Economic Inquiry

PARENTAL SUBSTANCE USE AND FOSTER CARE: EVIDENCE FROM TWO METHAMPHETAMINE SUPPLY SHOCKS

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Foster care caseloads have nearly doubled over the last three decades. Parental methamphetamine (meth) use grew significantly during the same period. While child welfare workers and law enforcement claim that parental meth use contributes to foster care growth, the evidence for a causal effect has not been determined. This paper presents the first evidence of a causal effect of meth on foster care admissions using two exogenous supply-side interventions in meth markets from the late 1990s for identification. First, we find that restrictions on meth precursor distribution caused meth use (proxied by white meth self-referred treatment cases) to decline 4.1%. Second, using two-stage least squares, we estimate a positive elasticity of foster care cases with respect to meth use of 1.54. We also estimate elasticities of 1.03 and 1.49 for cases of child neglect and parental abuse, respectively. These results suggest that child welfare policies should be designed specifically for the children of meth-using parents. (*JEL* I12, J13, K42)

I. INTRODUCTION

From 1986 to 2010, the U.S. foster care population increased from approximately 280,000 to 408,000—a rise of over 45% due primarily to increased admissions in the 1980s and 1990s (U.S. DHHS 1999a, 2006a, 2006b, 2011). This increase in the foster care population has generated significant monetary and non-monetary costs. Out of $22.2 billion spent in 2002 at federal, state, and local levels on child welfare programs, about $10 billion was allocated to out-of-home placements for children, including foster care and group homes (Scarbella et al. 2004). The rise in foster care enrollments could lead to large long-term social costs. Children in foster care are more likely to have behavioral, psychological, and physical health problems. Although many of these problems are believed to result from the circumstances that led to placement in foster care, recent research suggests that the foster care system aggravates these problems (Doyle 2007, 2008).

Given the growing costs of foster care, it is important to understand why more children are entering the foster care system, so that policymakers may know where resources for mediation are best directed. This paper explores the effect of use of a particular narcotic, methamphetamine, on foster care admissions. A body of media reports and child welfare publications links methamphetamine (meth) use with foster care admissions (see Nicosia et al. 2009). While

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ABBREVIATIONS

2SLS: Two-Stage Least Squares
AFCARS: Adoption and Foster Care Analysis and Reporting System
DEA: Drug Enforcement Administration
LATE: Local Average Treatment Effect
NBIV: Negative Binomial Instrumental Variable
OLS: Ordinary Least Squares
STRIDE: System to Retrieve Information from Drug Evidence
TEDS: Treatment Episode Data Set

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research has explored a broad set of explanatory factors, it is difficult to isolate the proximate effect of any particular variable on foster care because of omitted variable bias (Swann and Sylvester 2006).

To measure the effect of meth use on foster care admissions, we collect monthly data on foster care admissions and exits, meth drug treatment admissions as a proxy for the number of meth users, retail meth prices, and a variety of other potentially relevant factors for U.S. states from January 1995 to December 1999 and estimate instrumental variables models of the effect of meth on foster care admissions. The instrumental variable is the deviations in the real price of a pure gram of meth from national trends caused by large federal supply interdictions in 1995 and 1997 that created temporary shortages of critical inputs—chemical precursors—used in production. With this instrumental variable strategy, we find that a 1% increase in white meth use (proxied by white self-admitted meth treatment admissions) is associated with a 1.5% increase in white foster care admissions.[1]

We further investigate the routes that children take into foster care, including parental incarceration, child neglect, child abuse, and parental drug use. Our evidence is consistent with a positive, elastic relationship between meth use and child neglect and parental child abuse of 1.03 and 1.49, respectively. In one specification, parental meth use caused a decrease in foster care enrollments due to parental incarceration. This last result is not robust across specifications, but may merit further research.

We also contribute more generally to literature on the effects of meth. Dobkin and Nicosia (2009) examine the effects of meth on public health outcomes and crime in California. In a similar identification strategy that uses only the 1995 interdiction, Dobkin and Nicosia estimate that meth-related hospital and treatment admissions fell 50% and 35%, respectively, but find no statistically significant relationship between meth-related hospital admissions and crime. We build upon this strategy by using meth treatment admissions as the explanatory variable, both the 1995 ephedrine and 1997 pseudoephedrine regulations for identification, and a sample with national coverage. We do find significant effects of meth use on foster care.

The paper is organized as follows. Section II gives an overview of relevant details of foster care policy and the institution of foster care, the role of parental drug use in child maltreatment and foster care admissions, and the two federal interventions in 1995 and 1997 that increased the scarcity of two key meth precursors. Section III explains the data. Section IV discusses our empirical methodology. Section V reviews our results. Section VI concludes.

II. BACKGROUND

A. *Foster Care*

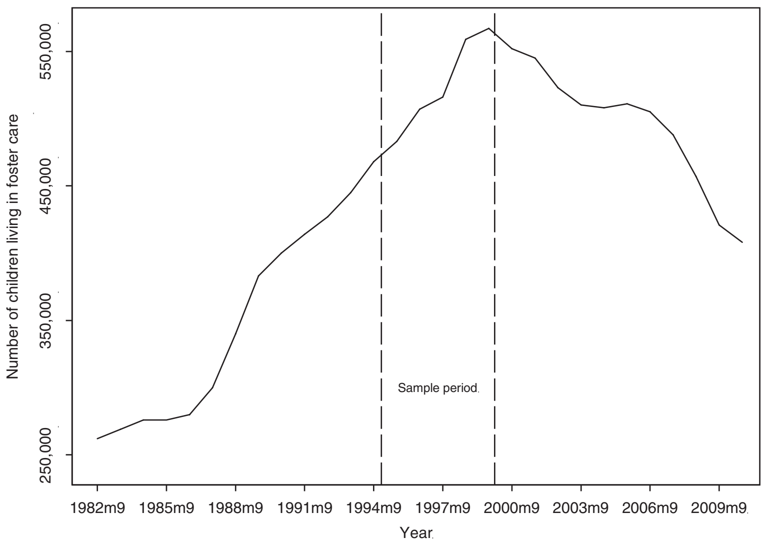
Foster care is a child welfare system in which a child, who has been made a ward of the state, is removed from his legal guardian's care due to maltreatment and abandonment and placed into residential care with either a state-certified residential group home or a surrogate family called the child's "foster parent." Its purpose is to provide temporary housing in a safe and stable environment until reunification with the child's birth parents or legal guardians is possible. Reunification happens once the state is convinced that the harmful factors that triggered removal no longer exist (see Barbell and Freundlich 2001).

The population of children living in foster care has increased dramatically over the last few decades. Figure 1 shows the number of U.S. children living in foster care from 1982 to 2010 using data compiled from U.S. DHHS (1999a, 2006a, 2006b, 2011). There was a stark increase in the foster care population from the mid-1980s to the late 1990s caused by rapid growth in entry with no associated uptick in exit. The exit of younger children from the system explains much of the decline in foster care after 1999 (U.S. DHHS 2006a).

A series of federal legislation expanded federal oversight of child welfare services, including foster care. The Adoption Assistance and Child Welfare Act of 1980 was enacted to address the growing number of placement transitions for children in foster care. It emphasized family reunification as an institutional priority whenever feasible. It promoted stable, permanent placements rather than the multiple placements known as foster care drift. In 1993 Congress passed the Family Preservation and Family Support Program/Promoting Safe and Stable Families Program. This act doubled

1. Blacks constitute a large part of the growing foster care population, but a negligible part of the meth-using population (as we show below). Consequently, the problems associated with black foster care are quite different. To focus on the population of children plausibly affected by parental meth use, we limit our sample to whites.

FIGURE 1
Number of U.S. Children Living in Foster Care, Annual, 1982–2010



Sources: U.S. DHHS (1999a, 2006a, 2006b, 2011).

federal funding for family preservation and support services. In 1997, the program was reauthorized as part of the larger Adoption and Safe Families Act that was structured to address the difficulty of placing special needs children from foster care into adoptions. This legislation brought a new strategy shift toward protecting child health—even if the child's health came at the expense of parental reunification (Barbell and Freundlich 2001).

