Policing Australia's 'heroin drought': using an agent-based model to simulate alternative outcomes

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Abstract Our paper examines how street-level drug markets adapt to a macro-level disruption to the supply of heroin, under three experimental conditions of street-level drug law enforcement: random patrol, hot-spot policing and problem-orientated policing. We utilize an agent-based model to explore the relative impact of abstractions of these three law enforcement strategies after simulating an 'external shock' to the supply of heroin to the street-level drug market. We use 3 years of data, which include the period of the 'heroin drought' in Melbourne (Australia) that commenced in late 2000 and early 2001, to measure changes in a selected range of crime and harm indicators under the three policing conditions. Our results show that macro-level disruptions to drug supply have a limited impact on street-level market dynamics when there is a ready replacement drug. By contrast, street-level police interventions are shown to vary in their capacity to alter drug market dynamics. Importantly, our laboratory abstraction of problem-orientated policing is shown to be the optimal strategy to disrupt street-level injecting-drug markets, reduce crimes and minimize harm, regardless of the type of drug being supplied to the market.

Keywords Agent-based simulation model · Australia · Heroin drought · Illicit drug · Law enforcement

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Introduction

From late 2000 to the start of 2001, the global production and supply of opiates was sharply reduced (UNODC 2007), creating a significant ‘heroin drought’ in Australia (Miller et al. 2001; Weatherburn et al. 2001). The Australian Federal Government claimed that the heroin drought was created through its national interdiction efforts and *Tough on Drugs* law enforcement strategy (AFP 2001). Indeed, it is true that the Australian Federal police seized 606 kg of heroin and dismantled a major drug-trafficking syndicate a few months before the drought (Gordon 2002). These off-shore and border interdiction efforts were an important cornerstone of Australia’s federal drug policy. Yet, the fact that the heroin shortage was clearly not isolated to Australia drove many experts to suggest that external factors such as strategic decisions and actions of the Asian crime syndicates supplying the Australian market were at stake (Bush et al. 2004).

Regardless of the *cause* of the global supply disruption, local-level drug markets in Australia experienced an indisputable shortage of heroin, commencing in late 2000 (Dietze et al. 2004). This reduction resulted in sudden price rises and reduced heroin purity on local drug markets [National Drug and Alcohol Research Centre (NDARC) 2002, Day et al. 2003, Bush et al. 2004]. At this time, many injecting heroin users adapted to the heroin shortage by increasing their demand for amphetamines, benzodiazepines, and prescribed opioids, resulting in a fairly constant number of injecting drug users in Melbourne (Dietze et al. 2004). The heroin drought thus created naturally occurring experimental conditions and provided an opportunity to explore a number of ‘what if’ law enforcement scenarios through artificial crime simulation techniques (Liu and Eck 2008).

Our paper examines how three street-level policing interventions—random patrols, hot-spot policing and problem-orientated strategies—influenced drug market dynamics in response to the macro-level disruption of the heroin supply chain. We used an agent-based simulation model to create an artificial policing experiment, exploring the relative impact of these three strategies on crime and harm outcome indicators. First, we describe the agent-based model (SimDrugDrought), created to simulate agents operating under fluctuating market conditions. Then, we examine the results of the street-level policing scenarios on crime and harm indicators. We compare and contrast our current results with outcomes from an earlier version of the model, operating under stable market conditions (SimDrugPolicing). Our results show the relative advantages of the problem-orientated strategy compared with the two other policing interventions under fluctuating market conditions. These results have important theoretical and policy implications for future research and practice.

Model description

Increasingly, agent-based simulation models are being used to explore how individuals (i.e. agents) interact within a given system and how system-level patterns emerge from the complex interplay of these local interactions (Epstein and Axtell 1996; Ferber 1999; Janssen 2002; Perez and Batten 2006). Without discarding the value of mathematical modelling (Baveja et al. 2000; Caulkins and Reuter 2006, agent-based simulations seem particularly appealing for studying illicit drug use and markets (Agar

2005; Brantingham and Brantingham 2004; Liu and Eck 2008). Research on the geography of crime (Weisburd and Green 1995; Eck 1998; Rengert et al. 2000, 2005), for example, finds street-level drug use and markets driven by local and spatial relationships within and across various social communities. Unger and colleagues (2004) describe illicit drug use as the result of complex interactions between posited risk and protective factors that operate at multiple levels of analysis. Previous research also suggests that drug markets are adaptive to external shocks affecting the system, such as the introduction of new drugs or new law enforcement policies (Caulkins and Reuter 2006; Caulkins et al. 2004). Agent-based simulation models offer the opportunity to explore the consequences of these types of external shocks.

