A small area analysis estimating the prevalence of addiction to opioids in Barcelona, 1993

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Abstract

Study objective—To determine the distribution of opioid use prevalence in small areas and its relation with socioeconomic indicators.

Design—Capture-recapture was applied using data from the Barcelona Drug Information System for 1993 (treatment demands, hospital emergency room visits, deaths from heroin acute adverse reaction and pre-trial prison admissions). To avoid dependence between sources, a log-linear regression model with interactions was fitted. For small neighbourhoods, where capture-recapture estimates were not obtainable, the Heroin Problem Index (HPI) was used to predict prevalence rates from a regression model. The correlation between estimated opioid use prevalence by neighbourhoods and their socioeconomic level was computed.

Main results—The city’s estimated prevalence was 12.9 opioid addicts per 1000 inhabitants aged 15 to 44 years (95% CI: 10.1, 17.2), which represents 9176 persons. The highest rate was found in the inner city neighbourhood. Comparing rates obtained for each neighbourhood with their unemployment rates, a high correlation coefficient was obtained (r = 0.80, p < 0.001).

Conclusion—The main contribution of this study is that of combining capture-recapture with the HPI to produce small area prevalence estimates, which would not have been possible using only one method. Areas with higher socioeconomic status showed proportionally low addiction prevalences, but in depressed areas, prevalences varied widely.

In recent years opioid consumption has been a cause of great concern because of its sociosanitary repercussions, in particular health problems (acquired immunodeficiency syndrome (AIDS), tuberculosis, hepatitis, etc) and the anti-social behaviour associated with it. Measuring the scope of this problem by gathering data regarding its spread and distribution is one of the most important steps towards evaluating and solving it.

The city of Barcelona has developed the Barcelona Drug Information System (SIDB), which in conjunction with the State Information System on Drug Abuse (SEIT), monitors various indirect indicators, such as drug treatment demands, deaths from acute adverse reaction to drugs, non-fatal drug related emergency room episodes, etc. Analysis of the system’s data shows that in recent years the spread of drug use, especially intravenous drug use, has been considerable in Barcelona; drug related deaths have become one of the main causes of premature death. Intravenous drug users are the group at greatest risk for contracting AIDS and tuberculosis is the first AIDS defining disease. Similar patterns have been seen in several other cities and industrialised countries.

Studies measuring the prevalence of drug abuse done in other communities have proposed various methods, which can be classified as direct or indirect. There are basically two direct methods: identification of cases in existing registers, and population surveys. The most important indirect methods include: inference methods, nominative techniques, and the capture-recapture method with indirect indicators. None of these allow us to make accurate estimates of prevalence, and all have their limitations. As often happens in social research, there is no ideal instrument of measurement. However, the capture-recapture method, using more than two sources, seems to be one of the most adequate.

Previous studies in Barcelona show that drug addiction is unevenly distributed across the city. With a single indirect indicator used for analysis, this non-homogeneous distribution is highly related to socioeconomic indicators of poverty, as well as to other contributing social factors, also recorded in other developed countries. Besides poverty itself, the crumbling of the traditional infrastructure that once provided a social safety net, the forced migration, a lack of facilities that promote social awareness among the young, and other factors such as unemployment, insufficient education, and a sense of solitude and distrust aggrivated by the physical surroundings in which many people live, are all byproducts of this decomposition.

To ascertain the extent and territorial distribution of regular opioid consumption in Barcelona, we have used the capture-recapture method to estimate prevalence. Our aims were to determine the distribution according to small areas (districts and neighbourhoods), and to establish the degree of correlation between socioeconomic indicators and opioid consumption.

Methods

The main data source for the study was the SIDB for the year 1993. It included treatment demands, hospital emergency room data, and...
Table 1 Patient distribution according to age and sex in indicator sources. (Barcelona 1993)

<table>
<thead>
<tr>
<th>Population age (y)</th>
<th>E* yes</th>
<th>E no</th>
<th>P yes</th>
<th>P no</th>
<th>M yes</th>
<th>M no</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barcelona total</td>
<td>0</td>
<td>19</td>
<td>0</td>
<td>157</td>
<td>0</td>
<td>771</td>
</tr>
<tr>
<td>Young men (15–29)</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>58</td>
<td>0</td>
<td>368</td>
</tr>
<tr>
<td>Young women (15–29)</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>45</td>
<td>0</td>
<td>138</td>
</tr>
<tr>
<td>Older men (30–44)</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>46</td>
<td>0</td>
<td>205</td>
</tr>
<tr>
<td>Older women (30–44)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>58</td>
</tr>
</tbody>
</table>

†Age of one man and one woman not known from emergency room files. We assumed they were 15–44 years old, because it is the most frequently attended group.