Foster care placements have grown for a number of reasons. Reports of child abuse and neglect grew from 1.1 million reports in 1980 to almost 3 million in 1999 (Barbell and Freundlich 2001). Foster care and group homes are increasingly used as an alternative to mental health and juvenile justice institutions. Landsverk and Garland (1999) estimate that between one-half and two-thirds of all children entering foster care have mental health disabilities that warrant mental health treatment. An increase in parental incarceration, and presumably the incarceration of mothers, helps explain a major portion of the rise in foster care placements (Swann and Sylvester 2006). Since families on welfare constitute a large share of families who enter the child welfare system, welfare reform legislation may have had an effect on foster care caseload flows through its effect on the labor force participation of poor mothers (Paxson and Waldfogel 2002). We examine the role of parental drug use in explaining the growth of foster care admissions.

B. Parental Drug Use and Child Maltreatment

Parental substance use is one of the most significant risk factors associated with child maltreatment and entry into foster care. The U.S. DHHS (1999b) reports that approximately 10%–20% of children who are prenatally exposed to drugs enter foster care at or around their birth and another third enter within a few years. Parental substance use can increase foster care levels by lengthening stays in foster care (Fanshel 1975), increasing noncompliance with child welfare treatments (Famularo et al. 1989), and lowering the likelihood of reunification with the child (Walker et al. 1994).

During the late 1980s and early 1990s, crack cocaine became widespread in U.S. urban areas. From 1986 to 1991, the average number of children in foster care increased nationwide 53%, but 50% of that overall growth was driven by only three states: California, New York, and Pennsylvania, all three of which were at the epicenter of the crack epidemic (U.S. GAO 1994). The proportion of children with health problems and prenatal exposure to drugs in these three states also increased from 1986 to 1991.

In a broad sense, the meth epidemic followed the crack epidemic chronologically, but affected very different populations.

Aside from surveys assessing the perceptions of child welfare workers,[2] researchers' understanding of the effect of parental meth use and child maltreatment is still relatively undeveloped. Some researchers have attempted to extrapolate from what is known from cocaine and alcohol studies but due to meth's longer half-life and the chemical mechanics involved in addiction to it, cocaine studies may not be reliable predictors for understanding prenatal meth exposure (Famularo et al. 1992; Kelleher et al. 1994; Smith et al. 2008). More recently, scientists have studied the brains of meth users and children prenatally exposed to meth using neuroimaging technology and found abnormalities in brain structure and chemistry (Chang et al. 2007).

Other evidence comes from our limited knowledge about the demographics of meth users. Compared to users of alcohol, cocaine, and heroin, meth users are more likely to be female and show signs of severe addiction (Brecht et al. 2004; Dluzen and Liu 2008; Gonzales et al. 2010; Shannon et al. 2011), and to have small children (Grella et al. 2006; Hser, Evans, and Huang 2005).

Although a strong association between meth use and child welfare has been documented, the mechanism linking the two is less understood. The most commonly mentioned are the pharmacological effects of meth on parents that can cause poor judgment, increased violence, and overall neglect (Gonzales et al. 2010), as well as exposure to toxic chemicals used in production (Nicosia et al. 2009). The relationship may also be due to unobserved heterogeneity. Meth use is correlated with use of other substances, such as alcohol, marijuana, and tobacco, each of which independently affect child welfare. Antisocial personality traits are associated with substance use and are themselves risk factors for child maltreatment (Kelleher et al. 1994). Reverse causality may also be a concern if other factors lead to maltreatment, possible removal of a child, and in turn cause the parent to experience social isolation, depression, and other disorders that trigger substance use. There is still considerable uncertainty as to whether the identified channels linking meth in a population and child welfare in the same population reflect a causal chain of events. This study helps to fill this gap.

2. In a 2005 survey of 300 counties, 40% of child welfare officials reported increases in out-of-home placements in the last year due to meth use in their communities (National Association of Counties 2005).

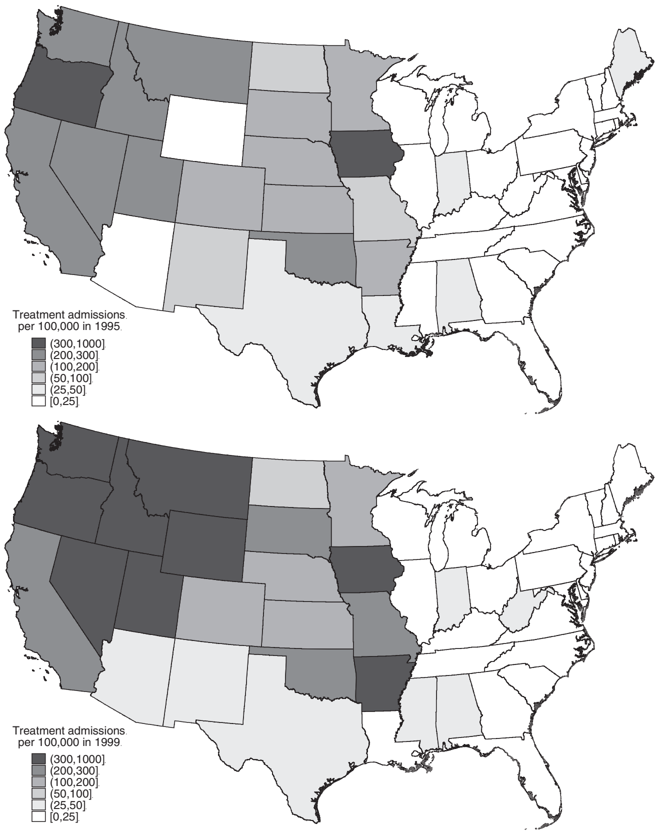
C. Methamphetamine

Due in part to the low price of methamphetamine and its addictive qualities, the Office of National Drug Control Policy (2006) warns that meth may be more heavily used than crack cocaine, LSD, PCP, ecstasy, and inhalants in the United States. Public health indicators, such as the number of meth-related emergency-room visits, show meth as a growing national issue (Nicosia et al. 2009). Meth use first showed signs of being a problem on the West coast. Over the 1990s, meth use intensified in those originating states and expanded eastward across the United States. In Figure 2, we show these changes over time by calculating the annual rate of admission to treatment facilities for meth for 1995 (the top map) and 1999 (the bottom map).

The social costs of meth are borne by many non-users. A recent study by the Rand Corporation estimates that the total social costs of meth were $23.4 billion in 2005, which the authors attribute to the cost of declining quality of life, increased drug treatment, health care, deaths, lost productivity, crime, child endangerment, and harm to the environment (Nicosia et al. 2009). The authors estimate that the meth-related costs of child endangerment, including foster care, totaled $904.6 million in 2005. Many law enforcement and social work practitioners make a strong connection between the rise of meth use and the expanding number of children in foster care, but our study is the first to estimate a causal relationship.

There are different varieties of meth: dextrorotatory methamphetamine (D-meth), levorotatory methamphetamine (L-meth), and racemic methamphetamine (DL-meth). The preferred street meth is the D-meth variety, a highly addictive stimulant that affects the central nervous system by releasing dopamine and adrenaline. The effects of D-meth include increased energy and alertness, decreased appetite, intense euphoria, and impaired judgment, all of which can last up to 12 hours (Rawson and Condon 2007). Long-term meth use can lead to psychotic behaviors including paranoia, visual and auditory hallucinations, insomnia, and aggression (Rawson, Anglin, and Ling 2001).

FIGURE 2
Meth Treatment Prevalence per 100,000 by State, Whites, TEDS, 1995 and 1999



Sources: Authors' calculations from TEDS. The upper graph shows the number of meth treatment episodes per 100,000 whites in each state from January to December 1995. The lower graph shows the episode rate from January to December 1999. Hawaii and Alaska are not shown for presentation. Arizona, the District of Columbia, Kentucky, Mississippi, West Virginia, and Wyoming have poor data quality for TEDS during some or all of the sample.

Meth is synthesized from a reduction of ephedrine or pseudoephedrine, the active ingredients in commonly used cold medicines. The chemicals used in synthesis are available in household products, but the process is extremely toxic. Meth is unique among illicit drugs for the concentration of the market for its precursor chemicals. As of 2004, nine factories manufactured the bulk of the world supply of ephedrine and pseudoephedrine (Suo 2004).