We refer to the agent-based simulation model presented in this paper as SimDrugDrought. SimDrugDrought is an extension of SimDrug (Perez et al. 2006) and SimDrugPolicing (Dray et al. 2008), created with the Common-pool resources and multi-agent systems (CORMAS)© environment (Bousquet et al. 1998) to understand the dynamics of street-level illicit drug markets better. Like its predecessors, SimDrugDrought was designed by an inter-disciplinary group of experts. The simulated dynamics and decision-making processes rely primarily on a collective and iterative analysis of published statistics from the Australian Bureau of Statistics (High Court and Magistrate Court orders), the Australian Crime Commission (illicit drug seizures), the Ambulance Service Records (attended overdoses), the Australian Institute of Health and Welfare (drug treatment services), the Australian Institute of Criminology (drug use monitoring in Australia, DUMA) and the National Drug and Alcohol Centre (illicit drug reporting system, IDRS). In order to secure enough consistency across the different data sources, most of the collected information corresponds to the situation in Melbourne between 1999 and 2001, one epicentre of the heroin drought in Australia. However, Dietze et al. (2004) noted that Melbourne was not an isolated case and that most of the major cities in Australia experienced the 'drought' during the same period.

Table 1 describes SimDrugDrought's main characteristics. We concentrate in the present paper on describing specific characteristics of SimDrugDrought; all components inherited from previous versions are described in Perez and Dray (2005), Perez et al. (2006) or Dray et al. (2008).

Time and repetitions

Simulations are run on a daily time step in order to capture behavioural patterns of injecting drug users (IDUs). Each simulation covers a 36-month period and uses input data on heroin price, purity and availability as monthly reported in Melbourne between early 1999 and late 2001 (Dietze et al. 2004). When a parameterization vector is selected, the corresponding simulation is repeated 100 times in order capture the stochasticity attached to random processes embedded in SimDrugDrought (e.g. the initial positioning of agents or friendship networks).

Illicit drug supply under external shock conditions

SimDrugDrought represents an archetypal street-level market under conditions of external shock to the supply of drugs to the local market place. Unlike

Table 1 Summary of SimDrugDrought's main characteristics

Component	Description
Time:	
Time step	Daily
Duration	36-month period simulation
Illicit drugs:	
Drug type	Heroin and 'other drug'
Price	Price of heroin fluctuates (see Fig. 1). Fixed price for 'other drug': \$125/g
Purity	Purity of heroin fluctuates (see Fig. 1). Fixed purity for 'other drug': 40%
Drug availability	Availability of heroin fluctuates (see Fig. 1). 'Other drug': inverse fluctuation
Individual harm	Overdose possible with heroin use only
Spatial environment:	
Type	Archetypal, based on cellular automata (see Fig. 2)
Conductive cell	A cell conducive to drug dealing, based on local risk and neighbourhood effects
Wealth	Assets available on a cell for crime committed by users: \$100 to \$500 (initial values)
Treatment Centre	1 special cell collecting all users under treatment
Police Station	1 special cell collecting all arrested dealers
Social entities:	
User	3,000 randomly located on the grid at $t=0$
Dealer	150 randomly located on the grid at $t=0$
Wholesaler	10 randomly located on the grid at $t=0$
Constable	10 randomly located on the grid at $t=0$
Outreach Worker	10 randomly located on the grid at $t=0$
Policing interventions:	
Random	Constables move randomly over the grid
Hot spot	Constables target specific areas during three consecutive time steps
Problem-orientated	Constables team up with outreach workers to target specific areas

SimDrugPolicing (Dray et al. 2008), in which characteristics of the local drug market are kept constant, SimDrugDrought involves variations in the availability of two illicit drug types to the market place: heroin and 'other drug', the latter being representative of amphetamine-type stimulants (ATS). Unlike heroin, for which we use monthly reports on import price, purity and availability (Fig. 1), the 'other drug' supply is characterized by fixed purity (40%) and import price (\$125/g) due to the lack of recorded evidence during that period. As Dietze et al. (2005), after analysing IDRS reports, suggested that the number of injecting users did not vary over that period, as many of them switched to other available drugs, we assume within SimDrugDrought that the availability of 'other drug' is inversely proportional to the heroin one. As such, the heroin drought simulated with SimDrugDrought is not an emerging property of the system but a forcing factor we want the system to respond to. Our artificial policing experiment aims to study whether this response affects street-level policing interventions.

