Parental Substance Abuse and Foster Care:
Evidence from Two Methamphetamine Supply Shocks

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Abstract

Foster care caseloads have almost doubled over the last two decades, but the cause of the growth is poorly understood. We study the role of parental methamphetamine (meth) use, which social workers have linked to recent growth in foster care admissions. To mitigate the impact of omitted variable bias, we take advantage of two significant, exogenous supply-side interventions in meth markets in 1995 and 1997, and find robust evidence that meth use has caused growth in foster care caseloads. Further, we identify the mechanisms by which increased meth use caused an increase in foster care caseloads. First, we find that treatment for meth abuse caused foster caseloads to fall in situations where a child was removed because of parental incarceration, suggesting that substance abuse treatment is a substitute for foster care services and more generally an effective demand-side intervention. Secondly, we find that parental meth use causes an increase in both child abuse and child neglect foster care cases. These results suggest that child welfare policies should be designed specifically for the children of meth-using parents.

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1 Introduction

From 1986 to 2008, the US foster care population increased from approximately 280,000 to 463,000—a rise of over 65% (US DHHS 1999a, 2006). 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, and although many of these problems are believed to result from the circumstances that led the child to be placed in foster care, recent research suggests that such problems may be aggravated by the foster care system (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 abuse of a particular narcotic, methamphetamine, on foster care admissions. A body of media reports and child welfare publications has linked methamphetamine (meth) abuse with foster care admissions (see Nicosia et al. 2009). While 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, meth drug treatment admissions as a proxy for the number of meth users, meth retail prices, and a variety of other potentially relevant factors for US states from September 1994 through March 2000. Using the deviations in meth prices from national trends caused by large federal supply interdictions in 1995 and 1997 as an instrumental variable, we find that a 1% increase in self-admitted meth treatments for whites is associated with a 0.5% increase in white foster care admissions. We focus on whites because meth users are overwhelmingly white, and this allows us to conduct a falsification test of our research design using the black subsample. To our knowledge, this paper is the first to identify the effect of a suspected cause of foster care enrollment using plausibly exogenous variation in drug use.

We further investigate the routes that children take into foster care, including parental incarceration and neglect. Our evidence is consistent with a negative, elastic relationship between meth treatments and foster care entries caused by parental incarceration, but a positive, inelastic relationship between meth treatments and foster care entries caused by neglect. That is, we find both that meth use causes harm to children via increased abuse and neglect, and that meth use causes increased admissions to foster care simply via the removal of a meth-using parent. Meth treatment is found to have smaller effects on alternative routes.

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. Using a similar identification strategy but with only the 1995 interdiction, Dobkin and Nicosia estimate that meth-related hospital and treatment admissions fell 50 and 35 percent, respectively, but find no statistically significant relationship between meth-related hospital admissions and crime. We build upon this strategy by using meth treatment (a less extreme outcome to proxy for meth use) and by using both the 1995 ephedrine and 1997 pseudoephedrine regulations, along with national data coverage. We do find significant effects of meth use on foster care.

The paper is organized as follows. Section 2 gives an overview of relevant details of foster care policy and the foster care institution, the role of parental drug abuse 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 3 explains the data. Section 4 discusses our empirical methodology. Section 5 reviews our results. Section 6 concludes.

2 Background

Foster care

Foster care is a social welfare service in the US that serves the needs of abused and neglected children. Child welfare workers are called to homes to respond to reports of child neglect or abuse. A social worker can remove a child if she determines that remaining with parents will jeopardize a child's welfare. Children are placed either with a surrogate "foster" family or in a residential treatment facility called a group home. The purpose in both cases 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. Using data compiled from US DHHS (1999a, 2006a, 2009), Figure 1 shows the number of US children living in foster care from 1982 to 2006. There was a stark increase in the foster care population from the mid-1980s to the late 1990s caused by a rapid growth in entry with no associated uptick in exit. Younger children exiting the system mostly explain the decline in foster care after 1999 (US DHHS 2006a).

A series of federal legislation expanded the 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. Though these policies temporarily stabilized the entry rate, eventually entry rates increased again. In 1993 Congress passed the Family Preservation and Family Support Program/Promoting Safe and Stable Families Program. This act doubled 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.

Parental drug abuse and child maltreatment

Parental substance abuse is one of the most significant risk factors associated with child maltreatment and entry into foster care. The US DHHS (1999b) report that approximately 10–20% of children prenatally exposed to drugs enter foster care at or around their birth and another third enter within a few years. Parental substance abuse 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, Zangrillo, and Smith 1994).

During the late 1980s and early 1990s, crack cocaine became widespread in US urban areas. From 1986 to 1991, the average number of children in foster care increased nationwide 53%, but that 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 (US 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.

Our understanding of the relationship between parental meth abuse and child maltreatment is considerably less developed than it is for parental abuse of alcohol and cocaine. Most of the evidence today is either measures of perception by child service workers or deductions from what is known about parental substance abuse in general. For example, a 2005 survey of 300 counties by the National Association of Counties found that 40% of child welfare officials reported increases in out-of-home placements in the last year due to meth abuse in their communities (National Association of Counties 2005).

A 2006 report prepared for the US Center for Substance Abuse Treatment identifies channels by which parental meth use may harm children: episodic meth use, chemical dependency on meth, prenatal exposure to meth, exposure to meth if parents work in toxic labs, and exposure if parents are employed as traffickers (Otero et al. 2006).

Most cases of child maltreatment are believed to be cases of neglect and physical abuse caused by episodic parental use. Parental meth abuse can pose dangers to children in the form of poor judgment, increase violence, failure to provide adequate supervision, and a variety of deteriorated living conditions (Gonzalez et al. 2010). The little that is known about the relationship between parental meth abuse and child health comes from our broader knowledge of the correlation between substance abuse in general and child maltreatment (Kelleher et al. 1994; Famularo et al. 1992). Prenatal exposure studies that focus on all substance abuse, such as McNichol (1999) who found that 62% of infants exposed to parental substance abuse during gestation had significantly more health and care giving needs, are also oftentimes used to predict the effects of meth on child outcomes. Meth users are more likely to be female and single parents living alone with their children, so there is reason to believe that parental meth use will have damaging effects on child outcomes given our broad knowledge about the causal effect of substance abuse on child outcomes in general (Brecht et al. 2004; Gonzales et al. 2010).

While parental meth abuse and child maltreatment are highly correlated, researchers are unsure as to whether the relationships are spurious due to unobserved heterogeneity or due to complex pathways by which parental meth consumption causes child maltreatment. Meth use is correlated with use of other substances, such as alcohol, marijuana, and tobacco (we show this below). Antisocial personality traits are associated with substance abuse and are themselves risk factors for child maltreatment (Kelleher et al. 1994). Reverse causality may be a concern if other factors lead to maltreatment, possible removal of a child, and in turn causes the parent to experience social isolation, depression, and other disorders that trigger substance abuse.

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 US. 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 abuse 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 US. In Figure 2, we show these changes over time by calculating the annual rate of admissions to treatment facilities for meth for September 1994 to August 1995 (the top map) and April 1999 to March 2000 (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 drug treatment, health care, deaths, lost productivity, crime, child endangerment, and harm to the environment (Nicosia et al. 2009). Many law enforcement and social work practitioners make a strong connection between the rise of meth abuse 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 et al. 2002).

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, and 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.[1] In 1988, Congress passed the Chemical Diversion and Trafficking Act, which gave the DEA the authority to control the diversion 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; US DEA 1997). All tablet forms of ephedrine and pseudoephedrine medical products, however, were exempt—a legal loophole that was heavily exploited by drug trafficking organizations.

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

[1] States have regulated meth precursors, but primarily after our sample period ended.

regulating the distribution of products that contained ephedrine as the only active medicinal ingredient (US DEA 1995; Cunningham and Liu 2003). The new legislation ignored pseudoephedrine tablets, so traffickers soon took advantage of the omission by substituting towards pseudoephedrine as a precursor. By 1996, pseudoephedrine was found to be the primary precursor in almost half of meth lab seizures (US 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 (US DEA 1997).

