Published in final edited form as:

GeoJournal. 2013 June 1; 78(3): 451–462. doi:10.1007/s10708-011-9428-4.

Exploring the Spread of Methamphetamine Problems within California, 1980 to 2006

William R. Ponicki, Lance A. Waller, Lillian G. Remer, and Paul J. Gruenewald
Prevention Research Center, 1995 University Ave., Suite 450, Berkeley, CA 94704

Abstract

Background—The introduction and spread of high potency methamphetamine has led to dramatic increases in drug-related problems in California. Prior research suggests that drug abuse rates are related to local demographic and economic characteristics, law enforcement activities, and sentencing practices. Methamphetamine abuse in particular has been shown to be reduced by laws regulating the raw materials needed for its production. This research models the regional effects of such laws on the spatio-temporal patterns of growth of methamphetamine-related problems across California from 1980 to 2006.

Methods—Amphetamine-related arrests and hospital discharges related to amphetamine abuse / dependence were assembled for California counties over the years 1980 through 2006. Varying-parameter Bayesian space-time models were used to relate the implementation of major laws controlling the distribution of methamphetamine precursors to observed patterns of arrests and discharges and to allow such associations to vary by location. The models used conditionally autoregressive (CAR) Bayesian spatial priors to allow spatial correlation in estimation of county-specific growth in these measures over three distinct time periods: before the 1989 law, between the 1989 and 1997 laws, and after the 1997 law. Growth of arrests and discharges were related to demographic and economic indicators to determine geographic areas more or less susceptible to the spread of methamphetamine problems.

Results—Although both problem measures increased during all three periods, each of the precursor laws was associated with short-term reductions in the growth of arrests and discharges. Growth was greatest in central California counties prior to 1989 and increased in coastal counties in later years. From 1980 to 1989 growth was highest for counties with low incomes and high proportions of white residents, while 1989-1997 growth was highest in counties with fewer whites and more Hispanics. Growth after 1997 was not significantly associated with county characteristics.

Conclusion—This research demonstrates that the precursor laws did suppress the growth of methamphetamine related arrests and hospital discharges. It also demonstrates specific geographic patterns in the growth of methamphetamine arrests and abuse across California during this time. Early patterns of growth were related to economic and demographic characteristics, while later patterns were not. This suggests that some counties were uniquely susceptible to the early spread of the methamphetamine epidemic, although problems eventually grew dramatically in all California counties.

INTRODUCTION

Methamphetamine is a primarily non-medicinal form of amphetamine marketed for recreational use with intense and long-lasting effects. Methamphetamine abuse has spread

rapidly in the United States during recent decades. Drug-treatment episodes with amphetamine or methamphetamine listed as the primary substance of abuse rose from approximately 21,000 in 1992 to over 170,000 in 2005; during this time methamphetamine's share of all drug treatment episodes rose from 0.9% to 8.3% (Substance Abuse and Mental Health Services Administration, SAMHSA, 2004; Substance Abuse and Mental Health Services Administration, SAMHSA, 2008). Across US cities the number of emergency department discharges that involved amphetamine or methamphetamine increased by 54% between 1995 and 2002 (SAMHSA, 2004b). Methamphetamine abuse has become particularly acute in the far western states, where 87% of law enforcement agencies cited it as the greatest drug threat in their jurisdictions (National Drug Intelligence Center, 2008).

As late as the 1960s amphetamine use in the U.S. was primarily by prescription, intended for treating conditions such as depression or obesity (Anglin, et al., 2000). In the 1970s, growing awareness of amphetamine's dangers led to enhanced restrictions on the pharmaceutical's legal production and distribution, resulting in a marked shift toward illegal methamphetamine production, originating with Northern California motorcycle gangs and spreading up and down the Pacific Coast (Lucas, 1997). The 1980s brought a new production method that shifted methamphetamine manufacturing toward Southern California, accompanied by greater involvement of Mexican traffickers (Morgan & Beck, 1997). This led to increasingly large-scale methamphetamine production in both California and Mexico, while also encouraging the gradual spread of methamphetamine abuse and production eastward over Mexican cartels' existing drug-distribution networks (Anglin, et al., 2000). Although methamphetamine abuse rates remain highest in the Western US, the drug has become increasingly more problematic in the other parts of the country, particularly the Plains, Midwestern and Southern states (SAMHSA, 2006).

Various policy interventions have been introduced over the past 30 years to reduce the availability and abuse of methamphetamine and other illegal drugs. Increased drug enforcement at the local level and tougher sentencing have been demonstrated to reduce drug sales and related problems (Harrison and Backenheimer, 1998). Because illicit methods of methamphetamine production typically require precursor chemicals (ephedrine or pseudoephedrine) that can only be created with highly-specialized equipment, it has also been feasible to reduce the methamphetamine supply via regulations aimed at these precursors (Cunningham and Liu, 2003). Although such enforcement and regulatory initiatives can substantially reduce drug availability in the short term, abuse levels frequently resume their growth once drug markets adjust to control efforts. For example, drug sales often move to adjacent neighborhoods in response to local enforcement (Caulkins, 2000). Similarly, successful Federal regulations restricting methamphetamine precursors in bulk form have resulted in manufacturers recruiting drug abusers to buy and collect retail cold or allergy medicines containing pseudoephedrine ("smurfing", National Drug Intelligence Center, 2009). These supply factors have contributed to the large differences observed in rates of growth in methamphetamine abuse and problems over space and time. There may also be sizeable differences between communities in the propensities of local populations to try or regularly use methamphetamine. Survey data indicate that methamphetamine abusers are more likely to be young, white, male, poor, and non-urban (Yacoubian, 2007; Iritani et al., 2007; SAMHSA, 2007). These demand factors interact with regional supply differences to affect spatial growth rates of methamphetamine abuse and problems.