Spatial environment

SimDrugDrought portrays an archetypal urban environment composed of street blocks aggregated into five adjacent suburban areas. Figure 2 shows the 50×50 square mesh in which each cell represents a street block belonging to one of the five spatial aggregates. Thus, SimDrugDrought purposely avoids focusing on spatial

Fig. 1 Evolution of heroin import price (left Y-axis), and purity and relative availability on the market (right Y-axis). Source: Dietze et al. (2004). The shaded area corresponds to the onset of the simulated heroin drought

realism to concentrate on decision-making processes and interactions between law enforcement, prevention and treatment strategies. While sharing the views of Brantingham and Brantingham (2004) on the importance of spatial configurations for urban crimes, our inter-disciplinary team of experts agreed on an incremental build-up of complexity in order to preserve the experimental nature of SimDrug-Drought, as recently stated by Liu and Eck (2008). As a consequence, the *Police Station* and *Treatment Centre* represented on the grid operate like synthetic spatial metaphors rather than realistic geographical entities. The size of the grid itself is selected to accommodate the number of interacting agents comfortably, without sacrificing calculus capacities.

An important attribute attached to each cell is its capacity to attract illegal activities like drug dealing (*conductivity*). At the beginning of a simulation, 150 conducive cells are located on the grid. Their (fixed) initial distribution generates an arbitrary heterogeneity between suburban areas, the top-left area supporting the highest density of conducive cells (Fig. 2). During the simulation, each conducive cell can host one or more *dealer* agent. A *wealth* attribute is also attached to each cell on the grid. This attribute acts as a proxy for the value of disposable goods available for crime (burglary, street-theft). The value of *wealth* decreases each time a crime is committed on the cell (Perez and Dray 2005). A third attribute describes the *risk* attached to a specific cell. This attribute is arbitrarily defined as a function of the number of *crimes*, *overdoses* and *users* located on the cell at each time step (t):

$$risk_{cell,t} = 10 \left(\sum crime_{cell,t} + \sum overdose_{cell,t} \right) + \sum user_{cell,t} \quad (1)$$

Fig. 2 Visualization grid at the beginning of the simulation. *Black dots* initial set of cells (150) conducive to illicit drug activities. Areas with *different shades of grey* correspond to distinct suburbs

Finally, the *risk* value is used to update the *conductivity* status of the cell and its neighbours (for more details, see Perez and Dray 2005).

The *Treatment Centre* has a maximum capacity of 1,000 enrollments at any given time step (t), irrespective of the type of treatment (detoxification, therapeutic community or methadone replacement). Probabilities of entry and success rates for the different types of treatment are derived from the Australian Treatment Outcome Study (ATOS) project (Teesson et al. 2006). Ten *outreach worker* agents are initially based at the *Treatment Centre*. At each time step (t) the *Police Station* collects arrested *user*, *dealer* and *wholesaler* agents before they are permanently retrieved from the system. Ten *constable* agents (i.e. patrol officers) are initially located at the *Police Station* and are directed to patrol a given area according to different law enforcement strategies (see below). *Constable* and *outreach worker* agents are not limited by jurisdictions; therefore, they can patrol the entire grid.

Social entities

Like the previous versions, SimDrugDrought includes different social entities: *user*, *dealer* and *wholesaler*, *constable* and *outreach worker* agents. A full description of these different types of agents is given in Perez and Dray (2005). The ‘modus operandi’ of each agent in the model derives from rule-based heuristics collectively developed by the inter-disciplinary panel of experts. A key issue is the deliberate choice to implement ‘open-system’ simulations whereby a removed agent is automatically replaced by a new one later on. In the model, when a *user* succumbs to a fatal overdose or successfully completes treatment, it is removed from the model at time step (t) and replaced by a new *user* at time step (t_{+1}). Likewise, when a *dealer* is arrested, it is replaced by a new *dealer* at the next time step. This strong and rather pessimistic assumption relies on the lack of evidence showing any

noticeable changes in the numbers of dealers or IDUs in Melbourne over the simulated period (Dietze et al. 2004).

User

Dietze et al. (2005) suggested that there were between 15,000 and 50,000 problematic heroin users in Melbourne in 2000. Assuming an average number of 30,000 injecting users over our simulated period, we created a 1:10 scale representation of that population in order to cope with calculus capacities during the simulations. Hence, each simulation is initialized with 3,000 *users* randomly located on the grid.