Due to the concentration of meth precursor markets, these two regulations may be the largest supply shocks in the history of US drug enforcement (Dobkin and Nicosia 2009). To estimate the effect of the interdictions on meth markets, we construct a monthly series for the expected price of a pure gram of *d*-meth from September 1994 to March 2000 using the DEA's seizure database, System to Retrieve Information from Drug Evidence (STRIDE).[2,3] Figure 3 shows various percentiles of the monthly expected price distributions for retail meth transactions in the US.[4] The 1995 interdiction caused a dramatic spike in meth prices, but the effect was relatively short lived. After six months, the prices returned to their pre-interdiction levels. The

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[2] Drug producers and distributors can alter the purity of retail narcotics to respond to market conditions (just as they vary the price). In order to compare prices over time and across local markets, it is necessary to estimate the expected price of a pure gram of a drug. These 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.
[3] 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.
[4] Retail transactions for meth are defined as those with a net weight between zero and 100 grams. This definition is based on the market quantity levels estimated in Arkes et al. (2004). For powder cocaine and heroin, a similar definition of retail would be 0–10 grams.

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 its effects on foster care admissions. Figure 4 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 September 1994).

We let the meth price data date the interventions precisely. We estimate quadratic national price trends, and measure when the prices deviate from the price trends after each intervention.[5] Figure 5 demonstrates graphically how we date the interventions in this way. 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 four-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 six months for the 1995 intervention (August 1995–January 1996). Our empirically driven timings for the supply shocks are consistent with these previous studies.

3 Data sources and descriptive statistics

We use a variety of data sources to study the effect of meth abuse on foster care admissions. We choose a sample period of September 1994 to March 2000 for all datasets. This starts one year before the first intervention and ends one year after the second intervention. The level of variation for our analytic sample is state by month.

[5] Estimates from these models are available from the authors.

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).[6] State participation began voluntarily in 1994, and by mandate in 1998. 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, and ethnicity. AFCARS is also valuable because it indicates whether a child was removed as a result of neglect, physical abuse, parental drug abuse, parental incarceration, etc.

Since AFCARS does not represent a balanced panel of states during our sample period, but does report the first time a child entered foster care, we create a retrospective variable of first entry. We attempt to remove duplicate child observations across years by matching children based on state of supervision, first removal date, and date of birth. Using this retrospective definition, we build a balanced panel of new foster care admissions by state and month from September 1994 to March 2000. Figure 6 shows the number of first entries into, latest entries into, and discharges out of foster care by month during the 1994–2000 sample period. The figure shows that the retrospectively measured first entry variables tracks well with the latest entry measured during the late part of the sample period when all states participated in AFCARS.

Route of admission into foster care is only reported for the latest entry, so we are restricted to the unbalanced panel of participating states. 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.

[6] 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.

Selected descriptive statistics from the foster care data are presented in Table 1. Although the majority 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. The most commonly cited reason for removal was child neglect (52%), followed by physical abuse (17%) and parental drug abuse (16%). Parental incarceration was cited in 5% of all cases. Figure 7 shows the trends in route of admission during the 1994–2000 sample for the white children who comprise our analytic sample. Parental drug abuse and incarceration are relatively rare, but they have the most growth during the sample.

Since there is no direct measure of meth use, we use the number of meth treatment admissions as a proxy. These data come from the Treatment Episode Data Set, which records the universe of all treatment admissions to federally funded inpatient or outpatient facilities.[7] 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.

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 this reason, we restrict our analytic sample to whites, and use the black subsample for a falsification test. Meth users have a referral profile that

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[7] 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.

is qualitatively similar to the population's. About a third of patients are self-admitted. Thirty-seven percent of meth patients are referred by the criminal justice system.

Figure 8 shows the secular trends for whites in treatment for meth, juxtaposed with the trends for cocaine and heroin. Meth has the largest percentage rise in treatment in-flows. A drop in treatment in-flows is also apparent during the two precursor intervention periods.

We calculate foster care and meth treatment rates at the state-by-month level by weighting each value by the population of 15-49 year olds by race. As most of our analysis focuses on whites, the weight is the number of white 15-49 year olds by state and month. These population estimates are state-race-month linear interpolations from the Bureau of the Census. Table 3 shows the per capita measures of meth treatment and foster care admissions that we use for our analysis. Using the first (latest) entry variable, there are 24.24 (34.77) children in foster care per 100,000 white children aged 0–19 years. Disaggregated by route, 2.01 white children for every 100,000 are in foster care due to parental incarceration, 14.65 due to parental neglect, 4.75 due to parental drug abuse, 6.22 due to parental abuse, and 11.86 to all other causes. The number of whites seeking treatment for meth is 12.09 per 100,000 whites aged 15–49 years, and the number who enter into treatment on their own accord is 2.88 per 100,000.

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 rate of alcohol abuse treatment for whites from TEDS. In some robustness checks, we also include the cocaine and heroin rates 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 BLS 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 taxes in each state. Descriptive statistics for all of these controls can be found in Table 3.

4 Model and identification

In this section, we develop an empirical approach that examines the extent to which the increase in meth use can explain changes in foster care admissions. Further, we use data on the reasons for a child's removal to identify the precise mechanisms that translate the growth in meth use to an increase in foster care admission rates.

We proxy for meth use with the number of self-referred cases of meth treatment so as to avoid any endogeneity with criminal justice referrals and law enforcement efforts that may have occurred during the 1995 and 1997 interdictions. As TEDS is the joint function of both substance abuse levels and the number of individuals seeking treatment in the state/month, interpretation can be a challenging task when an intervention causes treatment and consumption to diverge. Spikes in real prices, for instance, would be expected to decrease consumption, either because new users would be less likely to experiment with meth for the first time or because old users are income constrained. But spikes in price cause increases in the demand for treatment if treatment is used to reduce consumption. By focusing on the separate routes of admission into foster care, though, we were able to disentangle some of these effects.

We employ a two-stage least squares methodology to estimate the effect of meth on foster care enrollments because the number of meth users and foster care admissions may be jointly determined by unobserved factors and subject to reverse causality. This sign of the bias of OLS is indeterminate because these effects may go in opposite direction. Our instrument is correlated with meth use but not the factors determining foster care admissions, so it is a likely candidate for overcoming simultaneity bias that could confound the OLS estimate.

The 1995 and 1997 precursor control policies increased the cost of meth production—shifting the supply curve for meth upward and increasing prices for consumers. Consumption theoretically would have fallen as well. After producers substituted to alternative precursors, production costs would be expected to fall to their pre-interdiction levels. Thus the regulations cause deviations in the price of meth from their general trend line. We use the deviation of meth prices from the national trend as our instrumental variable. To identify the effect of the regulations on meth admissions, we estimated the following equation in the first stage of a two-stage model:

$$\log(\text{self-referred meth treatment rate})_{st} = \alpha_1 \text{price deviation}_t + \alpha_2 \mathbf{X}_{st} + \gamma_s + \phi_t + \tau_t + u_{st},$$

where log(meth treatment rate)$_{st}$ is the log of the number of self-referred meth treatment admissions for whites per 100,000 whites aged 15–49 years in state s during month t, price deviation$_t$ 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 fixed effect, τ_t is a linear time trend common to all states, and $\mathbf{X}_{st}$ is a vector of covariates including the cigarette tax, state unemployment rate, and the log of the alcohol treatment rate for whites.

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

$$\log(\text{first entry foster care rate})_{st} = \beta_1 \log(\text{self-referred meth treatment rate})_{st} + \beta_2 \mathbf{X}_{st} + \delta_s + \lambda_t + \omega_t + e_{st},$$

where log(first entry foster care rate)$_{st}$ is the log of first entries into foster care for whites per 100,000 whites aged 0–19 years in state s during month t, δ_s is a state fixed effect, λ_t is a month fixed effect, and ω_t is a linear time trend common to all states.