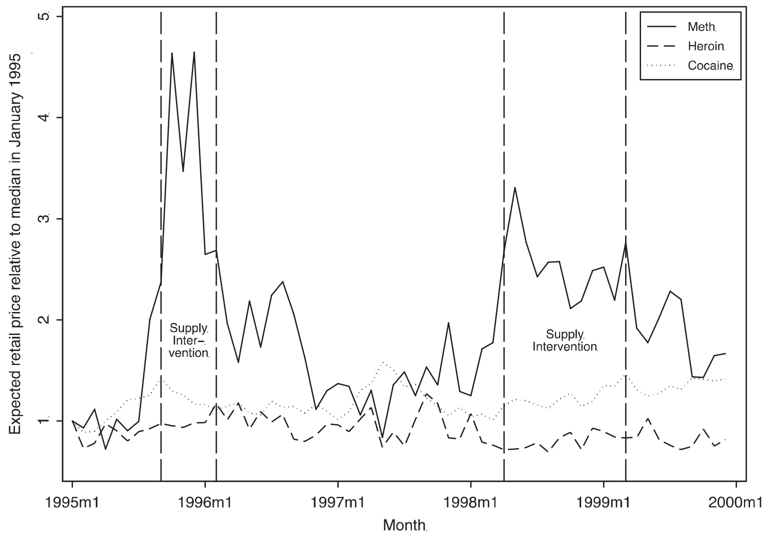
Since these precursors are distributed and packaged in different forms, the history of precursor control is one in which meth producers innovate around narrow restrictions on precursors created by federal legislation.[3] In 1988, Congress passed the Chemical Diversion and Trafficking Act that gave the Drug Enforcement Administration (DEA) the authority to control the wholesale distribution of precursors used to produce illegal drugs, such as meth, LSD, and PCP. The statute required bulk distributors of ephedrine and pseudoephedrine to notify drug enforcement authorities of imports and exports and keep records of purchasers (Suo 2004; U.S. DEA 1997). All tablet forms of ephedrine and pseudoephedrine medical products, however, were exempt—a legal loophole that drug trafficking organizations quickly exploited.

The primary sources of precursors following the 1988 regulation were wholesale and mail order distributors of ephedrine tablets.

3. States have regulated meth precursors, but primarily after our sample period ends.

FIGURE 3

Ratio of Median Monthly Expected Retail Prices of Meth, Heroin, and Cocaine Relative to Their Respective Values in January 1995, STRIDE, 1995–1999



Notes: Authors' calculations from STRIDE. Expected price estimates come from random coefficient models of both purity and price, following the methodology of Arkes et al. (2004). Estimates from these models are available from the authors. Prices are inflated to 2002 dollars by the All Urban CPI series.

In the early 1990s, there was little use of pseudoephedrine as a precursor. In 1994, ephedrine was identified as the source material in 79% of meth lab seizures, while pseudoephedrine was only found in 2% (Suo 2004). Congress sought to close the legal loophole in 1993 by passing the Domestic Chemical Diversion Control Act, which became effective August 1995. This new regulation provided additional safeguards by regulating the distribution of products that contained ephedrine as the only active medicinal ingredient (Cunningham and Liu 2003; U.S. DEA 1995). The new legislation ignored pseudoephedrine tablets, so traffickers soon took advantage of the omission by substituting toward pseudoephedrine as a precursor. By 1996, pseudoephedrine was found to be the primary precursor in almost half of meth lab seizures (U.S. DEA 1997). From 1996 to 1997, pseudoephedrine imports grew by 27% while sales of all cold medications grew only 4% (Suo 2004). As a consequence, the DEA sought greater controls over pseudoephedrine products. The Comprehensive Methamphetamine Control Act of 1996 went into effect between October and December 1997 and required distributors of almost all forms of pseudoephedrine to be subject to chemical registration (U.S. DEA 1997).

Due to the concentration of meth precursor markets, these two regulations may be the largest supply shocks in the history of U.S. drug enforcement (Dobkin and Nicosia 2009). To estimate the effect of the interdictions on meth markets, we construct a monthly series for the expected retail price of a pure gram of D-meth from January 1995 to December 1999 using the DEA's seizure database, System to Retrieve Information from Drug Evidence (STRIDE).[4,5] Figure 3 shows the median monthly expected retail prices of meth, heroin, and cocaine relative to their respective medians in January 1995. The 1995 interdiction caused a dramatic spike in meth prices, but the effect was relatively short lived. After 6 months, the prices returned to their pre-interdiction level. The 1997 regulation had a smaller but more sustained effect on prices—lasting approximately 12 months. It is these rapid shocks to the supply and market price of meth that we exploit to understand

4. See the Supporting Information for an explanation of the construction of the meth price series.

5. There is a debate about the ability of researchers to recover the distribution of market prices from STRIDE because its sampling is determined by law enforcement actions. See Horowitz (2001) for the critical argument and Arkes et al. (2008) for a rebuttal.

its effects on foster care admissions. Figure 3 also shows how meth prices were unique in their response to these interventions. There is no similar movement in the median prices for heroin or cocaine (relative to their medians in January 1995).

We let the meth price data date the interventions precisely. To time the durations, we regressed real expected meth prices onto a constant, a polynomial time trend, and an indicator variable for the intervention months. We then add a single fixed effect for each month after the intervention, and depending on the statistical significance of the additional month dummy, it is retained in the model. We continue these steps until the post-intervention contiguous month dummy is statistically insignificant. This method allows us to identify the number of months wherein the 1995 and 1997 regulations were practically effective in the output markets.[6] The 1995 intervention is in effect in August 1995, and we observe a deviation from the price trend between September 1995 and February 1996. The 1997 intervention comes into effect between October and December 1997, and we observe a deviation from the price trend between April 1998 and March 1999. Dobkin and Nicosia (2009) use a 4-month window for the 1995 intervention, but they limit their attention to California where the meth market is the most sophisticated and producers are arguably more adaptable. Cunningham and Liu (2003, 2005) use 6 months for the 1995 intervention (August 1995–January 1996). Our empirically driven timings for the supply shocks are consistent with these previous studies.

III. DATA SOURCES AND DESCRIPTIVE STATISTICS

We use a variety of data sources to study the effect of meth use on foster care admissions. We choose a sample period of January 1995 to December 1999 for all data sets. This starts 8 months before the first intervention and ends 9 months after the second intervention. The level of variation for our analytic sample is state-by-month.

Foster care enrollment data come from the Adoption and Foster Care Analysis and Reporting System (AFCARS). AFCARS is a federally mandated database that aggregates detailed case information on each child in foster care and each child who has been adopted under the authority of all state child welfare agencies (National Data Archive on Child Abuse and Neglect 2002).[7] State participation began voluntarily in 1994, and by mandate in 1998.[8] For each child in foster care in a particular year, states must report the date a child first entered and most recently entered into the foster care system, as well as demographic data such as the child's age, gender, race, and ethnicity. AFCARS is also valuable because it indicates whether a child was removed as a result of neglect, physical abuse, parental drug use, parental incarceration, etc.

Since penalties for non-compliance were not introduced until 1998, our AFCARS panel is an unbalanced selection of states that provided verified high-quality data in accordance with federal mandates. In robustness analysis, we limit the sample to years 1997–1999 to determine the importance of our selection criteria. We use the entire sample because some of the early AFCARS participants, such as California, were the epicenter of the meth trade in the mid-1990s and the use of both interventions should improve identification.

Figure 4 shows the number of seasonally adjusted latest entries/removals into and discharges out of foster care by month during the 1995–1999 sample period for California, Illinois, Massachusetts, New Jersey and Vermont—the five states with balanced panels throughout the sample. The correlation between foster care entries and the interventions is stark. Admissions fell from over 8,000 removals per month to approximately 5,500 following the 1995 intervention, and fell again to under 6,000 per month following the 1997 intervention.

Selected descriptive statistics from the foster care data are presented in Table 1. Although 54% of foster care children are white, black children are greatly overrepresented in the foster care system; they constitute over 40% during our sample period. Females and Hispanics make up 48% and 18% of the total foster care population, respectively. The average child entering foster care is typically young (6.9 at first entry, 7.2 at latest entry), and has been removed 1.3 times.