Initially, a *user* is randomly given a 'trusted' *dealer* and a network of close friends (one to five other *users*). The daily objective for a *user* is to 'score' from its *dealer*, according to its degree of dependence. The drug of choice is heroin, but a *user* might have to buy 'another drug' according to its *dealer's* supply. A *user* has a probability of 0.5% to experience an *overdose* if one of the following conditions is fulfilled:

- (1) the previous drug injected was not heroin
- (2) the variation in quantity between two injections is greater than 0.02 g
- (3) the user comes out from a failed treatment period

A *user* experiencing an overdose has a 90% probability of being rescued if there is another *user* around (i.e. on the same *street block*) to call for an ambulance. These two probabilities are partially calibrated against values for fatal and non-fatal overdoses in Melbourne (Dietze et al. 2004). Encounters with *outreach workers* or overdose experiences progressively influence *users'* motivation to undergo treatment. Each *user* receives \$200 fortnightly from a welfare-like payment. This amount represents between 50% and 80% of actual payments in Australia and takes into account withdrawal for other primary needs. *Users* can assess their financial situation against their drug need and decide whether they have to commit a crime to increase their revenue or whether they have enough money to buy bigger quantities of drug and start dealing themselves (becoming *user-dealers*).

Dealer

Estimating the number of drug dealers in a given area is anything but trivial. Fortunately, statistics on High Court and Magistrate Court orders provide a way to infer ratios between sentenced wholesalers, street dealers and occasional user-dealers [Australian Bureau of Statistics (ABS) 2004]. We used these proxies to apply a conservative 1:20 ratio between *users* and *dealers* in our model, hence creating 150 *dealers* at the beginning of a simulation. Figure 3 shows that a *dealer* is an economically rational agent applying differential mark-ups according to findings

Fig. 3 Mark-up chain applied for both drugs between wholesalers, dealers and user-dealers in the model. Source: Moore (2005)

from Moore et al. (2005). Currently, *dealers* can buy only one type of drug at a time from their *wholesaler* and then sell it to users. *Dealers* are trading on the street market, but they are able to detect the presence of *constables* in their surroundings and to freeze temporarily their illegal activities.

Wholesaler

If the same data-mining technique as above are used, and if the usual under-estimate of ‘big fish’ in High Court values are taken into account, a very conservative 1:15 ratio is applied between *dealers* and *wholesalers*, resulting in the creation of ten *wholesalers* at the beginning of a simulation. They are able to buy the two types of drugs available on the market and to supply the *dealers* with one or the other. Drawn from Moore et al. (2005), mark-up values are shown in Fig. 3.

Constable

Regardless of the policing intervention selected by the *Police Station* (see below), a *constable* (i.e. patrol officer) has a probability of 10% to arrest a *dealer* and a probability of 40% to arrest a *user-dealer* when located in the same street block. As this type of information is not available in the Australian context, we used data from Weisburd and Green (1995), related to the Jersey City Drug Market Analysis Experiment, to calculate these arrest probabilities. In SimDrugDrought, *constables* do not arrest *users* unless they are involved in occasional dealing, and the *Police Station* has a probability of 0.25% to receive a ‘tip-off’ about a *wholesaler*’s location.

Outreach worker

Ten *outreach workers* are created and initially located at the *Treatment Centre*. Their aim is to encourage *users* to undertake treatment programmes. Depending on the policing intervention strategy, the influence of *outreach workers* on the *users*’ motivation varies (see below).

Policing interventions

Using the classification by Mazerolle et al. (2006) of street-level drug law enforcement interventions, SimDrugDrought simulates three types of police intervention strategies: random patrols, hot-spot policing and problem-orientated strategy (Table 2). Unlike SimDrugPolicing (Dray et al. 2008), SimDrugDrought

Table 2 Summary of the simulated law enforcement strategies

Parameter	Random Patrol	Hot Spot Policing	Problem-Orientated Strategy
Constable’s destination	Random	Street blocks with highest risk values for three consecutive time steps	Street blocks with highest risk values
Outreach worker’s destination	Street block with highest overdose rates	Street block with highest overdose rates	Follows constable destinations

examines the impact of different police interventions under conditions of macro-level disruptions to the drug supply. Table 2 summarizes the characteristics of the different policing scenarios implemented.