Methamphetamine is less likely than other illegal drugs to be sold on the street, but rather tends to be purchased at a private residence from an acquaintance of the buyer (NIDA, 1998; Pennell et al., 1999). Although population surveys are successful at measuring drug demand, efforts to illuminate drug supply are hampered by the need for drug producers and sellers to

avoid detection by enforcement agents (National Institute on Drug Abuse, NIDA, 2002; Kadushin, et al., 1998). Although ethnographic and other qualitative research approaches (e.g., Eck and Gersh, 2000) are an invaluable source of information about the social networks of drug abusers that define local drug markets, they present only a fragmented and incomplete view of any market within any city or state in the nation (Goldstein, 1998). Since these markets span city, county, state and national boundaries, and remain largely private by intent, the majority of drug market activities remain invisible. For these reasons Caulkins and Pacula (2006) observe that much more is known about drug sales and demand than about markets and supply.

Since survey methods are unlikely to provide reliable or complete data on hidden drug markets, researchers turn to secondary indicators that are more consistently available over time and space despite various limitations. Many studies examine arrest data (e.g., Banerjee et al., 2008; Cunningham and Liu, 2005), but arrests are a function of law enforcement efforts as well as underlying drug market activities. Some differences in enforcement are likely due to factors unrelated to existing drug market activities (e.g., limitations of local government finances). In other cases the direction of causation may be less clear. For example, increased enforcement in one area may cause drug markets to move to a neighboring community, leading to subsequent increases in enforcement in the other areas. Such issues limit the usefulness of arrest data as an indicator of underlying drug activity. As an alternative to arrest data, other studies examine the medical consequences of drug abuse, such as hospital discharges with a drug-related diagnosis (Cunningham and Liu, 2003). While these data are less affected by law-enforcement activities, they suffer several other limitations. Drug abusers without medical insurance may be less likely to be admitted to a hospital, clinicians may change how they note a specific drug-related diagnosis in different communities or time periods, and hospital discharges may represent a lagging indicator of methamphetamine abuse. Due to the cumulative physical decline typically seen among methamphetamine abusers, such individuals may not appear at hospitals until related physiological damage is well progressed. For example, it has been noted the average methamphetamine abuser entering drug treatment has been using the drug for more than 7 years (Rawson et al., 2004).

The current study takes a geographic epidemiological approach to consider the degree to which two outcomes of methamphetamine abuse, arrests and hospital discharges, vary spatially across California counties over the years 1980 – 2006. Its purpose is to demonstrate statistical methods for modeling the growth and spatial spread of the largely hidden methamphetamine market using measurable outcomes associated with underlying abuse. It extends the literature by asking several additional questions: (1) Do precursor laws reduce methamphetamine problems more in some counties than in others? (2) Have statewide methamphetamine growth rates changed across three time periods (delimited by major precursor laws in 1989 and 1997)? (3) Have spatial patterns of county-specific methamphetamine growth rates evolved over the study period? (4) What county characteristics are associated with higher levels or faster growth of methamphetamine problems? Varying-parameter Bayesian space-time models (Bernardinelli et al., 1995) are modified to estimate county-specific differences in the growth of these outcome measures over three sub-periods.

METHODS

DATA

Counts of arrests in California were obtained from the Monthly Arrest and Citation Register (MACR) database for the years 1980 to 2006 (California Department of Justice, 2008). Amphetamine / methamphetamine arrests are reported in a residual grouping of other

“dangerous drugs” (MACR SumCode 14). This category is defined as felony arrests for possession, distribution and sales (but not manufacturing) of drugs other than marijuana and “narcotics” (e.g., cocaine, heroin, morphine, and codeine). In addition to amphetamine and methamphetamine, this residual category includes arrests related to LSD, PCP, and depressants. This data set includes separate counts for each law enforcement jurisdiction, including city police departments, county sheriffs, the California Highway Patrol and special-purpose police forces assigned to protect college campuses or local transit systems. This agency-by-month database was aggregated across 58 counties for 27 years ($n = 1,566$). As the blue line in Figure 1 shows, statewide dangerous-drug arrests per 10,000 residents increased by 148% between 1980 and 2006.

