 2016* (Washington, DC: Urban Institute, December 2017), https://www.acf.hhs.gov/sites/default/files/opre/2016_welfare_rules_databook_final_10_30_17_b508_2.pdf (accessed November 9, 2018).

⁴⁵Social Security Administration, *SSI Annual Statistical Report 2000-2015* (Washington, DC: Social Security Administration, 2001-2016).

⁴⁶A third program that welfare leavers could receive is the Social Security Disability Insurance (SSDI) program. To receive SSDI, individuals need to have contributed to the SSDI trust fund for a sufficient number of hours which means they need to have had a work history. Because there is no means test for receiving SSDI and many recipients are not low income, we have not included SSDI in our analysis. In 2015, there were about 1.6 million children in families receiving SSDI benefits. Social Security Administration, *Annual Statistical Report on the Social Security Disability Insurance Program, 2015* (Washington, DC: Social Security Administration, October 2016), https://www.ssa.gov/policy/docs/statcomps/di_asr/2015/di_asr15.pdf (accessed November 6, 2018).

1998 and 2015, the number of children who received TANF, SNAP, or SSI increased from about 87,000 to about 150,000, or about 72 percent.



Research design not sufficiently described for assessment.

The authors use a difference-in-differences (DiD) design to estimate the effect of changes in state TANF policies on child maltreatment reports, substantiated cases, and foster care placements, theorizing that stricter state TANF policies lead to increases in child maltreatment and foster care placements. DiD is a fairly common approach to evaluating state policies, in which the conditions of treatment and comparison groups are compared once before and once after a policy change or other intervention.⁴⁷

To create their dependent variables, the authors use national data on child maltreatment reports and substantiated cases (from the National Child Abuse and Neglect Data System)⁴⁸ and national data on foster care placement (from the Adoption and Foster Care Analysis and Reporting System).⁴⁹ To create their intervention variables, they use data from the Urban

⁴⁷Note: Throughout this paper we refer to the states that adopted a given policy change as “treatment” states but use the term “intervention variable” when discussing the variables used in the analysis that are meant to represent the particular policy being changed.

⁴⁸US Department of Health and Human Services, Administration for Children and Families, Children’s Bureau, “About NCANDS,” <https://www.acf.hhs.gov/cb/resource/about-ncands> (accessed November 7, 2018).

⁴⁹US Department of Health and Human Services, Administration for Children and Families, Children’s Bureau, “About AFCARS,” <https://www.acf.hhs.gov/cb/resource/about-afcars> (accessed November 7, 2018).

Institute’s Welfare Rules Database,⁵⁰ which identifies a number of state TANF policies that states have adopted. In addition, in their presentations, the authors include an intervention variable (“TANF denial rates,” see below), using data from the Office of Family Assistance.⁵¹ (See table 2.) Using Urban Institute policy data from 2005 to 2015, the authors create two treatment and two comparison groups for five work-related TANF policies and four behavioral requirements they examine. (See below for a discussion of these intervention variables.)

Table 2: TANF intervention variables used or mentioned (and number statistically significant, $p < 0.05$) and other TANF policies in Welfare Rules Databook not discussed, by source

TANF intervention variables	APPAM Paper	Presentations		
		University of Kansas	Committee on Children and Seniors	Social Services Budget Committee
Total benefit sanction	Used (3 of 6)	Used (4 of 12)	Used (4 of 12)	Used (4 of 12)
Time limits	Used (2 of 6)	Used (5 of 12)	Used (5 of 12)	Used (5 of 12)
Earnings disregard	Used (0 of 6)	Mentioned	Mentioned	
Reduction in age of exemption for mothers	Used (0 of 6)	Mentioned	Mentioned	Mentioned
All four of the above	Used (1 of 6)	Mentioned	Mentioned	
Education requirements	Used (2 of 6)	Mentioned	Mentioned	Mentioned
Financial incentives	Used (2 of 6)	Mentioned	Mentioned	Mentioned

⁵⁰Urban Institute, Income and Benefits Policy Center, “Welfare Rules Databook and Database,” <https://www.urban.org/policy-centers/income-and-benefits-policy-center/projects/welfare-rules-databook-and-databook> (accessed November 8, 2018).

⁵¹US Department of Health and Human Service, Administration for Children and Families, Office of Family Assistance, “TANF Application Data,” <https://www.acf.hhs.gov/ofa/resource/applications> (accessed November 8, 2018).

Immunization requirements	Used (1 of 6)	Mentioned	Mentioned	Mentioned
Mandatory health screenings	Used (1 of 6)	Mentioned	Mentioned	Mentioned
Increased denials of TANF applications ^a		Used (6 of 12)	Used (6 of 12)	Used (6 of 12)
Diversion payments				
Mandatory job search				
Family caps				
Asset limits				
Maximum monthly benefits				
TOTAL	12 of 54	15 of 36	15 of 36	15 of 36

Source: Authors' compilation.

Note: The terms “used” and “mentioned” are based on what we were able to glean from the authors’ APPAM paper and their presentations. They are defined as follows: “used” means that the intervention variable is discussed and results are included; “mentioned” means that the intervention variable is listed in a table (or otherwise) but no results are included, and thus, we are unable to determine whether it was used in the analysis.

^aData for this variable come from the US Department of Health and Human Services Office of Family Assistance.

In a DiD study, the comparison (or “nonprogram”) group represents the “natural change” over the period which is compared to the change, if any, in the treatment group. Outcomes and impacts are generally estimated by subtracting (differencing) the initial difference between the two groups (the first difference) from the difference after the intervention (the second difference).⁵² The assumption of the methodology is that, if the two groups are similar before the intervention (at baseline), then the observed pre-intervention difference is due to unobserved variables that will remain constant over time.⁵³

⁵²Alternatively, outcomes and impacts can be estimated by subtracting the difference between the pre- and post-treatment measures in the comparison group from the difference observed in the treatment group. Jeffrey M. Wooldridge, *Introductory Econometrics: A Modern Approach*, (Mason, OH: South-Western Cengage Learning, 2009), 454; and Joshua D. Angrist and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist’s Companion*, (Princeton, NJ: Princeton University Press, 2009), 227-243.

⁵³Douglas J. Besharov, *Methods for Identifying the Counterfactual: Part Two*, (College Park, MD: Welfare Reform Academy, 2016).

William Shadish, Thomas Cook, and Donald Campbell warn that comparison group designs (including DiD designs) can produce biased estimates if they do not capture all the differences between the groups being compared, particularly those that are time-varying and that may have a disproportionate effect on one group (or state) compared to another.⁵⁴ Regarding DiD designs, Bruce Meyer writes:

Changes in other state laws or macroeconomic conditions are not likely to always influence all groups in the same way. A recession may have a disproportionate effect on one income group compared to another or in one state than another. This design is most plausible when the untreated comparison group is very similar to the treatment group.⁵⁵

According to Meyer, DiD analyses require (1) at least two groups, one in which a change occurs (the treatment group) and another in which it does not (the comparison group) (this is sometimes referred to as “variation in treatment”); (2) data on the dependent variable, measured at least once before and after the change; and (3) similarity between the groups on the dependent variable before the change (often referred to as the “common slopes” or “parallel slopes” assumption).⁵⁶ The latter is considered satisfied if, after comparing the historical trend(s) of the dependent variable(s) in the treatment and comparison groups, the trend is similar and not subject to large fluctuations, especially immediately surrounding the measurement.

Thus, DiD designs are subject to concerns about selection bias if they are unable to account for unobserved differences between members of the treatment and comparison groups. And, as with other comparison group designs, researchers using DiD designs attempt to reduce selection bias by identifying treatment and comparison groups that are similar at baseline on observable characteristics or by creating similar comparison groups through propensity score matching.⁵⁷ The more similar the two groups, the more likely that the common slopes assumption is met.⁵⁸ It does not appear that the authors considered how to make the treatment groups and the

⁵⁴William R. Shadish, Thomas D. Cook, and Donald T. Campbell, *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*, (Boston: Houghton Mifflin Company, 2003): 136-144.

⁵⁵Bruce D. Meyer, “Natural and Quasi-Experiments in Economics,” *Journal of Business and Economic Statistics* 13, no. 2 (1995): 155.

⁵⁶Bruce D. Meyer, “Natural and Quasi-Experiments in Economics,” *Journal of Business and Economic Statistics* 13, no. 2 (1995): 154-155.

⁵⁷See, for example, Elizabeth A. Stuart, Haiden A. Huskamp, Kenneth Duckworth, Jeffrey Simmons, Zirui Song, Michael Chernew, and Colleen L. Barry, “Using Propensity Scores in Difference-in-Differences Models to Estimate the Effects of a Policy Change,” *Health Services and Outcome Research Methodology* 14, no. 4 (December 2014): 166–182; and Coady Wing, Kosali Simon, and Ricardo A. Bello-Gomez, “Designing Difference in Difference Studies: Best Practices for Public Health Policy Research,” *Annual Review of Public Health* 39 (2018): 453–469.

⁵⁸Andrew Ryan, “Everything You Wanted to Know About Difference-in-Differences but Were Afraid to Ask,” (presentation, University of Michigan, Ann Arbor, MI, February 3, 2017).

comparison groups similar. From what we can tell, states that made policy changes were compared to all states that did not make the change, regardless of whether those states were similar in size, geography, or demographics.

Without being able to ask them, we presume that the authors' assumption is that their model holds all other differences between states constant, and, therefore, that they can isolate the effect of each state TANF policy change. There are, however, major concerns with their apparent approach that make this assumption problematic, as detailed below.

Unclear whether common slopes requirement for difference-in-differences designs is satisfied. Regarding the common slopes assumption, the authors mention that one could test the assumption by altering their model to include an interaction between the treatment states and years preceding the policy change. According to the authors, "The parallel trends assumption indicates that the estimated coefficients on the interaction terms will be equal to zero in the years prior to treatment." This might be an appropriate test, however, the authors do not indicate whether they performed the test, and, if so, what they found.

Another method for assessing the common slopes assumption, discussed by Angrist and Pischke, would be to compare the historical trend lines for each treatment and comparison group pairing for each dependent variable. If the assumption holds, the trends should follow a similar pattern before the policy change.⁵⁹ Again, the authors do not indicate whether or not they did this. Even if they did, we would be unable to replicate the test because, as mentioned below, we do not know exactly which states they assign to treatment and comparison groups.

Since we are unable to test the common slopes assumption and the authors do not provide sufficient information to determine if they did so, we are unable to ascertain whether the common slopes assumption is satisfied, and thus whether the DiD methodology was appropriately applied. Furthermore, although we do not know which states they are comparing, based on our review of trend lines in California, Illinois, Texas, and Utah, this seems unclear.

Unclear (and potentially problematic) composition of treatment and comparison groups. To estimate the effect of the selected TANF policies on child maltreatment reports and foster care placements, for each policy, the authors compare states that adopted one of the policies between 2005 and 2010 to those states that, over the same period, did not (the first comparison group). They do the same for the period between 2010 and 2015. In addition, in their presentations, the authors include a separate analysis that focuses solely on estimating the effect of Kansas's policies, including where Kansas is the sole state in the treatment group and all states that did not change TANF policies are in the comparison group. (Later, we discuss how the authors apparently shift the set of policies they use, which, we fear, is an effort to achieve statistically significant results that support their hypothesis.)

⁵⁹Joshua D. Angrist and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, (Princeton, NJ: Princeton University Press, 2009): 230-232.

It is unclear, however, exactly which states comprise each treatment group (except when restricted to Kansas) and each comparison group. For example, between 2005 and 2015, three states (Maine, New Hampshire, and Washington) increased the severity of sanctions for TANF recipients who did not engage in a work activity; but we cannot tell whether these three states are compared to the remaining forty-seven states (and Washington, DC and Puerto Rico) that did not make a change during that period (regardless of whether they had a similar policy or whether they had less severe sanctions) or to the nine states that did not implement the change at any time (either before 2005 or during the study period).⁶⁰ Although the latter would seem to be more appropriate (because it would limit the comparison to states that adopted the policy to those that did not), the authors' APPAM paper suggests that they did the former. Doing so would compromise the comparison because it would estimate the effect of a policy by comparing the treatment group to a comparison group that includes states that already had the policy in effect.