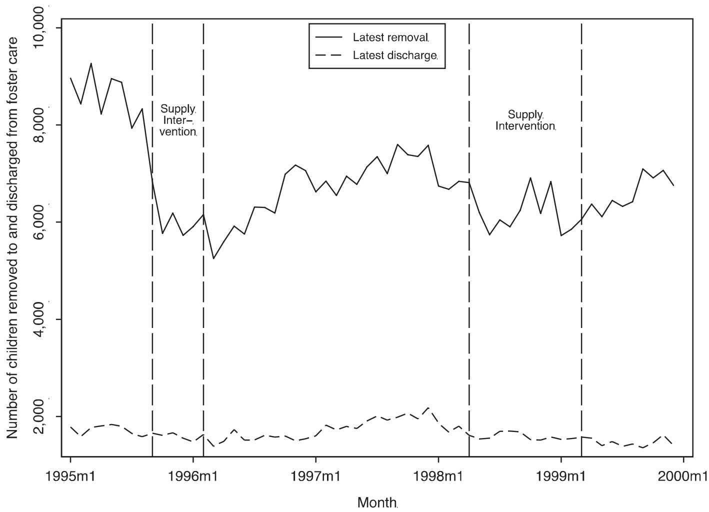
6. See the Supporting Information for a description of the model used to estimate the length of the disruptions.

7. AFCARS consists of two separate data files for foster care and adoption records. Throughout this paper, we use AFCARS to refer to the foster care file only.

8. In 1995, 14 states participated in AFCARS; in 1996, 17 states; in 1997, 18 states; in 1998, 44 states; in 1999, 50 states; and in 2000, 51 states (including the District of Columbia).

FIGURE 4

Number of Children Removed to and Discharged from Foster Care in a Set of Five States by Month, AFCARS, Seasonally Adjusted, 1995–1999



Sources: Authors' calculations from AFCARS. This figure contains AFCARS data only from California, Illinois, Massachusetts, New Jersey, and Vermont. These states form a balanced panel through the entire sample period.

TABLE 1

Foster Care Selected Descriptive Statistics, Adoption and Foster Care Analysis and Reporting System (AFCARS), 1995–1999

	All		Whites Only		Regression Sample	
Child Characteristics	***M* (*SD*)**	**Obs.**	***M* (*SD*)**	**Obs.**	***M* (*SD*)**	**Obs.**
Female	0.48	8,376,410	0.48	1,829,309	0.48	1,810,777
White	0.54	7,485,566	1.00	1,356,475	1.00	1,340,894
Black	0.41	7,485,566	—	—	—	—
Other race	0.05	7,485,566	—	—	—	—
Hispanic ethnicity	0.18	7,123,489	0.31	1,425,139	0.31	1,413,088
Age at first removal	6.89	8,101,436	7.58	1,706,948	7.57	1,691,607
	(5.44)		(5.42)		(5.42)	
Age at latest removal	7.18	8,355,884	7.79	1,825,189	7.79	1,806,628
	(5.51)		(5.45)		(5.45)	
Total number of removals	1.29	8,300,811	1.28	1,812,239	1.28	1,793,777
	(0.72)		(0.77)		(0.78)	
Route of most recent removal						
Parental drug use	0.16	7,567,806	0.11	1,615,805	0.12	1,541,297
Parental abuse	0.17	7,623,928	0.17	1,632,596	0.16	1,619,836
Parental neglect	0.52	7,645,084	0.45	1,636,756	0.45	1,623,995
Parental incarceration	0.05	7,496,838	0.04	1,575,780	0.04	1,563,020

Notes: Authors' calculations from AFCARS. Children may have no reported route or more than one route of admission to foster care, so proportions may not add to one. See Supporting Information for the sample restrictions used to generate the sample in the final column.

Child welfare workers can report more than one reason for removal. For each category, we classify a child as following that route if it ever shows up in his file. Thus, the route of admission proportions can add up to more than one. We report summary statistics for only the four most commonly cited reasons for removal. The most commonly cited reason for removal

TABLE 2
Drug Use Treatment Episodes Selected Descriptive Statistics, TEDS, 1995–1999

Drugs Used Prior to Episode	Means for All Patients	Means for Patients Reporting Meth Use	Means for Self-Admitted White Patients Reporting Meth Use (Full Sample)	Means for Self-Admitted White Patients Reporting Meth Use (Regression Sample)
Alcohol	0.74	0.57	0.56	0.57
Cocaine or crack	0.35	0.19	0.21	0.21
Marijuana	0.35	0.51	0.44	0.44
Heroin	0.18	0.08	0.12	0.13
Methamphetamine	0.08	1.00	1.00	1.00
Individual characteristics				
White	0.61	0.83	1.00	1.00
Black	0.26	0.03	0.00	0.00
Hispanic	0.11	0.10	0.03	0.03
Source of referral				
Self	0.33	0.31	1.00	1.00
Criminal justice system	0.33	0.37	0.00	0.00
Drug use treatment provider	0.12	0.08	0.00	0.00
Other health provider	0.07	0.07	0.00	0.00
School	0.01	0.01	0.00	0.00
Employer	0.01	0.01	0.00	0.00
Number of patients	8,061,003	621,724	158,791	156,792

Notes: Authors' calculations from TEDS. See Supporting Information for the sample restrictions used to generate the sample in the final column.

was child neglect (52%), followed by physical abuse (17%), parental drug use (16%), and parental incarceration (5%). We also report summary statistics for the white subsample and our regression sample.[9] Although dropping these observations increases age at first removal (7.6), and lowers both the share of parental drug use (11% and 12%) and neglect cases (45%), the samples are similar overall.

Since there is no direct measure of meth use available at the month and state level for this period (Cunningham and Liu 2003), we use the number of meth treatment admissions as a proxy. These data come from the Treatment Episode Data Set (TEDS), which records the universe of all treatment admissions for substance abuse to federally funded inpatient or outpatient facilities.[10] Admitted patients are interviewed for their primary, secondary, and tertiary substances used prior to entry, from which we calculate measures of treatment for five substances: alcohol, cocaine/crack, marijuana, heroin, and meth. Table 2 shows the characteristics of drug treatment patients in TEDS during our sample period. Meth is mentioned in 8% of TEDS treatment admissions.[11]

The second column of Table 2 shows how meth treatment patients differ from the population of patients. Meth users are more likely to be white and less likely to be black. Blacks constitute only 3% of meth treatment patients for the sample period. For this reason, we restrict our analytic sample to whites. Meth users have a referral profile that is qualitatively similar to the population's. About one-third of patients are self-admitted. Thirty-seven percent of meth patients are referred by the criminal justice system. The third column shows how self-admitted meth patients differ from all other meth patients in the TEDS, while the fourth column shows how our regression sample differs from the unrestricted sample.[12] Overall, we find that the characteristics of self-admitting meth patients are similar to those of the larger population of meth users.

9. See the Supporting Information for a discussion of AFCARS data quality.

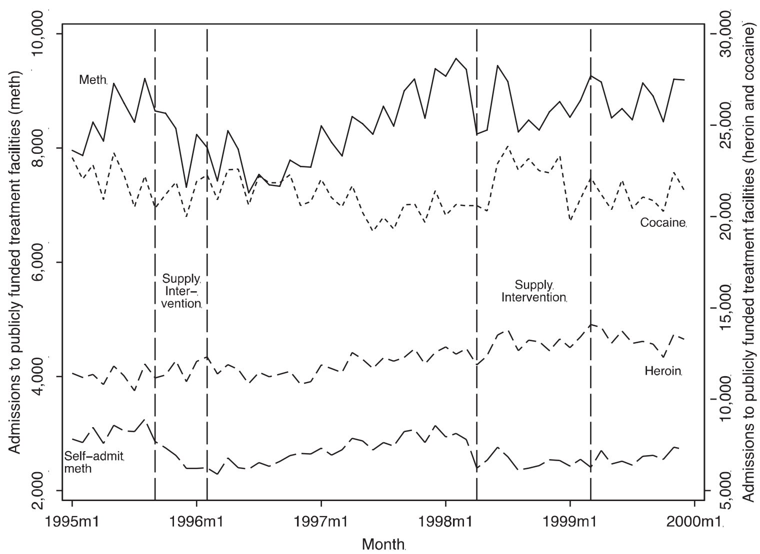
10. TEDS consists of two separate data files for admissions (TEDS-A) and discharges (TEDS-D). In this paper, we use TEDS to refer to the TEDS-A file.