Random patrols

Under this scenario, *constables* (i.e. police patrols) move randomly across the grid without targeting any given area, simulating random preventive patrols and attending quiet suburbs as well as crime hot spots. The *Police Station* randomly selects ten cells (i.e. *street blocks*) and allocates one *constable* to each. The *Police Station* has no memory of the places already visited. Thus, some places might be visited several times or not at all within one simulation. The *Treatment Centre* acts independently and sends its *outreach workers* to cells displaying the highest overdose rates.

Hot-spot crackdowns

Under this scenario, the *Police Station* adapts its strategy to changes in the simulated environment and directs *constables* to areas identified as 'hot spots'. A hot spot corresponds to a *conductive* cell with a high value of *risk*. In practice, the *Police Station* selects ten *street blocks* with the highest values of *risk* and allocates one *constable* to each (i.e. patrol resource allocation). The *Police Station* has a memory of the *street blocks* previously visited. By default, a targeted *street block* receives three consecutive visits from a *constable*, reflecting on the higher degree of attention paid to hot spots in this scenario. This default value (N_p) is, later on, subjected to a sensitivity analysis.

Problem-orientated policing

Under this scenario, the *Police Station* and the *Treatment Centre* create a partnership such that *constables* and *outreach workers* work together as a team on the grid. While acknowledging the diversity of tactics corresponding to problem-orientated policing (Goldstein 1990; Scott 2000), we use SimDrugDrought to simulate a geographically focused partnership (Mazerolle et al. 2006). Hence, *constables* still target hot spots with the highest value of *risk*, but, this time, they work jointly with *outreach workers*. The underlying assumption is that this kind of partnership enhances drug user's motivation to undertake treatment. In order to test this assumption, we hypothesized that the influence outreach workers have on users is, by default, multiplied by 5 in this scenario. This default value (I_{ow}) is, later on, subjected to a sensitivity analysis.

Analytical approach

Each policing scenario is run through the model 100 times in order to capture the stochastic divergence between simulations due to non-linear interactions and random processes characterizing SimDrugDrought. All graphs presented below include intervals of error based on calculated standard deviations. Each simulation is run

over the same 36-month period corresponding to the period between January 1999 and December 2001. Parametric tests are conducted at different time steps in order to determine the significance of the differences between scenarios; results are provided for a probability (P) of 0.05.

Results

The key outcome measures analysed in our model include: (1) the number of arrested *dealers*, (2) the number of *users* under treatment, (3) number of committed crimes, (4) number of aborted crimes, (5) prevalence of heroin use, (6) occurrence of overdoses and (7) spatial evolution of *conducive* clusters (see also Dray et al. 2008). In order to address the impact of street-level policing interventions on these outcome measures under conditions of external shock to the drug market dynamics (i.e. the heroin drought), we compared and contrasted our findings to results established under stable market conditions (heroin and ‘other drug’ covered 50% of the market each consistently over the simulated period). We used previously published results from the SimDrugPolicing model as our base for the comparison (see Dray et al. 2008).

Cumulative number of arrested dealers

Figure 4 shows that the *random patrol* scenario leads to the lowest rate of arrested dealers after 36 months, with an average of 91 arrests. Meanwhile, the *problem-*

Fig. 4 Cumulative number of arrested dealers and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. The shaded area corresponds to the onset of the simulated heroin drought

orientated scenario leads to an average of 189 arrests, and the *hot-spot* scenario to an average of 174 arrests. Differences between *random patrol* and the two other scenarios are statistically significant over the whole simulated period. The 8.6% difference in arrests between *problem-orientated* and *hot-spot* scenarios is not statistically significant. However, we note that, under stable market conditions, this difference is not to be observed (Dray et al. 2008). Part of the explanation is to be found in the smaller size of *conductive* clusters (see below) under the *problem-orientated* scenario, especially when many *users* have to turn to the cheaper and more available 'other drug'. A sensitivity analysis conducted on the number of consecutive patrols (N_p) in the same *street block* ($N_p \in [1, 5]$) shows no significant advantage in terms of arrests beyond $N_p=2$.

Percentage of users under treatment

Figure 5 shows that the *problem-orientated* scenario translates into large numbers of *users* undertaking treatment in the early stages of the simulation. The *Treatment Centre* operates at almost full capacity, with 33% of the population of *users* seeking treatment. In contrast, it takes 18 months for *random patrol* and *hot spot* scenarios to reach a plateau of only 17% of *users* undergoing treatment. The early oscillations characterizing the *problem-orientated* scenario result from a complex interplay of entries into and releases from treatment programmes of different durations. However, the reduction in admissions between May 2000 and March 2001, mirrored by the slight inflexion observed with the two other scenarios, corresponds to the onset of the 'drought'. Again, these patterns in treatment admissions are not observed under stable market conditions.