The parameter of interest is β_1, the elasticity of the first entry foster care rate with respect to the self-referred meth treatment rate. For β_1 to be consistent, the deviation in price that occurred during the treatment window must be both 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 very large, negative effects on meth treatment admissions. The argument for excluding the prices cannot be tested, but Figure 4 shows that there were no corresponding changes in the prices of heroin or cocaine and crack during the two meth intervention periods. We also do a series of robustness checks that suggest our results are not spurious.

5 Results

Because AFCARS foster care data contain information on the route of admission, we estimate several models separately. AFCARS records indicate whether a child was removed because of parental drug abuse, parental incarceration, parental physical abuse, or parental neglect. We find evidence that meth abuse causes increases in child maltreatment channels of foster care admissions. We also find evidence that meth treatment may cause foster care admissions to decrease, since during the episodes that we examine, we find a strong and negative causal effect of self-referral meth treatment on the number of children flowing into foster care via the parental incarceration route of admission.

Table 4 shows the results of our baseline model. Each pair of columns shows a different dependent variable: first, all foster care admissions for whites, and then broken down by route into foster care. Many of our OLS estimates are smaller in magnitude than our 2SLS estimates. For example, the 2SLS estimate in the total first entries into foster care model is almost eight times larger than the OLS estimate. Our 2SLS models in all cases have strong first stages as measured by the *F*-statistic (>10). We find that a 1% increase in meth treatment causes a 0.48% increase in foster care admissions. This positive effect is likely a reflection of the causal effect of meth use, as opposed to treatment, on child maltreatment. Other covariates in our model were also significant: unemployment was associated with lower incidence of child maltreatment, possibly reflecting the effect of the business cycle on state budgets. Cigarette taxes and alcohol treatment were both associated with decreases in foster care admissions.

Next we examine the effect of meth use on foster care by route of admission. Interestingly, we find that meth treatment admissions causes foster care admissions to fall for those children whose parents were incarcerated. A 1% increase in meth treatment admissions causes foster care removal due to parental incarceration to fall by 1.95%. A negative elasticity is consistent with a causal effect of meth treatment on child maltreatment, as opposed to meth use per se. We hypothesize that when parents seek treatment for meth abuse, their meth use decreases, lowering the risk of arrest and imprisonment, and in turn, reduces the number of children removed because of parental incarceration. For both child neglect and child abuse, we estimate positive elasticities of 0.66 and 0.77, respectively. Unlike parental incarceration, a positive elasticity is likely estimating the causal effect of parental meth abuse on child maltreatment directly. We do not find any statistically significant effect for the other routes.

Between 1994 and 2000, the foster care population grew from 468,000 to 552,000, a rise of 18% (see Figure 1). During the same period, the number of annual meth treatments increased approximately 20% (see Figure 8). If we use the estimated elasticity of 0.48 from the baseline model, this suggests that meth use caused a 9.6% increase in foster care admissions, or roughly half of the growth. Stated another way, if, in 1994, precursor controls had successfully eradicated meth use in the US, there would have been almost 45,000 fewer foster care cases in 2000 *ceteris paribus*.

Robustness checks

We conducted several robustness checks to strengthen the credibility of our baseline results. First, we control for state-specific linear time trends, causing all identification to come from variation around a state's trend (Table 5). Qualitatively, our results are unchanged, though magnitudes and precision changed in some cases. Controlling for state trends strengthened the first stage in all cases. Our 2SLS estimates for the total first entries model are smaller and less precise than what we estimated without state trends, while our estimate for the parental incarceration channel is smaller in magnitude (by almost a third) and is no longer statistically significant. Both child neglect and child abuse remain positive and precisely estimated, but are smaller in magnitude than our results from Table 4. The effect of meth treatment on other channels is also significant using 2SLS.

We also implement a placebo test in which black foster care admissions were regressed onto black meth treatment using OLS and 2SLS. As only 3% of meth users are black, there should not be any effect of meth use on foster care admissions. We do not find any discernible effect of black meth use on black foster care using 2SLS (Table 6). A caveat here is that this is not a high-powered test because the first-stage provides very little identification for blacks.

As a last robustness check, we use separate measures of our dependent variable, the instrumental variable, controls for cocaine and heroin abuse and different sample selections (Table 7). We report the baseline results from Table 4 for comparison. First, we use the date of latest entry instead of first entry for those states that consistently reported it over the entire panel to measure the number of children in foster care. This caused our sample to fall 40% since early reporting for "latest entry" was not reported by every state in the earliest part of the AFCARS panel in several states. Nevertheless, using this measurement causes our estimates to become more precise ($p<0.001$) and larger (0.78 vs. 0.47).

We also estimate the effect of meth admissions on the ratio of the number of children leaving foster care in a state/month/year (exit) to the number coming in (entry). We ultimately do not find any effect of meth admissions on this outcome, suggesting that the effects we are finding are primarily driven by changes in new children coming into the system.

Next, we instrument for meth treatment with state-varying price deviations instead of the national measure of price used in earlier regressions. Because some states have so few meth purchases by law enforcement, this instrument has more noise over the panel for several states. The first stage has an F-statistic of 7.97, and though this suggests a weak instrument problem, the Anderson-Rubin test (unreported) reports that estimates are robust to weak instruments ($p<0.05$). We estimate a positive elasticity of 0.70, though the estimate is less precise ($p<0.10$).

We also experiment with the composition of the state sample itself. Since meth is concentrated in the Pacific Northwest, Western, Midwest and Southwestern states, we limit our sample to only those states in the top 50% of the distribution of meth rates in 1994. Dropping those states in the lower half of the distribution slightly increased the magnitude of our estimated elasticity (0.51 vs. 0.47) and caused the precision to increase slightly. So as to determine whether our results were being driven by spurious contemporaneous drug abuse patterns, we estimated our baseline model with additional controls for heroin and cocaine/crack admissions. Including these controls causes the precision of our meth elasticity estimates to decrease slightly ($p<0.10$), but has almost no effect on the size or sign of the elasticity itself (0.48 vs. 0.47).

Finally, we limit our sample to 1997–2002 so that we could examine whether inconsistent data quality for some states in the early part of the AFCARS sample affects our estimates. Dropping 1995 and 1996 improves our confidence in data quality, but also requires that we exploit only the variation in meth caused by the 1997 pseudoephedrine regulation. This causes the strength of our instrumental variable to increase ($F=18.42$), as well as the coefficient on our instrument in the first stage to more than double (-0.0008 vs. -0.0004). The estimated elasticity fell slightly from 0.4770 to 0.4253 while increasing in precision ($p<0.001$). A similar elasticity across the two samples suggests that meth consumers are myopic with regards to the price series. If meth abusers were assumed to be rational and forward-looking, they presumably forecast a shorter spike in the price series in 1997 since they possess more information about the short duration of deviation in price caused by the 1995 shock. And yet while we do find some evidence for this since the 1997-only identification of meth's effect on foster care is lower than that when we use both 1995 and 1997, it is not considerably smaller in size. This lack of differential responsiveness may shed some light on the nature of addiction itself by implying future predicted prices are either not forecast or are not incorporated into the calculus of a meth user's consumption decision.[8]

[8] We thank an anonymous referee for this insight.

6 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, leading ultimately to a large underground supply chain that utilized only tablets. Congress corrected for this legal loophole in 1995 and 1997 by expanding regulations to tablet ephedrine and pseudoephedrine, respectively. These follow-up corrections, as we have documented, caused major disruptions in the market for *d*-meth by quadrupling (doubling) real purity-adjusted prices in 1995 (1997), which led to declines in meth 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).

By exogenously decreasing meth use, these two episodes provide researchers with an opportunity to answer empirical questions regarding substance abuse that have otherwise been difficult. Although we are careful not to extrapolate our findings beyond these episodes or to other abused substances, our findings are strongly suggestive that parental meth use harms children to such an extreme degree that it triggers out-of-home placements into foster care. Since the amount of child maltreatment is only partially captured by foster care admissions, and because meth use is highly concentrated in rural areas where welfare resources are considerably more strained, it is possible the effects are actually larger than what is estimated here.