11. Survey data from the 1997 National Survey on Drug Use and Health finds similar distributions to the TEDS data. In 1997, 5% of all respondents said they had ever tried illicit stimulants and 82% had ever tried alcohol. These are comparable to the 8% and 74% of all patients in treatment for meth and alcohol (from authors' estimates).

12. See the Supporting Information for a discussion of TEDS data quality.

FIGURE 5

Total Admissions to Publicly Funded Treatment Facilities by Drug and Month, Selected States, Whites, TEDS, Seasonally Adjusted, 1995–1999



Notes: Authors' calculations from TEDS. Arizona, the District of Columbia, Kentucky, Mississippi, West Virginia, and Wyoming are excluded because of poor data quality. Patients can report the use of more than one drug.

Figure 5 shows the seasonally adjusted trends for whites in treatment for meth (total cases and self-referred cases separately), juxtaposed with the trends for cocaine and heroin. Meth has the largest percentage rise in treatment in-flows for the sample period due in part to its lower prevalence overall in 1995 relative to cocaine and heroin. There appears to have been a drop in the level of meth admissions following the 1995 intervention, followed by a rebound in the rate of growth afterwards, whereas the 1997 intervention appears to be mainly associated with flat growth rates. Although suggestive that meth admissions may have fallen in response to rising meth prices, the fact that there are similar movements in the series outside the interventions suggests more rigorous statistical analysis is necessary.

We include a number of controls to address potential confounds to identification. Meth use may be correlated with other drug use, so we include the number of alcohol use treatment cases for whites from TEDS. In some robustness checks, we also include the number of cocaine, heroin, and marijuana cases for whites. Meth use may be a function of local economic conditions, so we control for the state unemployment rate estimated from the Current Population Survey. (The Bureau of Labor Statistics does not disaggregate these statistics by race, so we control for the overall unemployment rate.) Finally, we include a relatively exogenous measure of the price of a substitute drug. Orzechowski and Walker (2008) report the cigarette tax in each state. We also control for the state population of whites aged 0 to 19 years and aged 15 to 49 years. We see these as the appropriate denominators for foster care and drug use rates, respectively.

IV. MODEL AND IDENTIFICATION

In this section, we develop an empirical approach that examines the extent to which increases in meth use caused increases in foster care admissions from January 1995 to December 1999. Further, we use data on the reasons for a child's removal to identify the precise mechanisms that translate growth in meth use to an increase in foster care admissions. As we state above, we proxy for meth use with the number of self-referred meth treatment admissions.

Steady-state treatment admissions are determined jointly by the population of meth users in an area and the average effectiveness of local treatment options. First, it is reasonable to believe that meth use and meth treatment admissions in a local population are strongly, positively correlated. In log–log models, the coefficient on meth treatment admissions will be equivalent to the coefficient on meth users if we can assume that a constant proportion of users are in treatment in any cell up to a multiplicative error. The constant and fixed effects will absorb the parameter that scales users to treatment admissions, and the error term will absorb the proxy error.[13] Second, we assume that the average effectiveness of addiction treatment options does not vary systematically with temporary disruptions in meth precursor markets. Unanticipated, temporary deviations in the real price of meth should affect the number of meth users without influencing the average efficacy of treatment.

Another potential problem is that meth treatment and foster care admissions may have common unobserved shocks, such as economic factors or law enforcement resource allocations. The use of price instruments helps address this omitted variable bias because the 1995 and 1997 supply-side interventions were federally driven, and also had temporary effects on meth markets, causing real meth prices to spike for 6–12 months. This identification strategy eliminates competing explanations that are not contemporaneous to the precise duration of the two interventions.

To mitigate bias induced by the endogeneity of meth treatment admissions, we estimate two-stage least square models of foster care admissions on meth treatment admissions. The model starts with the following first stage:

$$\begin{aligned}&\log(\text{self-referred meth treatment})_{\mathrm{st}}\\ &\quad = \alpha_0 + \alpha_1 \text{price deviation}_{\mathrm{t}} + \alpha_2 \mathbf{X}_{\mathrm{st}} + \gamma_{\mathrm{s}}\\ &\qquad + \phi_{\mathrm{t}} + \tau_{\mathrm{st}} + u_{\mathrm{st}},\end{aligned}$$

where $\log(\text{self-referred meth treatment})_{\mathrm{st}}$ is the log of the number of self-referred meth treatment admissions for whites in state s during month t, price $\text{deviation}_{\mathrm{t}}$ equals the deviation in the expected price of meth from its trend line during precursor regulations and equals zero otherwise, γ_{s} is a state fixed effect, ϕ_{t} is a month-of-year fixed effect, τ_{st} is a state-specific linear time trend, u_{st} is an idiosyncratic error term, and $\mathbf{X}_{\mathrm{st}}$ is a vector of covariates including the log of the state population of whites aged 0–19 years, the log of the state population of whites aged 15–49 years, the cigarette tax, the state unemployment rate, and the log of the alcohol treatment cases for whites.

The second-stage equation estimates the relationship between meth admissions and foster care admissions:

$$\begin{aligned}&\log(\text{foster care})_{\mathrm{st}} = \beta_0 + \beta_1\\ &\quad \times \log(\text{self-referred meth treatment})_{\mathrm{st}}\\ &\quad + \beta_2 \mathbf{X}_{\mathrm{st}} + \delta_{\mathrm{s}} + \lambda_{\mathrm{t}} + \omega_{\mathrm{st}} + e_{\mathrm{st}},\end{aligned}$$

where $\log(\text{foster care})_{\mathrm{st}}$ is the log of foster care admissions for whites in state s during month t, δ_{s} is a state fixed effect, λ_{t} is a month-of-year fixed effect, ω_{t} is a state-specific linear time trend, and e_{st} is an idiosyncratic error term. All models are weighted by the population of whites aged 0–19 years.

The parameter of interest is β_1, the elasticity of latest entry into foster care with respect to self-referred meth treatment admissions. For the two-stage least squares (2SLS) estimator of β_1 to be consistent, the deviation in price during the intervention windows must be both strongly correlated with meth treatment admissions and uncorrelated with the error term in the second stage. As we will report, the spike in prices during the intervention window had large negative effects on meth treatment admissions. The argument for excluding the prices cannot be tested, but Figure 3 shows there were no corresponding changes in the prices of heroin or cocaine during the two interventions.[14] We also do a series of robustness checks that suggest our results are not spurious.

The log–log functional form results in the loss of some observations for which either foster care or meth treatment admissions are equal to zero. To test whether this affects our estimates, we also estimate an analogous negative binomial instrumental variable model using the levels forms of the dependent and independent variables.[15]

Since our identification strategy uses the exogenous variation in meth use caused by supply-side shifts in prices, our estimates are

13. In the Supporting Information, we model the measurement error of the treatment admissions proxy and show this formally. Note that the scaling parameter cannot be identified in the levels model even if it remains constant.

14. Ideally, we could make the same comparison with marijuana prices. However, most STRIDE marijuana observations are obtained by seizure rather than purchase. Seizure observations do not have associated prices, so it is impossible to construct a marijuana price series with these data.

15. See Mullahy (1997) for a discussion of this model.

only valid for the local average treatment effect (LATE) of meth for compliers affected by the precursor interventions. Our identification requires the instrument to be excludable from the structural equation and the effect of the treatment to be monotonic on the treatment population (Imbens and Angrist 1994). Monotonicity implies that state-by-month increases in our price instrument are always associated with state-by-month decreases in meth use. As the monotonicity assumption is untestable, we cannot confirm whether it is violated in our sample. We can only note that the first-stage coefficient on the price instrument is negative in all of our models, which we believe reflects reductions in meth use.

Another possible confounder is if law enforcement reallocated resources in response to rising meth prices toward such that this independently influenced child maltreatment and foster care admissions. While plausible, we do not believe this is a likely threat to identification. Federal actors were responsible for each intervention and each intervention lasted just 6–12 months. This concern also motivates our focus on self-admitted patients. These patients are less likely to be affected by any law enforcement or social services responses that may violate the excludability requirement for identification.