Hospitalization data related to amphetamine dependence / abuse for the years 1983 to 2005 were obtained from patient discharge data (PDD) collected by the California Office of Statewide Health Planning and Development (OSHPD). PDD records provide information on all discharges that result in at least one overnight hospital stay, including up to 24 ICD-9-CM (diagnostic) codes. This study selected discharges that included a primary or secondary diagnostic code of 304.4 indicating amphetamine dependence or 305.7 indicating amphetamine abuse (ICD-9- CM, 1991). By definition these two classifications include use of a variety of psychostimulant drugs, for example, amphetamine, dexadrine, methamphetamine, and whatever drugs may be covered by “street” names such as “speed.” In only 8.7 percent of cases is amphetamine dependence / abuse the primary diagnosis; in the other 91.3 percent of cases the dependence abuse diagnosis is secondary to hospital discharge for some other medical or injury condition. In 1989 OSHPD conducted a major reabstracting project to test the validity of various components of the patient discharge record that included primary and other diagnoses. Overall, sensitivity and specificity of better than 90 percent in record check and patient follow-up studies were observed (Abellara et al., 2005; Meux, 1993; Meux et al., 1990). Because patient addresses were not included in the publicly available data, each discharge was identified by the location of the hospital rather than of the patient. As a result two low-population counties (Alpine and Sierra) had to be excluded from these analyses, yielding a data set with 56 counties over 23 years ($n = 1,288$). The red line in Figure 1 indicates that statewide amphetamine related hospital discharges per 10,000 residents increased almost 17 fold between 1983 and 2005.

Neither the arrest nor hospital discharge data sets solely reflect methamphetamine abuse or dependence: both also include cases related to amphetamine and other drug use (e.g., the arrest counts include charges involving other drugs such as LSD and PCP). Figure 1 indicates very similar temporal patterns of these two indicators, however, supporting the conclusion that both measures are dominated by methamphetamine (Suo, 2004). In particular, both problem indicators suggest sizeable impacts of several major federal laws controlling methamphetamine precursors (Cunningham and Liu, 2003, 2005). The first law, the Chemical Diversion and Trafficking Act, restricted the availability of bulk precursors in powder form beginning in November, 1989. The second law, the Domestic Chemical Diversion and Control Act, restricted ephedrine sales starting in August, 1995. The third law, the Comprehensive Methamphetamine Control Act, restricted pseudoephedrine production and distribution beginning in October, 1997. Each of the three laws was followed by a drop in arrests and hospital discharges. However, none of these declines were long lasting and methamphetamine problems resumed their upward trend within two years of each law’s enactment. The 2006 decline in the arrest rate suggests a preliminary effect of the Combat Methamphetamine Epidemic Act of 2005 which was implemented in April 2006. This law mandated the storage of pseudoephedrine medications behind store and pharmacy counters and required logging of purchaser information.

The analyses presented below include controls for demographic and economic characteristics of California counties. County population data by age and race were obtained from the California Department of Finance. Personal income data for each county and year were obtained from the U.S. Bureau of Economic Analysis (2008).

ANALYSIS MODEL

The analyses below assume that methamphetamine abuse spreads from community to community via drug supply networks and interpersonal contact between drug abusers. As such, each outcome measure was analyzed using a Bayesian space-time model specifically designed to allow for spatial similarity of problem levels and growth between neighboring communities (i.e., spatial autocorrelation). These space-time models were derived from that of Bernardinelli, et al. (1995) and implemented in WinBUGS version 1.4.3 (Lunn et al., 2000) using code presented in Lawson et al. (2003). The basic model structure is as follows:

$$\begin{aligned} \text{ProbCnt}[i, k] &\sim \text{dpois}(\mu[i, k]) \\ \log(\mu[i, k]) &= \log(\text{eProbCnt}[i, k]) + \alpha + \beta * t[k] + u[i] + v[i] + \delta[i] * t[k] \end{aligned}$$

Here ProbCnt[i,k] refers to the Poisson probability distribution assumed to represent counts of arrests or hospital discharges in county i in year k. Arrest and discharge outcomes are regressed on exogenous measures represented by fixed and random effects. Variable eProbCnt[i,k] represents the expected number of events if the risk of an event is the same everywhere and does not depend on any of the covariates. It is computed under the assumption that total statewide problems are distributed over these counties and years strictly in proportion to total population. The fixed-effect parameter α is a state-level intercept. The fixed effect parameter β is the coefficient for a simple time trend related to t[k], the year index for a given record (1, 2, ...). The random effects u[i] and v[i] both allow for the possibility that some counties have consistently higher (or lower) problem rates throughout the study period than do others. The u[i] effect is assumed to be spatially autocorrelated, whereas the v[i] term allows for additional non-spatial county variation to the Poisson in order to control for overdispersion. The random effect $\delta[i]$ represents differences in time trends between places and is also assumed to be spatially autocorrelated. Estimates of both u[i] and $\delta[i]$ are implemented using conditional autoregressive (CAR) Bayesian priors, which help to smooth spatial patterns by having the predictions for each county “borrow strength” from nearby counties’ data (Waller and Gotway, 2004, Chapter 9).

This basic space-time model was expanded in three ways. First, three fixed effects were introduced to allow for statewide proportional shifts in problem counts following the precursor laws that took effect in November 1989, August 1995, and October 1997. These were implemented as simple dummy variables for years after a law took effect and pro-rated for changes happening part way through a given year. The coefficients on these law dummy variables were expected to be negative, indicating that the trend line for an outcome measure shifted downward in response to the precursor restrictions. Random effects allowing for county-specific variation in the impact of the precursor laws were considered, but were rejected because they did not improve model fit as measured by the Deviance Information Criterion (DIC, Spiegelhalter et al., 2002). Second, first order annual lags for the 1989 and 1997 law dummies were added to the models to account for the gradual impacts of the precursor laws. The laws gradually gained effectiveness when methamphetamine producers used up pre-existing supplies of precursors. Third, the model was extended to allow for changes in time trends across time intervals bracketed by precursor law changes. The time course of the data was divided into three sub-periods, each defined by the 1989 and 1997 precursor laws. The single time trend β was replaced by three fixed effects: β_{8089} , β_{8997} , and

β_{9706} . Similarly, the $\delta[i]$ random effect was replaced by three sub-period specific random trend effects: $\delta_{8089}[i]$, $\delta_{8997}[i]$, and $\delta_{9706}[i]$.

