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Research Paper

Estimating the size of crack cocaine users in France: Methods for an elusive population with high heterogeneity

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ABSTRACT

Background: Despite several sources corroborating an expanding market and increased visibility and greater diversity in users' profiles, very little is known about the number of crack cocaine users in France.
Method: The estimates rely on a single data source capture–recapture method. Annual data are extracted from treatment centres nationwide. To account for heterogeneity, we use an innovative zero-truncated geometric, regression-based estimator controlling for individual and centre characteristics. We use the well-known Zelterman estimator as a benchmark.
Results: The number of crack cocaine users received in treatment centres increased dramatically, from 3388 in 2010 to 5143 in 2017 (+52%). The estimated number of crack cocaine users is believed to have tripled over the course of the same period (from 9775, 95% CI [8288–11530] to 28983 [24876–33766], respectively), with prevalences below 1‰, similar to other European countries. The coverage rate (observed number/estimated number of users) decreased in a similar fashion, indicating lower utilization. In particular, females and younger users are underestimated by data from treatment centres.
Conclusion: The prevalence of crack cocaine use is fairly low but steadily increasing. The diversity in users' profiles is a challenge to prevention and public health policies that should expand their scope to a more inclusive perspective of what defines crack cocaine users. Our method overcomes several methodological issues (data sources, data linkage, heterogeneity) and can be easily applied to a wide range of settings.

Introduction

Since the beginning of the century, there has been persistent to growing concern about crack cocaine use in several European countries (EMCDDA, 2001, 2007). Recent evidence suggests that the availability of crack cocaine has increased (EMCDDA, 2018), with significantly increasing prevalence rates (EMCDDA, 2019; Hay, Rael dos Santos, Reed, & Hope, 2019), giving way to concern of a new epidemic. Crack cocaine use has long been associated with severe adverse socio-economic conditions (Fischer et al., 2015; Gonçalves & Nappo, 2015; Palamar, Davies, Ompad, Cleland, & Weitzman, 2015; Santos Cruz et al., 2013; Valdez, Kaplan, Nowotny, Natera-Rey, & Cepeda, 2015) and serious psychological and physical health outcomes, including respiratory damage and consequent infection (Self, Shah, March, & Sands, 2017; Story, Bothamley, & Hayward, 2008), the transmission of hepatitis C and other blood-borne diseases, and facilitation of the transmission of HIV through risky sexual behaviours (Prangnell et al., 2017; Werb et al., 2010).

First introduced in France in the early 1980s, crack cocaine use has long been restricted to the most disadvantaged street users living in extremely adverse conditions in Paris (Pfau & Cadet-Taïrou, 2018). However, in recent years, converging testimonies (ethnographical studies, on-site workers committed to hard-to-reach populations, focus groups, activity reports) suggest changes are occurring. First, use of crack cocaine appears to have increased in the past decade, coinciding with an expanding market (Gandilhon, Cadet-Taïrou, & Lahaie, 2013). Interestingly, this expansion has been accompanied by a diversification in the profiles of users: in addition to users from the Caribbean and western Africa, known to smoke cocaine, Eastern European migrants have gained visibility recently (Pfau & Cadet-Taïrou, 2018). These emergent users are known to inject crack, an infrequent behaviour previously documented among crack users in other countries (Barrio, De la Fuente, Royuela, Díaz, & Rodríguez-Artalejo, 1998; Leonard et al., 2008; Roy et al., 2013; Santibanez et al., 2005). Moreover, the diffusion of crack cocaine resulted in a more economically and socially integrated clientele, whom alternate between cocaine

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hydrochloride and other stimulants (Cadet-Taïrou, Gandilhon, Martinez, Milhet, & Néfau, 2017). As a consequence, crack cocaine use has appeared in remote areas recently, away from the original Parisian market, with samples of unprecedented purity levels more frequently reported (Gérome et al., 2018).

Given these shifts, updated information on the number of users is needed to forecast potential need for treatment, as well as to provide a key element in establishing and guiding prevention policies (Frisher, Heatlie, & Hickman, 2006; Jones et al., 2016). Prevalence of illicit substances use is also needed to help measure the dynamics of drug markets and provide a realistic basis upon which to measure the social cost of drug problems. But very little is known regarding the number of crack cocaine users in France. Crack cocaine users were thought to be 15,400 (95% credible interval = 11,400–20,000) in 2011 (Janssen, 2013). Almost ten years have passed and there is an acute need for updated information. Unfortunately, the illicit nature of their activities and its related social disapproval hinder any attempt of a direct count of crack cocaine users: a significant number of them escape traditional sampling techniques, as used in general population surveys. In addition to the population actually observed (i.e. the population sampled or that appears in registers), there is a hidden population whose size must be estimated (Pérez, Cruyff, Benschop, & Korf, 2013). Indirect methods may provide realistic figures.