Because of the information recorded about foster care enrollments, we were also able to determine the precise channels through which meth use was transformed into foster care. First, meth use appears to cause parents to neglect their children and to physically abuse them. Foster care placement is an extreme case—it occurs only when the damage is severe. Thus the effect of meth use on milder levels of neglect and abuse may be even more pronounced than we can measure here.

One implication, therefore, is that an argument could be made that a greater allocation of public resources to meth treatment and foster care is needed in areas with growing meth problems. As these areas have historically been mostly rural, they may already be underserved. As meth continues to move eastward, public officials should be prepared for the impact that parental use will have on children in communities.

Lastly, we conclude that there exists a negative elasticity of foster care enrollment due to the incarceration of the child's parents with respect to underlying meth treatment. This likely reflects the causal effect of meth treatment on child maltreatment. Treatment causes parents to stop using drugs while in treatment and for some after release as well. Treatment is relevant, in part, because it keeps a parent clean so that they cannot be arrested, and therefore, not lose their child due to incarceration. This causal mechanism suggests that one way to reduce foster care caseloads is to allocate more resources towards drug treatment. Earlier studies such as Rydell et al. (1996) and Jofre-Bonet (2001) have argued that treatment resources are currently suboptimal.

Meth treatment could potentially pay for itself by reducing both foster care and incarceration levels, which have also reached historic heights. Understanding the relative efficacy of supply versus demand anti-drug policies is crucial to lowering the social costs of substance abuse. Anderson (2010) shows that one particular type of demand intervention—an advertising campaign in Minnesota to raise meth awareness—was not effective at reducing meth abuse among teenagers. Our findings, on the other hand, show that treatment (another type of demand intervention) can reduce some of the social costs associated with meth use, which leads to the natural question as to under what circumstances do these different types of demand interventions prove to be effective. It may be that meth is unusual in that because its inputs are concentrated, policies aimed at limiting access to them can have stimulating effects on even demand policies as well. Research that compares the costs and benefits of the efficacy of different types of supply and demand interventions are therefore critically important for the construction of useful social policy in this area.

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Table 1: Foster care selected descriptive statistics, Adoption and Foster Care Analysis and Reporting System (AFCARS), 1994–2000

Child characteristics	Mean (S.D.)	Obs.
Female	0.48	8,376,410
White	0.54	7,485,566
Black	0.41	7,485,566
Other race	0.05	7,485,566
Hispanic ethnicity	0.18	7,123,489
Age at first removal	6.89 (5.44)	8,101,436
Age at latest removal	7.18 (5.51)	8,355,884
Total number of removals	1.29 (0.72)	8,300,811
Route of most recent removal		
Parental drug abuse	0.16	7,567,806
Parental abuse	0.17	7,623,928
Parental neglect	0.52	7,645,084
Parental incarceration	0.05	7,496,838

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.

Table 2: Drug abuse treatment episodes selected descriptive statistics, TEDS, 1994–2000

Drugs used prior to episode	Means for all patients	Means for patients reporting meth use
Alcohol	0.74	0.57
Cocaine or crack	0.35	0.19
Marijuana	0.35	0.50
Heroin	0.18	0.08
Methamphetamine	0.08	1.00
Individual characteristics		
White	0.60	0.83
Black	0.26	0.03
Hispanic	0.11	0.10
Source of referral		
Self	0.34	0.31
Criminal justice system	0.33	0.37
Drug abuse treatment provider	0.12	0.08
Other health provider	0.07	0.07
School	0.01	0.01
Employer	0.01	0.01
Other	0.08	0.13
Number of patients	9,025,485	690,951

Notes: Authors' calculations from TEDS.

Table 3: State-varying variables selected descriptive statistics, whites (for AFCARS and TEDS variables), 1994–2000

Variables	Source	Obs.	Mean	S.D.	Min.	Max.
Foster care at first date of entry	AFCARS	3,417	24.26	22.27	0	250.03
Foster care at latest date of entry		1,869	34.63	25.63	0	260.04
-by parental incarceration		1,869	2.01	4.18	0	71.68
-by parental neglect		1,869	14.64	13.85	0	237.48
-by parental drug abuse		1,869	4.66	6.59	0	126.20
-by parental abuse		1,869	6.16	7.74	0	82.52
Meth admissions	TEDS	3,256	11.38	17.92	0	163.79
-by self-referral route		3,256	2.72	4.53	0	48.36
Alcohol admissions		3,256	160.62	149.48	0.54	1,189.31
Cocaine/crack admissions		3,256	71.38	63.37	0.35	432.06
Heroin admissions		3,256	30.45	58.53	0.00	451.54
Unemployment rate	BLS	3,417	4.70	1.32	1.70	9.60
Cigarette tax per pack (2002 $)	Orzechowski and Walker (2008)	3,417	0.32	0.20	0.02	1.06

Notes: AFCARS variables are measured relative to 100,000 white children aged 0–19 years. TEDS variables are measured relative to 100,000 whites aged 156–49 years. The number of observations for first date of entry, latest date of entry and the entry into foster care under latest date of entry differ because not all states reported latest date of entry, but those states that did also reported the avenue into foster care.

Table 4: OLS and 2SLS regressions of foster care admissions on meth treatment admissions, whites, 1994–2000

Covariates	Log first entry foster care rate		Log latest entry via parental incarceration rate		Log latest entry via child neglect rate	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Log self-referred meth treatment rate	0.0608***	0.4770**	0.0760	-1.9537***	-0.0154	0.6608**
	(0.0222)	(0.2412)	(0.0688)	(0.7510)	(0.0419)	(0.3123)
Unemployment rate	-0.065***	-0.0642***	-0.5483***	-0.5694***	-0.0726**	-0.0548
	(0.0183)	(0.0210)	(0.1127)	(0.1280)	(0.0323)	(0.0415)
Cigarette tax per pack	-1.0317***	-0.8278***	0.0541	-0.3449	-0.3933***	-0.2219
	(0.0852)	(0.1478)	(0.4095)	(0.4208)	(0.1089)	(0.1429)
Log alcohol treatment rate	-0.2127***	-0.5629***	-0.1284	1.6747**	-0.0725	-0.6580**
	(0.0326)	(0.2058)	(0.1180)	(0.6757)	(0.0558)	(0.2749)
Month fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
Linear time trend	x	x	x	x	x	x
First stage						
Price deviation instrument		-0.0004***		-0.0008***		-0.0006***
		(0.0001)		(0.0002)		(0.0001)
F-statistic for IV in first stage		13.23		19.04		16.25
R^2	0.869	0.834	0.702	0.411	0.732	0.609
N	1,633	1,633	801	801	948	948

Table 4 (continued)

	Log latest entry via parental drug abuse rate		Log latest entry via physical abuse rate		Log latest entry via other routes rate	
	OLS (7)	2SLS (8)	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)
Log self-referred meth treatment rate	0.1603**	-1.3516	0.0814**	0.7718**	0.1571**	-0.2354
	(0.0635)	(1.1998)	(0.0393)	(0.3359)	(0.0789)	(0.4651)
Unemployment	-0.6385***	-0.7353***	-0.1085***	-0.0893**	-0.0777	-0.0869
	(0.1105)	(0.1408)	(0.0335)	(0.0400)	(0.0562)	(0.0559)
Cigarette tax per pack	0.5777	0.1699	-0.1582	0.0166	-1.1407***	-1.2258***
	(0.4771)	(0.5223)	(0.1198)	(0.1562)	(0.2038)	(0.2562)
Log alcohol treatment rate	-0.2974***	1.0355	-0.0348	-0.6326**	-0.1275	0.2139
	(0.0892)	(1.0617)	(0.0522)	(0.2934)	(0.0979)	(0.4056)
Month fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
Linear time trend	x	x	x	x	x	x
First stage						
Price deviation instrument		-0.0006***		-0.0006***		-0.0005***
		(0.0002)		(0.0001)		(0.0001)
F-statistic for IV in first stage		15.85		15.88		14.50
R^2	0.802	0.695	0.76	0.649	0.83	0.817
N	853	853	940	940	936	936

Notes: "All foster care placements" is a measure of the flow of natural log of the sum of all new foster care admissions per capita by state, race and month using the latest date of entry to denote the time of entry. Other models denote the flow of children into foster care via a given route of admission denoted by the column heading. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% respectively.

