A Concurrence of Crises: examining the impact of the U.S. opioid epidemic and socially stigmatized addiction treatments on child welfare caseloads

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Abstract

Many child welfare experts have claimed that the opioid epidemic is largely responsible for recent increases in child welfare cases in the U.S (U.S. Department of Health and Human Services 2018). Medication assisted treatment (MAT) has been clinically proven to alleviate opioid use disorder (OUD) among individuals, and is often cited as the best chance for OUD patients to maintain custody of their children (U.S. Department of Health and Human Services 2018). However, there is a lack of quantitative research in the child welfare literature to back up either of these assertions. The objectives of this study are 1) to determine whether the opioid crisis is actually responsible for recent increases in foster youths, and if so, 2) whether access to MAT reduces caseloads, in spite of obstacles to treatment that result from social stigmas. Negative binomial fixed effects regression models are run to analyze observational county-level panel data for the years 2011-2017. The results indicate that there is a positive, statistically significant relationship between indicators of prevalent OUD and the number of children entering the child welfare system at the county level. However, access to MAT services appears to have no significant effect. The results of a sensitivity analysis indicate that the state of California is overly influencing these findings, pointing to the need for more extensive analyses in future research in order to fully understand the impact of the opioid epidemic and MAT access on child welfare caseloads.

Introduction

Since the 1990's, the American opioid epidemic has devastated the health and well-being of not only millions of individuals, but that of children, families, and communities as well. Social workers have opined that the opioid crisis is the primary culprit for recent influxes of child welfare cases; nationally, the number of children entering state custody due to parental substance abuse is up nearly 150% compared to the year 2000, overwhelming an already exhausted child welfare system (U.S. Department of Health and Human Services 2018; Meinhofer and Anglero-Diaz 2019). Despite its intention of providing a safe and nurturing environment for children who have experienced maltreatment at home, the child welfare system all too often introduces additional hardships, disadvantages, and traumatic experiences (Doyle 2007). Ultimately, foster care has the potential to adversely impact youths' life trajectories, especially when state child welfare systems are overburdened (Doyle 2007). In addition, when these children cannot be reunited with their parents and are not adopted, they face a lack of support upon aging out of foster care, which results in an increased risk of homelessness, addiction, and other adverse life outcomes (Tyler and Menander 2010).

Medication assisted treatment (MAT) offers a promising solution for opioid use disorder (OUD), and is frequently cited as the best means by which individuals can overcome their addiction and avoid child welfare involvement in family life (U.S. Department of Health and Human Services 2018). However, MAT involves the administration of alternative substances such as methadone; consequently, a range of misconceptions and social stigma surround this particular form of addiction therapy, constructing significant barriers to its implementation and take-up within counties in need (Allen, Nolan, and Paone 2019).

The following analysis will focus on the relationships between opioid addiction, access to medication assisted treatment, and child welfare caseloads within populous counties. Thus far, there has been a lack of quantitative evidence in the child welfare literature to verify the claim that the opioid epidemic is the cause of recent increases in caseloads. In addition, much existing scholarly work surrounding issues of foster youth as a result of parental substance abuse has primarily taken place on an individual, rather than aggregate, basis (U.S. Department of Health and Human Services 2018). Similarly, studies that provide evidence of the effectiveness of MAT have typically focused on the health outcomes of individuals rather than on benefits for communities (Allen et al. 2019; Walsh 2019; Grubb and Clin 2019). The objective of this research is to fill this gap in the literature by answering the following:

1. Can indicators of prevalent opioid abuse actually explain recent increases in child welfare cases (controlling for observable county-level characteristics), thereby corroborating anecdotal and qualitative evidence?
2. If this is the case, does providing access to MAT services reduce the number of children removed from their homes due to parental substance abuse (regardless of the barriers to treatment that result from social stigmas)?

Fixed effects regression models are used to analyze panel data on foster youth caseloads, access to MAT, and a variety of geographic, demographic, and socio-economic variables at the county level in an effort to answer these questions.

If the opioid epidemic actually is the primary cause of recent increases in child welfare caseloads, it is unlikely that simply providing access to MAT services offers a complete solution. However, by analyzing differences in foster youth trends based on whether or not a county provides MAT services, this study aims to uncover the extent to which increased access to MAT may reduce child removals, and ultimately interrupt the chain reaction wherein widespread opioid use disorder results in negative outcomes for families and children. In turn, this analysis is intended to address the harm caused by social stigmas: they construct significant barriers to treatment, reinforce policy-makers' resistance to the implementation of MAT and similar services, and ultimately, harm the wellbeing not only of individuals struggling with addiction, but that of children, families, and communities as well (Yang, Wong, Grivel, and Hasin 2017).

Background

A Brief Overview of the American Opioid Epidemic

The American opioid crisis as it exists today is the culmination of three related but distinct waves. In years prior, opioids had primarily been used to medicate individuals suffering from chronic pain (CDC 2019). Beginning in the 1990's, prescription opioids became more widely available in the United States than ever before, amidst false assurances from medical professionals that patients were unlikely to develop addictions to these medications (CDC 2019). By the year 2010, enough prescription opioids were in circulation to medicate every American adult with a 5 milligram dose every four hours for a month (Keyes, Cerda, and Galea 2014). The second wave began shortly after: as states began to enforce opioid prescription limits, increases in the illicit production of heroin (an opioid synthesized from morphine) resulted in rapid growth in deaths caused by drug poisoning nation-wide (CDC 2019). In 2013, the third wave began; this time, synthetic opioids even deadlier than heroin, such as fentanyl, were primarily responsible for continuing increases in overdose deaths (CDC 2019). According to the CDC, the most recent comprehensive cause of death data reveals that unintentional poisoning is the leading cause of death among 25- to 64-year-olds; moreover, approximately 70% of those drug-related deaths involved the use of opioids (2019).

Addiction to illicit substances is frequently perceived to be primarily of concern among lower-income individuals (Griffith and La France 2018). Indeed, some of America's poorest regions, such as Appalachia, have experienced extremely severe devastation as a result of the epidemic (U.S. Department of Health and Human Services 2018). However, wealthier areas have not escaped unscathed; in fact, high-income individuals typically have access to a wider range of sources of expensive recreational drugs such as heroin (Griffith and La France 2018). As prescriptions for opioids have declined, well-connected individuals with large social networks are more easily able to access increasingly popular synthetic versions (Keyes et al. 2014). Therefore, in this case, traditional determinants of substance abuse are not always useful for predicting individuals' and communities' susceptibility to the crisis; opioids are effectively an "equal opportunity" substance, and the epidemic has impacted the entire nation (albeit to varying degrees) (Volkow 2017).

Current Trends in Child Welfare

Recently, the U.S. child welfare system has witnessed a substantial increase in the number of youths entering foster care, which appeared to accompany trends in opioid overdoses (U.S. Department of Health and Human Services 2018). There are a variety of county-level characteristics which may contribute to variation in caseloads, beyond differences in opioid use disorder rates. For example, although most individuals who experience financial instability do not maltreat their children, high rates of poverty and unemployment, as well as low levels of educational attainment, are generally associated with an increased risk of child abuse and neglect (Martin and Citrin 2014). This is especially the case when combined with individual-level risk factors such as social isolation, mental illness, and substance abuse (Martin and Citrin 2014). As a result, county-level poverty, unemployment, and high school dropout rates may serve as helpful predictors of child welfare caseloads. In addition, married-couple households are generally considered an (albeit imperfect) indicator of domestic stability and reduced risk of child maltreatment;

counties with larger proportions of married individuals may therefore see fewer child removals (Brown 2010).