The Bayesian space-time models were estimated in WinBUGS version 1.4.3. Models were allowed to burn-in for 50,000 Markov-Chain Monte Carlo (MCMC) iterations, after which parameter estimates from the posterior distribution were sampled for 50,000 iterations. Models were tried with multiple sets of initial values to assure that this did not affect convergence. Initial estimates included both spatial, $u[i]$, and non-spatial, $v[i]$, random intercepts. These exhibited poor convergence with respect to these parameters and the overall intercept, α . Thus alternative models were considered using either spatial ($u[i]$) or non-spatial ($v[i]$) random effects. Both of these models produced similar results for fixed-effect parameter estimates and spatial intercepts. Given that the random intercepts were spatially clustered, spatial random effects were included in the final models. Traces of MCMC iterations (not shown) demonstrated good convergence for all parameters in these analyses.

The posterior estimates of the spatial random intercepts represent the underlying level of the outcome measure in each county. The three spatial random time trends represent the growth rate of an outcome measure for the three sub-periods: prior to 1989, from 1989 to 1997, and after 1997. Pearson correlations were used to investigate specific county characteristics that might be associated with these random effects for each outcome measure. The random intercepts were related to racial composition, population density per square mile, and median income measured as of 1980. The sub-period- specific random slopes were related to these same characteristics as of 1985, 1993 and 2002, respectively.

RESULTS

Table 1 presents the results of Poisson analyses of the arrest (left) and hospital discharge (right) data. The median value from the posterior sample represents the best estimate of each parameter, while the 2.5 and 97.5 percentile values define the credible interval containing 95% of sampled posterior values. The results were consistent between the two models. Each analysis has a negative statewide intercept, both have positive growth trends within each of the three sub-periods, and all precursor law effects are negative. In both analyses, the fastest statewide growth took place during the middle sub-period from 1989 to 1997. Both arrests and hospital discharges were negatively associated with each indicator, and the lag of each indicator, for each of the three precursor laws. This indicates the desired reduction in outcomes took place as an immediate, if not long lasting, impact of the legislation.

The bottom section of Table 1 shows the DIC and the change in DIC that result from dropping various sets of variables from the model. These changes show a large increase in DIC (indicating worse model fit) in alternative versions that exclude the five precursor-law indicators, the two lagged precursor-law indicators, the random effects accounting for county differences in time trends, and an alternative version that assumes a single time trend across all three sub-periods. In contrast the DIC statistic was not improved in alternative specifications adding random effects to allow for differential effects of the law dummy variables between counties; thus these features were not included in the final model.

Figure 2 maps the estimated county-specific growth of each outcome within each of the three sub-periods. These estimates combined the fixed-effect statewide growth estimates within a sub-period (β_{8089} , β_{8997} , or β_{9706}) with the random effects by which individual counties may have relatively larger or smaller trends within the same sub-period ($\delta_{8089}[i]$, $\delta_{8997}[i]$, or $\delta_{9706}[i]$). For example, for each MCMC iteration, the estimated growth rate between 1989 and 1997 is calculated as follows:

$$TT_{8997}[i] = \exp(\beta_{8997} + \delta_{8997}[i])$$

The maps in Figure 2 represent the median value of these growth parameters for each county as sampled from the relevant posterior distribution. The top portion of the figure is derived from the arrest analysis. The absence of negative values portrayed in these maps indicates that all 58 counties exhibited positive growth in arrests over time during each of the three sub-periods. The top-left map indicates that the arrest growth between 1980 and 1989 tended to be slowest (lighter shades of blue) in the central coastal region between San Francisco and Los Angeles. The top-middle map shows that this pattern was reversed between 1989 and 1997, with those counties near the central California coast exhibiting higher growth. The top-right map shows that from 1997 to 2006 growth slowed, there was less total variation between counties, and there was less similarity among neighboring counties. Moran's I statistics (Moran, 1950) indicate significant positive spatial autocorrelation among the county-specific growth parameters for arrests within each of the three time periods.

The bottom portion of Figure 2 presents similar maps derived from the hospital-discharge analysis. Note that these maps exclude two counties that lacked hospitals and for this reason could not be separately included in the analysis (Alpine and Sierra, in the central eastern portion of the state). As was the case for arrests, all counties have positive projected growth in all three sub-periods, and the middle period (1989 to 1997) tended to have the greatest growth in amphetamine-related hospital stays. The lower-left and lower-middle maps show a similar pattern to those for arrests, although less clearly: hospitalizations from 1983 and 1989 exhibited somewhat less growth along the central coast, while these counties exhibited somewhat greater growth between 1989 and 1997. Moran's I statistics (Moran, 1950) do not identify significant spatial autocorrelation among county growth parameters in these hospital discharge analyses.