Table 5: OLS and 2SLS regressions of foster care admissions on meth treatment admissions with state time trends, whites, 1994–2000

Covariates	Log first entry foster care rate		Log latest entry via parental incarceration rate		Log latest entry via child neglect rate	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Log self-referred meth treatment rate	0.0995***	0.3297*	0.1273**	-0.3815	0.0679**	0.3554**
	(0.0194)	(0.1683)	(0.0632)	(0.3704)	(0.0270)	(0.1500)
Unemployment	-0.0654***	-0.0537**	-0.1098	-0.1211*	-0.0506**	-0.0304
	(0.0185)	(0.0214)	(0.0745)	(0.0728)	(0.0248)	(0.0280)
Cigarette tax per pack	-0.4980***	-0.4993***	-2.7849***	-2.8075***	0.0629	0.1054
	(0.0955)	(0.0878)	(0.5713)	(0.5343)	(0.1056)	(0.1065)
Log alcohol treatment rate	-0.1801***	-0.3655***	-0.2081**	0.2209	-0.1025***	-0.3427***
	(0.0258)	(0.1364)	(0.1028)	(0.3270)	(0.0349)	(0.1274)
Month fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
Linear time trend	x	x	x	x	x	x
State linear time trends	x	x	x	x	x	x
First stage						
Price deviation instrument		-0.0004***		-0.0011***		-0.0007***
		(0.0001)		(0.0002)		(0.0001)
F-statistic for IV in first stage		19.05		31.31		25.26
R^2	0.923		0.835		0.889	
N	1,633	1,633	801	801	948	948

Table 5 (continued)

Covariates	Log latest entry via parental drug abuse rate		Log latest entry via physical abuse rate		Log latest entry via other routes rate	
	OLS (7)	2SLS (8)	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)
Log self-referred meth treatment rate	0.1758***	-0.0736	0.0760**	0.4730**	0.0331	0.4168**
	(0.0486)	(0.3839)	(0.0339)	(0.1841)	(0.0378)	(0.1839)
Unemployment	-0.2002***	-0.2199***	0.0004	0.0290	-0.0156	0.0126
	(0.0658)	(0.0631)	(0.0316)	(0.0353)	(0.0379)	(0.0415)
Cigarette tax per pack	-3.3908***	-3.4316***	0.0797	0.1380	-0.2567*	-0.2010*
	(0.5855)	(0.5436)	(0.1167)	(0.1149)	(0.1312)	(0.1213)
Log alcohol treatment rate	-0.2322***	-0.0169	-0.0345	-0.3660**	-0.0404	-0.3593**
	(0.0689)	(0.3296)	(0.0494)	(0.1605)	(0.0587)	(0.1653)
Month fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
Linear time trend	x	x	x	x	x	x
State linear time trends	x	x	x	x	x	x
First stage						
Price deviation instrument		-0.0008***		-0.0007***		-0.0007***
		(0.0002)		(0.0001)		(0.0001)
F-statistic for IV in first stage		23.85		24.91		23.93
R^2	0.917		0.852		0.940	
N	853	853	940	940	936	936

Notes: Models are similar to those estimated in Table 4 but with the addition of state-specific linear time trends. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% respectively.

Table 6: OLS and 2SLS regressions of foster care admissions on meth treatment admissions, blacks, 1994–2000

Covariates	Log first entry foster care rate		Log latest entry via parental incarceration rate		Log latest entry via child neglect rate	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Log self-referred meth treatment rate	0.0707***	7.9756	-0.3181***	0.3744	0.0392	-2.6323
	(0.0247)	(47.6284)	(0.0878)	(1.2135)	(0.0398)	(7.6246)
Unemployment	-0.0144	-0.3378	-0.6765***	-0.7357***	-0.1509***	-0.1490
	(0.0352)	(1.9608)	(0.1309)	(0.1581)	(0.0509)	(0.1736)
Cigarette tax per pack	-1.0048***	-2.3526	-0.0761	-0.1870	-0.2370**	-0.1785
	(0.0967)	(8.1520)	(0.3968)	(0.4305)	(0.1066)	(0.5599)
Log alcohol treatment rate	-0.1362***	-2.0373	-0.1987*	-0.3324	-0.1100	0.4732
	(0.0419)	(11.4883)	(0.1171)	(0.2800)	(0.0777)	(1.6648)
Month fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
Linear time trend	x	x	x	x	x	x
First stage						
Price deviation instrument		-0.00004		0.0005		0.0001
		(0.00026)		(0.0004)		(0.0003)
F-statistic for IV in first stage		0.03		2.11		0.11
R^2	0.865		0.745		0.798	
N	886	886	377	377	489	489

Table 6 (continued)

Covariates	Log latest entry via parental drug abuse rate		Log latest entry via physical abuse rate		Log latest entry via other routes rate	
	OLS (7)	2SLS (8)	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)
Log self-referred meth treatment rate	0.1739**	15.2527	-0.0213	1.4385	0.0884	-4.5940
	(0.0764)	(33.1188)	(0.0437)	(5.9543)	(0.0828)	(21.0517)
Unemployment	-0.4376***	-1.0472	-0.1524***	-0.1546	-0.0422	-0.1064
	(0.1328)	(1.8277)	(0.0473)	(0.1054)	(0.0890)	(0.4121)
Cigarette tax per pack	1.4767**	-0.4781	-0.3691**	-0.4029	-2.1697***	-1.9868
	(0.5708)	(5.4135)	(0.1688)	(0.3673)	(0.2996)	(1.3382)
Log alcohol treatment rate	-0.0388	-3.1352	-0.0386	-0.3573	0.0281	1.0912
	(0.1373)	(6.9492)	(0.0617)	(1.3055)	(0.1298)	(4.7746)
Month fixed effects	x	x	x	x	x	x
State fixed effects	x	x	x	x	x	x
Linear time trend	x	x	x	x	x	x
First stage						
Price deviation instrument		0.0001		0.0001		0.0001
		(0.0004)		(0.0003)		(0.0003)
F-statistic for IV in first stage		0.17		0.07		0.04
R^2	0.837		0.774		0.880	
N	430	430	472	472	486	486

Notes: Models are similar to those estimated in Table 4 but with the black AFCARS and TEDS subsamples used to create the foster care, meth treatment, and alcohol treatment rates. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% respectively.

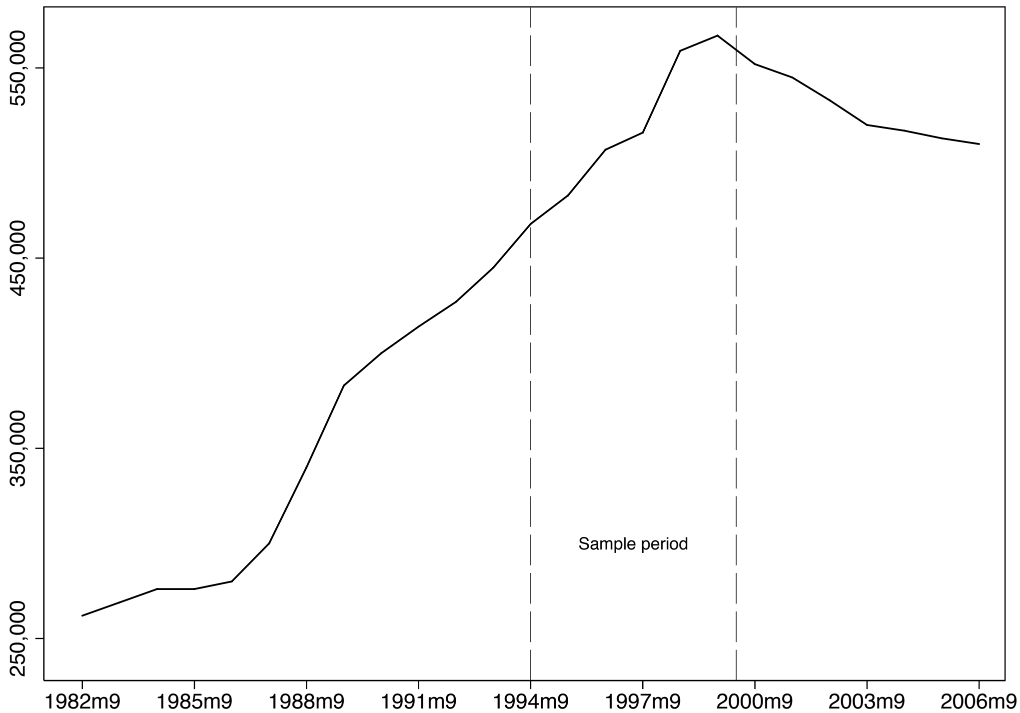
Table 7: Various robustness checks, whites, 1994–2000 (except as specified)