The authors further conflate these groups in their presentations by examining the effect of these policy changes on Kansas alone when, as far as we can tell, Kansas did not make some of the policy changes made by other states during the period of study. (For example, although Kansas has a work requirement, it was implemented prior to 2005.)

Regardless of how the comparison groups were constructed, there is substantial imbalance in the size of the treatment and comparison groups. This is concerning because one state is more likely to have greater year-to-year variation in the measure of a given dependent variable (e.g., the number of reports of child abuse or child neglect, or substantiated cases of either) than the average of a large number of states. As Angrist and Pischke note, DiD is sensitive to these fluctuations and can produce biased results if either the pre- or post-treatment data observation is a result of these seemingly random fluctuations and is not, therefore, representative of the overall trend.⁶¹

Once again, it would be preferable to have answers to these simple questions from the authors, but in their absences, we are forced to assume that they may have made problematic comparisons.

Incomplete and shifting intervention variables concerning TANF and other program changes. Intervention variables are the independent factors (“independent variables”) that represent the program being studied or evaluated. They are hypothesized to have a direct effect on the dependent variable(s), although they may have an effect on an “intervening”

⁶⁰ During this period, forty-three states had such a policy in effect in 2005 and forty-five in 2010. Assuming that none of the states that had previously implemented this policy removed it and that none both implemented and removed it during this period, it follows that two states implemented this policy change and thereby constitute the treatment group for this intervention variable for this period. It is not, however, clear whether this is indeed the case because a list of states comprising the treatment and comparison groups is not included.

⁶¹ Joshua D. Angrist and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion*, (Princeton, NJ: Princeton University Press, 2009): 227-243.

variable that, in turn, affects the dependent variable.⁶² The latter are also described as “mediating variables,” that is, they are the proximate cause of the change in the dependent variable.

No justification and inconsistency in the choice of state TANF policy changes. Not explained in the paper or presentations is why the authors chose the policy changes (“intervention variables”) they selected and not other variables that are included in the Welfare Rules Databook, such as diversion payments, mandatory job search at application, family caps, asset limits, and maximum monthly benefits. (See table 2.) In theory, all of these TANF policies could also contribute to a decline in the TANF caseload and therefore contribute to the increase in child maltreatment. States made more changes concerning these TANF policies over the period of interest than many of the variables selected by the authors. For example, fifteen states modified their mandatory job search policy, with some states adding and others dropping the requirement.⁶³

Likewise, it is unclear why the authors selected these particular behavioral requirements to include in the analysis, especially because minimal attention is given to them in both the paper and the presentations. In fact, the authors only present findings on these intervention variables in their paper. Moreover, the only mention of behavioral requirements in the authors’ presentations is a table that lists TANF policy changes and the number of states that had adopted each in 2005, 2010, and 2015. (The same table appears in their APPAM paper.) We did not find any discussion in their presentation slides that indicated these behavioral requirements were used in the analysis and no results are included in the presentations.

Failure to account for additional state TANF policy changes. The authors examine the effect of two categories of TANF policies, which they term (1) “TANF policies related to work,” and (2) “behavioral requirements on TANF recipients.”⁶⁴

The TANF policies related to work that are used in the APPAM paper are: (1) a work-related requirement that results in the total loss of benefits if unmet, (2) a time limit for receiving TANF benefits of less than sixty months, (3) no increase in the earnings disregard, (4) a requirement that participants return to work if they have a child under the age of one, and (5) all of the above policies. In their subsequent presentations, they seem to use a different set of policies.

⁶²Douglas J. Besharov, *Disentangling Causative Factors: Dependent and Independent Variables*, (College Park, MD: Welfare Reform Academy, 2016).

⁶³Urban Institute, *Welfare Rules Databook: State TANF Policies as of July 2016* (Washington, DC: Urban Institute, December 2017), https://www.acf.hhs.gov/sites/default/files/opre/2016_welfare_rules_databook_final_10_30_17_b508_2.pdf (accessed November 9, 2018).

⁶⁴Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 11-12, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

The behavioral requirements, used in both the paper and the presentations, are: (1) requirements for the children of TANF recipients to “attend school, achieve a minimum grade point average, or be involved in their children’s education;” (2) financial incentives if those school requirements are met; (3) immunization requirements for children of TANF recipients; and (4) mandatory health screenings for TANF recipients and their children.

The authors also identified a policy change in Kansas to decouple the application process for TANF and for family medical programs (Medicaid and SCHIP). The Department for Children and Families estimated that this policy change would reduce the number of families receiving TANF per month by about 1,975.⁶⁵ Despite raising this potentially significant confounding factor, the authors did not account for this policy change in their analytical model. Although they may plan on including this policy change in their revised paper, we do not know the extent to which it may have affected their estimates in the current paper.

Variation in implementation of state TANF policies, and, hence, questionable comparability. Another issue is that states (and even welfare offices within states) vary in their implementation of the selected TANF policies, thereby making it unclear what is actually being compared by the variables selected by the authors. For example, although a number of states have lifetime limits of TANF receipt below the federal limit of sixty months, there is wide variation in how they apply their revised limits. Some states grant extensions to TANF recipients who exceed the state’s lifetime limit but who are engaged in a work activity. Other states grant extensions to TANF recipients who are victims of domestic abuse or who are disabled. Even within states, the implementation of these extensions can vary.⁶⁶

In addition, the authors assume that if a state made a change to its TANF policy that the policy was immediately implemented in that year. (The Urban Institute’s Welfare Rules Databook only captures whether a state has made a change, not whether it has been implemented and how well.) In fact, there is often a lag between the decision to make a change to state policy and the full implementation of the policy.⁶⁷

Unclear why changes in minimum wage not included in the model. In a number of states, including Kansas, the minimum wage was raised during the study period. The authors report that they separately test the relationship between minimum wage and child maltreatment

⁶⁵Kansas Department for Children and Families, *TANF Caseload Reduction Report* (Topeka, KS: Kansas Department for Children and Families, 2015), <http://www.dcf.ks.gov/services/eas/Documents/Reports/Kansas%20FFY%202015%20TANF%20All%20Families%20Caseload%20Reduction%20Report.pdf> (accessed November 9, 2018).

⁶⁶Mary Farrell, Sarah Rich, Lesley Turner, David Seith, and Dan Bloom, *Welfare Time Limits: An Update on State Policies, Implementation, and Effects on Families* (Falls Church, VA: Lewin Group, April 2008).

⁶⁷See, for example, Alberto Martini and Michael E. Wiseman, *Explaining the Recent Decline in Welfare Caseloads: Is the Council of Economic Advisors Right?* (Washington, DC: Urban Institute, 1997).

reports, substantiated cases, and foster care placements. Using a “separate fixed effect regression” for each dependent variable, they estimate the effect of state minimum wages on child maltreatment reports, substantiated cases, and foster care placements. They find that “an increase in the minimum wage had no significant impact on reports or victims but increased total foster care placements by 18.9 to 22.7 [percent].”⁶⁸

This result is inconsistent with the authors’ underlying theory that better financial conditions for low-income families (whether from TANF or government benefits or earnings) would reduce child maltreatment. It is also inconsistent with the finding of Kerri Raissian and Lindsey Bullinger, which they cite earlier in their APPAM paper, to the effect that increases in the minimum wage led to a decline in overall child maltreatment reports, particularly neglect reports.⁶⁹

One would have thought they would have pursued this anomaly in their results, as it suggests a problem within their analysis. For example, it would be helpful to know what happens when the state’s minimum wage is included as a covariate in the analysis. The authors do not provide a reason for not doing so, and, again, we were unable to explore this with them.

Changes in child welfare policies and practices apparently not taken into account.

According to Peter Rossi, Howard Freeman, and Mark Lipsey, in order to estimate what, if any, effect an intervention has on a given dependent variable, “the evaluator must exclude or purge the confounding factors from the gross effects. That is, the influence of any extraneous factors that explain, in whole or in part, the observed changes in the target problem or population must somehow be removed.”⁷⁰ Although the authors include in their model a number of control variables to attempt to account for some of these confounding variables, there remain unaddressed a number of potentially serious factors.

Possible confounding variables

In attempt to minimize the threats to causal validity associated with these differences, the authors, like many other researchers when using DiD, employ both state and year fixed effects that, theoretically at least, capture (after the differencing) any remaining unobserved, fixed

⁶⁸Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 15-16, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

⁶⁹Kerri M. Raissian and Lindsey Rose Bullinger, “Money Matters: Does the Minimum Wage Affect Child Maltreatment Rates?” *Children and Youth Services Review* 72 (2017): 60-70, <https://www.sciencedirect.com/science/article/pii/S0190740916303139> (accessed November 16, 2018).

⁷⁰Peter H. Rossi, Howard E. Freeman, and Mark W. Lipsey, *Evaluation: A Systematic Approach*, 6th ed. (Thousand Oaks, CA: Sage Publications, 1999): 240-244.

differences between the states and any trend changes that affect both groups. In addition, they include a number of state-level covariates meant to capture any time-varying differences between the treatment and comparison groups. These covariates include economic and demographic characteristics for each state, including, but not limited to, the state unemployment rate, average personal income, share of single mothers, size of total population, and size of child population. In addition, the authors attempt to account for across-state variation in substance abuse by including in the list of covariates the variable, “crude drug death rate per 100,000.”

Despite the authors’ inclusion of these state demographic, economic characteristics, and secular trends, they do not account for a number of relevant state policy changes that also took effect during the assessment period and that may also have affected the number of child maltreatment reports, the number of substantiated cases, and the number of children placed in foster care. Also, as discussed below, their variable for substance abuse seems inadequate for capturing the effect of substance abuse on child maltreatment and foster care placements.

The authors’ model does not account for any state-level policy changes in child maltreatment that occurred during the period of study.⁷¹ As mentioned above, a DiD design assumes that the initial differences between states on the outcomes of interest will remain the same over the course of the period of interest, with any change being attributed to the intervention of interest. If another policy change occurred during this period that did not affect all states equally, then the difference-in-differences model would not be able to distinguish the effects of the intervention of interest on the outcomes from the effects of the other policy change, unless explicitly accounted for in the model.

During the period of 2005-2015, states made at least three major types of policy changes related to child maltreatment, all of which were policy changes conducted at the state and not national level. Thus, not all states made the changes and those states that did make changes implemented them at various times and to various degrees. The three major policy changes were:

Failure to account for changes in the definition of “mandatory reporter.” Twenty-nine states and Washington, DC changed the definition of the categories of individuals who are mandated to report if they suspect that a child is the victim of abuse or maltreatment. In all these states, states expanded the definition to include more categories, but the extent of that expansion

⁷¹The authors state that “future research will incorporate levels of evidence for substantiated reports as well as universal mandated reporting laws, changes in state definitions of abuse and neglect, caseload sizes for intake workers, and funding for CPS to control for variations in reports, investigations, and victimization within states over time.” It is, however, unclear whether the authors intend to include them in a later, final version of this paper or whether the intention is to consider these analyses for separate papers and publications. As we argue in this section, we think these controls should, indeed, be added to the current model.

differed between states.⁷² Eighteen states already had universal mandatory reporting laws prior to 2005 and three states did not make any changes to the categories of mandatory reporters during the study period.⁷³ The effect of these changes on child abuse and neglect reporting and on substantiated cases is uncertain because the introduction of new categories of mandatory reporters may or may not substantially increase reports and may or may not increase the ratio of substantiated versus unsubstantiated reports.