In that perspective, capture–recapture using several data sources has gained interest in the past decades (King, Bird, Overstall, Hay, & Hutchinson, 2013, 2014). However, strong legal restrictions protecting the anonymity of illicit substance users in France hinder any attempt of data linkage across multiple data sources. Thus, the restriction to a single data source constitutes a plausible alternative to obtain updated figures and prevalence. This study will attempt to provide reliable quantitative estimates of the number of crack cocaine users through an innovative capture–recapture method, taking into account its relatively moderate size and greater heterogeneity. It relies on a dataset collected within treatment centres. Extrapolating data from treatment centres is a common procedure to estimate prevalence of sub-groups of illicit substance users, whom are by essence elusive (Pérez et al., 2013; Simeone, Nottingham, & Holland, 1993). To extend the analysis, this study also provides for the first time estimates of crack cocaine users broken down by age, gender and geographical unit.

Method

Data

Each year, the French Monitoring Centre on Drugs and Drug Addictions (OFDT) produces an updated compendium on addictions and treatments (*Recueil commun sur les addictions et les prises en charge*—RECAP), carried out at the national level. Following the European protocol for registering treatment demands, one of the European Monitoring Centre on Drugs and Drug Addictions (EMCDDA)'s key indicators, all treatment centres are requested to provide data on clients admitted during a full calendar year. Treatment centres in France are publicly funded, medically-oriented entities located within each of the 96 *départements* (a sub-regional administrative areas). They provide free access to all individuals seeking treatment for addiction, both to licit and illicit substances, regardless of income or age, and aim at a complete cessation of substance use.

Until 2010, alcohol disorders and illicit substance misuses were treated separately, each in devoted premises. In 2011, the Social security released a unified protocol stipulating that all treatment centres were to provide attention to substance users, regardless of the nature of the substance involved. Treatment centres provide outpatient (including in-prison) and inpatient services. Both medication-assisted treatments, such as methadone maintenance and buprenorphine prescription, and psychosocial treatment are provided. To date, there is no standardized protocol toward crack cocaine users in France. Specific procedures, including psychiatric assessment, medication to reduce craving and related angst (benzodiazepine, anti-psychotic), behavioural therapy, motivational interviewing techniques, psycho-social guidance, are highly treatment centre-dependent. Overall, the number of individuals in RECAP is fairly high (more than 200,000 patients in 2017), and provides sufficient sample size to analyse the characteristics of certain sub-groups of patients. The survey has gained approval of the National Data Protection Authority.

Case definition

The paper focuses on all clients serviced in treatment centres in France between 2010 and 2017 (with the exception of 2014 in which data is unavailable due to a change in coding procedures). The face-to-face, standardized questionnaire includes information on substance use, health and sociodemographic characteristics. Any positive response to the relevant questions for crack cocaine (having used crack cocaine or stated they had smoked cocaine during the past month) classifies a patient as a crack cocaine user. Following the EMCDDA standard procedures, the population study was restricted to individuals aged 15–64 years old (Thanki & Vicente, 2013).

In order to preserve confidentiality, all clients are provided a unique identifier excluding any reference to their name or surname. While an automated software procedure allows linkage across visits at the treatment centres in order to update information each time a contact is made, the lack of a standard identifier procedure at the national level precludes linking to other external data sources. Treatment centres are also requested to provide information on the type of contact each individual establishes with the structure: first demand, uninterrupted treatment follow-up, and readmission. Readmission is defined as no contact with the referral centre for at least 6 months and labelled as a new contact with the treatment centre, in which case individuals are assumed to be recorded twice (Galai, Safaeian, Boltin, & Celetano, 2003; Genberg et al., 2011; Janssen, 2018).

Statistical analysis

Capture–recapture (CR) is a common, reliable procedure to provide realistic figures when a specific population escapes full coverage and is only partially observed (Bishop, Fienberg, & Holland, 1975; Hook & Regal, 1995). CR consists in capturing a sample of individuals. Marked individuals are released, some of whom are recaptured in another sample. Following a number of assumptions (demographic closure (i.e., no births, deaths, immigration, or emigration), perfect identification of the recorded individuals, no misdiagnosis (correct case definition), perfect data linkage, homogeneity (equal sampling probabilities)), the size of the unobserved population can then be estimated from the number of marked individuals recaptured. However, there are reasons to believe these assumptions can be violated; we describe how we overcome many of them, with a particular focus on homogeneity.