Figure 3 presents county maps of the median posterior estimates of the random intercept, $u[i]$, representing the spatial pattern of residual error picked up after adjusting for the fixed effects. The left map in this figure is from the arrest analysis, while the map on the right is from the hospital-discharge analysis. Whereas there was considerable similarity between the two analyses for the growth-rate maps in Figure 2, the spatial pattern of the random intercepts varies greatly between the outcome measures. These maps indicate whether, at the beginning of each outcome data series, a given county had higher or lower counts than would be expected if statewide rates were distributed in proportion to population. The left map suggests that, beginning in 1980, arrest counts were higher than expected in the areas around San Francisco, Los Angeles and San Diego, as well as in the Central Valley and the southeastern part of the state. The random intercept for arrests was lowest in the northern third of the state. In contrast, the right map suggests that some of the highest rates of amphetamine related hospital discharges circa 1983 were in the northern part of the state. The random intercept for hospitalizations was high near San Francisco and San Diego (similar to that for arrests), and it was generally lower in Los Angeles, the Central Valley and the southeastern counties. Each of these sets of random intercepts exhibited significant positive spatial autocorrelation as indicated by Moran's I statistics (Moran, 1950).

An important question to ask with respect to the observed differences in patterns of growth of the methamphetamine epidemic documented in Table 1 and Figures 2 and 3 is what characteristics of counties are correlated with greater growth rates? A preliminary answer to this question is provided by the data presented in Table 2, presenting Pearson correlations between several county characteristics and the county-specific posteriors displayed in

Figures 2 and 3. Again the correlations for the arrest analysis are presented on the left and those for the hospital-discharge analyses on the right.

As shown in Table 2, the spatial intercepts of both models were positively associated with percent Asian and Black populations, population density, and areas with greater average income in 1980. In addition spatial intercepts from the arrest analysis were positively associated with percent Hispanic, and negatively associated with percent White and Native American populations. Predicted growth in arrests from 1980 to 1989 were positively associated with percent White and negatively associated with percent Hispanic populations, indicating that growth rates were greatest in this early phase of the epidemic among Whites. Unique to the arrest analysis, negative associations were related to percent Asian and Black populations, population density, and areas with greater average income. (The signs but not the significances of these correlations are the same in the hospital discharge analysis.) The signs of significant correlations were reversed between the pre-1989 sub-period and the 1989 to 1997 sub-period, with methamphetamine growth going from being positively related to percent white and negatively related to percent Hispanic before 1989 to being positively related to Hispanic and negatively related to percent white in the latter period. This suggests changing patterns of growth within different subpopulations across the different sub-periods under investigation. Methamphetamine growth during the post 1997 period was not strongly related to county characteristics, with only one weak positive relationship between arrest growth and the county percentage of Hispanics.

DISCUSSION

The purpose of this study was to demonstrate statistical methods for modeling the growth and spatial spread of the largely hidden methamphetamine market using measurable outcomes associated with underlying abuse. The analysis model was designed to ask the following questions: (1) Do precursor laws reduce methamphetamine problems more in some counties than in others? (2) Have statewide methamphetamine growth rates changed across three time periods (delimited by major precursor laws in 1989 and 1997)? (3) Have spatial patterns of county-specific methamphetamine growth rates evolved over the study period? (4) What county characteristics are associated with higher levels or faster growth of methamphetamine problems? These questions were addressed by applying varying-parameter Bayesian space-time analyses to two distinct outcome measures, arrests and hospital discharges, improving this study's ability to identify the underlying spatial spread of methamphetamine sales and abuse despite limitations specific to each of these problem indicators.

Confirming prior research, the current results indicate that each of the precursor laws (1989, 1995, and 1997) was associated with significant declines in the statewide levels of methamphetamine-related arrests and hospital discharges. Significant negative coefficients on one-year lagged versions of the indicator variables for the 1989 and 1997 laws suggest that precursor restrictions affected the methamphetamine supply somewhat gradually as producers used up their existing supplies of raw materials. Question 1 above was investigated using an alternative model adding county random effects to allow for spatial variation in these precursor-law effects. This alternative did not improve model fit (deviance information criterion, DIC), suggesting that the effectiveness of these precursor restrictions did not vary substantially from county to county. Question 2 was investigated by allowing for three separate statewide (fixed-effect) time trends for sub-periods prior to, between, and after the 1989 and 1997 precursor laws. The fixed-effect results in Table 1 suggest that, after controlling for impacts of the precursor laws on the level of methamphetamine abuse, statewide methamphetamine problems increased more quickly after 1989 with growth declining somewhat after 1997. Question 3 was addressed by the spatial county-specific

growth rates presented in Figure 2. These maps suggest that 1980–1989 methamphetamine-related arrests and hospital discharges grew slowest among counties near the central California coast, but these same areas exhibited relatively faster growth during the 1989–1997 period. Question 4 was investigated by correlating these county-specific intercepts and growth rates to county socio-demographic characteristics. These correlations suggest that before 1989 methamphetamine problems grew fastest in counties characterized by high percentages white, low percentages Hispanic and low average income. This pattern reversed for the correlations between 1989 and 1997, where growth was positively related to percent white and negatively related to percent Hispanic.