The greater effectiveness of the *problem-orientated* scenario to direct *users* into treatment relies on a better capacity of *outreach workers* to convince *users* ($I_{ow}=5$) than in the two other scenarios ($I_{ow}=1$). Hence, a sensitivity analysis on I_{ow} is performed with values ranging from 1 to 10. With a value of 1, the *problem-*

Fig. 5 Percentage of users under treatment and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. The shaded area corresponds to the onset of the simulated heroin drought

orientated scenario performs as poorly as the other scenarios, sending only 18% of *users* for treatment. Conversely, for values of I_{ow} greater than 4, under the problem-orientated policing scenario, the *Treatment Centre* reaches its full capacity after a short period of time. These findings have two important consequences in terms of treatment: (1) problem-solving partnerships need to enhance the influence of outreach workers, to be effective, and (2) effective partnerships need to be followed by adequate treatment capacities.

Monthly crimes committed by users

Over 3 years, the *problem-orientated* scenario leads to a monthly average of 2.6 crimes per *user*. In comparison, the *hot spot* and *random patrol* scenarios lead, respectively, to 2.9 and 3.9 crimes per *user*. Having hypothesized in the model that users in desperate need of money commit crimes, we find that the significantly lower crime rate exhibited by the *problem-orientated* scenario is partly due to the fact that 33% of *users* are rapidly diverted into treatment. However, the good results also displayed by the *hot spot* scenario show that repeated crackdowns, partnership or not, are effective as well.

The initial glut observed in Fig. 6 is an artefact of the model, whereby most *users* do not have enough money at the beginning of the simulation and commit crimes to finance their drug addiction. The peak of the crime epidemic is followed by a recession phase, as an increasing number of *users* reach a more stable financial position. The *problem-orientated* scenario does not display such a glut, as 33% of *users* are rapidly diverted into treatment. A sensitivity analysis conducted on the number of consecutive patrols (N_p) into the same *street block* ($N_p \in [1, 5]$) shows no significant reduction in the number of daily crimes beyond $N_p=3$. However, the absence of replication ($N_p=1$) brings the *hot spot* scenario to nearly the same level of criminality as that of the *random patrol* scenario (409 and 445 daily crimes, respectively).

Fig. 6 Monthly averages of crimes committed daily by users and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. The shaded area corresponds to the onset of the simulated heroin drought

A slight inflexion in the number of crimes committed over time (Fig. 6) is the only noticeable influence of the heroin drought. This moderate effect is partly due to the fact that the 'drought' takes place just after the above-mentioned glut, during its recession phase. Other reasons involve the capacity of many *users* to absorb the heroin price inflation due to already established savings (cash or drug) or to switch to the cheaper 'other drug'. Nevertheless, the inflexion period is not to be observed under *stable market* conditions, crime rates reaching a steady plateau soon after the glut (498, 417 and 397 daily crimes for *random patrol*, *hot spot* and *problem-orientated* scenarios, respectively).

Monthly aborted crimes

The effectiveness of the simulated policing interventions can also be assessed by examining the number of aborted crimes (i.e. intended crimes that are aborted because of the presence of the *constables* in the neighbourhood). Figure 7 shows the monthly averages of daily aborted crimes. The *random patrol* scenario confirms its very limited impact on criminal activities, compared with the other two strategies, with only 90 aborted crimes by the end of the simulation. By comparison, the *hotspot* scenario is 2.7-times more effective, with nearly 240 aborted crimes. Interestingly, the problem-orientated policing scenario leads to an average of 156 aborted crimes. On closer inspection, we note that the higher proportion of *users* undertaking treatment limits the number of *users* intending to commit a crime. Indeed, the ratio of aborted crimes to committed crimes does not express any significant variation between *hot spot* and *problem-orientated* scenarios (62% and 56%, respectively).