Demographic composition may also play a role in a community's child welfare caseloads. Black children are overrepresented in the foster care system; although they only account for about 20% of the nation's children, they make up nearly half of the children removed from their homes annually (Hill 2004). This is due in part to the disproportionate distribution of risk factors such as poverty and unemployment among minority groups, as well as racial biases in reports of maltreatment, the nature and extent of investigations into reported cases, and judicial decisions in family court (Hill 2004). For instance, prior research has found that among mothers whose newborns tested positive for illicit drugs, black women were more likely than white women to be reported for child maltreatment (Hill 2004). In this way, the percent of a particular community made up of white versus minority individuals may have an effect on the amount of (un)substantiated reports of abuse and therefore in the number of children entering child welfare each year.

Clearly, a variety of factors may contribute to variation in child welfare caseloads within counties. However, recent trends have appeared to surpass these anticipated fluctuations: the number of children removed from their homes by Child Protective Services (CPS) due to parental substance abuse is up a staggering 147% compared to the year 2000 (Meinhofer and Anglero-Diaz 2019). As shown in Figure 1, a rise in the number of children entering foster care apparently began in 2012 (AFCARS 2020). Anecdotal evidence relayed from social workers in the field has indicated that the majority of this growth is due to increases in deaths due to drug poisoning (including opioid overdose), as displayed in Figure 2 (U.S. Department of Health and Human Services 2018; CDC 2019).

Figure 1. National Trend in Child Welfare Cases, 2011 to 2017 (source: Kids Count Data Center 2020)

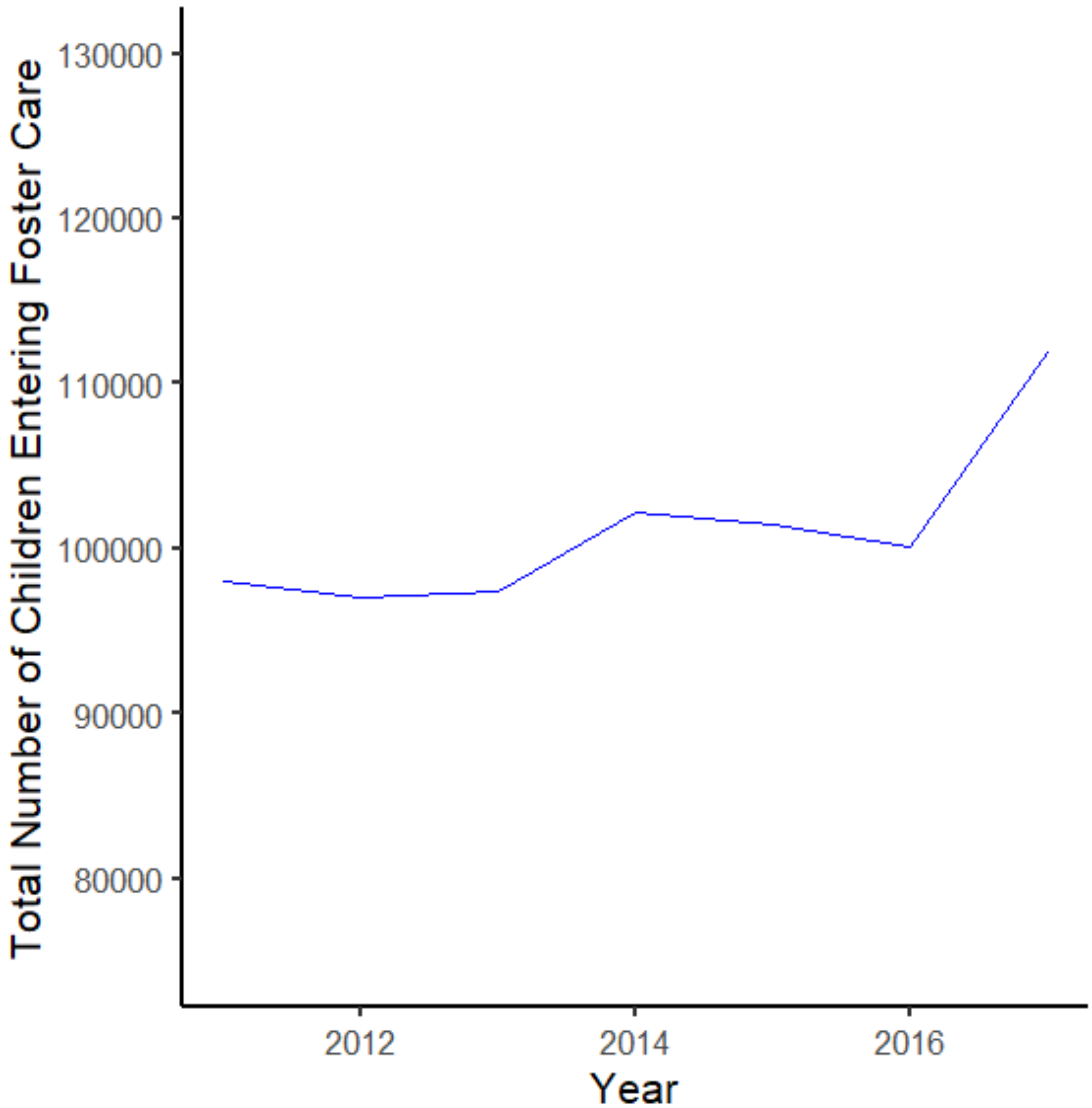
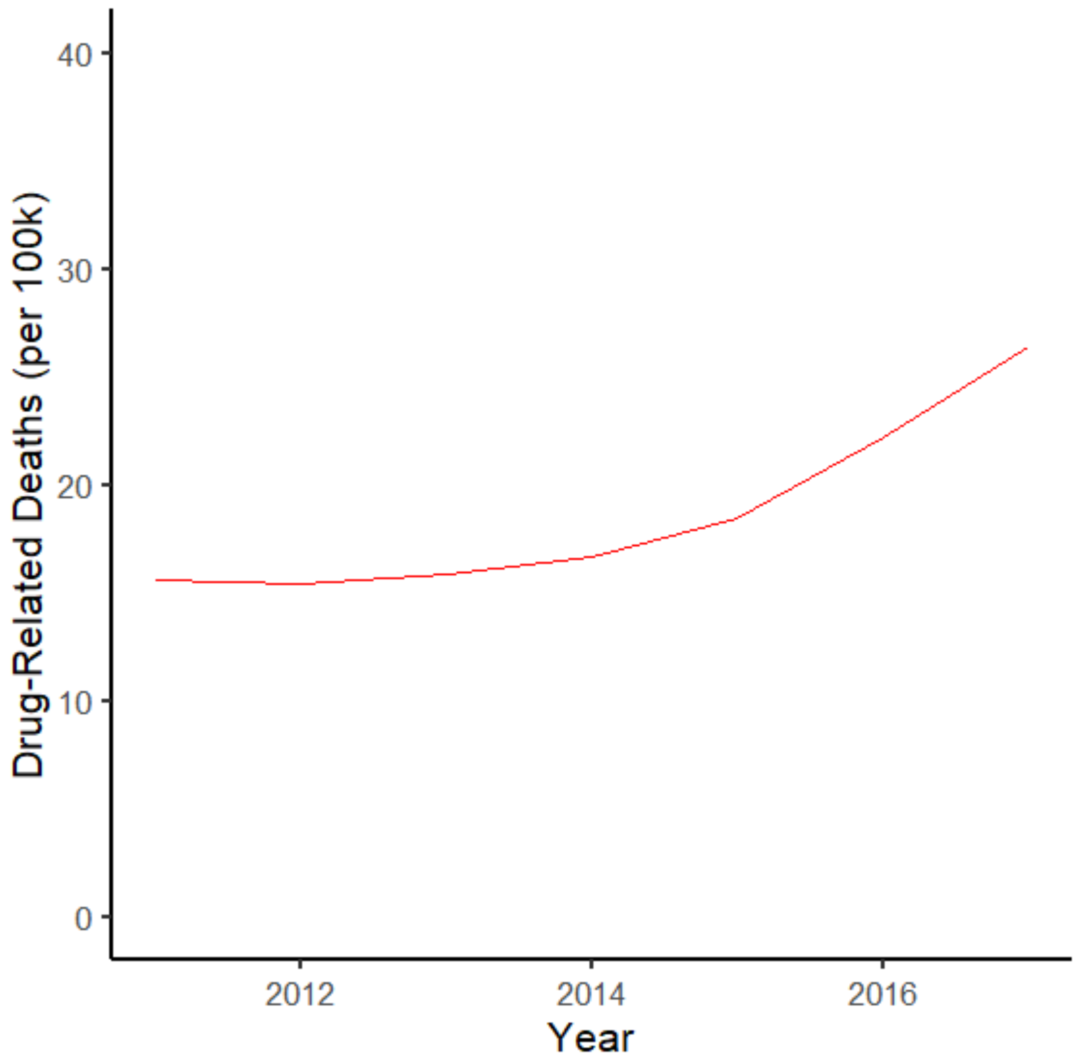