We describe the statistical theory briefly here, referring readers to the Statistical Appendix for full derivation. The estimated number of unobserved individuals is summed with those observed to form the total size of a given population, approximated by the general Mantel-Haenszel formula: $\hat{n} = n + n_0 = n/1 - p_0$. That is, $\hat{n}$ defines a population whose size is to be estimated; n is the observed/recorded population, where $n = \sum_{i=1}^{x} f_1 + f_2 + \ldots + f_x$, or the sum of observed individuals recorded 1, 2,…, x times; n_0 is the invisible population, that is, unrecorded individuals whose number is to be determined; and p_0 is the proportion of the population that is invisible. More recently, indicators and estimators of $\hat{n}$ based on single-data sources have gained increasing interest and visibility. Single-data sources overcome legal restrictions hampering data linkage. They also benefit from standardized procedures and methodologies. Among the many existing indicators (Bunge & Fitzpatrick, 1993; Wilson & Collins, 1992), the Zelterman indicator (Zelterman, 1988) has gained popularity in the field of drug studies for

their simplicity of calculations and robustness. It is defined as $\hat{n}_Z = n/1 - \exp(2f_2/f_1)$. Uncontrolled heterogeneity (i.e. unequal probabilities of being sampled as a consequence of the diversity of the studied population) is a violation of one of the CR fundamental theoretical assumptions, and yields severely downward biased estimates (van der Heijden, Cruts, & Cruyff, 2013). To date, accounting for high heterogeneity remains one of the major challenges in CR studies. The primary solution has been the inclusion of covariates (Böhning, van der Heijden, & Bunge, 2017). For example, the original Zelterman estimator, has been extended to a regression-based procedure by using a zero-truncated Poisson distribution and focusing only on the individuals recorded once or twice (Böhning & van der Heijden, 2009):

$$\hat{n}_Z = \sum_{i=1}^{n} \frac{1}{1 - exp(-2\hat{p}_i/(1-\hat{p}_i))} = \sum_{i=1}^{n} \frac{1}{1 - exp(-2\hat{\lambda}_i)}$$

This is known to be robust in case of mild heterogeneity. As an additional strategy, we propose the selection of an alternative theoretical distribution to better account for high unobserved heterogeneity not captured by individual characteristics. In particular, the geometric distribution has gained the attention of researchers for its ability to explicitly control for heterogeneity and its easy-to-use, robust indicators (Niwitpong, Böhning, Van der Heijden, & Holling, 2013). Similar to the extension of Zelterman's estimators, we define a regression-based geometric estimator that allows us to control for individual characteristics, based on individuals recorded once or twice only. We follow Niwitpong and colleagues' derivation of the zero-truncated geometric distribution (Niwitpong et al., 2013). We show that a general zero-truncated regression-based geometric (ZTG) estimator is (see Appendix for proof):

$$\hat{n}_G = \frac{n}{p(1-p)} \approx \sum_{i=1}^{n} \frac{1}{\hat{\lambda}_i(1-\hat{\lambda}_i)}$$

Where $\hat{p}_i$ is an (unbiased) estimate of individual probability p of being recorded once or twice, $\hat{p}_i = e^{\alpha+\beta X_i} = \hat{\lambda}_i$. In our data, we assume a right-censored geometric distribution because our empirical data collection is restricted to individuals observed once or twice. The final censored geometric regression estimator is:

$$\hat{n}_{G\_C} = n + \hat{n}_0 \approx n + \sum_{i=1}^{n} \frac{1-\hat{\lambda}_i}{\hat{\lambda}_i} = n + \sum_{i=1}^{n} \left(\frac{1}{\hat{\lambda}_i}\right) - n = \sum_{i=1}^{n} \frac{1}{\hat{\lambda}_i}.$$

This estimation allows us to control individual characteristics and account for high heterogeneity. We ran a two-level logistic regression model of individual nested in centres. We ran a full model to estimate the probability of being observed twice controlling for gender, age, access to Health insurance, last month use of opioids, of stimulants other than crack cocaine, of hallucinogenics, and the type of treatment centre (non-ambulatory facility vs ambulatory), eliminating non-significant variables in a stepwise procedure.