Failure to account for changes in the level of evidence for substantiating a report of child maltreatment. Between 2005 and 2015, eight states made changes to the level of evidence required for substantiating a child maltreatment report. Seven of these states increased the level of evidence required from either “credible” or “reasonable” evidence to a “preponderance of evidence.”⁷⁴ One state, Pennsylvania, reduced the level of evidence required to substantiate a child maltreatment report from “clear and convincing evidence” to a “preponderance of

⁷²For example, Pennsylvania expanded the categories of mandatory reporters to include: “Any person, paid or unpaid, who, on the basis of the person’s role in the program, activity, or service, is a person responsible for the child’s welfare or has direct contact with children;” “An emergency medical services provider;” “an individual supervised or managed by person listed above who has direct contact with children;” “an independent contractor;” “an attorney affiliated with an agency, institution, or other entity, including a school or established religious organization that is responsible for the care, supervision, guidance, or control of children;” “a foster parent;” “an adult family member who is a person responsible for the child’s welfare and provides services to a child in a family living home, community home for individuals with an intellectual disability, or licensed host home for children.” “In addition, the definitions of some categories were changed to be more expansive such as “school administrators, teachers, or school nurses” being expanded to “school employees” which includes anyone who is “employed by a school or who provides an activity or service sponsored by the school” and where school is defined as “a facility providing elementary, secondary, or post-secondary educational services, including public and nonpublic schools, vocational-technical schools, and institutions of higher education.” Child Welfare Information Gateway, *Mandatory Reporters of Child Abuse and Neglect: State Statutes* (Washington, DC: US Department of Health and Human Services, 2016): 46.

⁷³Child Welfare Information Gateway, *Mandatory Reporters of Child Abuse and Neglect: Summary of State Laws* (Washington, DC: US Department of Health and Human Services, 2005); and Child Welfare Information Gateway, *Mandatory Reporters of Child Abuse and Neglect: State Statutes* (Washington, DC: US Department of Health and Human Services, 2015).

⁷⁴US Department of Health and Human Services, *Child Maltreatment: 2005* (Washington, DC: US Department of Health and Human Services, 2007); and US Department of Health and Human Services, *Child Maltreatment: 2015* (Washington, DC: US Department of Health and Human Services, 2017).

evidence.”⁷⁵ Thus, depending on the state, the difficulty in substantiating a report has either decreased or increased.

Failure to account for changes in definition of child maltreatment. Between 2005 and 2015, many states changed their definitions of what constitutes physical abuse, neglect, sexual abuse and exploitation, emotional abuse, and abandonment. In some states, the definitional changes were minor, such as only adding sex trafficking to the definition of sexual abuse. In other states, such as Pennsylvania, the definitions were expanded to include detailed lists of activities that constitute abuse or neglect.⁷⁶ As with the definition of mandatory reporting, because of the variability in the new statutes, the effects on the number of child maltreatment cases and substantiated cases are uncertain.

In addition to state policy changes related to child maltreatment, there were several prominent child abuse cases during this period that affected public attitudes in some states more than others that easily could have contributed to increased vigilance on the part of mandatory reporters.⁷⁷

Failure to account for changes in kinship care policies. In addition to changes in the state definitions of child maltreatment and mandatory reporters, there was also a fairly significant policy change related to foster care that may have affected the number of families on TANF. In 2008, the US Congress passed the Fostering Connections to Success and Increasing Adoptions Act. As part of this legislation, the federal government provides funds for states to operate Guardianship Assistance Programs, which provide assistance to foster parents of related children. According to the Government Accountability Office, as of 2014, thirty-two states were operating Guardianship Assistance Programs.⁷⁸

⁷⁵As of 2015, only one state (Kansas) requires “clear and convincing evidence” to substantiate a child maltreatment report. According to Steve Greene, Director of Policy & Legislative Affairs at the Kansas Department of Children and Families, “In July 2016, Kansas changed our level of evidence from ‘Clear and Convincing’ to ‘Preponderance.’ In addition to our finding category of substantiated, as of July 2016, another finding category of affirmed was added. Affirmed is defined as a reasonable person weighing the facts and circumstances would conclude it is more than likely than not (preponderance of the evidence) the alleged perpetrator’s actions or inactions meet the abuse/neglect definition per Kansas Statutes Annotated (K.S.A.)” Email message from Steve Greene to the authors, October 29, 2018.

⁷⁶Child Welfare Information Gateway, *Definitions of Child Abuse and Neglect: State Statutes* (Washington, DC: US Department of Health and Human Services, 2017); and National Clearinghouse on Child Abuse and Neglect Information, *Definitions of Child Abuse and Neglect: Summary of State Laws* (Washington, DC: US Department of Health and Human Services, 2005).

⁷⁷An example of such a case is the Jerry Sandusky scandal in Pennsylvania where a former Pennsylvania State University coach was found to have abused children for years, but the allegations of such abuse had only been reported to other coaches and campus officials, not to law enforcement.

⁷⁸Government Accountability Office, *HHS Needs to Improve Oversight of Fostering Connections Act Implementation* (Washington, DC: Government Accountability Office, May 2014).

In order to receive the amount of assistance, kinship care foster parents need to be licensed by the state. Because foster care benefits are much larger than TANF benefits, TANF recipients caring for a related child who become officially licensed as foster care parents are removed from the TANF rolls while the child is counted as entering the foster care system. According to a 2012 US Department of Health and Human Services report: “state licensing practices still vary greatly. A five-state study reports one state licenses virtually all kin caregivers and uses TANF primarily as support during the process, while another licenses only about 10 percent of these caregivers.”⁷⁹

It does appear, however, that this option is being increasingly used. Between 2008 and 2015, the percentage of foster care children being placed in kinship care has increased from 24 percent to 30 percent.⁸⁰

With wide state variation in the application of kinship care policies, it is difficult to assess if the decline in the TANF caseload is leading to an increase in foster care placements as the authors assert or if the increase in licensing of TANF recipients acting as guardians has caused the decline. Regardless, these policy changes are not accounted for in the authors’ model.

Growth in substance abuse not sufficiently taken into account

As discussed in more detail in the appendix below, substance abuse is considered an important factor in the prevalence and severity of child maltreatment. Given the widespread opioid epidemic (and general growth in substance abuse), its likely disproportionate effect between states, and the relationship between substance abuse and child maltreatment, the control variable employed by the authors seems inadequate, and therefore unlikely to sufficiently account for changes in the dependent variable that are the result of substance abuse.

Although the authors attempt to control for the increase in substance abuse on the increases in child maltreatment reports, substantiated cases, and foster care placements during the period of study, the variable that they use (the drug death rate per 100,000) is unlikely to sufficiently capture the extent of substance abuse. First, the authors’ measure only captures deaths due to substance abuse; not the overall increase in substance abuse prevalence in the United States. And although death rates and prevalence rates are correlated, death rates from overdose, however, are no longer an accurate barometer of trends in drug abuse. Although two jurisdictions may have the same prevalence rates of substance abuse, the death rates may vary

⁷⁹Olivia Golden and Amelia Hawkins, *TANF Child-Only Cases* (Washington, DC: Urban Institute, 2012).

⁸⁰Kid’s Count Data Center, “Children in Foster Care by Placement Type,” datacenter.kidscount.org (accessed October 25, 2018).

based on the type of substance that is being abused, the availability of naloxone treatments, the training of emergency responders and various other demographic and contextual variables.⁸¹

Research by Alexander Walley et al., for example, suggests that the number of deaths due to opioid-related overdoses may have been reduced through the use of overdose education and naloxone distribution (OEND) programs; that is, programs that provide training to “people who use opioids and their families, friends, and social service providers to prevent, recognize, and respond to overdoses.”⁸² Similarly, Daniel Rees et al. find that the adoption of a Naloxone Access Law “is associated with a 9 to 11 percent reduction in opioid-related deaths.”⁸³

Second, even if the authors had included an adequate prevalence rate variable, the available data may not capture the underlying true prevalence rate. In a March 2018 paper, US Department of Health and Human Services analysts Robin Ghertner, Melinda Baldwin, Gilbert Crouse, Laura Radel, and Annette Waters assessed the relationship between increasing foster care placements and the independent variables of substance abuse death and prevalence rates. The authors conclude that their study is constrained because:

The two indicators of substance used [that is, the drug overdose rate and the drug-related hospitalization rate] do not perfectly measure actual substance use prevalence, particularly among parents. We do not have a good measure of county-level substance use disorder or substance misuse prevalence, and thus we used indicators that have been correlated with substance misuse and use disorder as surrogates.⁸⁴

Since the authors use a similar substance abuse death rate variable and do not include a substance abuse prevalence variable, we think that the concerns of the HHS researchers apply to their study as well.

⁸¹Karin A. Mack, Christopher M. Jones; and Michael F. Ballesteros, “Illicit Drug Use, Illicit Drug Use Disorders, and Drug Overdose Deaths in Metropolitan and Nonmetropolitan Areas — United States,” *Surveillance Summaries* 66, no. 19 (October 2017): 1–12.

⁸²Alexander Y. Walley, Ziming Xuan, H. Holly Hackman, Emily Quinn, Maya Doe-Simkins, Amy Sorensen-Alawad, Sarah Ruiz, and Al Ozonoff, “Opioid Overdose Rates and Implementation of Overdose Education and Nasal Naloxone Distribution in Massachusetts: Interrupted Time Series Analysis,” *BMJ* 346 (2013): f174, <https://www.bmj.com/content/346/bmj.f174.full.pdf+html> (accessed November 27, 2018).

⁸³Daniel I. Rees, Joseph J. Sabia, Laura M. Argys, Joshua Latshaw, and Dhaval Dave, “With a Little Help from My Friends: The Effects of Naloxone Access and Good Samaritan Laws on Opioid-Related Deaths,” *NBER Working Paper Series*, no. 23171 (2017), <https://www.nber.org/papers/w23171.pdf> (accessed November 27, 2018).

⁸⁴Robin Ghertner, Melinda Baldwin, Gilbert Crouse, Laura Radel, and Annette Waters, *The Relationship between Substance Use Indicators and Child Welfare Caseloads* (Washington, DC: US Department of Health and Human Services, March 2018): 7.

Problematic interpretations of results.

As mentioned above, the authors employ a DiD design with state and year fixed effects in addition to a host of covariates. Their model intends to hold constant all but the five changes in state TANF policies in order to causally attribute them to changes in child maltreatment reports, substantiated cases, and foster care placements.

We have six primary concerns, detailed below, about their analytical model and the statistical conclusion validity of the results.

Small sample sizes lead to large confidence intervals and the possible loss of other possible causal explanations. The authors' unit of analysis is the fifty US states as well as Washington, DC and Puerto Rico. (They, as is the recommended practice, cluster the standard errors on the state.) Given their resources, choosing states as the unit of analysis is probably necessary, but the result is a small sample size, consequently increasing the size of the standard errors (and, concomitantly, the confidence intervals).

Of the standard errors that the authors report, nearly all of the statistically significant findings ($p < 0.05$) are at the cutoff of significance. In fact, many of the statistically significant findings would not be significant if the coefficients were rounded to the nearest hundredth instead of thousandth. Moreover, the resultant confidence intervals indicate that the estimates are imprecise and, although some may be statistically significant, it is impossible to determine the magnitude of the true effect. For example, the authors find that the implementation of the work requirement leads to a 23.3 percent increase in the number of substantiated neglect cases. Assuming a sample size of fifty-two and a two-tailed significance test (t-test), the 95 percent confidence interval would place the true effect somewhere between 0.1 and 46.6 percent.

In addition to the loss of precision, small sample sizes and the resultant large standard errors reduce the statistical power of the analysis. This means that other important, potentially valid results will be dismissed. For example, in their APPAM paper, the authors find only one statistically significant effect of adopting all four work-related TANF policies: A 32.2 percent increase in foster care placements. Included in the authors' table 3, however, there are large effects reported for substantiated cases of both abuse and neglect (30.4 and 32.0 percent, respectively). These effects are only modestly smaller (1.8 and 0.2 percent, respectively) than the statistically significant foster care finding, and larger than some of the other statistically significant findings.⁸⁵ (For example, implementing the work requirement was found to lead to a 12.3 percent increase in the number of substantiated cases of abuse.) Presumably the lack of statistical significance is largely driven by the inclusion of only one state in the treatment group. This is a likely explanation for the change in the intervention variables that the authors use.

⁸⁵Donna K. Ginther and Michelle Johnson-Motoyama, "Do State TANF Policies Affect Child Abuse and Neglect?" (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): table 3, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

Unexplained changes in the policy changes (intervention variables) used. As mentioned above, in the initial APPAM paper, the authors use five work-related intervention variables: (1) a work-related requirement that results in the total loss of benefits if unmet, (2) a time limit for receiving TANF benefits of less than sixty months, (3) no increase in the earnings disregard, (4) a requirement that participants return to work if they have a child under the age of one, and (5) all of the above policies.