Figure 2. National Trend in Drug-Related Deaths per 100,000 Persons, 2011 to 2017 (source: CDC 2017)



The social ramifications of swift increases in child welfare cases are severe. Although foster care is often the best option for children who have experienced severe parental abuse, involvement in the child welfare system is frequently associated with a range of adverse effects, both throughout residence in foster care as well as in life afterward. In addition to the traumatic event of removal from their homes, foster youths are often uprooted from entire support systems, transferred to new schools, and separated from their siblings (Doyle 2007). Some children even experience physical or emotional abuse at the hands of their foster parents (Tyler and Menander 2010). As a result, compared to non-foster youth, children placed in child welfare are at a higher risk of depression and PTSD, teen pregnancy, dropping out of school, involvement in criminal activity, substance abuse, long-term unemployment in adulthood, and more (Doyle 2007). In addition, as cases surge, state child welfare systems are increasingly forced to resort to large-capacity group homes; prior research has determined that youths in these situations are at an even greater risk of the aforementioned negative outcomes compared to those placed in family foster homes or in the care of relatives (Doyle 2007).

Although foster care is intended to serve as a temporary living arrangement, approximately 25% of foster youths remain in state custody until the age of 18 (Doyle 2007). Upon aging out of the system, these individuals face a lack of structural support and an increased risk of unemployment, poverty, and homelessness (U.S. Department of Health and Human Services 2018). A recent study from the University of Chicago found that approximately one third of homeless youths were enrolled in the child welfare system at one point in their lives (Morton, Dworsky, and Samuels 2017). In turn, homeless youths, especially those who have been previously exposed to environments of substance abuse, are more likely to engage in high-risk behaviors; 30% of youths living on the streets have reported engaging in the misuse of prescription drugs, including opioids (Grubb and Clin 2019). Of course, due to the sensitive and self-incriminating nature of this subject, these findings are likely underestimates.

The danger of this chain of events is abundantly clear, and can be extremely difficult to escape without assistance. Parents who struggle with opioid use disorder (OUD) are more likely to have their children removed from the home and placed in the child welfare system, where they face potential disadvantages in education, employability, mental and physical well-being, and beyond (U.S Department of Health and Human Services 2018; Doyle 2007). Those who age out of the system face an increased risk of homelessness, and are in turn at a greater risk of misusing prescription medications themselves (Grubb and Clin 2019). If the opioid epidemic is to blame for recent growth in child welfare cases, supplying adequate treatments for OUD would likely serve as a helpful strategy for interrupting this devastating cycle.

Medication Assisted Treatment and the Role of Social Stigma

Medication assisted treatment (MAT) is an evidence-based, highly effective intervention for opioid addiction. By combining psychotherapeutic methods with the administration of safer alternatives to deadly and highly addictive drugs, MAT has been clinically proven to reduce individual incidents of opioid use disorder and associated engagement in illicit activity (Magwood et al. 2020). According to one clinical study, opioid abstinence rates were at least twice as high among individuals who completed MAT programs compared to those who had received a placebo (Gerry 2016). Many professionals in the field of social work have even stated that MAT offers the best chance for parents suffering from opioid use disorder to maintain custody of their children (U.S. Department of Health and Human Services 2018).

However, the prevalence of social stigmas surrounding the condition of addiction and the use of alternative substances for treatment has impeded the ability of MAT to benefit individuals and communities in need. A stigma, as defined by Canadian sociologist Erving Goffman, is a characteristic or behavior, either visible or not, which is "deeply discrediting" and results in ostracism from "normal" society (1963, p. 3). More recently, sociologists Link and Phelan defined stigma as existing when "elements of labeling, stereotyping, separation, status loss, and discrimination occur together in a power situation that allows them" (2001, p. 377). In his book *The Rules of Sociological Method,* Émile Durkheim illustrates the inevitability of social stigmatization through a thought experiment. He invites the reader to imagine:

> "a society of saints, a perfect cloister of exemplary individuals. Crimes, properly so called, will be there unknown; but faults which appear venial to the layman will create there the same scandal that the ordinary offense does in ordinary consciousness. If, then, this society has the power to judge and punish, it will define these acts as criminal and will treat them as such" (Durkheim 1895/1982, p. 100)

Durkheim thus argues that societies will reliably construct and identify undesirable behaviors and individuals, even if this can only be accomplished via the arbitrary degradation of personal traits (1895/1982).

In a similar way, addiction has historically been viewed as an individual flaw or lifestyle choice, rather than as an affliction (Yang et al. 2017). Individuals who struggle with addiction are often perceived as dangerous, unpredictable, and even immoral, which typically results in discrimination and "restricts such individuals from responsible societal roles" (Yang et al. 2017, p. 6). Similarly, treatments such as MAT are burdened by stigmatization. Since addiction treatment is not normally included in medical education curricula, misconceptions surrounding MAT exist among medical professionals as well as the general public (Allen et al. 2019). For example, a particularly common and false notion is that MAT simply replaces one addiction with another. However, physical dependence and addiction are not interchangeable terms: whereas addiction indicates an inability to independently cease use of a particular substance, dependence refers to the bodily adaptations (such as tolerance and withdrawal symptoms) that occur as a result of prolonged use of a drug (National Institute on Drug Abuse 2018). While dependence almost always accompanies addiction, the reverse is not the case. However, recovery from OUD is typically unrealistically regarded as beginning no earlier than the day on which treatment medications such as methadone are discontinued from an individual's use (White 2012). In the words of health researcher William White,

> "the historical stigma attached to methadone and the broader arena of medication-assisted treatment has denied MAT patients the status of recovery and left them isolated from mainstream community life and existing in limbo between cultures of addiction and cultures of recovery" (2012, p. 6).