Results

Overall estimates are shown in Table 1. The observed number of crack cocaine users admitted to a treatment centre provides support to the diffusion of crack cocaine: the number of users dramatically increased, ranging from 3388 in 2010 to more than 5143 in 2017 (+52%). We provide figures according to the generalized Zelterman estimator ($\hat{n}_Z$), to be used as a benchmark, and estimates using the ZTG regression-based model ($\hat{n}_{G\_C}$). Here, the known downward heterogeneity-induced bias of the generalized Zelterman estimator appears explicitly, with these estimates significantly lower than the ZTG estimates in all years. The ratio of both estimators ($\hat{n}_{G\_C}/\hat{n}_Z$) increases over time, suggesting increasing heterogeneity. Following the observed peak in treatment demand for crack cocaine, 2011 appears to be a breaking point, initiating an upward trend. The estimated number of crack cocaine users is demonstrated to have tripled over time, from 9775 (95% credible interval: 8288–11,530) in 2010 to 28,983 (24,876–33,766) in 2017. Meanwhile, the coverage rate, i.e. the proportion of users in treatment ($n/\hat{n}$), experienced a dramatic decrease: it was 34% in 2010 and was cut almost by half, to less than 18% in 2017 – that is, less than one user in five.

An attractive feature of the regression-based estimates lies in their ability for decomposition, a technique unavailable for simple indicators. Estimates according to gender, age groups and region are shown in Table 2. (For full and reduced models, see Supplementary Tables A1 and A2, respectively.) Crack cocaine users are mostly males, although increasing use among females is visible, from 22.5% in 2010 to 26.4% in 2017. Age groups remain fairly stable, with 30-44 year-olds as the major category. The geographic measure yields interesting results, with considerable changes over time and increasing relative weight of the Northeast and Southwest areas, competing with Paris, the traditional market.

Coverage rates (observed vs estimated number of crack cocaine users) broken down by categories for each year considered are displayed in Table 3. From 2010 to 2013, the observed percentages are extremely similar to those estimated. However, increasing gaps show from 2015 onwards. In particular, females (21.8% observed vs 26.4% estimated in 2017) and crack cocaine users less than 30 years old (22.1% vs 27.6%) are now underrepresented in treatment centres, while users from the Paris region are overrepresented. This finding implies that treatment centres currently have less success in reaching female and younger crack cocaine users, as well as users located away from the capital city.

Table 1
Estimates of the number of crack cocaine users in France, 2010–2017.

	2010	2011	2012	2013	2015	2016	2017
Observed once	2492	3614	2499	3734	3397	3542	4176
Observed twice	896	1584	829	1018	759	810	967
Total observed (n)	3388	5198	3328	4752	4156	4352	5143
Proportion observed twice	0.264	0.305	0.206	0.214	0.183	0.186	0.188
Generalized Zelterman estimator ($\hat{n}_Z$)	6779	10,975	8276	12,858	14,942	14,410	17,309
(95% CrI)	(5964–7852)	(9308–13,137)	(6951–9974)	(10,557–15,974)	(12,289–18,322)	(12,446–16,774)	(14,555–20,811)
Censored geometric estimator ($\hat{n}_{G\_C}$)	9775	16,165	13,622	20,552	25,498	24,202	28,983
(95% CrI)	(8288–11,530)	(12,927–20,214)	(11,052–16,828)	(15,853–26,864)	(20,916–31,083)	(20,499–28,575)	(24,876–33,766)
$\hat{P}$	0.24	0.40	0.33	0.51	0.63	0.60	0.72
(95% CrI)	(0.42–0.57)	(0.64–0.98)	(0.55–0.82)	(0.79–1.31)	(1.04–1.52)	(1.02–1.39)	(1.24–1.65)
$n/\hat{n}$ – observed/estimated (full model)	0.34	0.32	0.30	0.23	0.16	0.18	0.18
$\hat{n}_{G\_C}/\hat{n}_Z$	1.46	1.47	1.65	1.60	1.71	1.68	1.67

95% CrI: 95% credible intervals, n = observed, $\hat{n}$ = estimated number, $\hat{P}$ estimated prevalence per 1000 of 15–64 years old. Source: Recap authors' calculations.

Table 2
Estimates of the number of crack cocaine users in France broken down by categories, 2010–2017.