Our identification strategy assumes that meth prices impact foster care only through their impact on meth use, but it is possible that there is a direct effect on foster care. For example, if the price elasticity of demand for meth is inelastic, then the spike in prices we observe led to increased spending on meth, substitutions away from other forms of consumption, and declines in real income. Insofar as child health is a normal good, then the spikes themselves could directly harm children and therefore increase foster care. We are skeptical of this explanation for two reasons. First, we find that meth treatment admissions declined during the price shocks. Second, we observe declining foster care admissions during the two interventions (Figure 4), not increases.

Finally, our identification uses only national variation in meth prices. Any time series factors net of month-of-year fixed effects that move with the rise and fall of meth prices during the two interventions could explain our results, but the variable would have to follow the same steep spike and immediate decline in prices observed in this time. We do a robustness check with a price deviation instrument that varies at the Census-division level to address this potential confound.

V. RESULTS

Because AFCARS foster care data contain information on entry, exit, and route of admission, we estimate and report several models in each table. Let us summarize our main findings. We find evidence for a positive elastic relationship between foster care admissions and meth use. We do not find any effect on exits, suggesting the causal effect of meth on the foster care system has been one of net growth. By analyzing the effect separately by route of admission into foster care, we find that the result of meth may be primarily to increase child abuse and neglect, as both routes are strongly positive and statistically significant in almost all models and robustness tests.

Table 3 shows the results of our baseline model. Each pair of columns shows a different dependent variable: first, all foster care admissions for whites ("latest entry"); then broken down by route into foster care; and finally exits from foster care. Most of the ordinary least squares (OLS) estimates differ considerably from the 2SLS estimates. For example, the OLS estimate of meth's effect on latest entry is almost perfectly inelastic, whereas the elasticity estimated with 2SLS is greater than one.

The value of the F-statistics testing the null hypothesis that the instrument is equal to zero in the first stage is always greater than 10 in our 2SLS models, so we are not concerned about a weak instrument. Using the latest entry model's first-stage coefficient as an example, a one-standard deviation in the price instrument is associated with a 4.1% reduction in the number of self-referred individuals seeking treatment for meth use ($-0.0005 \times 82 = 0.041$). We find that a 1% increase in white meth use (proxied by the log of white meth treatment admissions) causes a 1.54% increase in white foster care admissions. The 2SLS model is well identified, so this positive effect likely measures the causal effect of the meth-using population on foster care entry and child maltreatment. Meth use is highly addictive and debilitating, and meth users are more likely to be female and have young children than users of other drugs. Therefore, our large estimated elasticity of foster care with respect to meth use may reflect these demographic differences and a relatively

TABLE 3
OLS and 2SLS Regressions of Foster Care Admissions on Meth Treatment Admissions with State Linear Trends, Whites, 1995–1999

	Log Latest Entry into Foster Care		Log Latest Entry via Parental Incarceration		Log Latest Entry via Child Neglect	
Covariates	**OLS (1)**	**2SLS (2)**	**OLS (3)**	**2SLS (4)**	**OLS (5)**	**2SLS (6)**
Log self-referred meth treatment rate	0.01	1.54***	0.23***	−0.38	0.03	1.03**
	(0.02)	(0.59)	(0.05)	(0.32)	(0.02)	(0.41)
Unemployment rate	−0.06**	−0.00	−0.04	−0.04	−0.07***	−0.03
	(0.02)	(0.05)	(0.06)	(0.06)	(0.02)	(0.04)
Cigarette tax per pack	−0.01	0.02	−2.02***	−1.96***	0.15	0.16
	(0.10)	(0.17)	(0.42)	(0.42)	(0.12)	(0.16)
Log alcohol treatment rate	−0.04	−1.26***	−0.37	0.13	−0.05	−0.85***
	(0.03)	(0.46)	(0.09)	(0.28)	(0.03)	(0.32)
Log population 0–19 year old	3.68	2.25	−42.61*	−40.43*	2.12	1.28
	(2.59)	(3.60)	(22.74)	(22.24)	(2.66)	(3.21)
Log population 15–49 year old	−15.48***	−10.61*	−27.20	−32.24	−8.93*	−5.66
	(5.44)	(6.19)	(22.20)	(21.35)	(5.11)	(5.52)
Month-of-year fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
State linear time trends	x	x	x	x	x	x
First stage						
Price deviation instrument		−0.0005***		−0.0009***		−0.0005***
		(0.0001)		(0.0002)		(0.0001)
F-statistic for IV in first stage		17.60		25.99		18.78
R^2	0.864		0.818		0.855	
N	1,343	1,343	1,068	1,068	1,317	1,317

	Log Latest Entry via Parental Drug Use		Log Latest Entry via Physical Abuse		Log Number of Exits from Foster Care	
	OLS (7)	**2SLS (8)**	**OLS (9)**	**2SLS (10)**	**OLS (11)**	**2SLS (12)**
Log self-referred meth treatment rate	0.21***	−0.20	0.04	1.49**	0.06*	−0.14
	(0.04)	(0.34)	(0.03)	(0.62)	(0.03)	(0.28)
Unemployment	−0.17***	−0.18***	−0.11***	−0.05	−0.02	−0.03
	(0.05)	(0.05)	(0.04)	(0.06)	(0.03)	(0.03)
Cigarette tax per pack	−2.80***	−2.80***	0.17	0.20	−1.05***	−1.05***
	(0.37)	(0.36)	(0.14)	(0.19)	(0.15)	(0.15)
Log alcohol treatment rate	−0.24***	0.10	−0.01	−1.16**	−0.04	0.12
	(0.07)	(0.28)	(0.05)	(0.49)	(0.04)	(0.22)
Log population 0–19 year old	−13.30	−10.59	0.81	−0.44	9.50***	9.69***
	(17.74)	(18.22)	(3.73)	(4.18)	(3.60)	(3.51)
Log population 15–49 year old	−0.71	−6.01	−8.74	−4.01	−20.22***	−20.90***
	(33.63)	(34.71)	(6.83)	(7.01)	(5.39)	(5.33)
Month-of-year fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
State linear time trends	x	x	x	x	x	x
First stage						
Price deviation instrument		−0.0007***		−0.0005***		−0.0005***
		(0.0001)		(0.0001)		(0.0001)
F-statistic for IV in first stage		24.45		18.29		17.70
R^2	0.90		0.80		0.84	
N	1,161	1,161	1,293	1,293	1,318	1,318

Notes: 'Log latest entry into foster care" is the natural log of the sum of all new foster care admissions by state, race, and month. Models 3 to 10 denote the flow of children into foster care via a given route of admission denoted by the column heading. Models 11 and 12 use the natural log of the sum of all foster care exits by state, race and month.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

fast transition by mothers with young children from initial use to chemical dependency. Other covariates in our model are also significant: alcohol treatment admissions and the size of the 15- to 49-year-old population are associated with decreases in foster care admissions.

Next, we examine the effect of meth use on foster care by route of admission. For neglect and abuse, we find positive, statistically significant elasticities of 1.03 and 1.49, respectively. We do not find any statistically significant effect for the parental incarceration, parental drug use, or total exit models. The last result is consistent with a net positive impact of meth on foster care caseload growth.

A. *Robustness Checks*

Given that illicit drugs may be substitutes, our supply interventions may indirectly affect the use of other narcotics and thereby affect foster care. To examine this confound, we include additional controls for heroin, cocaine/crack, and marijuana treatment admissions. The inclusion of these controls (Table 4) does not substantially change our baseline results.