Consequently, the stigma that surrounds the condition of addiction and lingers upon individuals who undergo MAT programs, and the social isolation and ostracism which result, have the potential to impact individual life outcomes, including but not limited to employability and income levels, criminal activity, physical and mental well-being, and housing stability (Link and Phelan 2001). Stigmas are also likely to "reduce willingness of policy-makers to allocate resources, reduce willingness of providers to screen for and address substance abuse problems, and may limit willingness of individuals with such problems to receive treatment" (Yang et al. 2017, p.1). This ultimately results in a positive feedback loop, wherein "stigmatized patients receive stigmatized treatments" (Allen et al. 2019, p. 461).

Even counties that do offer MAT services typically only provide one mode, due to misconceptions and uncertainty about the various drugs which may be used for the purpose. Currently, three drugs have received approval from the FDA for the medication assisted treatment of opioid use disorder: buprenorphine, methadone, and naltrexone (Jones, Honermann, Sharp, and Millet 2018). These three drugs are accompanied by different treatment methods, each of which are not necessarily suitable for all individuals. For example, prior to initiating a naltrexone treatment program, patients must complete an intensive week-long detoxification process, which obviously is not feasible for the most urgent of cases (Jones et al. 2018). Methadone comes with a particularly large share of social stigma; frequently referred to as “liquid handcuffs”, it is often conspicuously absent from addiction treatment programs (Allen et al. 2019). As a result, many of the nation’s substance abuse treatment facilities cannot fulfill the diverse needs of their patients because they do not offer all modes of MAT.

In its 2018 research brief on the state of the child welfare system, the U.S. Department of Health and Human Services included increased access to MAT among its top policy recommendations, stating that it is paramount for effectively combatting the opioid epidemic and reducing the number of child removals that are believed to result from prevalent parental OUD. However, while a multitude of clinical studies have offered insights into the efficacy of MAT for individual OUD patients, its impact on communities and families has yet to be determined (Gerry 2016). Even if access is provided, it may be that social stigmas present too lofty an obstacle for a substantial number of individuals to seek treatment. On the other hand, echoing what social workers have previously stated, providing access to such services likely represents the best chance for parents with OUD to keep their families together. The following analysis will investigate whether the opioid epidemic has significantly contributed to recent increases in child welfare cases, and if so, whether the provision of MAT (either limited or comprehensive) is sufficient to reduce caseloads at the county level, in spite of the obstacles put in place by social stigmas.

Data

Child Welfare Caseloads

The dependent variable of interest in this analysis is the annual number of children entering foster care each year. First, for the purpose of visualization, state-level caseload data for all 50 states was retrieved from the Kids Count Data Center. This data repository, provided by the Annie E. Casey Foundation, provides the total number of youths entering the child welfare system within each U.S. state from 2011 to 2017.

In contrast, the regression analyses utilized in this study focus on patterns within counties rather than states because lower geographic levels provide more granular detail. For example, rural, urban, and metropolitan counties within a given state are likely to exhibit substantial variation in populations, cultures, policies, socio-economic characteristics, and beyond. Aggregating these variables at the state level would result in a loss of these local differences, a much smaller sample size, and an underpowered study.

County-level child welfare caseload data was retrieved from the Adoption and Foster Care Analysis and Reporting System (AFCARS). AFCARS collects and distributes anonymized case-level data for foster youth[1] from all 50 states and Puerto Rico. The AFCARS data reports for the years 2011 to 2017 were accessed via the National Data Archive on Child Abuse and Neglect (NDACAN), a repository housed at Cornell University's Bronfenbrenner Center for Translational Research. For each year, the number

[1] "Foster youth" includes children living in group or congregate care, emergency shelters, residential facilities, pre-adoptive homes, traditional non-relative foster homes, and official kinship care. Informal arrangements, which typically involve children being placed with family friends or close relatives without official registration in the child welfare system, are not included.

of cases[2] wherein a child had entered (or re-entered) the child welfare system were totaled by county. This is used as the response (dependent) variable in the models below, with each county-year[3] as a unit of observation.

Although the AFCARS reports provide data for the county level, the names of counties with less than 1000 youths in state custody are withheld from public view in order to maintain confidentiality of vulnerable individuals. National child welfare data indicates that there are currently around 450,000 children registered in the child welfare system, and a vast majority of the United States' 3,141 counties fall far below the 1000-case benchmark for inclusion in the publicly available dataset (Child Trends 2018). As such, only those counties with a sufficiently large foster youth population (and by extension, large populations in general) are included in the analysis. Therefore, the findings that result may only be generalized to large urban counties.

[2] Though the case-specific reason for removal is included for a small portion of records in the dataset, this information was not utilized in the analysis, as individual social workers may record these details in inconsistent ways. "Neglect" is the most common reason cited for child removal by CPS; however, the term frequently captures cases involving underlying substance abuse that could also fall under the "parental substance abuse" category (Sepulveda and Williams 2019). As a result, the "reason for removal" field recorded in the AFCARS data is not sufficiently precise for inclusion in this analysis.

[3] A "county-year" refers to a record in the aggregated dataset; there is one record per county per year.

Indicators of Opioid Use Disorder

In order to determine the nature of the relationship between the opioid crisis and foster youth caseloads (if one does in fact exist), the annual number of deaths as a result of drug poisoning (per 100,000 persons) was retrieved from the Centers for Disease Control and Prevention (CDC). This measure is used as the first key independent variable in the regression models, and includes deaths as a result of poisoning from both illegal and prescription drugs. State-level estimates were retrieved for visualization purposes (see Figure 3), and county-level estimates were included in the regression models.

There is no data available for a more specific breakdown of cause of death (for example, the rate of deaths caused by opioid poisonings in particular) due to inconsistencies in death certificate completions and data quality across counties and states (CDC 2017). Furthermore, although county-level opioid prescription rates are publicly available, the current state of the opioid epidemic is largely fueled by illegally manufactured forms of opioids such as fentanyl; in fact, opioid prescriptions have actually dropped substantially in recent years as a result of state-imposed limits (CDC 2019). However, as mentioned previously, the CDC estimates that close to 70% of drug-related deaths involve opioids (CDC 2019). Therefore, the overall rate of drug-related deaths serves as a reasonable indicator of the prevalence of opioid use disorder within counties.

Access to MAT

The second key independent variable of interest is the provision of medication assisted treatment within counties. The Substance Abuse and Mental Health Services Administration (SAMHSA) website provides the annual status of MAT access by county, and records whether 1) *any* form or 2) *all*[4] forms of MAT are offered. (Once again, this distinction is important because not all modes of MAT are suitable for all OUD patients.) This information was used to create two binary variables. The first variable records whether or not a county-year offers *at least one* mode of MAT (coded 0 if it did not, and 1 for the first year at least one form of MAT is offered and each year thereafter) and appears as "Any MAT" in the models below. The second binary variable, "Comprehensive MAT", indicates whether or not a county-year offered *all modes* of MAT (coded 0 if not, and 1 for the first year all modes are offered and each year thereafter)[5]. These variables are utilized to determine whether access to MAT (either limited or comprehensive) has any effect on foster youth entries. Most counties in this analysis began offering at least one form of MAT in the time between 2011 and 2017, but none offered comprehensive MAT services before 2013.

Control Variables

As mentioned previously, in order to accurately examine the nature of the relationship between the opioid epidemic, MAT, and foster youth caseloads, a variety of demographic and socio-economic factors must be taken into consideration, as they serve as helpful indicators of a community's baseline "risk" of pervasive child maltreatment. In order to account for these, a number of county-level, time-varying characteristics were

[4] Methadone, naloxone, and buprenorphine are all provided.