These results have important implications for understanding the temporal increase and spatial spread of methamphetamine abuse in California during recent decades. The temporal pattern of statewide methamphetamine growth – highest in the middle years of the study – is consistent with the introduction of a new type of drug into a state with other pre-existing drug markets. Adoption of the new drug would ramp up gradually as supply networks developed during the early years of the drug's availability. Yet rates of increase would eventually decline as the market matures and the population segment most likely to try the drug has already done so. This hypothesis is also supported by the changing spatial patterns of methamphetamine growth over the three periods investigated (Figure 2). During the early years of the study methamphetamine problems grew fastest in lower-income counties away from the central California coast with high concentrations of white residents. This suggests that these communities were most susceptible to early infiltration by this emerging drug market. The middle years of the study exhibited a reversal of this trend, with faster methamphetamine growth shifting to higher-income counties with lower proportions of white residents. This suggests that the methamphetamine markets in early-adopting counties had begun to mature by this middle time period, whereas the later-adopting communities were still in the markets' original growth phase. The later years of the study are characterized by lower (although still very significant) statewide growth rates without notable spatial patterns across counties, suggesting that the methamphetamine market may have reached a more mature phase throughout California.

LIMITATIONS AND FUTURE DIRECTIONS

This study represents an innovative geographic examination of a drug epidemic at the spatiotemporal level of resolution while accounting for major policy interventions and correcting for the effects of spatial autocorrelation. It analyzes decades of methamphetamine growth across California, a key state in the spread of this drug, and provides an approach for studying the emerging markets for this drug in other parts of the United States. An important limitation of the study is that each of the two outcome measures is a flawed indicator of current methamphetamine problems within a geographic area. Arrests reflect not only underlying crime rates but also enforcement activities, and the “dangerous drugs” arrest category also includes some non-methamphetamine drugs such as LSD and PCP. Amphetamine-related hospital discharge rates include some stimulants other than methamphetamine, are a lagging indicator of underlying abuse, and may also be influenced by unequal access to hospital services. The inclusion of non-methamphetamine drugs in each outcome measure would be especially important early in the methamphetamine epidemic, and this might explain the inconsistency of spatial intercepts between the two outcome measures (Figure 3). Despite these weaknesses, however, the consistency of estimated methamphetamine growth patterns between these two outcome measures suggests that each indicator is reasonably representative of later methamphetamine abuse.

Another limitation of the current approach is the paucity of exogenous measures in the Bayesian space-time model, with socio-demographic influences measured via correlations with modeled random-effect estimates. This simple approach was chosen because of the

exploratory nature of this study; a major goal was to map the “natural” development of methamphetamine markets across California, controlling only for the external influence of Federal precursor legislation. One potential enhancement of these models is to explicitly allow for the effects of population “frailties” that make some areas more susceptible than others to methamphetamine problems. Such frailties might be indicated by an area’s economic and demographic circumstances, which could be associated with potential demand for methamphetamine. Frailties could also be indicated by high lagged rates of non-methamphetamine drug problems; such communities presumably have below-average abilities to combat criminal activities in general, and their pre-existing drug distribution networks might expand to carry methamphetamine. It would also be very informative to extend these models to all counties in the United States. The larger sample would increase statistical power, enhance the ability to track spatial spread over long geographic distances, and provide greater contrast between long-established methamphetamine markets in the western states with just-emerging markets in the eastern part of the country.

Acknowledgments

Research for and preparation of this manuscript was supported by NIDA Grant R21 DA024341 and NIAAA Center Grant P60 AA 006282 to Dr. Gruenewald, and by NIAAA grant R21 AA016632 to Dr. Waller.

References

- Banerjee, A.; LaScala, EA.; Gruenewald, PJ.; Freisthler, B.; Treno, A.; Remer, L. Social disorganization, alcohol and other drug markets, and violence: A space-time model of community structure. In: Cheung, Ivan, editor. *The Geography of Illegal Drug Markets*. National Institute on Drug Abuse and American Association of Geographers monograph; 2008. in press
- Bernardinelli L, Clayton D, Pascutto C, Montomoli C, Ghislandi M, Songini M. Bayesian analysis of space-time variation in disease risk. *Statistics in Medicine*. 1995; 14(21–22):2433–2443. [PubMed: 8711279]
- Bureau of Economic Analysis. *Regional Economic Accounts, Series CA1-3: Personal income, population, per capita personal income*. U.S. Department of Commerce; 2008. Available online at <http://www.bea.gov/regional/reis/> [Accessed on 11/21/08]
- Caulkins, J. Measurement and analysis of drug problems and drug control efforts. In: Duffey, D., editor. *Measurement and Analysis of Crime and Justice*. Washington, D.C: U.S. Department of justice; 2000. p. 391-449.
- Caulkins J, Pacula RL. Marijuana markets: Inferences from reports by the household population. *Journal of Drug Issues*. 2006; 36:173–200.
- Cunningham JK, Liu L-M. Impacts of federal ephedrine and pseudoephedrine regulations on methamphetamine-related hospital admissions. *Addiction*. 2003; 98:1229–1237. [PubMed: 12930210]
- Cunningham JK, Liu L-M. Impacts of federal precursor chemical regulations on methamphetamine arrests. *Addiction*. 2005; 100:479–488. [PubMed: 15784062]
- Eck, JE.; Gersh, JH. Drug trafficking as a cottage industry. In: Natarajan, M.; Hough, M., editors. *Illegal Drug Markets: From Research to Prevention Policy*. Monsey, NY: Criminal Justice Press; 2000. p. 241-272.
- Goldstein PJ. Drugs, violence, and federal funding: A research odyssey. *Substance Use & Misuse*. 1998; 33:1915–1936. [PubMed: 9718184]
- Harrison LD, Backenheimer M. Editor’s introduction: Insights into the drug-crime nexus. *Substance Use and Misuse*. 1998; 33:1763–1777. [PubMed: 9718179]
- Puckett, Craig D., editor. *The Educational Annotation of ICD-9-CM. 4*. Channel Publishing; Reno, Nevada: 1991. ICD-9-CM.
- Iritani BJ, Halfors DD, Bauer DJ. Crystal methamphetamine use among young adults in the USA. *Addiction*. 2007; 102:1102–1113. [PubMed: 17567398]