	Log first entry foster care rate baseline (Table 4, Columns 1 and 2)		Log latest entry foster care rate		Log of ratio of latest exit to latest entry (exit rate)		Log first entry foster care rate with state-varying price deviation instruments	
Covariates	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)	OLS (7)	2SLS (8)
Log self-referred meth treatment rate	0.0608***	0.4770**	0.0117	0.7848***	0.0277	0.1453	0.0608***	0.7005*
	(0.0222)	(0.2412)	(0.0242)	(0.2527)	(0.0441)	(0.3507)	(0.0222)	(0.4114)
First stage								
Price deviation instrument		-0.0004***		-0.0005***		-0.0005***		-0.0003***
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
F-statistic for IV in first stage		13.23		15.71		15.67		7.87
R^2	0.869		0.857		0.727		0.869	
N	1,633	1,633	968	968	933	933	1,633	1,633

	Log first entry foster care rate using sample of highest meth-using states in 1992		Log first entry foster care rate with additional heroin and cocaine/crack treatment controls		Log first entry foster care rate using 1997–2000 balanced panel sample period	
Covariates	OLS (9)	2SLS (10)	OLS (11)	2SLS (12)	OLS (13)	2SLS (14)
Log self-referred meth treatment rate	0.0831***	0.5127**	0.0397	0.4678*	0.0205	0.4253***
	(0.0300)	(0.2354)	(0.0251)	(0.2792)	(0.0190)	(0.1538)
First stage						
Price deviation instrument		-0.0005***		-0.0004***		-0.0008***
		(0.0001)		(0.0001)		(0.0002)
F-statistic for IV in first stage		14.94		11.08		18.42
R^2	0.904		0.870		0.923	
N	1,225	1,225	1,585	1,585	848	848

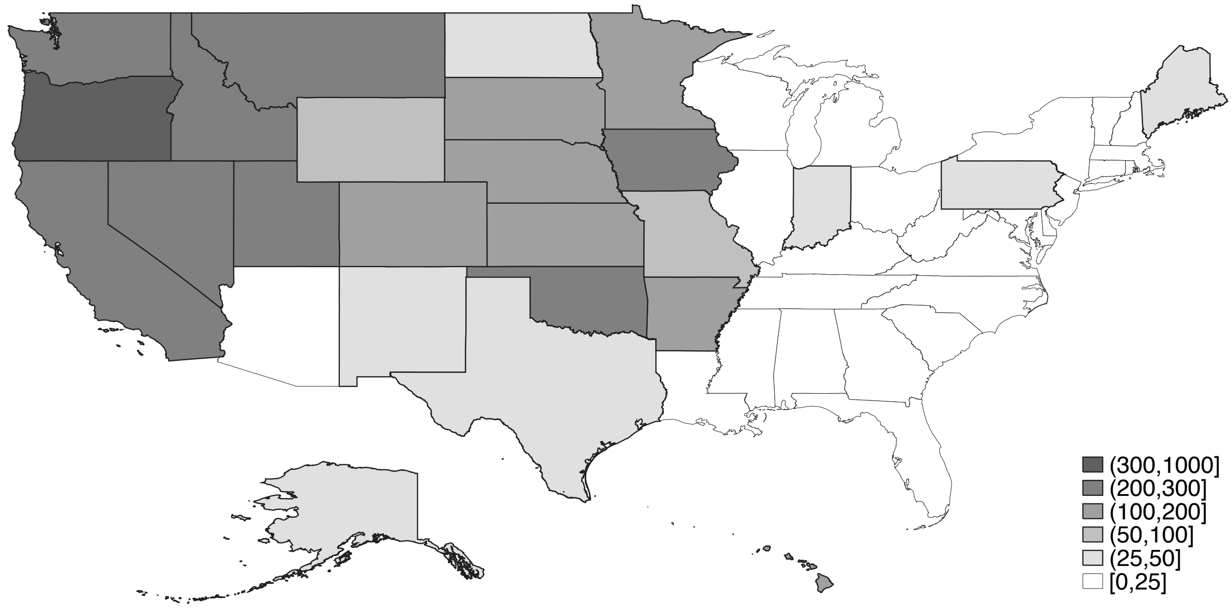
Note: All models include the baseline controls from Table 4 but the parameter estimates are suppressed for brevity. Asterisks ***, ** and * denote statistical significance at the 1%, 5% and 10% respectively.

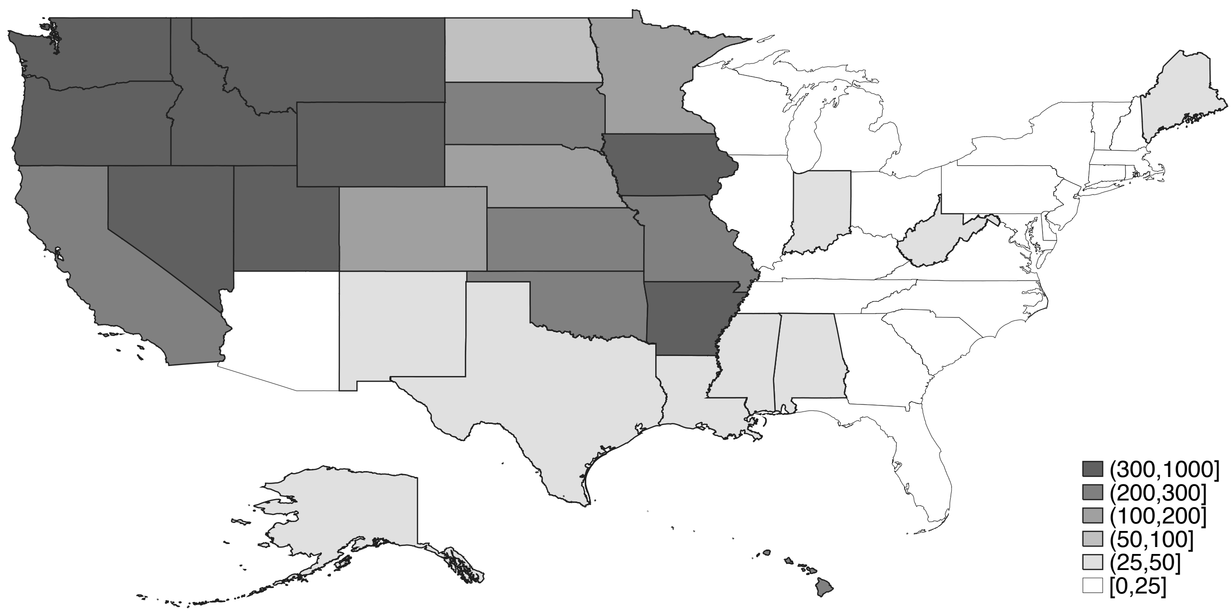
Figure 1: Number of US children living in foster care, 1982–2006



Sources: US DHHS (1999a, 2006a, 2009).