[5] Note that if the second binary variable ("Comprehensive MAT") is coded as 1, the first ("Any MAT") must also be coded as 1. In contrast, a county-year which offers limited MAT (only 1-2 modes) would have "Comprehensive MAT" coded as 0 and "Any MAT" coded as 1.

retrieved from the American Community Survey (ACS) 1-Year Estimates, which are publicly available via the U.S. Census website for all geographies with a population of at least 65,000[6] persons. These control variables include poverty and unemployment rates, demographic composition (percent white), educational attainment level (percent without a high school degree), marital status (percent married), and child population size.

Lastly, it is important to consider the scale of the United States when conducting an analysis of aggregated data. With a population of over 300 million and substantial cultural differences among its various regions, social patterns frequently vary between individual states and counties. The opioid epidemic, for example, has been particularly severe in Appalachia and New England, and less so in the West (U.S. Department of Health and Human Services 2018). Therefore, the extent to which opioid abuse is responsible for increases in child welfare cases is likely to vary accordingly. For this reason, the models include a final control for the region in which each county is located, as delineated by the U.S. Census Bureau in Table 2.

[6] All counties in the final AFCARS dataset meet the 65,000-person population requirement.

Table 2. U.S. Census Bureau Statistical Regions

REGION	STATES
NORTHEAST	Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont
MIDWEST	Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin
SOUTH	Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia
WEST	Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming

Missing Data

The initial AFCARS dataset provided child welfare case data for 131[7] unique counties for the years 2011 to 2017. However, 22 counties saw the number of youths registered in child welfare fall below the 1000-case threshold in at least one year during the seven-year period, so not all counties have complete data for all seven years[8].

Additionally, seven counties were missing either MAT availability or drug-related deaths data (or both) from the SAMHSA and the CDC datasets respectively for the entire 2011-2017 period, reducing the number of unique counties included in the dataset to 124[9]. Among these 124 counties, 70[10] were missing drug-related death rates for a single year. The final dataset is therefore comprised of 642 county-years, including 124 unique counties across 34 states.

Descriptive statistics for all variables are displayed in Table 1 (see Results section).

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[7] After excluding anonymized counties with less than 1000 children currently registered in the foster care system throughout the 7-year period from 2011-17, and excluding observations where the county name is unknown or missing, the dataset included 131 unique counties.

[8] Of the 917 county-years that would result from a balanced panel (131 counties*7 years), 156 were below the 1000-child threshold for inclusion in the AFCARS reports, resulting in a total of 761 county-years.

[9] 712 county-years remain after removing the 49 county-years (7 counties*7 years) that are missing MAT and/or drug-related death rates from the original 761 county-years.

[10] Removing these 70 county-years results in a final dataset of 642 county-years.

Methods

Using the observational panel data described above, the following analysis will investigate the association between indicators of opioid addiction and MAT access on counties' annual child welfare caseloads. Fixed effects regression models estimate the change in the dependent variable over time within each unit (i.e. county). In this way, each unit acts as its own control, and as a result, any unobserved time-invariant differences between individual units are cancelled out, leaving behind the effects of the time-varying factors of interest. A generic fixed effects model is represented by the following equation:

For each county i *in year* t *where:*
y *represents the dependent variable*
α *represents the time-invariant factors*
β *represents the regression coefficients for the independent variables*
x *represents the set of time-varying independent variables*
u *represents the error term (assumed to be random)*

$$y_{it} = \boldsymbol{\beta}\mathbf{x}_{it} + \alpha_i + u_{it}$$

$$\Rightarrow \quad \Delta y_{it} = \boldsymbol{\beta}\Delta\mathbf{x}_{it} + \Delta u_{it}$$

The results of these models indicate whether changes in the independent variables of interest have a statistically significant relationship with changes in the dependent variable. In particular, this analysis will determine whether changes in drug-related deaths and MAT access are associated with changes in child welfare caseloads within each county over time.

The dependent variable of interest (child welfare caseloads) is discrete and exhibits an over-dispersed distribution[11]. Therefore, negative binomial regression models are the most suitable choice for this analysis. County and year fixed effects are included in each of

[11] The observed variance is greater than that of a Poisson distribution, wherein the mean and variance are assumed to be equivalent.

the models to control for systematic patterns across individual counties and over time which may explain in part the observed variation in foster youth caseloads. Child population size is included as an exposure variable[12] and the standard errors are clustered[13] by state.

First, for the purpose of visualizing large-scale regional patterns, state-level correlations between the percent of the child population entering foster care and drug-related death rates for each year are calculated and displayed on a map (see Figure 3 in Results section). The correlation coefficient represents the relationship between two variables, measured on a continuum from -1 to 1. The sign indicates the direction of the relationship (i.e. whether it is positive or negative) and the absolute value indicates the strength of the relationship (0 indicates there is no relationship, 1 indicates a perfect relationship).

Next, in order to measure the extent to which the opioid crisis is responsible for recent increases in child welfare caseloads, a preliminary negative binomial fixed effects regression model, including only one independent variable, is run to verify the existence of a relationship between drug-related death rates and the number of youths entering the foster system annually. Then, control variables are added to a second model to reduce the potential for spurious findings. As mentioned previously, these controls include characteristics associated with a county's relative risk of child abuse and neglect (poverty

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[12] The exposure variable accounts for the fact that some units (counties) have more opportunities for the "event" (child removal and placement in foster care) to occur than others, due to differences in child population sizes.

[13] Clustering the standard errors in this manner accounts for the likelihood that large counties within the same state share similar characteristics.

and unemployment rates, educational attainment levels, and percent married), its demographic composition (percent white), and its location (region).

Several of the variables associated with a county's relative risk of child maltreatment are highly correlated with one another: for instance, counties in this dataset with high unemployment rates generally also see high rates of poverty, high school dropouts, and unmarried individuals. In order to account for this interrelationship, these four predictors were combined to create a single multidimensional composite variable. This was accomplished by standardizing each variable (i.e., calculating their Z-scores) and then adding them together. The resulting predictor appears in the below models as "Socioeconomic disadvantage".

The last two models examine whether access to MAT has a significant effect on the number of new child welfare cases within each county. The presence of at least one form of MAT ("Any MAT") is included in the third model, and the final model includes the binary variable which indicates whether or not comprehensive MAT is offered in each county. The results of all four models are displayed in Table 2.

Finally, a sensitivity analysis is performed in order to determine whether a single state is overly influencing the results of the models in the main analysis. This is accomplished by excluding the observations that are expected to be overly influential, re-running the regression models detailed above, and checking whether the results remain consistent with the initial models. The most likely candidate is the state of California, which contributes 109 county-years across 17 unique counties and accounts for nearly 17% of the total records in the dataset. The negative binomial regression models in Table 2 are re-run for the 533 counties that remain after excluding those located in California. The results of this sensitivity analysis are displayed in Table 3.

Tables 2-3 display the incident rate ratios[14] (IRRs) that result from each model. The IRR represents the rate of increase or decrease in the event of interest (in this case, a child entering foster care) caused by a one-unit change in the given predictor variable, holding the other variables constant. A value of less than 1 indicates a decrease, a value equal to 1 represents no change, and a value greater than 1 indicates an increase.

Data management and the creation of data visualizations[15] were primarily conducted using R version 3.6.1. Regression models were run in STATA version 16.