- Kadushin C, Reber E, Saxe L, et al. The substance use system: social and neighborhood environments associated with substance use and misuse. *Substance Use and Misuse*. 1998; 33:1681–1710. [PubMed: 9680088]
- Lawson, AB.; Browne, WJ.; Vidal Rodeiro, CL. *Disease Mapping with WinBUGS and MLwiN*. Chichester, U.K: John Wiley and Sons; 2003.
- Lucas, SE. Publication No. SMA 96-801 3. Rockville, Maryland: U.S. Department of Health and Human Services; 1997. Proceedings of the National Consensus Meeting on the Use, Abuse, and Sequelae of Methamphetamine with Implications for Prevention, Treatment and Research.
- Lunn DJ, Thomas A, Best N, Spiegelhalter D. WinBUGS -- a Bayesian modelling framework: concepts, structure, and extensibility. *Statistics and Computing*. 2000; 10:325–337. WinBUGS version 1.4.3 available at <http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml>.
- Meux, EF.; Stith, SA.; Zach, A. Report of results from the OSHPS reabstracting project: An evaluation of the Reliability of Selected Patient Discharge Data July Through December 1988. Patient Discharge Data Section Office of Statewide Health Planning and Development; Sacramento, CA: Dec. 1990 p. 35pages plus appendices A–I
- Meux EF. How many diagnoses and procedures? *Discharge Data Review*. 1993 Dec.20:1.
- Miller, MA. History and Epidemiology of Amphetamine Abuse in the United States. In: Klee, H., editor. *Amphetamine Misuse: International Perspectives on Current Trends*. Reading, U.K: Harwood Academic Publishers; 1997.
- Moran PAP. Notes on Continuous Stochastic Phenomena. *Biometrika*. 1950; 37:17–33. [PubMed: 15420245]
- Morgan, P.; Beck, JE. The legacy and the paradox: hidden contexts of methamphetamine use in the United States. In: Klee, H., editor. *Amphetamine Misuse: International Perspectives on Current Trends*. Reading, U.K: Harwood Academic Publishers; 1997.
- National Drug Intelligence Center. National Methamphetamine Threat Assessment, 2009. U.S. Department of Justice; 2008. Available at <http://www.usdoj.gov/ndic/pubs32/32166/32166p.pdf> [Accessed on July 30, 2009]
- National Drug Intelligence Center. Situation report: Pseudoephedrine Smurfing Fuels Surge in Large-Scale Methamphetamine Production in California. U.S. Department of Justice; 2009. Available at <http://www.usdoj.gov/ndic/pubs36/36407/36407p.pdf> [Accessed on August 11, 2009]
- National Institute on Drug Abuse. NIDA Community Drug Alert Bulletin - Methamphetamine. Bethesda, MD: NIDA; 1998 Oct. Available at <http://www.drugabuse.gov/MethAlert/MethAlert.html> [accessed August 5, 2009]
- National Institute on Drug Abuse. NIDA Research Report Series. Bethesda, MD: NIDA; 2002. Methamphetamine Abuse and Addiction. NIH Publication Number 06-4210 Available at <http://www.nida.nih.gov/researchreports/methamph/methamph.html> [accessed April 7, 2008]
- Pennell, S.; Ellett, J.; Rienick, C.; Grimes, J. Meth Matters: Report on Methamphetamine Users in Five Western Cities. U.S. Department of Justice; 1999. Publication NCJ 176331. Available at <http://www.ncjrs.gov/pdffiles1/176331.pdf> [Accessed August 12, 2009]
- Rawson RA, Marinelli-Casey P, Anglin MD, Dickow A, Frazier Y, Gallagher C, Galloway GP, Herrell J, Huber A, McCann MJ, Obert J, Pennell S, Reiber C, Vandersloot D, Zweben J. the Methamphetamine Treatment Project Corporate Authors. A multi-site comparison of psychosocial approaches for the treatment of methamphetamine dependence. *Addiction*. 2004; 99:708–717. [PubMed: 15139869]
- Spiegelhalter DJ, Best NG, Carlin BP, van der Linde A. Bayesian deviance, the effective number of parameters and the comparison of arbitrarily complex models. *Journal of the Royal Statistical Society, Series B (Statistical Methodology)*. 2002; 64 (4):583–640.
- Substance Abuse and Mental Health Services Administration (SAMHSA). Treatment Episode Data Set (TEDS), 1992–2002. United States Department of Health and Human Services; 2004. Available at http://www.dasis.samhsa.gov/teds02/2002_teds_rpt.pdf [Accessed August 7, 2009]
- Substance Abuse and Mental Health Services Administration (SAMHSA). Amphetamine and methamphetamine emergency department visits 1995–2002. United States Department of Health and Human Services; 2004b. Available at <http://www.oas.samhsa.gov/2k4amphetamines.pdf> [Accessed August 7, 2009]