Table 2 Distribution of number of addicts estimated from emergencies, treatment, and prison; rates according to sex and age group. (Barcelona 1993)

<table>
<thead>
<tr>
<th>Population age (y)</th>
<th>Indicator sources</th>
<th>Number found</th>
<th>Interactions</th>
<th>Deviance</th>
<th>Degrees of freedom</th>
<th>Missing cases (95% CI)</th>
<th>Estimated total cases (95% CI)</th>
<th>Prevalence rates per 1000 inhabitants (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barcelona total (15–44)</td>
<td>ETP*</td>
<td>2227*</td>
<td>E.T + E.P</td>
<td>0.945</td>
<td>1</td>
<td>6494 (4961, 9995)</td>
<td>9176 (7188, 12222)</td>
<td>12.9 (10.1, 17.2)</td>
</tr>
<tr>
<td>Total men (15–44)</td>
<td>ETP</td>
<td>1641</td>
<td>E.T + E.P</td>
<td>0.65</td>
<td>1</td>
<td>6081 (4069, 9475)</td>
<td>7722 (5710, 11116)</td>
<td>21.9 (16.2, 31.5)</td>
</tr>
<tr>
<td>Total women (15–44)</td>
<td>ETP</td>
<td>586</td>
<td>E.P</td>
<td>0.60</td>
<td>1</td>
<td>897 (669, 1209)</td>
<td>1483 (1255, 1795)</td>
<td>4.2 (3.5, 5.0)</td>
</tr>
<tr>
<td>Young men (15–29)</td>
<td>ETP</td>
<td>1021</td>
<td>E.T + E.P</td>
<td>0.00</td>
<td>1</td>
<td>3993 (2402, 7161)</td>
<td>5014 (3423, 8182)</td>
<td>25.9 (17.7, 42.2)</td>
</tr>
<tr>
<td>Young women (15–29)</td>
<td>ETP</td>
<td>403</td>
<td>E.P</td>
<td>0.74</td>
<td>2</td>
<td>475 (337, 669)</td>
<td>878 (740, 1072)</td>
<td>4.7 (3.9, 5.7)</td>
</tr>
<tr>
<td>Older men (30–44)</td>
<td>ETP</td>
<td>619</td>
<td>E.T + E.P</td>
<td>1.84</td>
<td>3</td>
<td>2066 (1105, 4303)</td>
<td>2685 (1724, 4922)</td>
<td>16.9 (10.8, 30.9)</td>
</tr>
<tr>
<td>Older women (30–44)</td>
<td>ETP</td>
<td>182</td>
<td>—</td>
<td>1.78</td>
<td>3</td>
<td>546 (314, 996)</td>
<td>728 (496, 1178)</td>
<td>4.3 (2.9, 6.9)</td>
</tr>
</tbody>
</table>

estimation in neighbourhoods, the smallest territorial division within the district, there were too few subjects to apply this method, so two procedures were combined. Firstly, for each of the neighbourhoods the Heroin Problem Index (HPI)\(^2\) was calculated. This was achieved by ranking all neighbouring groups, from low to high, for each of the components of the index (specific neighbourhood rates for four capture-recapture sources: emergency rooms, treatment admissions, mortality and pre-trial admissions) and assigning a rank score accordingly. The component rank scores were then summed by neighbourhood, giving the HPI for each of them. Then, for those neighbourhoods for which we had high enough numbers (did not have any empty cell, except the unknown one) to compute capture-recapture, neighbourhood prevalence was estimated. Finally, using these neighbourhood prevalence estimates as anchor points, we fitted a regression model relating prevalence rates to HPI. Hence, the remaining neighbourhood rates were taken to be the fitted regression values for prevalence dependent on HPI. For clarity of expression, we shall refer to the rates estimated from the capture-recapture model as being “estimated rates” and those derived from the regression model (RM) as being “RM fitted rates”.