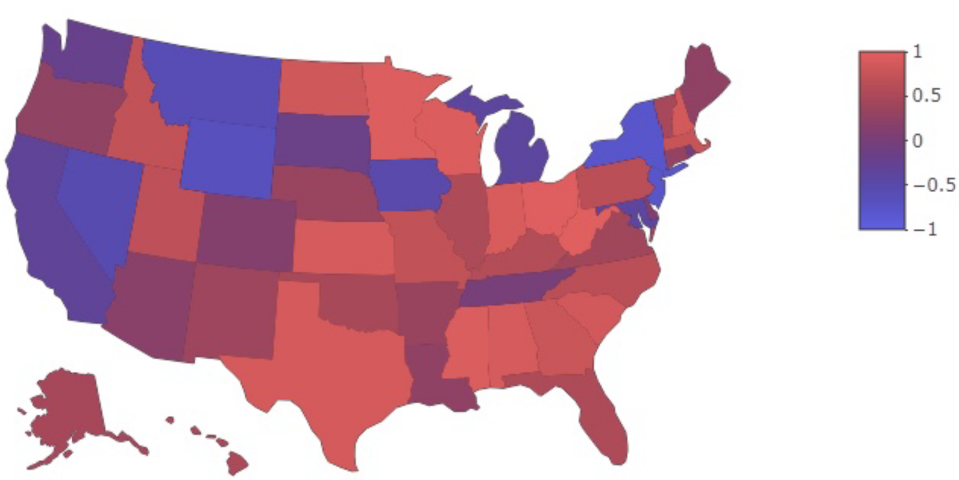
[14] The IRRs are the exponentiated form of the coefficients that result from a negative binomial regression model.

[15] The line plots in Figures 1-2 were created using the "ggplot2" package. The map in Figure 3 and the bar graph in Figure 4 were created using the "plotly" package.

Results

Figure 3 illustrates the necessity of accounting for the impact of location in this analysis. For each state, the correlation between drug-related death rates and the percent of children entering foster care (out of the total child population size) was calculated for the years 2011-2017 and plotted on a map of the U.S. The bright red color indicates states with a strong positive relationship between drug-related death rates and the rate of children entering foster care over the seven-year time period, while dark blue indicates a strong negative relationship. States colored in purple or dark red hues indicate the lack of a strong relationship between the two variables in either direction. Clearly, the relationship in question is not uniform across the nation. The South, for example, shows a fairly consistent, positive relationship between drug poisonings and child welfare caseloads across states, while there appears to be more variability among states located in the West.

Figure 3. Correlation Between Drug-Related Deaths (per 100k) and Rate of Children (Out of the Total Child Population Size) Entering Foster Care by State, 2011 to 2017 (sources: Kids Count Data Center 2020, CDC 2017)



As shown in Table 1, the number of youths entering foster care varies to a higher degree between individual counties than within counties over time. Overall, the average number of children entering the foster care system within a given county each year is just over 1000. Year to year, this number fluctuates by approximately 200 cases on average within counties. The maximum value of 12,159 comes from Los Angeles County, California, one of the most populous counties in the United States and home to more than 2 million children (U.S. Census Bureau 2017).

The overall average drug-related death rate among the counties included in the analysis is 18.95 per 100,000 people. This value appears to deviate substantially both between as well as within counties, as evidenced by standard deviations of approximately 10.64 and 5.76 per 100,000 respectively. The overall range of drug-related deaths is staggering, from a minimum value of just over 2 to a maximum of nearly 100 per 100,000 persons. The county with the highest drug-related death rate in the dataset, at 98.8 per 100,000, is Montgomery County, Ohio. Dayton, Montgomery County's largest city, has been severely impacted by the opioid crisis, and displayed one of the highest opioid-overdose death rates in the nation in 2017 (Kaiser Health News 2018). Within Montgomery County, an average of 409 children, or approximately 0.3% of its average child population, entered foster care each year between 2011 and 2017.

Table 1. Descriptive Statistics for All Variables, Including Standard Deviations Between and Within Counties and Overall[16], 2011-2017

	Mean	Range	SD (overall)	SD (between)	SD (within)
Dependent Variable					
New foster care cases	1103.28	254, 12159	1394.19	1229.40	201.90
Independent Variables					
Drug death rate (per 100K)	18.95	2.40, 98.8	10.36	10.64	5.76
Any MAT offered (%)	68.69	0, 100	46.41	26.21	41.26
Complete MAT offered (%)	33.33	0, 100	47.18	34.60	37.33
Control Variables					
Poverty rate	15.71	6.30, 34.29	4.46	4.25	1.41
Unemployment rate	7.93	3.08, 19.06	2.91	2.35	2.05
Percent white	69.90	20.81, 92.61	13.59	13.32	1.45
Percent without HS diploma	12.81	5.39, 38.50	5.26	4.94	0.83
Percent married	45.63	27.76, 59.03	4.56	4.59	0.78
Exposure					
Child Population size (1K)	278.43	28.12, 2378.37	293.12	275.28	7.68

N = 642; n = 124; T = 7

[16] The overall SD indicates the standard deviation across all county-years.

Figure 4. Number of Counties (Out of the 124 Included in the Analysis) Offering Comprehensive (All 3 Modes) and Limited (1 or 2 Modes) Medication Assisted Treatment, 2011-2017 (source: SAMHSA)

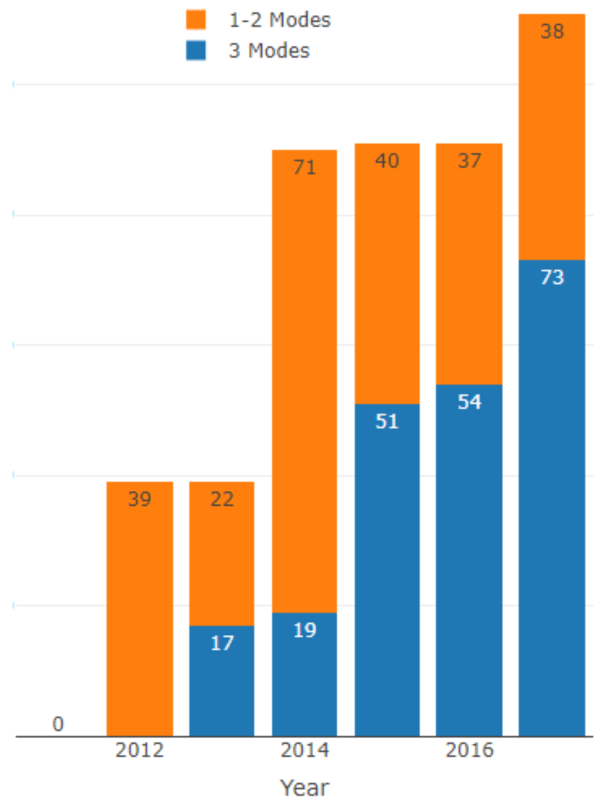


Figure 4 displays the number of counties, out of the 124 included in the dataset, that offer MAT each year. In 2011, none of the counties offered any form of MAT services. A year later, in 2012, 39 counties offered limited treatment, and access to both limited and comprehensive MAT continued to grow over the next several years. By 2017, 111 out of these 124 counties were providing MAT, 73 of which included all three modes (buprenorphine, methadone, and naltrexone). In total, 214 county-years offered comprehensive MAT services, 247 county-years offered limited MAT (1-2 modes), and the remaining 181 county-years offered no MAT. According to Table 1, approximately 70% of the county-years offered at least one mode of MAT, and 30% offered no mode.