- Substance Abuse and Mental Health Services Administration (SAMHSA). The NSDUH Report. United States Department of Health and Human Services; 2006. State estimates of past year methamphetamine use. Available at <http://www.oas.samhsa.gov/2k6/statemeth/stateMeth.htm> [Accessed August 4, 2009]
- Substance Abuse and Mental Health Services Administration (SAMHSA). Treatment Episode Data Set (TEDS), 1996–2006. United States Department of Health and Human Services; 2008. Available at <http://www.dasis.samhsa.gov/teds06/teds2k6aweb508.pdf> [Accessed August 7, 2009]
- Suo S. Unnecessary Epidemic. The Oregonian. Oct 3.2004 Accessed November 12, 2009 Available at http://www.house.gov/larsen/meth/press_20041003_oregonian_unnecessaryepidemic.shtml
- Waller, L.A.; Gotway, C.A. Applied Spatial Statistics for Public Health Data. Hoboken, NJ: John Wiley and Sons; 2004.
- Yacoubian GS. Assessing environmental prevention strategies for reducing the prevalence of associated harms of methamphetamine use. Journal of Drug Education. 2007; 37(1):31–53. [PubMed: 17982934]

California Arrests and Hospital Discharges Related to Amphetamine Abuse

Figure 1.
California Arrests and Hospital Discharges Related to Amphetamine Abuse

Varying Time Trends

Dangerous Drugs Arrests

Amphetamine Abuse/Dependence
Hospital Patient Discharges

Figure 2.
Varying Time Trends

Varying Intercept

Figure 3.
Varying Intercept

Table 1

Varying-Parameter Poisson Results

	Arrests		Hospital Discharges	
	58 Counties, 1980 – 2006	56 Counties, 1983 – 2005	2.5%	97.5%
Fixed Effects (Statewide):				
Intercept	-1.851	-1.813	-2.881	-2.650
Trend for 1980–1989	0.139	0.143	0.153	0.190
Trend for 1989–1997	0.303	0.308	0.313	0.491
Trend for 1997–2006	0.048	0.050	0.052	0.190
1989 Precursor Law Dummy	-0.253	-0.235	-0.217	-0.617
1995 Precursor Law Dummy	-0.756	-0.738	-1.033	-0.926
1997 Precursor Law Dummy	-0.201	-0.187	-0.174	-0.391
Lag of 1989 Precursor Law Dummy	-0.671	-0.651	-0.629	-0.516
Lag of 1997 Precursor Law Dummy	-0.246	-0.233	-0.220	-0.372
Deviance Information Criterion (DIC)	47,137			12,796
Δ DIC for Groups of Variables:				
Removing Law Dummies and Lags	19,039			9,725
Removing Lags Only for Law Dummies	5,666			1,154
Removing Random Effects for Trends	96,188			12,002
Force Equivalent Trends for All Years	61,490			7,821

Notes: Results are from Bayesian spatial Poisson models sampled for 50,000 iterations after a burn-in period of 50,000 iterations using WinBUGS software. Outcome measure is count of arrests or hospital discharges in a given county and year. Each analysis

Table 2

Correlations of Model County Effects with County Characteristics

	Arrests			Hospital Discharges		
	Intercept	Trend 1980–1989	Trend 1989–1997	Trend 1983–1989	Trend 1989–1997	Trend 1997–2005
% White	-.549** (0.00)	.598** (0.00)	-.406** (0.00)	0.257 (0.06)	-.374** (0.00)	-0.186 (0.17)
% Hispanic	.368** (0.00)	-.506** (0.00)	.513** (0.00)	-.272* (0.04)	.467** (0.00)	0.160 (0.24)
% Asian	.475** (0.00)	-.431** (0.00)	0.022 (0.87)	-0.066 (0.63)	-0.029 (0.83)	0.026 (0.85)
% Black	.569** (0.00)	-.412** (0.00)	-0.026 (0.85)	-0.079 (0.56)	0.053 (0.70)	0.199 (0.14)
% Native American	-.259* (0.05)	.321* (0.01)	-0.139 (0.30)	0.090 (0.51)	-0.177 (0.19)	0.051 (0.71)
Population Density	0.390** (0.00)	-.0248 (0.06)	-0.200 (0.13)	-0.038 (0.78)	-0.119 (0.38)	0.069 (0.61)
Average Income	0.227 (0.09)	-.373** (0.00)	-0.021 (0.87)	-0.171 (0.21)	-0.137 (0.31)	-0.140 (0.30)

Each cell contains the Pearson correlation for that pair of variables, with the p-value in parentheses. The random intercept for each county is correlated against the county's racial breakdown and average income in 1980. The varying time trend in each sub-period is correlated against the racial breakdown in the middle year of the sub-period (1985, 1993, or 2002) and the average income over the entire sub-period. **Bold** type indicates $p < 0.10$;

* indicates $p < 0.05$;

** indicates $p < 0.01$.