It appears, that in the subsequent presentations mentioned above, that the authors dropped the earnings disregard variable in favor of a new intervention variable they have constructed that attempts to capture state policy changes that led to an increase in the percentage of denied TANF applications (“denials”). Because the authors do not have official documentation to prove the policy changes took place, they instead use a proxy for the implementation of a policy change: if the denial rate in a state is above the national average and increases about 20 percentage points within a two-year period.

This new variable is potentially problematic. First, the justification for the change is not explained. The rationale for the requirement that a state’s denial rates must be above the average prior to the jump is not apparent and the choice of size and duration of the spike seems arbitrary. Moreover, the inference that meeting these criteria indicates a change in policy is not sufficiently supported. For example, the authors compare TANF denial rates in Mississippi to Oklahoma and in Kansas to Missouri from 2000 to 2015, showing large spikes in Kansas and Mississippi that begin in 2011, which leads the authors to infer that a policy change occurred in 2011. They do not, however, provide any supporting evidence that, in fact, such a policy change occurred.

In addition, it is not clear why they opted to drop the earnings disregard variable. One possibility is that the earnings disregard variable may have been dropped because the authors found that it had no statistically significant effect on any of the dependent variables. But we do not know because, as mentioned, they have chosen not to explain to us their analytic decisions.

Unexplained changes in the manifestations of child maltreatment (dependent variables) used. In their APPAM paper, the authors estimate the effect of state TANF restrictions on six dependent variables, including the total number of: (1) reports of child abuse; (2) reports of child neglect; (3) substantiated cases of child abuse (what they call, “abuse victims”); (4) substantiated cases of child neglect (“neglect victims”); (5) children placed in foster care; and (6) children placed in foster care due to neglect.

Their subsequent presentations, however, shift to six similar, but distinct, dependent variables. These include the total number of: (1) total reports of both abuse and neglect; (2) reports of child neglect; (3) total substantiated cases of both abuse and neglect; (4) substantiated cases of neglect; (5) children placed in foster care; and (6) children placed in foster care due to neglect. The authors do not give a reason for the shift nor mention any previous analyses that used a different set of dependent variables. We did not see an explanation why abuse is no longer considered separately, and we think this should have been explained.

Moreover, it should be noted, that while the presentations state that the authors used total reports and total substantiated cases as dependent variables, the coefficients contained in the table are the same as those reported in their paper for number of abuse reports and number of substantiated abuse cases. And the values for the remaining dependent variables did not change for either the work requirement or time limit restrictions. This is odd given that the intervention variables changed (three were removed and one was added), which should have resulted in a change in the coefficients, and presumably, their statistical significance.

Incomplete set of robustness checks. The authors report two robustness checks in their paper (none are included in the presentation slides), finding that four of the six statistically significant findings ($p < 0.05$) from their investigation of work-related TANF policies are robust. (They do not report performing a robustness check on their analysis of behavioral requirements.)

In the first robustness check, the authors employ a regression that includes together all five policy changes (instead of regressing separately each dependent variable on each TANF restriction). In the second, the authors estimate the effect of including lead measures on two of the TANF restrictions to identify whether the total number of substantiated cases and foster care placements were increasing in the three “periods” prior to the policy change. (It is unclear what constitutes a “period,” however.) The authors find that none of the coefficients on any of the three lead periods were statistically significant. In fact, it appears as though, on average, there was a decline in these dependent variables prior to the policy change.

This second robustness check, however, suffers from two weaknesses. First, it creates and uses a new dependent variable, “total victims,” that combines the number of substantiated cases of both abuse and neglect. Presumably, “total victims” is meant to be a robustness check for the number of substantiated abuse cases. This, however, seems to be a weak test because of the dissimilarity between the two dependent variables, that is, the “total victims” variable includes not only the number of substantiated cases of abuse, but also of neglect. A more rigorous test would compare how adding lead measures affected the substantiated cases of abuse variable.

Second, unlike the Granger test,⁸⁶ which uses both lead and lag periods, no lag periods were included in the authors’ procedure. As a result, the authors test whether the number of victims and foster care placements increased prior to the change in TANF policy, but do not indicate whether they decrease in the periods after, and thus, we are unable to ascertain whether there is some degree of regression to the mean or state-level secular trend captured in their estimates.

In addition, the authors do not test the sensitivity of their findings to changes in measurement of the dependent variables or to the research design. We think that the paper and its

⁸⁶Discussed in Angrist and Pischke (2009, pp. 237-238), the Granger test is widely used in DiD analyses when three or more periods of data are available.

conclusions would be strengthened by considering how the results would be affected by using rates of reported child maltreatment and substantiated cases (instead of total number), or by using individual (in this case, state) fixed effects (with or without year fixed effects) without DiD.

Failure to account for multiple comparisons (or “multiple hypothesis testing”). In their APPAM paper, the authors estimate separately the effect of each state TANF restriction on each dependent variable (a total of thirty regressions), each with its own significance test. Another six tests were used in their analysis of the behavioral requirements. Thus, in total, the authors’ paper presents the results of thirty-six significance tests (not including those conducted as part of the various robustness checks).

The authors’ presentations indicate that many more regressions and significance tests were conducted (our best guess is between twelve and twenty-four). On its face, this raises the strong possibility that the authors were “fishing” for a result in accordance with their hypothesis, called “data mining.”

As Hervé Abdi states, “The larger the number of tests, the easier it is to find rare events and therefore the easier it is to make the mistake of thinking that there is an effect when there is none.”⁸⁷ In order to account for the increased risk of type I error (or “false positives”), one common approach is to adjust downward the alpha level used for each significance test, which therefore reduces the overall (or “experiment-wise”) likelihood of type I error. (The most common approach is the Bonferonni correction, which uses the number of comparisons made in adjusting the alpha level.)

The authors make no mention of any adjustment to account for multiple comparisons, and, given the large number of significance tests, we are concerned that the results they report (despite their reported statistical significance) may be due to chance rather than to changes in state TANF policies. It would be preferable to have an answer to this simple question from the authors, without it, we are forced to assume that no adjustments for multiple comparisons were made.

Failure to sufficiently caution about the uncertainty of their results and the limitations of their estimates. As mentioned above, although the authors usually describe their findings as “preliminary,” their published statements make it seem that their findings are conclusive, and that they are merely finalizing their report. In their APPAM paper, they state:

States that adopted a policy of sanctioning all benefits in the case of non-compliance with work requirements increased child abuse victims, neglect victims, total foster care placements, and foster care placements for reasons of neglect by 12 to 23 percent. States that restricted benefits to less than 60 months saw increases in child abuse victims and

⁸⁷Hervé Abdi, “The Bonferonni and Šidák Corrections for Multiple Comparisons,” in *Encyclopedia of Measurement and Statistics*, ed. Neil Salkind (Thousand Oaks, CA: Sage, 2007).

neglect victims of over 30 percent. When states adopted all four sanctions, foster care placements increased by 32 percent. These are large and significant effects on victims and foster care placements.⁸⁸

Later, they state: “Future research will incorporate levels of evidence for substantiated cases as well as universal mandated reporting laws, changes in state definitions of abuse and neglect, caseload sizes for intake workers, and funding for CPS to control for variations in reports, investigations, and victimization within states over time.”⁸⁹ They also mention that future analyses will consider changes to the state-level administration of TANF benefits. In their presentation to the Kansas House Standing Committee on Children and Seniors, when mentioning “more work to do,” they include “estimate counterfactual outcomes and other robustness checks to support causal argument.”⁹⁰

We assume that this means the authors intend to incorporate these factors into their analysis as control variables. If this is the case, however, we could find no mention of how they expected their results to change as a result of these additional control variables. For the reasons described throughout this review, we think these are very significant issues that, if used as control variables, seem likely to alter the authors’ findings, and thus the conclusions they are able to reach.

The passages above, however, imply that the authors expect no serious changes to their findings, namely that “restrictions on access to the safety net appear to have unintended and dire consequences.”⁹¹ This and other strong assertions are made without sufficient consideration to the limitations the authors, themselves, describe and their potential to alter their findings in future work, and without sufficient caution about the uncertainty of their findings. For example, in neither their paper nor presentations do the authors mention the large standard errors

⁸⁸Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 16-17, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

⁸⁹Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 18-19, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

⁹⁰Michelle Johnson-Motoyama, “Do Changes to the Social Safety Net Affect Child Maltreatment? A Preliminary Study of TANF” (presentation, Kansas House Standing Committee on Children and Seniors, Topeka, KS, January 30, 2018), http://www.kslegislature.org/li/b2017_18/committees/ctte_h_children_and_seniors_1/documents/testimony/20180130_01.pdf (accessed November 5, 2018).

⁹¹Michelle Johnson-Motoyama, “Do Changes to the Social Safety Net Affect Child Maltreatment? A Preliminary Study of TANF” (presentation, Kansas House Standing Committee on Children and Seniors, Topeka, KS, January 30, 2018), http://www.kslegislature.org/li/b2017_18/committees/ctte_h_children_and_seniors_1/documents/testimony/20180130_01.pdf (accessed November 5, 2018).

associated with their estimates and what they means for both the interpretation of their findings and, subsequently, their policy implications. As described above, the large standard errors indicate substantial uncertainty, regardless of whether a given result is statistically significant.

Adding the word “preliminary” is not sufficient.

Overall assessment of study

We agree with the authors that it is important to ascertain the possible negative effects of policy decisions on vulnerable populations. It is also important to ensure that arguments for or against policy decisions are based on evidence meeting the standards of scientific rigor. As we said in the introduction, although the authors have called their publicized findings “preliminary,” in fact, their findings have entered the policy debate and, therefore, are fairly subject to outside assessment. Reviewing the public materials in support of their findings, we have raised a number of questions. To recount, we judge that: (1) the causal hypothesis is based on incomplete data and analysis, (2) the research design is not sufficiently described for assessment, (3) there are incomplete and shifting variables concerning TANF and other program changes, (4) the changes in child welfare policies and practices apparently are not taken into account, (5) the growth in substance abuse is not sufficiently taken into account, and (6) the authors’ interpretation of results is problematic.

No research study is flawless, and many important advances in knowledge have been achieved through imperfect research. Nevertheless, we think that our enumeration of problems with the authors’ work establishes that, whatever might be the actual relationship between the availability of welfare benefits and child maltreatment and foster care placement, what we know about their analysis establishes that their study does not support their publicized findings.

Simply put, this is a work in progress that should not be used as the basis of causal conclusions or policy recommendations.

Appendix A

Literature Review

The link between poverty and maltreatment has been well established. Twenty-five years ago, Douglas Besharov and Lisa Laumann noted that available data reveal “an unambiguous association between maltreatment and poverty.”⁹²

The authors cite a small portion of the large literature on the subject. As they suggest, the best of this research goes no further than to find an association between maltreatment and poverty—leaving open the strong possibility that various psychosocial factors are at work, influencing both family income and possible child maltreatment and foster care placement. The authors summarize:

While none of these factors in isolation have been proven to cause child maltreatment, studies over the past four decades have repeatedly demonstrated the association between economic determinants and child abuse and neglect (e.g., Paxson, Berger, & Waldfogel, 2002; Pelton, 2015; Shook, 1999; Slack et al., 2004; Berger & Waldfogel, 2011; Lindo, Schaller & Hansen 2013; Lindo & Schaller, 2014).⁹³

As the well-worn axiom goes, however, “correlation is not causation.”

Unsettled in the most careful research is how poverty and child maltreatment are related. As Kristen Slack, Lawrence Berger, and Jennifer Noyes observe, “Despite the vast number of studies that point to correlations between various economic indicators and child maltreatment, there is scant research that attempts to understand the causal role of economic factors in child maltreatment.”⁹⁴

Further complicating this research is the likelihood that the greater surveillance by public and private agencies under which poor families live leads to more reporting than is the case for middle-class families. For example, Mark Chaffin and David Bard find that “surveillance bias was substantial during time periods when clients were actively engaged in services.” They define

⁹²Douglas Besharov and Lisa Laumann, “Don’t Call It Child Abuse If It’s Really Poverty,” *Journal of Children and Poverty* 3, no. 1 (1994): 5-36.