One concern with our baseline model is that the log transformation drops zero state-month counts in dependent or independent variables. This is a particular concern when we use subsamples, such as particular routes of admission. (This is less a concern in very small states since they receive correspondingly small regression weights.) To examine the effect of losing all these cells with the log model, we replicate our baseline models with analogous negative binomial and negative binomial instrumental variables models (Table 5 Panel A). In almost all cases, the estimated signs and statistical significance match our earlier results. The estimated elasticities for latest entry, child neglect, and

TABLE 4

OLS and 2SLS Regressions of Foster Care Admissions on Meth Treatment Admissions with Additional Drug Controls, Whites, 1995–1999

	Latest Entry Foster Care		**Latest Entry via Parental Incarceration**		**Latest Entry via Child Neglect**	
Covariates	**OLS (1)**	**2SLS (2)**	**OLS (3)**	**2SLS (4)**	**OLS (5)**	**2SLS (6)**
Log self-referred meth treatment	0.02	1.51***	0.25***	−0.41	0.03	1.00**
	(0.02)	(0.56)	(0.06)	(0.31)	(0.03)	(0.40)
Log heroin treatment	−0.06**	−0.01	−0.02	−0.03	−0.06**	−0.03
	(0.03)	(0.05)	(0.06)	(0.06)	(0.02)	(0.04)
Log cocaine or crack treatment	−0.03	−0.10	−1.98***	−1.87***	0.11	0.06
	(0.10)	(0.16)	(0.40)	(0.41)	(0.12)	(0.15)
Log marijuana treatment	−0.05	−0.31	−0.13	−0.12	0.06	−0.10
	(0.10)	(0.30)	(0.29)	(0.31)	(0.12)	(0.22)
Log alcohol treatment rate	−0.00	0.01	0.06	0.06	0.04	0.05
	(0.03)	(0.11)	(0.08)	(0.09)	(0.04)	(0.07)
Unemployment	0.11	−0.14	−0.47***	−0.29	0.03	−0.14
	(0.07)	(0.18)	(0.17)	(0.21)	(0.07)	(0.14)
Cigarette tax per pack	−0.09	−0.83**	0.14	0.52	−0.18*	−0.66**
	(0.09)	(0.39)	(0.29)	(0.34)	(0.10)	(0.29)
Log population 0–19 year old	3.33	1.22	−40.04*	−38.04*	1.79	0.49
	(2.57)	(3.46)	(22.40)	(21.82)	(2.65)	(3.10)
Log population 15–49 year old	−15.21***	−9.07	−25.30	−32.91	−8.37	−4.26
	(5.42)	(5.95)	(21.84)	(20.96)	(5.11)	(5.34)
Month-of-year fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
State linear time trend	x	x	x	x	x	x
First stage						
Price deviation instrument		−0.0005***		−0.0009***		−0.0005***
		(0.0001)		(0.0002)		(0.0001)
F-statistic for IV in first stage		18.15		29.25		19.48
R^2	0.87		0.82		0.86	
N	1,318	1,318	1,047	1,047	1,292	1,292

TABLE 4
Continued

Covariates	Latest Entry via Parental Drug Use OLS (7)	Latest Entry via Parental Drug Use 2SLS (8)	Latest Entry via Physical Abuse OLS (9)	Latest Entry via Physical Abuse 2SLS (10)	Number of Exits from Foster Care OLS (11)	Number of Exits from Foster Care 2SLS (12)
Log self-referred meth treatment	0.23***	−0.26	0.04	1.48**	0.07**	−0.14
	(0.05)	(0.34)	(0.04)	(0.60)	(0.03)	(0.27)
Log heroin treatment	−0.15***	−0.17***	−0.11***	−0.05	−0.02	−0.03
	(0.05)	(0.05)	(0.04)	(0.06)	(0.03)	(0.03)
Log cocaine or crack treatment	−2.70***	−2.66***	0.13	0.06	−1.05***	−1.03***
	(0.35)	(0.35)	(0.14)	(0.18)	(0.15)	(0.15)
Log marijuana treatment	−0.11	−0.08	0.34**	0.11	−0.06	−0.02
	(0.19)	(0.20)	(0.16)	(0.31)	(0.15)	(0.15)
Log alcohol treatment rate	0.06	0.07	0.02	0.03	0.01	0.01
	(0.06)	(0.07)	(0.05)	(0.12)	(0.04)	(0.04)
Unemployment	−0.60***	−0.52**	−0.11	−0.35*	−0.01	0.02
	(0.22)	(0.25)	(0.10)	(0.18)	(0.09)	(0.10)
Cigarette tax per pack	0.43	0.74**	−0.28**	−1.00**	0.00	0.10
	(0.27)	(0.32)	(0.12)	(0.41)	(0.11)	(0.18)
Log population 0–19 year old	−12.76	−9.82	0.62	−1.27	9.38***	9.65***
	(16.90)	(17.34)	(3.67)	(4.06)	(3.56)	(3.45)
Log population 15–49 year old	−1.98	−8.58	−8.08	−2.06	−20.23***	−21.10***
	(31.96)	(33.05)	(6.82)	(6.80)	(5.36)	(5.30)
Month-of-year fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
State linear time trend	x	x	x	x	x	x
First stage						
Price deviation instrument		−0.0007***		−0.0005***		−0.0005***
		(0.0001)		(0.0001)		(0.0001)
F-statistic for IV in first stage		23.15		18.96		18.50
R^2	0.90		0.80		0.84	
N	1,138	1,138	1,271	1,271	1,293	1,293

Notes: Models are similar to those estimated in Table 3, but with additional controls for marijuana, cocaine/crack, and heroin treatment admissions.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

abuse are positive, but considerably smaller in magnitude than the ones presented in Table 3.

The negative binomial instrumental variable (NBIV) models also reveal a negative and statistically significant inelastic relationship between foster care inflows due to parental incarceration and meth use of −0.66. A possible explanation is that meth use crowds out parental incarceration cases as child welfare agencies reallocate resources toward meth-related child maltreatment. We only find this result in the NBIV model, however, so we believe it calls for further research.

During the sample period, meth problems were concentrated along the West coast, as well as the Midwestern and Mountain states. Although meth use grew throughout the United States during the 2000s, most states in this time still had relatively small meth problems. We focus, therefore, only on those states with the worst meth problems given the geographic concentration of the epidemic in this period (Table 5 Panel B). We limit our sample to only those states in the top 50% of the distribution of meth treatment admissions in 1995. Dropping those states in the lower half of the distribution slightly increases the magnitude of the latest entry elasticity from 1.54 to 1.74. Child neglect and physical abuse models also reveal larger elasticities using this smaller sample, whereas parental incarceration, parental drug use, and exit remain insignificant.

Although we only use states with high quality data, the samples used in Tables 3 and 4 are not balanced. To address the possibility that our imbalanced sample affects our results, we

TABLE 5
Various Robustness Checks, Whites, 1995–1999 (Except for Second Intervention Model)

	Latest Entry Foster Care		Latest Entry via Parental Incarceration		Latest Entry via Child Neglect	
Panel A: Negative binomial count model						
	NB (1)	NBIV (2)	NB (3)	NBIV (4)	NB (5)	NBIV (6)
Log self-referred meth treatment	0.03***	0.41***	−0.02	−0.66**	0.01	0.26*
	(0.01)	(0.13)	(0.049)	(0.31)	(0.01)	(0.15)
F-statistic for IV in first stage		14.32		14.13		14.13
Panel B: High meth use states						
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Log self-referred meth treatment	0.04	1.74***	0.25***	−0.37	0.05	1.21***
	(0.05)	(0.66)	(0.08)	(0.37)	(0.04)	(0.46)
F-statistic for IV in first stage		23.19		25.96		24.69
Panel C: Second intervention only (1997–1999)						
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Log self-referred meth treatment	−0.01	0.25***	0.17***	0.02	0.02	0.03
	(0.01)	(0.09)	(0.06)	(0.31)	(0.02)	(0.10)
F-statistic for IV in first stage		21.40		25.39		23.48
Panel D: Census-divisional instruments						
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Log self-referred meth treatment	0.01	2.53	0.23***	0.17	0.03	1.65
	(0.02)	(1.67)	(0.05)	(0.46)	(0.02)	(1.04)
F-statistic for IV in first stage		4.47		12.01		5.65