	2010	2011	2012	2013	2015	2016	2017
Males	7575 (6422–8933)	12,666 (10,131–15,836)	10,238 (8205–12,776)	16,456 (12,695–21,511)	18,922 (15,522–23,067)	18,855 (15,970–22,261)	21,339 (17,702–25,733)
Females	2200 (1865–2595)	3513 (2810–4392)	2698 (2162–3367)	4097 (3158–5353)	6576 (5394–8016)	5339 (4522–6303)	7644 (6058–9648)
15–29 years old	3090 (2620–3644)	4624 (3698–5781)	3965 (3178–4948)	5537 (3837–7940)	5897 (4837–7188)	6680 (5658–7887)	8008 (6445–9956)
30–44 years old	5217 (4423–6153)	8677 (6940–10,849)	7047 (5647–8793)	9675 (7391–12,677)	14,137 (11,597–17,234)	13,367 (11,321–15,781)	16,060 (13,334–19,352)
45–64 years old	1469 (1245–1732)	2878 (2302–3599)	1925 (1543–2402)	5341 (4626–6247)	5463 (4482–6660)	4156 (3520–4907)	4915 (3980–6075)
Paris MR	4044 (3428–4769)	7413 (5929–9268)	5475 (4388–6832)	7486 (6002–9362)	8770 (7194–10,691)	6286 (5324–7422)	6940 (5681–8486)
Northwest	461 (391–543)	725 (580–906)	841 (674–1050)	1431 (1049–1972)	1885 (1546–2298)	2289 (1939–2703)	2896 (2374–3535)
Northeast	2320 (1967–2736)	3213 (2570–4017)	2854 (2287–3561)	5416 (4164–7104)	6128 (5027–7470)	7297 (6180–8615)	8753 (7193–10,659)
Southeast	1240 (1052–1463)	2064 (1651–2581)	1622 (1300–2024)	3007 (2205–4142)	4042 (3316–4927)	4166 (3528–4918)	5043 (4132–6159)
Southwest	1711 (1451–2019)	2765 (2211–3457)	2144 (1719–2676)	3213 (2433–4284)	4673 (3834–5697)	4165 (3528–4917)	5351 (4380–6543)
Overall	9975 (8391–11,673)	16,165 (12,927–20,214)	13,622 (11,052–16,828)	20,552 (15,853–26,864)	25,498 (20,916–31,083)	24,202 (20,499–28,575)	28,983 (24,876–33,766)

95% CrI: 95% credible intervals in parenthesis. Paris MP: Paris metropolitan region. Source: Recap, authors' calculations.

Table 3
Observed and estimated percentages of crack cocaine users according to categories, 2010–2017.

%	2010		2011		2012		2013		2015		2016		2017	
	Obs'd	Est'd	Obs'd	Est'd	Obs'd	Est'd	Obs'd	Est'd	Obs'd	Est'd	Obs'd	Est'd	Obs'd	Est'd
Males	77.6	77.5	78.3	78.3	79.4	79.1	80.0	80.1	79.7	74.2	78.4	77.9	78.2	73.6
Females	22.4	22.5	21.7	21.7	20.6	20.9	20.0	19.9	20.3	25.8	21.6	22.1	21.8	26.4
15–29 years old	31.6	31.6	28.8	28.6	27.5	30.7	8.8	26.9	22.3	23.1	23.1	27.6	22.1	27.6
30–44 years old	53.2	53.4	53.6	53.6	55.2	54.5	35.5	47.1	55.9	55.4	55.6	55.2	56.2	55.4
45–64 years old	15.2	15.0	17.7	17.8	17.3	14.9	55.7	26.0	21.8	21.4	21.3	17.2	21.8	17.0
Paris MR	42.0	41.4	45.0	45.8	43.7	42.3	42.2	36.4	34.6	34.4	28.0	26.0	25.7	23.9
Northwest	4.7	4.7	4.6	4.5	6.3	6.5	5.6	7.0	7.4	7.4	8.9	9.5	9.5	10.0
Northeast	23.0	23.7	20.4	19.9	21.6	22.1	26.1	26.4	24.9	24.0	29.5	30.1	30.6	30.2
Southeast	12.9	12.7	12.7	12.8	12.2	12.5	11.7	14.6	15.6	15.9	16.8	17.2	16.6	17.4
Southwest	17.4	17.5	17.2	17.1	16.2	16.6	14.5	15.6	17.6	18.3	16.8	17.2	17.6	18.5

Obs'd: observed percentages in treatment centers. Est'd: estimated percentages. Paris MP: Paris metropolitan region. Source: Recap, authors' calculations.

Discussion

Following in-the-field information documenting the spreading and increasing visibility of crack cocaine use in France, this paper attempted to provide reliable estimates of the number of users between 2010 and 2017. We took advantage of a nationwide, standardized survey conducted annually in treatment centres. Being an elusive population, we used a CR framework and relied on two new estimators stemming from a zero-truncated and censored geometric distribution, commonly used to address high heterogeneity. Heterogeneity here is regarded as an empirical consequence of diversity, and its impact on individual sampling probabilities. Disregarded, heterogeneity is known to induce severely downward biased figures likely to lead to faulty conclusions. It also appears that the proportion of being observed twice in the collected data is quite small, providing support for a geometric-based estimator. This method provided a formal estimation of the size of crack cocaine users at the national level.