Prevalence of heroin use

Initially, nearly 90% of *users* are able to score their drug of choice—heroin— independently of police intervention scenarios. While *random patrol* and *hot-spot*

Fig. 7 Monthly averages of daily aborted crimes and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. The shaded area corresponds to the onset of the simulated heroin drought

scenarios slowly adjust to the initial conditions of the supply market (80% heroin and 20% ‘other drug’), the *problem-orientated* scenario experiences a sharp drop to 65% of consumption (Fig. 8). Again, this is a direct consequence of the large number of *users* undertaking treatment at that time. The onset of the heroin drought corresponds to a significant decrease in heroin use across the different scenarios. March 2001 corresponds to the lowest point of heroin availability (35%) but it takes nearly 5 months for the *problem-orientated* scenario to reach an equivalent percentage of heroin use, as a consequence of the heroin stocks held by *wholesalers* and *dealers*. Interestingly, the *random patrol* scenario retains a significantly higher rate of heroin consumption (44%), after the drought, as a consequence of (1) larger numbers of crimes being committed (better affordability of heroin) and (2) faster turnover of drug stocks. As expected, under *stable market* conditions, the population of *users* displays a stable pattern of drug use (56% heroin and 44% ‘other drug’).

Monthly occurrence of overdoses

The occurrence of overdoses in SimDrugDrought is a consequence of complex interactions between market conditions, prevalence of crimes and treatment efficiency. Figure 9 shows no statistically significant differences ($P=0.05$) between the three scenarios, due to the limited number of occurrences (between ten and 40 overdoses per month). The *problem-orientated* scenario seems to perform best though. The initial decrease in the number of overdoses matches the early trends in heroin use (Fig. 8). The onset of the heroin drought triggers a second phase of overdose decline across the different scenarios, reaching, in March 2001, the following monthly values: 17, 20 and 24 for *problem-orientated*, *hot spot* and *random patrol* scenarios, respectively. Again, under *stable market* conditions the three scenarios display stable patterns of occurrences much earlier during the simulation, without statistically significant differences between scenarios. These

Fig. 8 Prevalence of heroin use among agents (as a percentage) and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. The shaded area corresponds to the onset of the simulated heroin drought

Fig. 9 Monthly occurrence of overdoses among users and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. The shaded area corresponds to the onset of the simulated heroin drought

findings confirm that, if a constant number of users and dealers in the system are assumed, police intervention scenarios have a very limited impact on the occurrence of overdoses, due to the interplay of many different factors.

Spatial evolution of conducive clusters

Figure 10 shows an example of the visualization grid at the end of a simulation (*hot spot* scenario, one simulation only). Under the influence of drug dealing, criminal activities and police interventions, *conductive* cells tend to aggregate into dynamic *conductive clusters* that can be interpreted as computer metaphors for actual problematic suburbs. Tracking the footprints of these clusters becomes a challenging objective under our stochastic and comparative approach. Our *cluster density* (C_d) variable tries to encapsulate as much information as possible into a rather simple indicator:

$$C_d = \left(\sum_i \sum_j C_i \cdot c_{ij} \right) / \left(\sum_i C_i \right) \quad (2)$$

with:

C_i the number of clusters of class i with $i=1, 2 \dots 7$.

c_{ij} the number of cells belonging to cluster j of class i

We have defined seven classes of clusters according to their number of cells: class 1 (one cell), class 2 (two to ten cells), class 3 (11 to 50 cells), class 4 (51 to 100 cells), class 5 (101 to 200 cells), class 6 (201 to 500 cells) and class 7 (501 to 1,000 cells). At each time step, we store the distribution of clusters and cells, then, we calculate the average value of C_d and its standard deviation over 100 repetitions of the same scenario. Figure 11 shows the evolution of cluster densities for the three policing intervention scenarios. Variations across scenarios are highly significant ($P=0.05$)

Fig. 10 Visualization grid at the end of the simulation (*hot spot* scenario). *Black dots* indicate cells conducive to illicit drug activities clustered into ‘hot spots’. *Areas with different shades of grey* correspond to distinct suburbs

over the entire simulated period. The *random patrol* scenario generates the highest densities, with a final value of 27, corresponding to a topology where one giant cluster (more than 600 cells) is mostly surrounded by isolated unit clusters (one cell). The *problem-orientated* scenario ends up with the lowest densities and a final value of 17. It corresponds to a topology where two massive (class 6) clusters are surrounded by smaller or unit clusters (classes 1, 3 and 4). The *hot spot* scenario displays intermediate densities, with a final value of 22. The corresponding topology displays a fluctuating behaviour, regularly switching from one giant cluster to more distributed configurations.

Under the *random patrol* scenario, it appears that *constables* are not able to control the evolution of the first massive cluster forming in the early phase of the

Fig. 11 Evolution of cluster densities and associated standard deviations for three different law enforcement strategies. There were 100 repetitions and a daily time step, simulated over a 36-month period. *The shaded area* corresponds to the onset of the simulated heroin drought

simulation. Conversely, the *problem-orientated* scenario depicts a situation whereby the first massive cluster is maintained at a reasonable size and dealers regularly try to settle in new and smaller clusters, analogous to the spatial displacement phenomenon. The *hot spot* scenario displays a kind of punctuated equilibrium, whereby giant clusters are able to form before being dispersed by police crackdowns. Again, these evolving but resilient patterns exist because of the 'open-system' configuration of our model (i.e. replacement of removed *dealers* and *users*).