	Latest Entry via Parental Drug Use		Latest Entry via Physical Abuse		Log Number of Exits from Foster Care	
Panel A: Negative binomial count model						
	NB (7)	NBIV (8)	NB (9)	NBIV (10)	NB (11)	NBIV (12)
Log self-referred meth treatment	0.02	0.04	0.03***	0.35**	0.03*	0.15
	(0.04)	(0.21)	(0.01)	(0.16)	(0.02)	(0.12)
F-statistic for IV in first stage		14.13		14.13		14.32
Panel B: High meth use states						
	OLS (7)	2SLS (8)	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)
Log self-referred meth treatment	0.25***	0.31	0.01	1.66**	0.10*	−0.03
	(0.07)	(0.35)	(0.07)	(0.69)	(0.06)	(0.29)
F-statistic for IV in first stage		30.97		24.55		22.78
Panel C: Second intervention only (1997–1999)						
	OLS (7)	2SLS (8)	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)
Log self-referred meth treatment	0.13***	−0.12	0.02	0.17	0.03	0.11
	(0.04)	(0.26)	(0.03)	(0.15)	(0.04)	(0.18)
F-statistic for IV in first stage		24.22		23.07		23.75
Panel D: Census-divisional instruments						
	OLS (7)	2SLS (8)	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)
Log self-referred meth treatment	0.21***	0.09	0.04	2.39	0.06*	−0.34
	(0.04)	(0.36)	(0.03)	(1.55)	(0.03)	(0.41)
F-statistic for IV in first stage		13.50		5.54		4.15

Notes: Models include the same controls as models in Table 3, but for brevity we report only the estimated coefficient on meth, its robust standard error, and the F-statistic testing the significant of the instrument in the first stage. Panel A estimates using negative binomial and negative binomial IV regressions to account for values of zero in some state/month/race cells. Panel B uses only the upper 50th percentile of state-level total meth use for the first 12 months. Panel C uses only the 1997 regulation for the 1997–1999 years. Panel D uses price instruments that vary across Census-division in place of the national price instrument.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

use only states providing consistent data for 1997 to 1999, which requires that we use only the 1997 pseudoephedrine regulation for identification (Table 5 Panel C). Doing so results in a considerably stronger first stage ($F = 21.4$ for latest entry). As we saw with the NBIV model, the estimated elasticity for latest entry falls with this modification in the sample—this time from 1.54 to 0.25 while increasing in precision ($p < .001$). A lower elasticity using the latter sample may be consistent with rational and forward-looking meth use if users in the second period learn from the first intervention that price shocks are likely to be temporary. This suggests meth users may update their prior beliefs about future rising prices which could suggest differential responses to price fluctuations over time or simply heterogeneity in general.[16]

A final potential challenge is that our instrument lacks spatial variation because of the small number of meth price observations in some regions, particularly the Northeast. To improve identification, we also constructed a price instrument that varies at the Census division level. This instrument is noisier and the first stage is correspondingly weaker. The latest entry, neglect, and abuse models are poorly identified, but we are able to identify the parental incarceration and parental drug abuse models. For both parental incarceration and parental drug use, we find no effect of foster care crowd out. As with previous models, we estimate positive elasticities for latest entry, neglect, and abuse with the caveat that the models are weakly identified.

VI. CONCLUSION

The 1988 Chemical Diversion and Trafficking Act regulated the bulk distribution of all ephedrine and pseudoephedrine products, but granted exemptions to all tablet forms of ephedrine and pseudoephedrine, which led ultimately to a large underground supply chain that relied on tablets. Congress corrected this loophole in 1995 and 1997 by expanding regulations on tablet ephedrine and pseudoephedrine, respectively. As we document in Figure 3, these follow-up corrections caused major disruptions in the market for D-meth by quadrupling (doubling) real purity-adjusted retail prices in 1995 (1997), which led to declines in meth treatment admissions. The impact on meth markets was so profound that some have suggested that these interdictions may be the greatest disruption in the supply of any illicit substance in the history of drug enforcement (Dobkin and Nicosia 2009).

16. We thank an anonymous referee for this insight.

By exogenously decreasing meth use, these two episodes provide researchers with an opportunity to answer empirical questions about substance use that have otherwise been difficult. Although we are careful not to extrapolate our findings beyond these episodes or to other abused substances, our findings suggest strongly that the social costs of parental meth use include child maltreatment and net growth in foster care placements. To show this, we use detailed case information recorded for foster care enrollments to determine the precise channels through which meth use impacts foster care. Meth use appears to cause foster care caseloads to increase through higher numbers of parental neglect and physical abuse cases. Since the amount of child maltreatment is only partially captured by foster care admissions and since meth use is highly concentrated in rural areas where welfare resources are considerably more strained, we believe these estimates are the lower bound for the child welfare costs associated with meth use.

It would help to put our results in the context of research on the relationship between drug use and child maltreatment. These papers arguably have research designs with variation that is less exogenous or less striking. Markowitz and Grossman (2000) examine the effect of beer taxes and cocaine prices on child abuse using two waves of the Physical Violence in American Families Survey and estimate an elasticity of child abuse with respect to beer taxes of -0.23. Their estimate of the elasticity of child abuse with respect to cocaine prices is ultimately not robust to the inclusion of state fixed effects. Paxson and Waldfogel (2002) study how the economic circumstances and cocaine use of parents affects child maltreatment. These authors also compile a panel of states on the number of children in foster care but use the antecedent to AFCARS, the Voluntary Cooperative Information System. The authors do not find a statistically significant relationship between cocaine arrest and foster care or child maltreatment. Our findings suggest that measurement error and unobserved heterogeneity in population measures of drug use may confound estimates from these models.

The external validity of our study is limited by the temporary impact of the supply-side interventions. Insofar as future regulations do not mimic the conditions of these transitory events, these estimated elasticities may not provide guidance. Nevertheless, a back-of-the-envelope calculation of the impact of meth on foster care illuminates the challenges policymakers face to mitigate the growing meth problem in a cost-effective manner. From August 1995 to December 1995, white meth self-admissions fell 26.5% due to the 1995 ephedrine regulation. As noted, the regulation was temporary as drug producers immediately substituted to pseudoephedrine (Suo 2004). White meth self-admissions grew 25.6% from December 1995 to February 1998, which nearly erased the entirety of the gains made from the first interdiction. Using an estimated elasticity of foster care of 1.54 from the 2SLS model in Table 3, the 25.6% growth in white meth self-referrals from December 1995 to February 1998 caused 2,257 children to enter foster care.[17]

Given the large social costs of meth use on child maltreatment, policymakers face a significant challenge to reduce meth use. We have shown that supply interventions can have dramatic effects on prices and use, but it is also clear that suppliers responded quite quickly to these particular precursor controls. This is frustrating given the elastic reductions we find in foster care admissions during these periods. One implication from this study, then, is that regions with intensive meth use should consider greater resources for meth treatment and child welfare services. These areas have historically been rural or exurban and so may already be underserved.

States continue to experiment with precursor controls as well as demand-side approaches to curb meth use. For example, some states have experimented with advertising campaigns to decrease meth demand, but recent analysis has found their perceived benefits were spurious (Anderson 2010). Oregon and Mississippi have taken more radical steps to drive meth out of their states by scheduling pseudoephedrine and ephedrine products, so that consumers can only purchase them with a doctor's prescription. While law enforcement figures have noted a rapid decline in meth lab seizures in both states following scheduling regulations, neither the short-run nor the long-run impacts of the regulations are currently known. It is therefore vital for researchers to study the relative efficacy and cost effectiveness of supply- versus demand-side policies aimed at lowering the social costs of meth.

17. The percentage change in white foster care admissions is equal to the estimated elasticity multiplied by the percentage change in white meth self-referrals, or 39.4% ($1.54 \times 0.256 = 0.394$). We record 5,729 white children placed into foster care in our sample in December 1995, which given a 39.4% predicted growth rate from meth implies 7,986 white children entered foster care in February 1998. Had the first intervention successfully blocked producers' access to precursors in the long-run, there would have been 2,257 fewer white children in foster care 27 months later.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

TABLE S1. State-Varying Variables Selected Descriptive Statistics, Whites (for AFCARS and TEDS Variables), 1995–1999.

FIGURE S1. Density of State Meth Price Observations (Minimum, Median, and Maximum) by Month, STRIDE, 1995–1999.

FIGURE S2. Construction of Meth Price Instrumental Variable as Deviations of Expected Retail Price of Meth During Interventions from Overall Trend Lines, STRIDE, 1995–1999.

FIGURE S3. Data Quality Analysis, TEDS and AFCARS, 1995–1999.