⁹³Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 3, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

⁹⁴Kristen S. Slack, Lawrence M. Berger, and Jennifer L. Noyes, “Introduction to the Special Issue on the Economic Causes and Consequences of Child Maltreatment,” *Children and Youth Services Review* 72 (2017): 1-4, https://www.researchgate.net/publication/309960371_Introduction_to_the_special_issue_on_the_economic_causes_and_consequences_of_child_maltreatment (accessed November 19, 2018).

“surveillance bias” as “any increased, systematic, outcome-related scrutiny that may exist for some individuals or groups but not others.”⁹⁵ Other researchers, however, such as Brett Drake, Melissa Johnson-Reid, and Hyunil Kim, find that “surveillance bias effects appear to exist, but are very small.”⁹⁶

Various psychosocial factors, in addition to poverty, are associated with child maltreatment. As the authors note, in addition to poverty or financial hardship, most researchers have found various psychosocial factors to be associated with child maltreatment.

The determinants of child abuse and neglect are typically approached from the perspective of developmental-ecological theories (Garbarino, 1977; Belsky, 1993) that suggest child abuse and neglect result from the interactions between a number of risk factors including parent and child characteristics, parent-child interactions, family characteristics, socioeconomic status and economic resources, and the social and environmental contexts in which the child and family are situated (Stith et al., 2009; Coulton et al., 2007).⁹⁷

In fact, most studies find that these various factors or a combination of them are more predictive of child maltreatment than poverty or financial hardship alone. Thus, a 2001 longitudinal analysis of over 14,000 children in the United Kingdom conducted by Peter Sidebotham and Jean Golding found that for both mothers and fathers, age, educational achievement, and a history of psychiatric illness were primary factors in an understanding of child maltreatment.⁹⁸

In a 2018 meta-analytic review of the “risk factors for child neglect,” Tim Mulder et al. examined 437 studies, 36 of which met their inclusion criteria for a systematic analysis. These were studies published since 1990, “primarily because earlier attitudes on and definitions of types of child maltreatment differ substantially from contemporary notions of child maltreatment

⁹⁵Mark Chaffin and David Bard, “Impact of Intervention Surveillance Bias on Analyses of Child Welfare Report Outcomes,” *Child Maltreatment* 11, no. 4 (2006): 301-312, <https://journals.sagepub.com/doi/pdf/10.1177/1077559506291261> (accessed November 19, 2018).

⁹⁶Brett Drake, Melissa Johnson-Reid, and Hyunil Kim, “Surveillance Bias in Child Maltreatment: A Tempest in a Teapot,” *International Journal of Environmental Research and Public Health* 14, no. 9 (2017): 1, <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5615508/pdf/ijerph-14-00971.pdf> (accessed November 19, 2018).

⁹⁷Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 3, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

⁹⁸Peter Sidebotham and Jean Golding, “Child Maltreatment in the ‘Children of the Nineties’: A Longitudinal Study of Parental Risk Factors,” *Child Abuse and Neglect* 25, no. 9 (2001): 1177-1200.

(Goode, 1971; Gelles, 1980).”⁹⁹ The 36 primary studies covered a total sample of 729,840 children. The risk factors extracted from these studies were classified into twenty-four domains and then categorized as family level, parental level, child level, and “other” factors. (See table A-1, below).

Among the many statistically significant results, their findings indicate that the strongest predictors of child neglect involved parental characteristics, such as a “history of antisocial behavior/criminal offending,” “history of mental/psychiatric problems,” and low educational level. Mother-related risk factors were slightly larger than father-related factors. Six of the domains revealed non-significant results: a family experiencing “low social support/low social network,” the occurrence of “prenatal problems,” “parental substance (ab)use,” “adverse parental cognitions regarding pregnancy,” a “child being female,” and a “child being younger.”¹⁰⁰

Overall, Mulder et. al. “found that multiple risk factors were involved in the occurrence of child neglect. These findings confirm that child neglect is more likely determined by multiple causes, than by one specific factor.”¹⁰¹ They did, however, find that “the strongest predictors of child neglect can be found in parental characteristics.”¹⁰² (As discussed below, it is striking that parental substance abuse was among the non-significant risk factors in the meta-analytic review. Five of the thirty-six studies reviewed in that analysis examined substance abuse as a risk factor.)¹⁰³

Kelly Fong used qualitative methods to examine the links between poverty and involvement with child protective services. Fong interviewed 40 poor parents who were subject to child welfare investigations, analyzing how these respondents interpreted the 107 incidents they identified as leading to child welfare investigations. According to Fong: “Many respondents traced their child welfare involvement not to poverty directly, but to related adversities:

⁹⁹Tim M. Mulder, Kimberly C. Kuiper, Claudia E. van der Put, Geert-Jan J.M. Stams, and Mark Assink, “Risk Factors for Child Neglect: A Meta-Analytic Review,” *Child Abuse and Neglect* C, 77 (2018): 8, https://pure.uva.nl/ws/files/21849594/Manuscript_UvA_DARE.pdf (accessed November 19, 2018).

¹⁰⁰Tim M. Mulder, Kimberly C. Kuiper, Claudia E. van der Put, Geert-Jan J.M. Stams, and Mark Assink, “Risk Factors for Child Neglect: A Meta-Analytic Review,” *Child Abuse and Neglect* C, 77 (2018): 198-210.

¹⁰¹Tim M. Mulder, Kimberly C. Kuiper, Claudia E. van der Put, Geert-Jan J.M. Stams, and Mark Assink, “Risk Factors for Child Neglect: A Meta-Analytic Review,” *Child Abuse and Neglect* C, 77 (2018): 25, https://pure.uva.nl/ws/files/21849594/Manuscript_UvA_DARE.pdf (accessed November 19, 2018).

¹⁰²Tim M. Mulder, Kimberly C. Kuiper, Claudia E. van der Put, Geert-Jan J.M. Stams, and Mark Assink, “Risk Factors for Child Neglect: A Meta-Analytic Review,” *Child Abuse and Neglect* C, 77 (2018): 25, https://pure.uva.nl/ws/files/21849594/Manuscript_UvA_DARE.pdf (accessed November 19, 2018).

¹⁰³Tim M. Mulder, Kimberly C. Kuiper, Claudia E. van der Put, Geert-Jan J.M. Stams, and Mark Assink, “Risk Factors for Child Neglect: A Meta-Analytic Review,” *Child Abuse and Neglect* C, 77 (2018): 19-23, https://pure.uva.nl/ws/files/21849594/Manuscript_UvA_DARE.pdf (accessed November 19, 2018).

substance abuse, mental illness, domestic violence, and criminal justice. Yet these adversities cannot be fully separated from respondents' poverty."¹⁰⁴

In a 2009 meta-analytic review of the research on risk factors related to both child neglect and physical abuse, Sandra Stith et al. located 867 relevant studies, of which 155 met their criteria for inclusion. These studies covered a much broader time period than Mulder et al.'s meta-analysis, including studies from the 1970s to the 2000s, and contained 656 results for which effect sizes were either provided by the study author or calculated by Stith et al. The effect sizes were then classified into thirty-nine risk factors for either child physical abuse or child neglect and further categorized into one of four "microsystems": (1) "parent/child interaction/parental report of child behavior," (2) "parent characteristics independent of the child," (3) "child characteristics, excluding parents," and (4) "family characteristics." Their findings indicate that risk factors such as parent anger/hyper-reactivity, anxiety, and psychopathology were more strongly related to physical abuse than the most frequently cited factors of parent stress, social support, and single parenthood. Parental psychopathology, self-esteem, and anger had stronger relationships to physical abuse and neglect than socio-economic status. They also find that "the phenomena of child neglect may be different from child physical abuse and deserves its own investigation into cause and treatment."¹⁰⁵

¹⁰⁴Kelly Fong, "Child Welfare Involvement and Contexts of Poverty: The Role of Parental Adversities, Social Networks, and Social Services," *Children and Youth Services Review*, 72 (2017): 5-13.

¹⁰⁵Sandra M. Stith, Ting Liu, L. Christopher Davies, Esther L. Boykin, Meagan C. Alder, Jennifer M. Harris, Anurag Som, Mary McPherson, J.E.M.E.G. Dees, "Risk Factors in Child Maltreatment: A Meta-analytic Review of the Literature," *Aggression and Violent Behavior* 14, no. 1 (2009): 14-29.

Table A-1: Risk domains for child neglect, according to Mulder, Kuiper, van der Put, Stams, and Assink

Family level

Parents not married
Physical violence in the home environment
Large family size (> 2 children)
Low family
Child is not living with two biological parents
Problematic family behavior and cognitions
Low social support/small social network

Parental level

History of antisocial behavior/criminal offending
History of mental/psychiatric problems
Prenatal problems
Low education
Mental/physical problems
History of abuse
Age factors
Unemployment
Substance (ab)use
Adverse childhood experiences
Adverse cognitions regarding pregnancy.

Child level

Being non-Caucasian
Perinatal problems
Mental/physical/behavioral problems
Being female
Being younger

Other

Adapted from: Tim M. Mulder, Kimberly C. Kuiper, Claudia E. van der Put, Geert-Jan J.M. Stams, and Mark Assink, "Risk Factors for Child Neglect: A Meta-Analytic Review," *Child Abuse and Neglect* 77 (2018): 19-23, https://pure.uva.nl/ws/files/21849594/Manuscript_UvA_DARE.pdf (accessed November 19, 2018).

Although the authors do not express it this quite way, underlying their hypothesis linking safety-net tightening to child maltreatment is the idea that the lack of money triggers a change in some other aspect of parental condition or capacity (the “intervening variable”) that, in turn, leads to child maltreatment. In relation to child *neglect*, the authors describe the triggering mechanism as follows:

Economic determinants influence stability, and the degree of predictability and consistency in a child’s environment, and they create social contexts for neglect when families are unable to invest in a child’s basic needs for food, housing, medical care, clothing, and appropriate child care. Economic factors may influence the extent to which a parent or caregiver is available and able to nurture and respond to their child’s needs when factors such as low income, income instability, food insecurity, or lack of health insurance contribute to parental stress, anxiety, or depression, factors that are associated with child neglect (Stith et al., 2009; Slack et al., 2011).¹⁰⁶

At another point, they seem to make reference to the somewhat separate causes of child *abuse*:

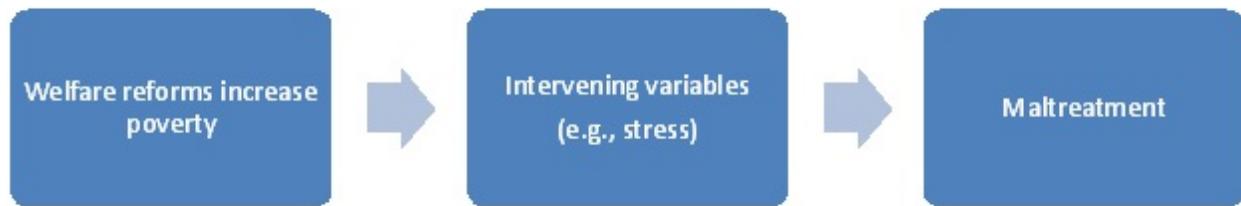
Shocks during periods of economic instability such as male layoffs, loss of employment, declines in consumer confidence, and housing foreclosures have also been associated with increased risks of child abuse and neglect and increased probabilities of CPS involvement (Berger et al., 2015; Huang et al., 2011; Lindo, & Schaller, 2014; Lindo, Schaller & Hanson, 2013; Wood et al., 2012; Brooks-Gunn, Schneider, & Waldfogel, 2013).¹⁰⁷

These descriptions of causality have strong face plausibility, but have not been validated through rigorous research.

¹⁰⁶Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 5, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

¹⁰⁷Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 3-4, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

Figure A-1: The intervening variables linking welfare reforms and child maltreatment



An alternative causal theory suggests that adverse parental characteristics, such as mental illness and drug abuse, are antecedent variables that are strongly associated with *both* poverty and maltreatment. That is, increases in mental illness and substance abuse might simultaneously increase both the prevalence of child maltreatment and poverty.