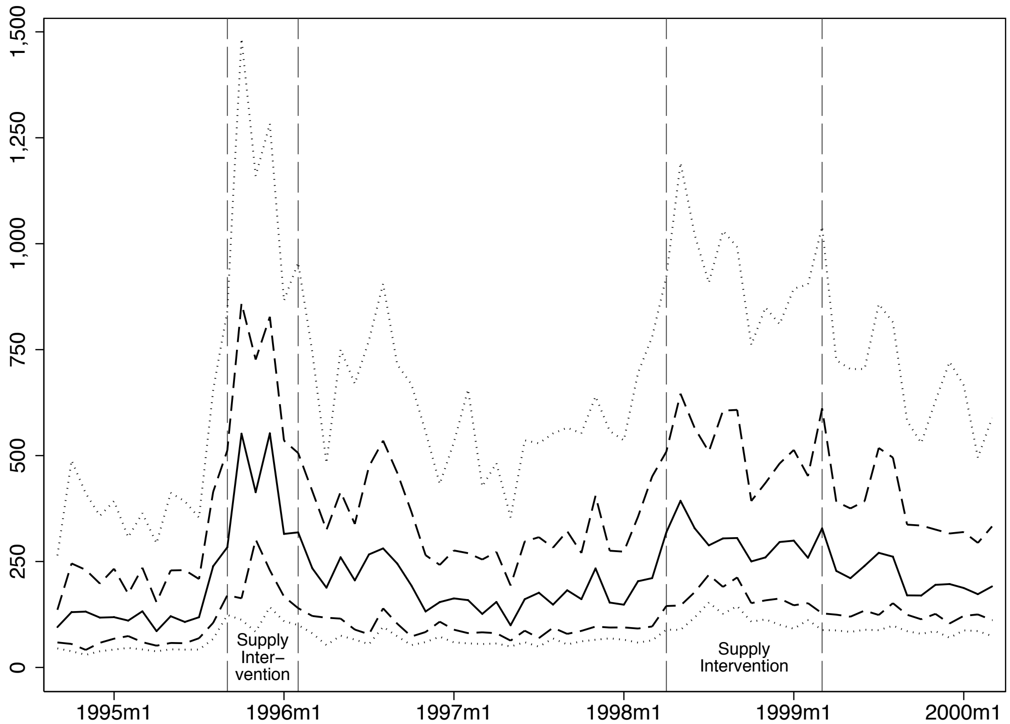
Figure 2: Meth treatment prevalence per 100,000 by state, whites, TEDS, 1994 and 2000





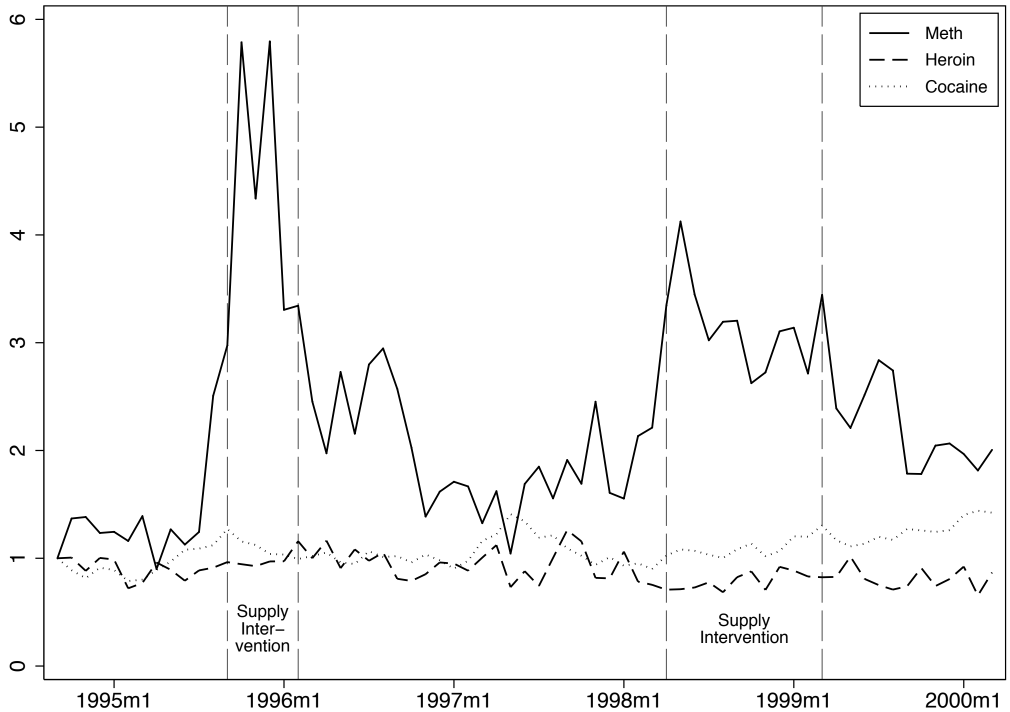
Sources: Authors' calculations from TEDS. The upper graph shows the number of meth treatment episodes per 100,000 whites in each state from September 1994 to August 1995. The lower graph shows the episode rate from April 1999 to March 2000.

Figure 3: Percentiles (5th, 25th, median, 75th, 95th) of expected retail price of pure gram of meth, in 2002 dollars, by month, STRIDE, 1994–2000



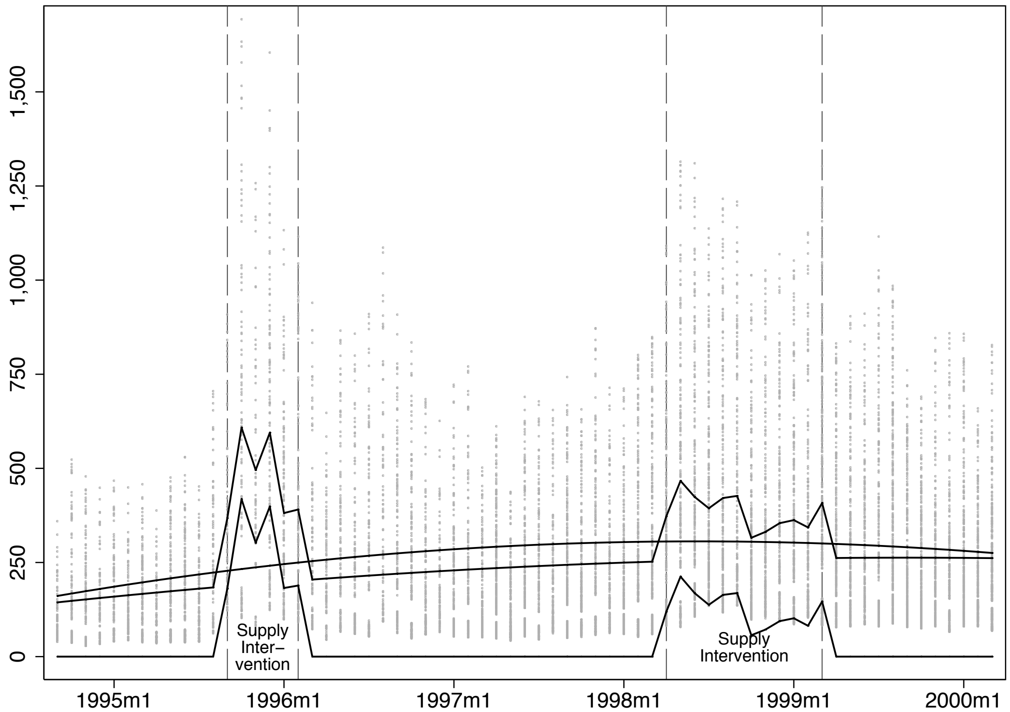
Notes: Authors' calculations from STRIDE. Expected price estimates come from random coefficient models of both purity and price, following the methodology of Arkes et al. (2004). Estimates from these models are available from the authors. Prices are inflated to 2002 dollars by the All Urban CPI series.