Prevalence rates were estimated using the resident population, between the ages of 15 and 44, for the year 1991. Unemployment and illiteracy rates for this age range, obtained from the 1991 census survey interviews,\(^3\) were the socioeconomic level indicators used. Correlation between estimated prevalence by neighbourhoods and their socioeconomic level was carried out by means of Spearman correlation coefficient statistics.

### Results

Our sample consisted of 2310 people, 1077 of whom came from the treatment demand indicator (T); 1033 from the emergency room indicator (ER); 425 from pre-trial prison admissions (P); and 119 from the mortality register (M). Table 1 shows the frequency distributions by source and the degree of overlap among registers.

Samples were compared two by two using the formula derived by Chapman.\(^4\) The estimates for the whole group ranged between 5000 and 8000 people, depending on the sources analysed. The estimates from two logistic Poisson regression models for every age and gender strata were compared, one based on three sources (ER; T; P) (table 2) and the other with a fourth additional source (M) (table 3). For both models, interactions between the sources were modelled so as to account for any dependence between samples. Both resulted in similar estimates, however those from the “four-source” model were less stable, as there were empty cells in different strata.

As table 2 shows, the city’s estimated prevalence rate was 12.9 opioid addicts per 1000 inhabitants between the ages of 15 and 44 years (95%CI 10.1, 17.2), which is derived from the estimated total of 9176 persons in this age group addicted to opioids in Barcelona. Rates were not distributed uniformly, either between sexes or age groups. Men were the most affected, particularly young men. Adding up the estimated rates separately for each sex and for different age groups, we see that the result is similar to the city’s overall estimate.

Patients included in the indicator sources were only 24.3 per cent of the total estimated. A similar figure was obtained for men alone (21.3
per cent). In the case of women the source indicators found 39.5 per cent of the total. By age groups, no differences were seen, with the figure remaining around 21 per cent, except for young women, where it was 45.9 per cent. Emergency room files report 11.3 per cent of the total cases; treatment initiation, 11.7 per cent; and pre-trial prison admissions, only 4.6 per cent.

Applying log-linear models to residence area (table 4), we found the highest prevalence rate in Ciutat Vella, the inner city, where the rate was three times as high as the city as a whole. Next came Nou Barris with a rate more than two thirds lower. However, totalling the estimates for each of the areas did not equal the city total. This fact is probably because of small numbers of subjects in each area not allowing dependence between sources to be introduced in all of them.

When relating estimated prevalence rates for the six neighbourhoods used as anchor points with their HPI, the following RM was obtained: Neighbourhood prevalence rate = e(2.2552−0.02586×HPI + 0.00025079×HPI²).

This function fitted the data well (r² = 98.6); simpler functions either did not give good fit or produced unrealistic shapes. Applying this curve we were able to estimate the prevalence rate for the remaining neighbourhoods (fig 1).

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**Figure 1** Heroin Problem Index and opioid addiction prevalence rates obtained with regression model by neighbourhood. Anchor point characteristics from some neighbourhoods. Barcelona 1993.

**Figure 2** Distribution of fitted prevalence rates for opioid addiction by neighbourhood obtained from regression model. HPI values for each neighbourhood and anchor points. Barcelona 1993.
From the above formula fitted well to the intermediate anchor points. But at the upper extreme (maximum rates), RM underestimated the value found with the capture-recapture methods, while in the lower end the curve had a tendency to rise (fig 1). Therefore, in the lower HPI distribution we assumed that there were no differences between neighbourhoods, and all of them were subsequently assigned an estimated prevalence rate of 4.9 per 1000 inhabitants, the lowest anchor point calculated by the capture-recapture method. These RM fitted rates show a level of heterogeneity not seen in the distribution by district (fig 2), showing nine neighbourhoods with rates greater than the average for all Barcelona.

Comparing prevalence rates obtained using the above procedure with the unemployment rates for people aged from 15–44 years in each neighbourhood (fig 3), we observed a high correlation ($r = 0.80, n = 38, p < 0.0001$). A similar figure was obtained when unemployment rates were substituted by illiteracy for the same age group.