Figure A-2: The role of antecedent variables on the relationship between poverty and child



Although these are two of the major theoretical causal perspectives, there are other explanations, including: behavioral problems of children, the intergenerational transmission of maltreatment and poverty, and the view that the causal link between poverty and antecedent variables such as drug abuse could run in the other direction (i.e., the despair of poverty leading to drug abuse).

Research cited by the authors on the role of the safety net is limited. What about the role of safety-net programs in regards to child maltreatment, the heart of the authors' argument? "A small body of research," they note, "has also demonstrated relationships between economic and social safety net policies and child abuse and neglect (Paxson & Waldfogel, 2002; 2003; Berger et. al. 2014; Klevens et al., 2015; Berger, Font, Slack & Waldfogel, 2016; Raissian & Bullinger, 2017; Wildeman & Fallesen, 2017)."¹⁰⁸ The studies they cite, however, are either correlational or appear not sufficiently rigorous to support their argument.

In the second study by Christina Paxson and Jane Waldfogel cited by the authors, the researchers used fixed effects to explore how policy changes introduced by welfare reform were associated with the "number of substantiated and indicated cases of maltreatment, the number of substantiated and indicated cases of neglect, and the number of substantiated and indicated cases of neglect. . . . [and] the number of children in out-of-home care (primarily foster care)."¹⁰⁹ According to the authors:

[Paxson and Waldfogel (2003)] found that reductions in welfare benefits were associated with increases in out-of-home care, and lifetime welfare limits and sanctions for noncompliance were associated with increases in substantiated child abuse and neglect cases. However, these studies suffer from both methodological and data limitations. . . . Therefore, we agree with Paxson and Waldfogel's conclusion that their 2003 results are preliminary: "These factors indicate that welfare reforms may have greater long-run effects on maltreatment than this evidence indicates." (Paxson & Waldfogel, 2003 p. 109).¹¹⁰

With that caveat in mind, Paxson and Waldfogel's findings included significant relationships between rising welfare benefits and declining levels of maltreatment and foster care placements. Specifically, their statistical analysis estimates that a 10 percent increase in the maximum welfare benefit for a family of four would reduce neglect by 39 percent and foster care by nearly 20 percent. However, the significant negative relationship between benefit levels and neglect did not hold for other types of maltreatment. In fact, the data revealed a reverse effect: as welfare benefits increased so did rates of physical and sexual abuse. The authors note that the latter effects were smaller than the relation to neglect and the estimates were not precise, and, as the authors note, may be the result of "methodological and data limitations."

¹⁰⁸Donna K. Ginther and Michelle Johnson-Motoyama, "Do State TANF Policies Affect Child Abuse and Neglect?" (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 4, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

¹⁰⁹Christina Paxson and Jane Waldfogel, "Welfare Reforms, Family Resources, and Child Maltreatment," *Journal of Policy Analysis and Management* 22, no. 1 (2003): 93, <https://onlinelibrary.wiley.com/doi/epdf/10.1002/pam.10097> (accessed November 20, 2018).

¹¹⁰Donna K. Ginther and Michelle Johnson-Motoyama, "Do State TANF Policies Affect Child Abuse and Neglect?" (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 6-7, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

The next study the authors discuss is a self-described “correlational” study, so that its significance is limited. Moreover, its findings may reflect only spurious associations:

In their exploration of policies for the reduction of child abuse and neglect, Klevens et al. (2015) identified several state longitudinal data sources and explored the association between poverty reduction policies, affordable housing, affordable child care, access to pre-Kindergarten, and children’s and parent’s access to health care. After controlling for childhood poverty, high school graduation, unemployment, demographic characteristics, and the child dependency ratio they find only a few policy variables that are associated with state-level child maltreatment investigation rates. In particular, wait lists for child care increase child maltreatment investigations while continuity of eligibility for Medicaid/SCHIP decreases investigations.¹¹¹

The next study the authors review is by Lawrence Berger et al. who use “potential EITC benefit available to a family” as an instrumental variable (“IV”) method to estimate the effect of income on child maltreatment. In addition to reporting estimates from the IV design, which they describe as their “preferred specification,” the authors also present results from four other regression models, finding that “at least among single-mother families and, to a slightly lesser extent, families with greater number of children, our (preferred) IV specification produces larger and more frequently significant estimates of the effect of income on behaviorally approximated neglect and CPS involvement than models that less rigorously address selection.”¹¹² Berger et al. note: “We find no evidence of a causal link between income and child abuse.”¹¹³ According to the authors:

[Berger et al.] find that an increase in income via the EITC is associated with reductions in involvement with CPS. However, they do not investigate whether the EITC is associated with the number of child victims nor involvement in out-of-home care.

¹¹¹Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 8, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

¹¹²Lawrence M. Berger, Sarah A. Font, Kristen S. Slack, and Jane Waldfogel, “Income and Child Maltreatment in Unmarried Families: Evidence from the Earned Income Tax Credit,” *Review of Economics of the Household* 15, no. 4 (2017): 1352-1361, <https://link.springer.com/article/10.1007/s11150-016-9346-9> (accessed November 19, 2018).

¹¹³Lawrence M. Berger, Sarah A. Font, Kristen S. Slack, and Jane Waldfogel, “Income and Child Maltreatment in Unmarried Families: Evidence from the Earned Income Tax Credit,” *Review of Economics of the Household* 15, no. 4 (2017): 1361, <https://link.springer.com/article/10.1007/s11150-016-9346-9> (accessed November 19, 2018).

Furthermore, instrumental variables strategies depend critically on the validity of the instrument and may be subject to change when different instruments are used.¹¹⁴

This study is based on the self-reports of parents in the Fragile Families and Child Well-Being Study which are interpreted post hoc and introduces uncertainty about the validity of the measures. Thus, the researchers are careful to warn that “none of our behaviorally approximated measures necessarily meet statutory definitions of maltreatment.”¹¹⁵ Furthermore, when fixed effects are added to the model, the results tend to diminish and lose statistical significance.

Kerri Raissian and Lindsey Bullinger in another study cited by the authors, used fixed effects to estimate the effect changes in minimum wage have on the rate of child maltreatment reports.¹¹⁶ According to the authors:

Raissian and Bullinger (2017), using child maltreatment reports from NCANDS from 2004 to 2013, found that increases in the minimum wage led to a decline in overall child maltreatment reports, particularly neglect reports. Estimating the effect of the minimum wage on child maltreatment using weighted least squares regression, they find that a \$1 increase in the minimum wage implies a statistically significant 9.6% decline in neglect reports, an effect that was concentrated among young children (ages 0-5) and school-aged children (ages 6-12). However, this study examined the minimum wage only without taking into account the effects of other economic or social safety net policies, and did not use a difference-in-differences approach to identify the causal effect of state minimum wages.¹¹⁷

Unmentioned by the authors is that the study found no statistically significant effects on the overall “report rate,” the “physical abuse report rate,” the “other abuse report rate,” the

¹¹⁴Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 8, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

¹¹⁵Lawrence M. Berger, Sarah A. Font, Kristen S. Slack, and Jane Waldfogel, “Income and Child Maltreatment in Unmarried Families: Evidence from the Earned Income Tax Credit,” *Review of Economics of the Household* 15, no. 4 (2017): 1349, <https://link.springer.com/article/10.1007/s11150-016-9346-9> (accessed November 19, 2018).

¹¹⁶Kerri M. Raissian and Lindsey Rose Bullinger, “Money Matters: Does the Minimum Wage Affect Child Maltreatment Rates?” *Children and Youth Services Review* 72 (2017): 60-70, <https://www.sciencedirect.com/science/article/pii/S0190740916303139> (accessed November 16, 2018).

¹¹⁷Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 8-9, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdfd1c58dfd496b3.pdf> (accessed November 5, 2018).

“substantiation rate,” or the “removal rate.”¹¹⁸ Regardless of any other strengths or weakness of the study, this suggests that the finding was a chance result.

The last study described by the authors uses a difference-in-differences model, and is perhaps the most relevant to their own study.¹¹⁹

Wildeman and Fallesen (2017) used Danish registry data and a 2004 policy shock to estimate the effect of a substantial decrease in welfare generosity (a monthly reduction in disposable income of 30% for those who were on a specific form of welfare for six consecutive months or more) on children’s risk of out-of-home placement among women who lacked unemployment insurance and had been long-term recipients on welfare benefits. Their results indicate that this decrease in welfare generosity increased children’s risk of out-of-home placement by about 1.5 percentage points in any given year, representing an increase of about 25% in the annual risk of out-of-home placement. Their research, which relied on a difference-in-difference framework, demonstrated that substantial changes in economic conditions of the poorest families can have a substantial effect on the probability that their children will be placed in out-of-home care. However, their dependent variable was limited to out-of-home care placement and their study was conducted in a European context, which limits the generalizability of findings.¹²⁰

This appears to a well-conducted difference-in-differences study with two major possible exceptions. First, no baseline characteristics are reported for the mothers in the treatment and comparison groups, so it is unclear how similar the two groups are, and thus, whether the two groups should be or can be compared. Second, it is difficult to tell whether the common slopes assumption is satisfied because in the year preceding the policy change, for the treatment group, the out-of-home placement risk increased just prior to the policy change whereas it decreased for the comparison group. The changes are small, but it is unclear if these changes were the beginning of a larger overall trend or simply random fluctuations. If the former, the divergent shift would indicate that the trends were dissimilar at the time of the policy change thus violating the common slopes assumptions and rendering invalid the results.

¹¹⁸Kerri M. Raissian and Lindsey Rose Bullinger, “Money Matters: Does the Minimum Wage Affect Child Maltreatment Rates?” *Children and Youth Services Review* 72 (2017): 64, <https://www.sciencedirect.com/science/article/pii/S0190740916303139> (accessed November 16, 2018).

¹¹⁹Christopher Wildeman and Peter Fallesen, “The Effect of Lowering Welfare Payment Ceilings on Children’s Risk of Out-of-Home Placement,” *Children and Youth Services Review* 72 (January 2017): 82–90.

¹²⁰Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 9, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

Child abuse vs. child neglect. The two meta-analyses previously discussed signal the importance of distinguishing between the causes of child abuse and causes of child neglect—which the authors only partially address.

In their 2009 meta-analysis, Stith et al. also found important differences between factors related to child abuse and child neglect. For example, factors related to parental adequacy, competency and resilience were strongly related to neglect but not physical abuse. While alcohol and drug abuse were significantly related to physical abuse anxiety there were no findings reported on their relationship to neglect.¹²¹ The authors suggest that the phenomena of child neglect may be different from child physical abuse and that each deserves its own investigation into cause and treatment.¹²²

In total, these two meta-analyses (Mulder et al. and Stith et al.) examined over 1,000 studies of child maltreatment (not including cases of sexual and emotional abuse), identifying more than 150 that met the inclusion criteria for a rigorous analytic assessment of empirical relationships. The meta-analyses revealed a number of important factors that had a bearing on maltreatment including the parents’ cognitive issues, mental illness, physical illness, anger control, substance abuse, socio-economic status, educational level, and personal relationship. Evidence concerning the weight that should be given to these various factors was inconclusive. The research also suggested that different risk factors are more or less associated with the categories of neglect and physical abuse. Overall, these results alert researchers and policy makers to the measurement difficulties, the complexity of the multi-faceted causal relationship and the uncertainties surrounding the findings about the causes of child maltreatment.

The authors point out that: “For the most part, past research has studied the relationship of economic and social safety net policies to child maltreatment without examining specific maltreatment subtypes or effects on subgroups of children.¹²³ As we will see, their study finds evidence of causation only in regard to child neglect.

The long shadow of substance abuse. Like child maltreatment, alcohol and drug abuse (“substance abuse”) has a multiplicity of causes, some psychosocial and some relating to medical

¹²¹Sandra M. Stith, Ting Liu, L. Christopher Davies, Esther L. Boykin, Meagan C. Alder, Jennifer M. Harris, Anurag Som, Mary McPherson, J.E.M.E.G. Dees, “Risk Factors in Child Maltreatment: A Meta-analytic Review of the Literature,” *Aggression and Violent Behavior* 14, no. 1 (2009): 14-29.