The increasing number of last-month users documented between 2010 (9975 individuals) and 2012 (13,622) are line with a prior estimate suggesting a number of 15,000 in 2011 (Janssen, 2013). This increase has persisted ever since. The estimated number of users reached more than 28,000 individuals in 2017; that is, a tripling over a 7-year period. However, the prevalence of crack cocaine use remain below those recorded in the US (SAMHSA, 2018), the UK (Hay et al., 2019) or the Netherlands (Pérez et al., 2013). Despite gaining considerable attention, crack cocaine use in France remains modest according to epidemiological standards, in line with a trend recently observed in Europe, where use is fairly low but steadily increasing (EMCDDA, 2019). Beyond numbers, our results provide evidence of a renewal of crack cocaine users in France and highlight the issue of heterogeneity, revealing a population that is younger and with more women compared to almost a decade ago. Similar trends have been observed in the Netherlands (Pérez et al., 2013). Another feature of interest lies in the geographical location of users, with new clusters located in the Northeastern and the Southwestern areas. This change is important given the proximity of these regions to Spain, one of the most important entry points of cocaine in Europe. The significant increase of crack cocaine use occurs alongside an overall increasing popularity and availability of cocaine hydrochloride, together with increasing importation and a rise in unprecedented purity at street level (Cadet-Taïrou et al., 2017). We believe the phenomenon stems from a two-sided process involving complementary supply and demand perspectives.

The notable increase of crack cocaine users between 2010 and 2011 makes sense alongside results from field studies (Gandilhon et al., 2013). Between 2010 and 2012, the local crack cocaine market underwent considerable changes. In this period, dealers from project housing in the northern suburbs took over the crack market in Paris. They eschewed small-scale sales in favour of much more elaborate distribution networks. Simultaneously, evidence was collected on

sporadic selling points of crack in other parts of France, which attracted economically more advantaged users. These issues coincided with poor quality of street cocaine, which is thought to have driven powder cocaine users toward a more powerful product – crack cocaine.

From a supply perspective, crack cocaine in France is now widely available and more affordable than is powder cocaine. The increasing diffusion of crack cocaine use has expanded toward new markets, reflecting adaptive and anticipative behaviours from suppliers reminiscent of legitimate marketing strategies. Suppliers retain the most vulnerable users selling at a quarter gram, or ten-euro-bill doses. More recently, suppliers have mimicked sophisticated strategies observed for the selling of powder cocaine, including home delivery, cocaine call centres and cocaine drives to attract more well-off users (Cadet-Taïrou, Gandilhon, Martinez, & Néfau, 2015). Attenders of partying events (indoors, free and rave parties) have been explicitly targeted since the early 2000s. Moreover, crack cocaine has been located among more economically advantaged cocaine hydrochloride users (Gandilhon et al., 2013; Pfau & Cadet-Taïrou, 2018). For instance, 11% of crack cocaine users attending a treatment centre in 2010 stated they were homeless, compared to 6% in 2017. Conversely, 36% owned their housing versus 44% seven years later.

From a demand perspective, crack cocaine experimentation takes place within the escalation of a sensation-seeking process, after developing a greater tolerance to cocaine powder (Gérome et al., 2018). The stigma of using crack appears to have declined in recent years. A plausible reason is the shift of crack cocaine to self-produced freebase cocaine. The main arguments put forward by these users to justify their self-involvement in the making of the product are ease of production, distrust in the supply chain command, a will to ensure quality product and securing its availability and access (Gérome et al., 2018). They label themselves as freebasers in order to distinguish themselves from the ill-perceived marginalized crack cocaine users (Reynaud-Maurupt, 2012). Similar to crack users in Mexico City (Valdez et al., 2015), freebasers in France declare intermittent or sporadic use. They do not label their use as problematic and steer clear from treatment centres or harm reduction facilities. Contacts with these users are mostly established during harm reduction missions in outdoor settings. This self-rating may explain the low and decreasing proportions of users in treatment as suggested by the declining rate of coverage ($n/\hat{n}$). This evidence suggests that treatment centres have not been able to expand their coverage toward the growing number of users, nor to deal with the greater diversity of their drug-using and individual profiles. These shifts necessitate a strong call to expand the scope of prevention policies towards an incrementally more inclusive perspective of what defines crack cocaine users.