Conclusion

Our paper describes an agent-based simulation model that explores the relative impact of three law enforcement strategies—random patrol, hot-spot policing and problem-orientated policing—on a street-level drug market. We simulated an 'external shock' disrupting the macro-level heroin supply chain by using data sets covering the period of the 'heroin drought' in Melbourne between 1999 and 2001. In essence, we used SimDrugDrought to simulate an artificial crime experiment, studying the way our three policing intervention scenarios had an impact on market dynamics, in response to this external shock. We examined the impact of our three scenarios on several outcome variables, including (1) number of arrested *dealers*, (2) number of *users* under treatment, (3) number of committed crimes, (4) number of aborted crimes, (5) prevalence of heroin use, (6) occurrence of overdoses and (7) spatial evolution of *conductive* clusters. Our depiction of the naturally occurring experiment was compared with stable market conditions described in a previous paper (Dray et al. 2008).

Within the limits of our experimental conditions, three findings emerged from our research:

- (1) Street-level policing interventions not only disrupted criminal activities to various degrees, but also influenced other aspects of drug market dynamics, such as individual or social harm.
- (2) If the overall availability of illicit drugs remained constant, external market fluctuations had a limited impact on relative responses to street-level interventions.
- (3) Street-level interventions were more likely to disrupt local markets and illicit drug use than were macro-level interdiction efforts.

First, the *problem-orientated* scenario not only succeeds in obtaining the highest percentage of arrested *dealers* and the lowest percentage of committed crimes, but it also has a significant impact on the prevalence of heroin use, the percentage of *users* undertaking treatment and the spatial extension of *conductive clusters*. Except for the occurrence of overdoses, the *problem-orientated* scenario displays statistically significant ($P=0.05$) differences from the *random patrol* scenario over the 36-month simulated period. The *hot spot* scenario demonstrates the same ability to disrupt criminal activities (arrested *dealers* and committed crimes) but fails to minimize individual harm (percentage of *users* under treatment) or social harm (cluster density) in the same proportions. Partnership between *constables* and *outreach workers* also allows a better allocation of policing forces: to maintain the same level

of committed crimes, the hot spot scenario needs 1.8-times as many interventions to deter ill-intentioned *users* (aborted crimes).

Secondly, the relative responses to the three policing intervention scenarios simulated with SimDrugDrought confirm most of the results previously recorded under *stable market* conditions (Dray et al. 2008). Hence, supply-chain disruptions resulting only in displacements from one illicit drug to another have little chance of critically modifying street-level responses to local interventions. Once again, this conclusion holds within the limits of our experimental conditions, including: (1) a constant global offer of illicit drugs and (2) a stable structure of criminal networks, regardless of the types of illicit drug available on the street markets. Although the simulated ‘heroin drought’ did not modify the relative advantages of the different policing interventions, it often influenced the rates at which one response variable evolved over time. This was particularly the case for the prevalence of heroin use, the occurrence of overdoses and, to a more limited extent, the committed and aborted crimes.

Finally, our findings suggest that a macro-level interdiction effort that results only (directly or indirectly) in a market displacement, whereby one type of illicit drug replaces another one, has hardly any chance to disrupt street-level markets so long as the overall offer or the supply chain is not durably affected. By comparison, problem-orientated policing interventions are more likely to disrupt street-level markets effectively.

From a theoretical perspective, these results are consistent with new research that revisits the importance of the community setting of street-level drug markets (Rengert et al. 2005). Mazerolle et al. (2006), in their systematic review of street-level drug law enforcement, conclude that further research is needed to examine the differential impacts of different policing approaches on different types of drug markets. The results presented in this paper, however, suggests that the dynamics of street-level drug markets are probably better explained by characteristics of the community setting, as described by Rengert et al. (2005), than by the characteristics of the illicit drug market itself. In this context, computer simulations, as suggested by Liu and Eck (2008), have much to offer to help us explore the complex interplay of criminal activities, police interventions and community responses. SimDrugDrought is just another link in a long chain of attempts to understand this complexity better, from drug initiation (Agar 2005) to geography of crime (Brantingham and Brantingham 2004).

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