¹²²Sandra M. Stith, Ting Liu, L. Christopher Davies, Esther L. Boykin, Meagan C. Alder, Jennifer M. Harris, Anurag Som, Mary McPherson, J.E.M.E.G. Dees, “Risk Factors in Child Maltreatment: A Meta-analytic Review of the Literature,” *Aggression and Violent Behavior* 14, no. 1 (2009): 14-29.

¹²³Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017): 9-10, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).

practices (and abuses) coupled with the relative easy availability of substances to misuse.¹²⁴ Here is how the Alvarado Parkway Institute Behavioral Health System, a psychiatric care facility in San Diego, California, described what is known about the causes of substance abuse:

The cause of substance use disorders is still unknown, though genetics are thought to account for 40% to 60% of a person's risk. Substance use often starts as a way to feel good or out of curiosity in childhood or early adolescence. Repeated use of the substance and increased tolerance pave the way to substance use disorder and addiction. Some adults who develop a substance use disorder have a co-occurring mental illness, such as depression, anxiety, or bi-polar disorder, and begin using drugs or alcohol to cope with their symptoms. Other risk factors that may lead to a substance use disorder include: Family history of addiction, Sleep problems, Chronic pain, Financial difficulties, Divorce or the loss of a loved one, Long-term tobacco habit, Tense home environment, Lack of parental attachment in childhood, [and] Relationship issues.¹²⁵

And, indeed, many of the factors that can lead to substance abuse can also lead to child maltreatment.

Substance abuse, however, is also an independent cause of child maltreatment. Parents and caretakers who abuse alcohol and drugs have a higher likelihood of abusing or neglecting their children—even if not deliberately. According to the Child Welfare Information Gateway, parents (both mothers and fathers) “are less likely to be able to function effectively in a parental role. This can be due to: Impairments (both physical and mental) that occur while under the influence of alcohol or other drugs, Expenditure of often limited household resources on purchasing alcohol or other drugs, time spent seeking out drugs, [and] Time spent using alcohol or other drugs.”¹²⁶ As a result:

¹²⁴Vincent J. Felitti, Robert F. Anda, Dale Nodenberg, David F. Williamson, Alison M. Spitz, Valerie Edwards, Mary P. Koss, and James S. Marks, “Relationship of Childhood Abuse and Household Dysfunction to Many of the Leading Causes of Death in Adults,” *American Journal of Preventative Medicine* 14, no. 4 (1998): 245-258, [https://www.ajpmonline.org/article/S0749-3797\(98\)00017-8/pdf](https://www.ajpmonline.org/article/S0749-3797(98)00017-8/pdf) (accessed November 27, 2018); Mayo Clinic, “Drug Addiction (Substance Use Disorder),” <https://www.mayoclinic.org/diseases-conditions/drug-addiction/symptoms-causes/syc-20365112> (accessed November 27, 2018); National Institutes of Health, National Institute on Drug Abuse, “Drugs, Brains, and Behavior: The Science of Addiction,” <https://www.drugabuse.gov/publications/drugs-brains-behavior-science-addiction/drug-misuse-addiction> (accessed November 27, 2018); Sunrise House, “The Cause and Effect of Substance Abuse and Mental Health Issues,” <https://sunrisehouse.com/cause-effect/> (accessed November 27, 2018).

¹²⁵Alvarado Parkway Institute Behavioral Health System, “Different Types and Causes of Substance Abuse,” December 11, 2017, <https://www.apibhs.com/blog/types-causes-of-substance-abuse> (accessed November 28, 2018).

¹²⁶Child Welfare Information Gateway, *Substance Abuse and Child Maltreatment* (Washington, DC: US Department of Health and Human Services, Children's Bureau, 2014), https://www.childwelfare.gov/pubPDFs/subabuse_childmal.pdf (accessed November 28, 2018).

The basic needs of children, including nutrition, supervision, and nurturing, often go unmet due to parental substance abuse, resulting in neglect. Additionally, families in which one or both parents abuse substances, and particularly families with an addicted parent, often experience a number of other problems including mental illness, unemployment, high levels of stress, and impaired family functioning, all of which can put children at risk for abuse.¹²⁷

Barry Zuckerman expands on the effects on mothers: “Heavy use of drugs—especially actual addiction—interferes with a mother’s ability to provide the consistent nurturing and caregiving that promote children’s development, self-esteem, and ability to regulate their affect or impulses. . . . All aspects of the self are affected—the physical, the psychological, and the spiritual. With addicted women, their primary relationship is with their drug of choice, not with their child.”¹²⁸ (Furthermore, Richard Barth, Claire Gibbons, and Shenyang Guo add: “Intrauterine exposure to cocaine and other drugs can have a biobehavioral impact on the child, which may [sic] makes the child more difficult to care for and thus more prone to child maltreatment [Black & Mayer, 1980, Magura & Laudet, 1996].”)¹²⁹

Indeed, almost a quarter of a century ago, Richard Famularo, Robert Kinscherff, and Terence Fenton’s analysis of 190 randomly selected records from the caseload of a large juvenile court in which there was a finding of “significant child maltreatment” revealed that the parents were substance abusers in 67 percent of these cases.¹³⁰ More recently, Kathryn Wells advised that: “Pediatricians and other medical providers caring for children need to be aware of the dynamics in the significant relationship between substance abuse and child maltreatment. A caregiver’s use and abuse of alcohol, marijuana, heroin, cocaine, methamphetamine, and other drugs place the child at risk in multiple ways.”¹³¹ Consequently, many states describe parental substance abuse as an element in the definition of child abuse or neglect. In eight states, for

¹²⁷Child Welfare Information Gateway, *Substance Abuse and Child Maltreatment* (Washington, DC: US Department of Health and Human Services, Children's Bureau, 2014), https://www.childwelfare.gov/pubPDFs/subabuse_childmal.pdf (accessed November 28, 2018).

¹²⁸Barry Zuckerman, “Effects on Parents and Children,” in *When Drug Addicts Have Children*, ed. Douglas J. Besharov (Washington, DC: Child Welfare Leagues of America, 1994): 52.

¹²⁹Richard P. Barth, Claire Gibbons, and Shenyang Guo, “Substance Abuse Treatment and the Recurrence of Maltreatment among Caregivers with Children Living at Home: A Propensity Score Analysis,” *Journal of Substance Abuse Treatment* 30, no. 2 (2006): 94, [https://www.journalofsubstanceabusetreatment.com/article/S0740-5472\(05\)00202-3/pdf](https://www.journalofsubstanceabusetreatment.com/article/S0740-5472(05)00202-3/pdf) (accessed November 28, 2018).

¹³⁰Richard Famularo, Robert Kinscherff, and Terence Fenton, “Parental Substance Abuse and the Nature of Child Maltreatment,” *Child Abuse and Neglect* 16, no. 4 (1992): 475-483.

¹³¹Kathryn Wells, “Substance Abuse and Child Maltreatment,” *Pediatric Clinics of North America* 56, no. 2 (2009): 345-362.

example, drug-related circumstances that are considered maltreatment include: “Using a controlled substance that impairs the caregiver’s ability to adequately care for the child.”¹³²

Moreover, in its more severe forms, substance abuse also leads to foster care placements. According to the Child Welfare Information Gateway:

Once a report is substantiated, children of parents with substance use issues are more likely to be placed in out-of-home care and more likely to stay in care longer than other children (Barth, Gibbons, & Guo, 2006; HHS, 1999). The National Survey of Child and Adolescent Well-Being (NSCAW) estimates that 61 percent of infants and 41 percent of older children in out-of-home care are from families with active alcohol or drug abuse (Wulczyn, Ernst, & Fisher, 2011).¹³³

At the same time that a rise in substance abuse is likely to be reflected in increased child maltreatment and foster care placements, it can also worsen rates of poverty and financial hardship. Misusing alcohol and drugs can reduce the ability to hold down a job—or even remain in the workforce—hence, reducing earnings capacity. Using a sample of “African-American and Latina mothers living in an inner-city neighborhood of Chicago” with data collected during the last trimester of pregnancy and one year after birth, Evelyn Lehrer, Kathleen Crittenden, and Kathleen Norr found that the magnitude of the association between illicit drug use and reliance on welfare is very large. Although they caution that “it is not possible based on our analysis to make definitive statements regarding causality from a substance use problem to reliance on welfare, because our instruments are not ideal, [but] the estimates presented here are strongly suggestive of a very large influence.”¹³⁴

More recently, Alan Krueger found that increases in opioid prescriptions may account for as much as 20 to 25 percent of the total observed decline in workforce participation between 1999 and 2005. These findings are subject to omitted variable bias, as Krueger cautions: “For example, the incidence of obesity has increased in the United States, and it is plausible that the rise in obesity has led to increased back pain and other health ailments, which in turn have

¹³²US Department of Health and Human Services, Administration for Children and Families, Children’s Bureau, *Parental Drug Use as Child Abuse* (Washington, DC: US Department of Health and Human Services, 2016).

¹³³Child Welfare Information Gateway, *Parental Substance Use and the Child Welfare System* (Washington, DC: US Department of Health and Human Services, Children’s Bureau, 2014), <https://www.childwelfare.gov/pubs/factsheets/parentalsubabuse/> (accessed November 28, 2018).

¹³⁴Evelyn L. Lehrer, Kathleen Crittenden, and Kathleen F. Norr, “Illicit Drug Use and Reliance on Welfare,” *Journal of Drug Issues* (2002): 193-199, <https://journals.sagepub.com/doi/pdf/10.1177/002204260203200108> (accessed November 28, 2018).

caused both labor force participation to decline and demand for pain medication to rise.”¹³⁵ Subsequently, Ben Gitis estimated that nearly one million people between the ages of 25 to 54 were absent from the workforce because they were dependent on opioid drugs.¹³⁶

Hence, there is a two-way causal relationship between substance abuse and poverty that complicates parsing out the causes of child maltreatment. Moreover, when deciding what may be behind a rise in child maltreatment, this two-way relationship spotlights the importance of knowing whether rates of substance abuse are rising. And, of course, they are.

Substance abuse has long been a serious American problem, although there have been periods of increase followed by decline. Peter Reuter, Patricia Ebener, and Dan McCaffrey write: “Initiation into the use of drugs (as measured by the percentage of 17-year-olds experimenting with drugs) rose through the late 1970s and perhaps into the early 1980s, but began to decline by the middle of the 1980s. . . . Not unexpectedly, the number of drug *abusers*—those persons with serious drug problems—only a modest share of all drug users may only have begun to decline in 1989.”¹³⁷

Most recently, this long-standing problem has been aggravated by the growth of opioid use. According to the National Institute on Drug Abuse, between 1999 and 2013, the number of opioid pain relievers prescribed has nearly tripled from about 76 million to nearly 207 million. The Center reports: “This greater availability of opioid (and other) prescribed drugs has been accompanied by alarming increases in the negative consequences related to their abuse. For example, the estimated number of emergency department visits involving nonmedical use of opioid analgesics increased from 144,600 in 2004 to 305,900 in 2008.”¹³⁸ In 2017, the Substance

¹³⁵ Alan B. Krueger, Where Have All the Workers Gone? An Inquiry into the Decline of the US Labor Force Participation Rate, *Brookings Papers on Economic Activity* (2017) : 49, <https://www.brookings.edu/wp-content/uploads/2018/02/kruegertextfa17bpea.pdf> (accessed November 27, 2018).

¹³⁶ Katie Zezima, “Nearly 1 Million People Were Out of the Workforce Because of Opioid Addiction in 2015, According to Study,” *Washington Post*, March 27, 2018, https://www.washingtonpost.com/news/post-nation/wp/2018/03/27/more-than-4-million-people-left-the-workforce-because-of-opioid-addiction-according-to-study/?utm_term=.260b5f254562 (accessed November 27, 2018).

¹³⁷ Peter Reuter, Patricia Ebener, and Dan McCaffrey, “Patterns of Drug Use,” in *When Drug Addicts Have Children*, ed. Douglas J. Besharov (Washington, DC: Child Welfare Leagues of America, 1994): 4.

¹³⁸ National Institute on Drug Abuse, “America’s Addiction to Opioids: Heroin and Prescription Drug Abuse,” <https://www.drugabuse.gov/about-nida/legislative-activities/testimony-to-congress/2014/americas-addiction-to-opioids-heroin-prescription-drug-abuse> (accessed November 28, 2018).