Despite the novelty of the study, some limitations should be acknowledged. First, heterogeneity appears as the most common violation of CR assumptions. This issue is dealt with by focusing on users recorded once or twice, the use of a geometric-based estimator and the explicit inclusion of covariates in a multilevel setting. However, the empirical hypothesis of similarity between unobserved individuals and individuals seen once cannot be tested. Second, the concept of high heterogeneity, a topic of major importance here, does not have a formal definition or cutoff. Defining the threshold depends on the researcher's assessment, which must rely on external, more objective measurement. Additional factors that were unaccounted for, such as housing and housing stability, educational level, professional activity or incomes can also influence capture probabilities, but contained many missing values and consequently were not included. By law, questions on ethnicity are banned in France, impeding any attempt to provide estimates broken down by ethnic groups. Finally, the case definition applied here does not distinguish between crack cocaine use as the primary problematic drug and other drugs used. The figures shown here refer to past-month use only; hence, they should be considered lower bound estimates.

In conclusion, this study used an original single data source capture–recapture method accounting for high heterogeneity to provide reliable estimates of the number of crack cocaine users. The procedure can be easily applied to a wide array of situations. However, we strongly suggest upon its application being guided by findings from qualitative studies that prove indispensable for the study of hard-to-reach populations. Accordingly, crack cocaine has gained greater visibility in France. It encompasses an increasing number of users with greater sociodemographic and economic diversity. Both changes in numbers and profiles represent a public health challenge and a strong call for ambitious prevention policy and investment in treatment capacities. This research has shown that treatment services need more effective ways of reaching crack cocaine users and providing treatment which meets their specific needs.

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Declaration of Competing Interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.drugpo.2019.102637.

Appendix

Capture–recapture (CR) is a common, reliable procedure to provide realistic figures when a specific population escapes full coverage and is only partially observed (Bishop et al., 1975; Hook & Regal, 1995). CR consists in capturing a sample of individuals. Marked individuals are released, some of whom are recaptured in another sample. The size of the unobserved population can then be estimated from the number of marked individuals recaptured. The estimated number of unobserved individuals is summed with those observed to form the total size of a given population, $\hat{n} = n + n_0$. A similar approach can be applied to individuals recorded in one or several files.

The size of an elusive population can be approximated by the general Mantel–Haenszel formula:

$$\hat{n} = n + n_0 = \frac{n}{1 - p_0}$$

That is, $\hat{n}$ defines a population whose size is to be estimated; n is the observed/recorded population, where $n = \sum_{i=1}^{x} f_1 + f_2 + ...+f_x$, or the sum of

observed individuals recorded 1, 2,…, x times; n_0 is the invisible population, that is, unrecorded individuals whose number is to be determined; and p_0 is the proportion of the population that is invisible. Traditional CR relies on multiple samples or sources of information. Following Leo Goodman's seminal work (Goodman, 1968), three or more sources can be easily incorporated (King, Bird, Overstall, Hay, & Hutchinson, 2014).

More recently, indicators and estimators of $\hat{n}$ based on single-data sources have gained increasing interest and visibility. Single-data sources overcome legal restrictions hampering data linkage. They also benefit from standardized procedures and methodologies. Among the many existing indicators (Bunge & Fitzpatrick, 1993; Wilson & Collins, 1992), the Zelterman indicator has gained popularity in the field of drug studies for their simplicity of calculations and robustness. It is defined as $\hat{n}_Z = n/[1 - \exp(-2f_2/f_1)]$(Zelterman, 1988). Its popular use is partly explained by the restriction made to individuals counted once or twice:

1. It relies on an empirical assumption of greater similarity of individuals recorded once or twice with unrecorded individuals, as compared with individuals recorded/observed more often.
2. Individuals recorded more than twice often present specific profiles that are likely to induce potential distortion, and therefore are to be discarded (outliers effect).
3. In practice, this restriction reaches a greater range of application. Unlike zero truncated Poisson and negative binomial, there is no need for a formal count of all events, which in practice would imply the need for continuous observation of all cases over a standardized period of time.

The aforementioned proposals provide great improvement in handling low to moderate heterogeneity. Heterogeneity results from the diversity of the population of interest, which has a direct impact on the probability of being selected/recorded. Uncontrolled heterogeneity is a violation of one of the CR fundamental theoretical assumptions, and yields severely downward biased estimates (van der Heijden et al., 2013). To date, accounting for high heterogeneity remains one of the major challenges in CR studies. Two solutions have been put forward. The first solution consists of adjusting the estimators to account for individual characteristics; that is, estimators allowing for covariates. Several refinements have been introduced enabling the use of a single data source, including covariates and estimates of the size of sub-populations (Böhning et al., 2017). Similarly, both estimators described above have been extended to a similar regression-based perspective. The Zelterman estimator uses a zero-truncated Poisson distribution and focuses only on the individuals recorded once or twice (Böhning & van der Heijden, 2009):

$$\hat{n}_Z = \sum_{i=1}^{n} \frac{1}{1 - exp(-2\hat{p}_i/(1-\hat{p}_i))} = \sum_{i=1}^{n} \frac{1}{1 - exp(-2\hat{\lambda}_i)}$$