Figure 4: Median monthly expected prices of meth, heroin, and cocaine relative to median expected price of each in September 1994, STRIDE, 1994–2000



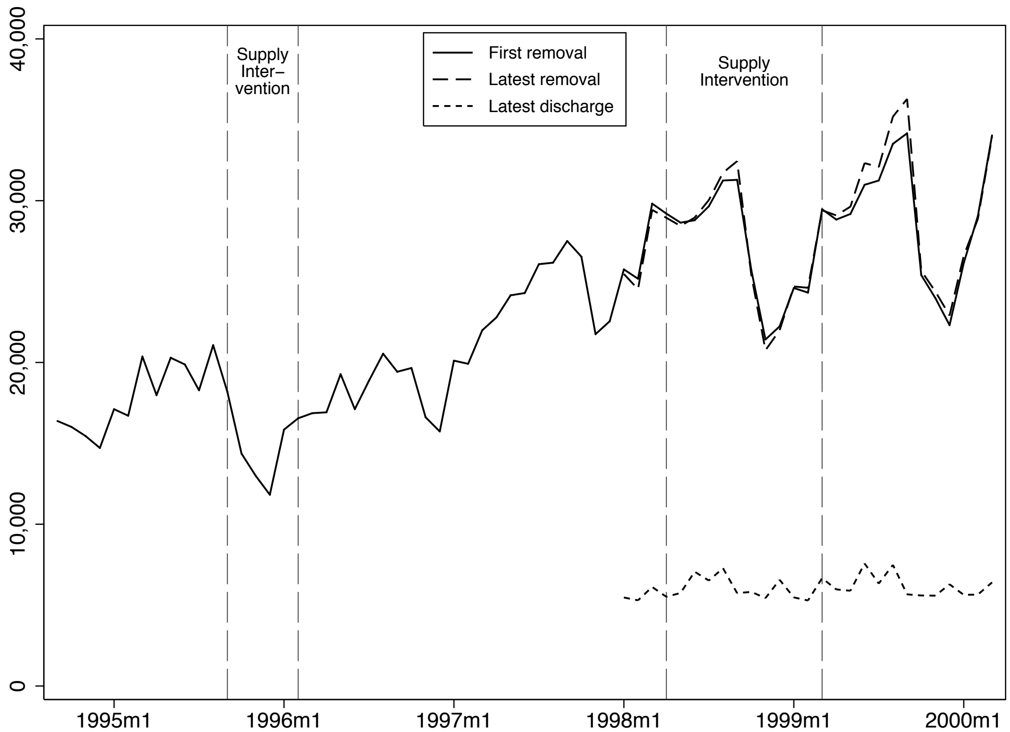
Notes: Authors' calculations from STRIDE. Expected price estimates come from random coefficient models of both purity and price, following the methodology of Arkes et al. (2004). Estimates from these models are available from the authors. Prices are inflated to 2002 dollars by the All Urban CPI series.

Figure 5: Construction of the instrumental variable as deviations from the national meth price trend, STRIDE, 1994–2000



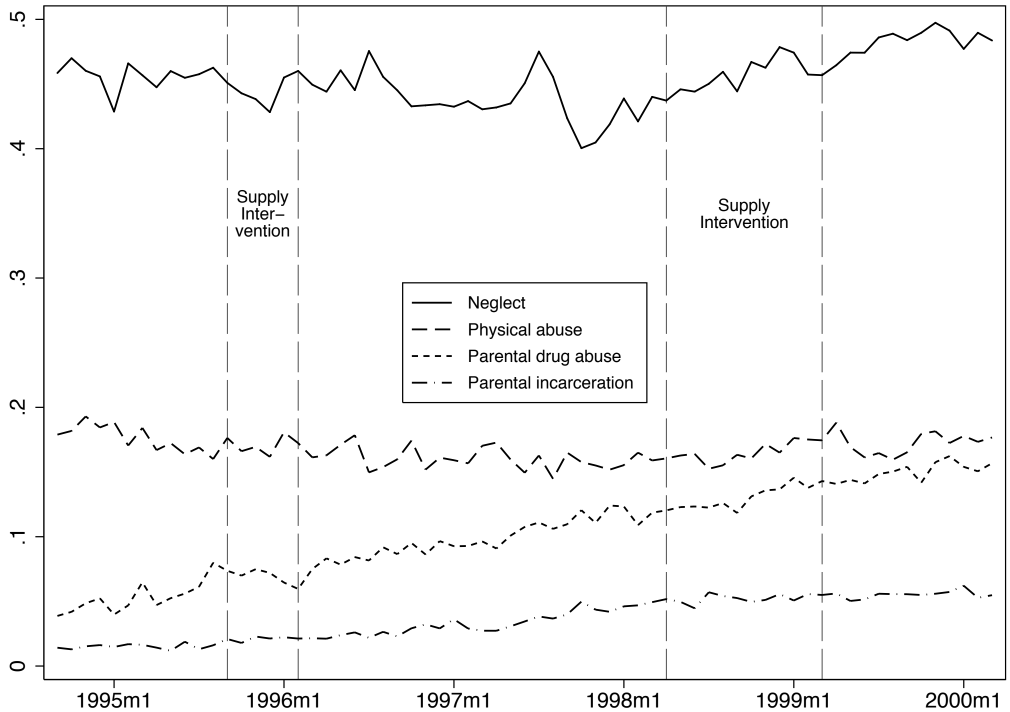
Notes: Authors' calculations from STRIDE. Dots represent individual observations for the expected price of pure meth. The smooth curve is the quadratic monthly time trend of expected meth prices. The bottom dark line is the instrumental variable—equal to zero outside of the supply interventions, and equal to the deviation off the trend during the intervention.

Figure 6: Number of children removed to and discharged from foster care in the US, AFCARS, 1994–2000



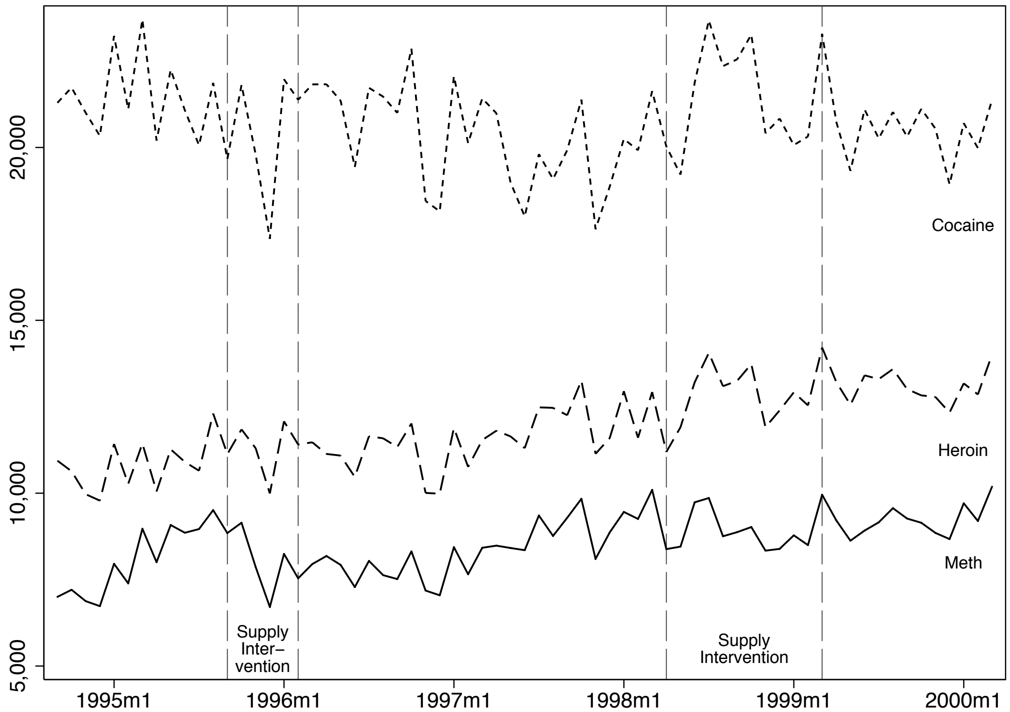
Sources: Authors' calculations from AFCARS.

Figure 7: Proportion of monthly foster care admissions reporting a particular route of admission, AFCARS, 1994–2000



Notes: Authors' calculations from AFCARS. Child welfare workers may report no reasons or more than one reason for removal, so proportions may not add to one.

Figure 8: Total admissions to publicly funded treatment facilities by drug and month, whites, TEDS, 1994–2000



Notes: Authors' calculations from TEDS. Patients can report the use of more than one drug.