Abuse and Mental Health Services Administration estimates that 11.1 million people over the age of twelve misused opioids.¹³⁹

Although less dramatic, there has been also been a steady increase in the prevalence of drug use among those ages twelve and over. According to the CDC, the percent of this population using any illicit substances in the past month has increased from 8.3 in 2002 to 10.2 in 2014. The largest increases over this period were for adults 18 to 25 years (from 20.2 to 22.0 percent) and 26 to 34 years (from 10.5 to 15.1 percent).¹⁴⁰

This higher rate of opioid use is reflected in concomitant growth in overdose deaths from all illegal drugs. According to data from the US Centers for Disease Control and Prevention, between 2000 and 2017, the death rate because of drug overdose more than tripled, from 6.2 to 21.7 per 100,000 people (from about 17,415 deaths to about 70,237 deaths).¹⁴¹ Much of this increase is attributable to opioid overdoses. Between 2000 and 2017, the opioid overdose death rate more than quadrupled, going from 3.0 to 14.9 per 100,000 people (from about 8,400 deaths to about 47,800 deaths) and the percent of all drug overdose deaths due to opioids increased from about 48 percent to about 68 percent. The increase in opioid-related deaths has been the highest for non-Hispanic whites, going from 3.1 to 17.5 deaths per 100,000.¹⁴²

¹³⁹Substance Abuse and Mental Health Services Administration, *Key Substance Use and Mental Health Indicators in the United States: Results from the 2017 National Survey on Drug Use and Health* (Washington, DC: US Department of Health and Human Services, 2018): 18, <https://www.campusdrugprevention.gov/sites/default/files/files/2017%20NSDUH%20Findings.pdf> (accessed November 27, 2018).

¹⁴⁰Due to changes in the National Survey on Drug Use and Health (on which these numbers are based) that occurred in 2002 and again in 2015, data from the years before and after these dates are not comparable. Centers for Disease Control and Prevention, *Health, United States, 2015: With Special Feature on Racial and Ethnic Health Disparities* (Washington, DC: US Department of Health and Human Services, 2016), [https://www.cdc.gov/nchs/data/15.pdf](https://www.cdc.gov/nchs/data/hus/15.pdf) (accessed November 27, 2018).

¹⁴¹Centers for Disease Control and Prevention, “Drug Overdose Death Data,” <https://www.cdc.gov/drugoverdose/data/statedeaths.html> (accessed November 27, 2018); and Holly Hedegaard, Arialdi M. Minino, and Margaret Warner, *Drug Overdose Deaths in the United States, 1999–2017* (Hyattsville, MD: National Center for Health Statistics, November 2018), <https://www.cdc.gov/nchs/data/databriefs/db329-h.pdf> (accessed November 29, 2018).

¹⁴²Centers for Disease Control and Prevention, “Multiple Cause of Death, 1999–2015,” <https://wonder.cdc.gov/controller/datarequest/D77> (accessed June 9, 2017); Puja Seth, Lawrence Scholl, Rose A. Rudd, and Sarah Bacon, *Overdose Deaths Involving Opioids, Cocaine, and Psychostimulants—United States, 2015–2016: Morbidity and Mortality Weekly Report* (Washington, DC: US Department of Health and Human Services, 2018), <https://www.cdc.gov/mmwr/volumes/67/wr/mm6712a1.htm> (accessed November 27, 2018).

These increased death rates from drugs are palpably reducing life expectancy, being driven by deaths among whites.¹⁴³ According to Anne Case and Angus Deaton, in the fifteen years between 1999 and 2015, overall mortality rates increased by 8.9 percent for all whites ages 50-54 (from 463 to 504 per 100,000), while decreasing by over 30 percent for blacks (from 945 to 703 per 100,000) and by about 16 percent for Hispanics (from 405 to 341 per 100,000). For whites with education levels of high school or below, mortality rates are now higher than those for African Americans. Case and Deaton report that “mortality rates of non-Hispanic whites with a high school degree or less, which were around 30 percent lower than mortality rates of blacks (irrespective of education) in 1999 (722 vs. 945 per 100,000), by 2015 were 30 percent higher (927 vs. 703 per 100,000).”¹⁴⁴

Significantly for this meta-evaluation, these increases in the prevalence of substance abuse and in overdose deaths occurred during the same time period as Ginther and Johnson-Motoyama’s study period.

These increases in opioid use appear to be related to increased reports of child maltreatment. In a 2011 report for the US Centers for Disease Control and Prevention, Robin Ghertner et al. analyzed nationally representative data at the county level (which provided a much larger sample than the fifty states) using a mixed methods design and an alternative theoretical perspective which focuses attention on the drug abuse-maltreatment nexus.¹⁴⁵ After acknowledging the limits of their statistical model and of the use of surrogate drug abuse measures, they summarize:

Combining evidence from statistical analysis and qualitative research, we find a strong positive relationship between select indicators correlated with substance use and each of the three examined measures of child welfare involvement. From 2011 through 2016, counties with higher rates of drug overdose deaths and drug-related hospitalization had higher rates of child maltreatment reports, substantiated reports, and foster care entries. In

¹⁴³Sherry L. Murphy, Jiaquan Xu, Kenneth D. Kochanek, and Elizabeth Arias, *Mortality in the United States, 2017* (Hyattsville, MD: National Center for Health Statistics, November 2018), <https://www.cdc.gov/nchs/data/databriefs/db328-h.pdf> (accessed November 29, 2018).

¹⁴⁴Anne Case and Angus Deaton, *Mortality and Morbidity in the 21st Century* (Washington, DC: Brookings Institution, May 2017), https://www.brookings.edu/wp-content/uploads/2017/03/casedeaton_sp17_finaldraft.pdf (accessed June 9, 2017).

¹⁴⁵They operationally defined drug abuse rates with the surrogate measures of drug overdose deaths and drug-related hospitalizations. Their statistical model controlled for various demographic and economic characteristics of the counties and used the false discovery rate to adjust for multiple tests of significance. The team also conducted 188 interviews with child-welfare professionals on the ground across the US. Robin Ghertner, Melinda Baldwin, Gilbert Crouse, Laura Radel, and Annette Waters, *The Relationship between Substance Use Indicators and Child Welfare Caseloads: ASPE Research Brief* (Washington, DC: US Department of Health and Human Services, 2018).

addition, higher rates of substance use indicators are correlated with more complex and severe cases of child maltreatment.

The research team expressed confidence in these findings because they were corroborated through 188 interviews in 11 communities with caseworkers and court professionals who explicitly noted that increases in caseloads were due in large part to parental substance use. Nevertheless, they cautiously conclude: “While substance use may not be the only factor causing increases [in child maltreatment], it clearly plays a role nationally.”¹⁴⁶ Similarly, in an earlier longitudinal analysis, Isabel Wolock and Stephen Magura found that, “parental substance abuse does greatly increase the likelihood of poorer family functioning and re-reports for maltreatment to the CPS agency.”¹⁴⁷

In addition, according to the US Department of Health and Human Services, from 2010 to 2016, the percentage of substantiated cases of abuse and neglect with the “drug abuse caregiver risk factor” (defined as “the compulsive use of drugs that is not of a temporary nature”) increased from 18.0 to 28.5 percent.¹⁴⁸ Substantially more states reported in the second year (twenty-eight vs. thirty-five), so that the comparison may overstate or understate the change. (Limiting the comparison to only the twenty-five states that provide data in both years, the percentage only increases from 18.6 to 23.2 percent.)

The misuse of opioids also appears to be associated with high levels of foster care placements. According to a US News and World Report article by David Crary, in 2016, “substance abuse was a factor in 34 percent of the 2016 cases in which a child was removed from home. . . About 92,000 children were removed from home because at least one parent had a drug abuse issue.”¹⁴⁹ A US Department of Health and Human Services brief by Laura Radel et al. estimates the size of the effect:

¹⁴⁶Robin Ghertner, Melinda Baldwin, Gilbert Crouse, Laura Radel, and Annette Waters, *The Relationship between Substance Use Indicators and Child Welfare Caseloads: ASPE Research Brief* (Washington, DC: US Department of Health and Human Services, 2018).

¹⁴⁷Isabel Wolock and Stephen Magura, “Parental Substance Abuse as a Predictor of Child Maltreatment Re-reports,” *Child Abuse and Neglect* 20, no. 12 (1996):1191.

¹⁴⁸US Department of Health and Human Services, Administration for Children and Families, Children’s Bureau, *Child Maltreatment: 2010* (Washington, DC: US Department of Health and Human Services, 2010), <https://www.acf.hhs.gov/cb/resource/child-maltreatment-2010> (accessed November 27, 2018); US Department of Health and Human Services, Administration for Children and Families, Children’s Bureau, *Child Maltreatment: 2016* (Washington, DC: US Department of Health and Human Services, 2018), <https://www.acf.hhs.gov/cb/resource/child-maltreatment-2016> (accessed November 27, 2018).

¹⁴⁹David Crary, “More US Kids in Foster Care; Parental Drug Abuse a Factor,” *US News and World Report*, November 30, 2017, <https://www.usnews.com/news/us/articles/2017-11-30/more-us-kids-in-foster-care-parental-drug-abuse-a-factor> (accessed November 27, 2018).

We estimate that in the average county nationwide, a 10 percent increase in the overdose death rate corresponded to a 4.4 percent increase in the foster care entry rate. Similarly, a 10 percent increase in the average county’s drug-related hospitalization rate corresponded to a 2.9 percent increase in its foster care entry rate. . . . [and] higher drug overdose death rates also predicted higher rates of maltreatment reports and substantiated maltreatment reports.¹⁵⁰

Thus, in some places, such as Ashtabula, Ohio, “drug abuse is one of the leading reasons parents are losing custody of their children. . . . [with] 90 to 95 percent of the kinship child custody cases [stemming] from drug addiction.”¹⁵¹

A “direct link” between TANF changes and child maltreatment? In the context of the author’s study, the fundamental issue is whether changes in safety-net programs that are presumed by the authors to cause financial hardship might lead a parent to become abusive or neglectful. The key assertion is that the link is “direct”:

The link between social safety net programs and neglect is *direct*: to the extent that social assistance in the form of programs such as the Temporary Assistance to Needy Families (TANF) provide resources for basic needs, reduction in access may result in increased child neglect [emphasis added].¹⁵²

As described above, the authors seem to appreciate that, if financial hardship (here a tightening of TANF provisions) causes a rise in child maltreatment and foster care placements, it works though intervening variables—but they seem to be satisfied that their methodology can avoid the need to take them into account.

¹⁵⁰Laura Radel, Melinda Baldwin, Gilbert Crouse, Robin Ghertner, and Annette Waters, *Substance Use, The Opioid Epidemic, and the Child Welfare System: Key Findings from a Mixed Methods Study: ASPE Research Brief* (Washington, DC: US Department of Health and Human Services, 2018), <https://aspe.hhs.gov/system/files/pdf/258836/SubstanceUseChildWelfareOverview.pdf> (accessed November 27, 2018).

¹⁵¹Warren Dillaway, “Drug Abuse is Leading Cause of Custody Loss in Ashtabula County,” *Star Beacon*, March 15, 2014, <https://advance.lexis.com/document/?pdmfid=1516831&crd=80730c34-7e8c-434b-a622-72eb96a10b9c&pddocfullpath=%2Fshared%2Fdocument%2Fnews%2Furn%3AcontentItem%3A5BRW-XCF1-JC6P-C03M-00000-00&pddocid=urn%3AcontentItem%3A5BRW-XCF1-JC6P-C03M-00000-00&pdcontentcomponentid=169235&pdteaserkey=sr4&pditab=allpods&ecomp=5ynk&earg=sr4&prid=f6908b11-4ff2-43e0-b8b5-636a003ed494> (accessed November 27, 2018).

¹⁵²Donna K. Ginther and Michelle Johnson-Motoyama, “Do State TANF Policies Affect Child Abuse and Neglect?” (paper presented at the APPAM Annual Research Conference, Chicago, IL, October 27, 2017):4, <https://pdfs.semanticscholar.org/fd31/a0ce1ff65da9f078b869bdf1c58dfd496b3.pdf> (accessed November 5, 2018).