Table 2. IRRs Resulting from Negative Binomial Fixed Effects Models: Estimates of the Relationship Between County-level Drug-related Death Rates and the Number of New Child Welfare Cases, 2011-2017

	Model 1	Model 2	Model 3	Model 4
Drug-related deaths (per 100k)	1.003*	1.003**	1.003**	1.003**
	(0.002)	(0.002)	(0.002)	(0.002)
Socioeconomic disadvantage		1.021*	1.021*	1.021*
		(0.012)	(0.012)	(0.012)
Percent white		0.711	0.711	0.713
		(0.525)	(0.524)	(0.521)
Region†				
Northeast		1.415***	1.416***	1.407***
		(0.079)	(0.078)	(0.085)
South		0.223***	0.224***	0.223***
		(0.022)	(0.021)	(0.023)
West		0.820***	0.821***	0.819***
		(0.040)	(0.039)	(0.039)
Any MAT = 1			0.990	0.989
			(0.024)	(0.024)
Comprehensive MAT = 1				1.006
				(0.024)
Pseudo R^2	0.197	0.198	0.198	0.198

N = 642; n = 124; T = 7
Robust SE in parentheses
*** p<0.01, ** p<0.05, * p<0.10
†Reference category = Midwest

Table 2 displays the incidence rate ratios (IRRs) that result from the negative binomial fixed effects regression models. Broadly, across all four models in Table 2, there is evidence of a statistically significant, positive relationship between drug-related death rates (per 100,000 persons) and foster youth caseloads within counties over time. This relationship is consistent after the inclusion of controls in Model 2. In particular, a one unit increase in drug-related deaths (per 100k population) is associated with a 0.3% increase in youths entering foster care, controlling for time-varying, county-level characteristics and region. For example, referring back to Table 1, an increase in a given county's drug-related death rate of 5 per 100,000 (approximately one within-county standard deviation) translates to a 1.5% increase in foster youth entries within that county, *ceteris paribus*[17].

As expected, the coefficient for region is statistically significant; it appears that a county's location is a useful predictor for the number of new child welfare cases in a given year. In particular, the rate of foster youth entries among counties in the Northeast is 1.415 times that of the Midwest[18], controlling for drug-related death rates, socioeconomic disadvantage, and percent white. In contrast, compared to the Midwest, counties in the South and the West are associated with approximately 80% and 20% fewer foster youth entries respectively, holding the other variables constant. Furthermore, a one unit increase in the socioeconomic disadvantage variable (comprised of poverty and unemployment rates, the percent married, and the percent without a high school diploma within each county) is associated with a statistically significant 2.1% increase in foster youth entries, controlling for the other factors included in the model. However, the percent of the population comprised of white individuals appears to have no effect. Lastly, the pseudo R^2 value of 0.198 indicates that Model 2 is a better fit for explaining changes in foster youth caseloads than Model 1.

Model 3 includes the first binary variable that measures access to MAT: "Any MAT" indicates whether or not a county offers at least one form of MAT in the given year

[17] "All else being equal" (i.e. controlling for the other variables in the model).

[18] Midwest is the reference category for the "region" variable.

(coded 1 if it does and 0 if it does not). While the relationship between drug-related deaths and new foster youth cases is similar to that of Model 2, there does not appear to be a statistically significant effect of the presence of at least one form of MAT on the dependent variable. Finally, Model 4 investigates whether or not a county that offers comprehensive MAT in the given year (coded 1 if it does and 0 if it does not) results in a change in caseloads. Once again, the association between drug-related deaths and the number of youths entering foster care is consistent with Models 1-2, and the values of the coefficients among the control variables have barely changed. However, neither one of the MAT variables indicate a statistically significant effect, when present, on the number of new child welfare cases.

In order to examine whether the state of California, comprising a large proportion[19] of the units of observation, is overly influencing these models, the results of a sensitivity analysis are displayed in Table 3. Among the 533 county-years that remain after removing those located in California, the coefficients for region and the socioeconomic disadvantage variable largely reflect the findings from the models in Table 2. Interestingly, the demographic variable (percent white) now appears to significantly predict the number of youths entering foster care, controlling for the other factors: in these models, a one-unit increase in the percent of the population comprised of white individuals is associated with an approximate 80% reduction in the rate of new child welfare cases, *ceteris paribus*. However, once again, neither MAT variable appears to have a statistically significant effect on the dependent variable when controlling for the other factors included in the models.

[19] California contributed 17 counties and 109 county-years to the analysis. Excluding these results in a dataset comprised of 107 counties and 533 county-years.

Lastly, the magnitude of the coefficient for the rate of drug-related deaths is consistent with the findings of the main analysis; however, it is no longer statistically significant. This holds true across all four models, including the same controls as the main analysis.

Table 3. IRRs Resulting from Sensitivity Analysis of Negative Binomial Fixed Effects Models: Estimating the Relationship Between County-level Drug-related Death Rates and the Number of New Child Welfare Cases (Excluding California), 2011-2017

	Model 1	Model 2	Model 3
Drug-related deaths (per 100k)	1.002	1.003	1.003
	(0.002)	(0.002)	(0.002)
Socioeconomic disadvantage		1.026*	1.026**
		(0.014)	(0.013)
Percent white		0.210***	0.216***
		(0.106)	(0.113)
Region†			
Northeast		1.507***	1.482***
		(0.082)	(0.107)
South		0.194***	0.193***
		(0.018)	(0.017)
West		0.860***	0.856***
		(0.039)	(0.042)
Any MAT = 1			0.979
			(0.026)
Comprehensive MAT = 1			1.016
			(0.026)
Pseudo R^2	0.200	0.202	0.202

N = 533; n = 107; T = 7
Robust SE in parentheses
*** p<0.01, ** p<0.05, * p<0.10
†Reference category = Midwest

Discussion

Anecdotal evidence and expert opinion have pointed to the culpability of the opioid epidemic as the cause of overwhelming increases in foster youth cases over the past decade (U.S. Department of Health and Human Services 2018). Similarly, numerous social workers and health professionals have expressed their endorsement of MAT as an important means by which patients can overcome OUD and reduce the risk of CPS involvement in their families (U.S. Department of Health and Human Services 2018). However, prior to this study, there has been a lack of research to back up either one of these assertions. This analysis has attempted to fill these important gaps in the child welfare literature.

First, Figure 3 demonstrated regional variations in the relationship between drug-related death rates and child welfare caseloads by calculating the correlation coefficient for each state and plotting the results on a map. In addition to the time-varying factors outlined previously (which were included as controls in the models above), some of these dissimilarities may be explained by state-level variation in health and welfare policies; for example, the number and type of addiction treatment services which are covered by Medicaid, legal definitions of child maltreatment, and mandatory reporting laws each vary by state. However, these policies typically do not change year to year, and fixed effects models are by definition able to account for factors that did not vary over the timeframe of interest (i.e. the years 2011-17). In any case, it is evident that location plays an important role in the patterns to be discussed. This is reflected in Table 1, which indicates that many of the variables of interest vary to a higher degree between than within individual counties.

Overall, the results of the main analysis suggest that there is indeed a positive and statistically significant relationship between the relative severity of the opioid epidemic (operationalized as drug-related death rates) and increases in child welfare cases within counties over time, controlling for county-level time-varying factors and location. In addition, the region in which a county is located was found to be a significant predictor for the number of youths entering foster care in a given year, as was the socioeconomic disadvantage variable (comprised of the percent married, poverty and unemployment rates, and percent without a high school degree). These initial results are relatively consistent with findings from prior qualitative studies and interviews with CPS workers (U.S. Department of Health and Human Services 2018).