**Discussion**

We believe that one of this study’s main contributions is the combining of analyses to estimate prevalences in small areas. To estimate the population in a small stratum where capture-recapture cannot be applied is one of the most important challenges in this field. Combining the capture-recapture method with HPI, a methodology previously unused, allowed us to make estimates that would not have been possible by using only one method. This technique gave us a numeric estimation, an advantage over the HPI, which affords only a ranking order. With this estimation, the difference between numbers of addicts per neighbourhood may be appreciated. In public health, knowing the approximate number of patients affected by disease is very important in designing resources for planning, intervention and evaluation. Here lies the importance of this study, which demonstrates how such prevalence rates can be estimated when no other method is available.

Before discussing the results, study limitations, such as the lack of specificity of some indicators, must be considered. In relation to disease definition, in the emergency room source the patient himself declared whether or not he had consumed an opioid. A previous study revealed that 92 per cent of these patients tested positive for the substance they claimed to have taken. In treatment and prison we can assume the specificity of case definition because a physician had carried out a detailed examination. Another limitation is the violation of the assumption of capture homogeneity. As some authors have pointed out, we may have fallen short in the capture of habitual consumers from the upper social classes as well as those whose opioid use is less problematic. Patients who attended emergency rooms or treatment had an average length of consumption of seven years; therefore, short-term consumers are less likely to be counted among our sources. Although both the emergency room and prison sources are likely to be more sensitive to these cases the study may underestimate the real prevalence, and may reflect more the prevalence of problematic long term opioid use.

Although with log-linear regression models we try to control source dependence by including all significant interactions into the model, small capture samples may preclude the inclusion of interaction terms. This was the case for district estimates where not including interaction terms controlling for positive dependence led to an underestimate for most of them, reflected in the discrepancy between the estimate for Barcelona and the sum of district estimates. However, to force interactions into the model may lead to a lack of precision in the estimated interaction coefficient, and in turn this affects the constant value from which the estimate for the unknown cell is derived. Attempting to build a saturated model, as Hook and Regal propose, always produces very wide confidence intervals and it may even be impossible to achieve a stable model. A measure to eliminate temporal dependence between sources was to collect data at different time periods, for example, prison and treatment.

When calculating prevalence rates as “RM fitted” for those neighbourhoods with small numbers, we have another limitation as all RM...
fitted rates are based on six anchor points with their estimated prevalence. However, as those anchor points covered a large range of HPI scores, interpolation of data was feasible. Nevertheless, the use of a small area analysis in the estimation of prevalence is a better alternative in this context, as is the methodological framework we present here in the paper. 

The results obtained confirm that HPI is a good estimator of the true prevalence of opioid addicts in the area, as is the methodological framework we present here in the paper.

Thanks to the small area analysis, we were able to pinpoint where opioid consumption is most rampant and destructive. Viewing these small areas in relation to socioeconomic indicators, we find that all the small areas with higher socioeconomic status show proportionally low addiction prevalences. On the other hand, among the most depressed areas, prevalences vary widely. Perhaps the factor explaining this variability lies among “group context variables”, as the interaction among people in the community affects the transmission of beliefs, behaviours and values. This phenomenon, described in the study of contagious diseases, may be applicable to health-related behaviours. Where social learning plays an important part, as in the case of opioid addiction. Perhaps for addiction the behaviour of the individual person is not independent of that of others, and some kind of synergism occurs in the group. This may explain why in neighbourhoods with similarly high unemployment rate prevalences vary considerably, and these differences have been widening over recent years.

Another explanation could be that while poverty and deprivation are major risk factors for drug use in a community, a firm social structure may act as a buffer. Although difficult to measure, this concept may be represented by what has been called social capital, that is, the organizational capacity of a society to act as a self-regulator. In fact, some authors have reported that informal social control and cohesion are good indicators to predict lower rates of violence.

A third possible explanation is the so called social disintegration, by which a whole area finds itself on the margin of society because a small number of people within that area have undergone a process of marginalization. This leads to the development of the phenomenon known as “inner city”. We think that all three of these explanations are interrelated, making it impossible to determine which causes another.

This type of research is of particular interest for resource allocation, management and policy making. Along this line, we point out that addicts from prison may not be included in health services registers, leading to the observation that this group should be taken into account when resources are distributed. Small area analysis of addiction prevalence helps us to set such priorities in the field of prevention as well as in the management of this chronic illness.


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