However, the results of a sensitivity analysis, detailed in Table 3, are inconsistent with the main analysis in Table 2, indicating that the state of California is overly influencing the results: when counties located in California are excluded from the models, the relationship between drug-related deaths and the number of youths entering the child welfare system is about the same magnitude as in the main analysis, but it is no longer statistically significant. In other words, there is no evidence of a statistically significant relationship between the two variables, and in this case, it cannot be conclusively stated that the opioid epidemic is the cause of recent increases in child welfare cases. This may be due in part to the AFCARS confidentiality constraints, because only a fraction (approximately 3.95%) of the United States' more than 3000 counties were eligible for inclusion in the analysis. Therefore, the scope of the analysis is extremely limited relative to that which would be involved in a nation-wide analysis. It is logical, then, that a largely urban state such as California is swaying the results.

None of the models provide evidence for the presence of a statistically significant relationship between access to any or all modes of medication assisted treatment and the number of youths entering the child welfare system each year. Once again, the lack of a significant association is probably explained in part by the limited scope of this analysis. However, the prevalence of stigmas and other obstacles to treatment that individuals face in both the social and medical arenas likely plays an important role in these patterns as well. Perhaps communities' apparent inability to sufficiently address the impact of (opioid) addiction on families and children is not wholly a problem of access to treatment; rather, social stigmas, and a consequent variety of cultural, personal, and healthcare-related barriers, may obstruct individuals from seeking treatment for addiction, especially one as controversial as MAT (Allen et al. 2019). Furthermore, medical biases against the use of alternative substances such as methadone are likely to impede the extent to which MAT services are sought out by OUD patients (White 2012). Even beyond issues related to access and social acceptance, in order for MAT to be truly effective, the public would need to be made aware of the availability of these treatments and encouraged to inquire about them. Additionally, facilities offering MAT must be within reasonable traveling distance of patients and accessible by public transport in order to accommodate low-income individuals (Grubb and Clin 2019). Simply supplying access to addiction treatments such as MAT is probably insufficient on its own to alleviate the social problems that may have arisen in communities hit hardest by the opioid crisis.

There are several limitations in this analysis to address. First, this study makes use of aggregate rather than individual-level data. Any individual effects of OUD and enrollment in MAT on parents' likelihood of committing child abuse, and consequent child removal by CPS, is missed. Based on the literature, it is also reasonable to assume that the social stigmas surrounding addiction treatment may prevent a large number of individuals from partaking in MAT services even if they are provided within their county of residence. However, obtaining individual-level data detailing the outcomes of OUD patients who actually undertake medication assisted treatment programs would likely be difficult, due to confidentiality and data quality concerns. Even if this data was available, it would not be possible to determine which MAT patients have children registered in foster care, as a result of the absence of a centralized data system capable of linking case-level healthcare and welfare information.

Furthermore, there may be additional unobserved, time-varying differences within counties that influence the number of children entering foster care each year. For example, the capacity of foster homes within each county tends to fluctuate from year to year, and counties frequently face shortages in the number of beds and guardians available (U.S. Department of Health and Human Services 2018). Additionally, CPS prioritizes placing foster youth with relatives whenever possible, meaning children may be moved and processed in a system outside of their home county or state, or enter into an informal (and therefore unregistered) relative caregiver arrangement (AFCARS 2020).

This analysis is limited to populous, largely urban counties, ultimately due to data confidentiality constraints; since youths in foster care are a highly vulnerable population, it is difficult to obtain data for counties with low counts of children currently registered in the welfare system. As a result, the findings of this analysis cannot be generalized to a large majority of the United States' counties. Furthermore, regional differences in both opioid usage and child maltreatment rates are apparent in both the models and the visualization in

Figure 3. Indeed, whereas a wide variety of factors are likely to lead to child removals in urban counties, the opioid crisis is growing ever more severe in rural areas; in fact, "opioid poisonings in non-metropolitan counties have increased at a rate greater than threefold the increase in metropolitan counties…even after adjusting for population density" (Keyes et al. 2014, p. 52). Furthermore, approximately 70% of rural counties lack access to MAT services of any kind (Grubb and Clin 2019). Even where MAT services are available, rural areas are no less susceptible to the effects of stigmatization; smaller population sizes often fortify barriers to medication assisted treatment take-up because patients are more likely to encounter someone they know in their local substance abuse treatment facility (Allen et al. 2019). Clearly, the problems that urban counties face are no less pressing, and are perhaps even magnified, in rural areas.

Future research should seek ways to attain more extensive child welfare data, or perhaps less sensitive information such as indirect indicators of child welfare caseloads, in order to obtain more conclusive evidence as to the impact of the opioid epidemic on foster youth cases. Attention must be paid to rural regions in particular in order to address the unique obstacles which OUD patients, foster youths, child welfare systems, and addiction treatment facilities face in those areas. In addition, changes in policy may require consideration in any future attempts to quantify the impact that the opioid epidemic and access to services such as MAT have on child welfare systems nationwide. For example, the recent passing of the Family First Prevention Services Act in 2018 invokes a national effort to overhaul the current child welfare system by reducing funds for group and congregate homes in favor of family foster homes and evidence-based prevention services that would allow foster candidates to stay with their parents under state supervision. This research has largely operated under the assumption that the child welfare system is too often an extremely damaging experience for children's mental, social, and physical well-being, and frequently harms where it seeks to help. However, if recent reforms can improve the system and provide greater benefits for those who enter it, it may become less imperative to reduce the number of children placed in foster care.

Conclusion

Societal attitudes likely play an important role in the social patterns that have been observed both quantitatively and anecdotally. The stigma that surrounds addiction has persisted for generations, and has likely constructed social barriers to individuals in need of treatment. Addiction is frequently viewed as a lifestyle choice rather than a disease, and this outlook harms more than just individual lives; it negatively impacts families, and by extension, communities. As foster homes and state child welfare systems grow increasingly overwhelmed by influxes of cases, it becomes ever more imperative that the broad societal impacts of the opioid epidemic are adequately measured, acknowledged, and addressed. Before this can be accomplished, however, we must confront the stigma that has been placed around individuals afflicted by addiction as well as the method of medication assisted treatment itself. Cultural resistance to bestowing "in-recovery" status upon individuals who are physically dependent on methadone and other alternative substances likely renders the provision of MAT programs virtually useless. In the concluding paragraphs of their article "The underutilization of medications to treat opioid disorder", public health researchers Allen, Nolan, and Paone state:

> "Ensuring widespread, unencumbered access to effective MAT must remain a top priority. But more access would not necessarily translate to more uptake unless we present these treatments to people who use drugs and their families, friends, and social networks in compassionate ways that work to break down stigma without unintentionally reifying it." (2019, p. 461)

If these social stigmas are addressed and eliminated and MAT is made more widely available, perhaps we will see less children entering the child welfare system as a result of substance abuse, fewer individuals aging out of the system, and more thriving communities.

The manner in which individuals and communities respond to large-scale public health crises can have tremendous social implications. One need only consider the events of the current year for proof of this; the 2020 outbreak of COVID-19 has shed light on the additional damage which social stigmas, misconceptions, and resultant community resistance to the implementation of healthful practices, often in spite of scientific evidence, are capable of inflicting. These perceptions and behaviors are by no means the sole cause of the widespread devastation which follows events such as the COVID-19 pandemic or the opioid epidemic. However, addressing them and acknowledging their consequences may serve as a single important step toward safeguarding individuals, families, and communities against additional and avoidable harm in future crises.

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