A log-linear model with only two possible outcome categories (ones and twos) on a cross-table, estimated with a Poisson with a log-link, is the same as the logit model (Agresti, 2013). In other words, $\hat{\lambda} = e^{\alpha+\beta X'}$ and $\alpha + \beta\mathbf{X}$' is a linear predictor of the probability that an individual is observed twice according to a set of **X** independent variables. This linear predictor can be approximated by a logistic regression. The method has been extrapolated to provide reliable estimates of substance users at the national level, using multilevel modelling (Janssen, 2016, 2018).

The above-mentioned estimator is unbiased as long as heterogeneity is captured through the regression process, and is known to be robust in case of mild heterogeneity. However, unobserved heterogeneity not captured by individual characteristics remains uncontrolled for. Selection of an alternative theoretical distribution to better account for high heterogeneity represents another strategy. Recently, the geometric distribution has gained increasing interest and become a highly regarded, flexible distribution used in real life survival data. In particular, it has come to the attention of researchers for its ability to explicitly control for heterogeneity. The geometric distribution is a specific case of the negative binomial (NB) distribution (Hilbe, 2012), which can be written as:

$$\frac{\Gamma(x + 1/\theta)}{\Gamma(x+1)\Gamma(1/\theta)}\left[\frac{1}{1+\theta\mu}\right]^{1/\theta}\left[\frac{\theta\mu}{1+\theta\mu}\right]^{x}$$

The NB collapses into a Poisson distribution when the overdispersion parameter $\theta = 0$, and into a geometric distribution when $\theta = 1$. Niwitpong and colleagues used the zero-truncated geometric distribution functions to derive a family of easy-to-use, robust indicators (Niwitpong *et al.*, 2013): $n_G^* = nS/(n - S)$ where $S = \sum_{i=1}^{x} if_i$. Note that this family of indicators encompasses a revision of Chao's indicator, as well as a geometric version of the Turing indicator based on individuals observed once only (Anan, Böhning, & Maruotti, 2019). Similar to the extension of Zelterman's and Chao's estimators, the underlying idea is to define a regression-based geometric estimator allowing to control for individual characteristics, based on individuals recorded once or twice only.

The geometric random variable with parameter $0 < p < 1$ with support (1,2,…) describes the number x of Bernoulli trials needed to get one success. This form with no zero in the support, referred to as the zero truncated geometric (ZTG) distribution, is defined as:

$$P(x) = p(1-p)^{x-1}, \quad x = 1, 2...$$

That is,

$$P(x) = \frac{P(x)}{1 - p_0} = \frac{p(1-p)^x}{1 - p_0} = p(1-p)^{x-1}, \quad x = 1, 2...$$

Simple calculation yields

$$p_0 = 1 - \frac{p(1-p)^x}{p(1-p)^{x-1}} = 1 - p(1-p)$$

Plugging the latter equation in the general Mantel–Haenszel estimator yields the new estimator:

$$\hat{n}_G = \frac{n}{1 - (1 - p(1-p))} = \frac{n}{p(1-p)},$$

with success probability p yet to be estimated. Similar to the Zelterman and Chao estimators, we focus on individuals counted once or twice, thought to have greater similarity with unobserved individuals than individuals recorded more often. Hence, the probability p for $x = 1,2$ can be expressed as a function of individual characteristics by a GLM with logit link since only cases observed once or twice are considered, that is $\hat{p}_i = e^{\alpha+\beta\mathbf{X_i}} = \hat{\lambda}_i$. That

is, a general regression-based geometric estimator is:

$$\hat{n}_G = \frac{n}{p(1-p)} \approx \sum_{i=1}^{n} \frac{1}{\hat{\lambda}_i(1-\hat{\lambda}_i)}$$

Next, we assume a right-censored geometric distribution because our empirical data collection is restricted to individuals observed once or twice (or a data collection merging individuals recorded twice or more). Assuming that all counts greater than 1 are censored, i.e. $P(x=1)=p$ and $P(x>1)=\sum_{i>1}^{x} f_2 + \ldots + f_x = 1-p$, Niwitpong et al. (2013) used the ZTG log–likelihood function conditional upon n:

$$LL(p) = Sln(1-p) + n(ln(p) - ln(1-p))$$

Again $S=\sum_{i=1}^{x} if_i$, $i = 1,2,\ldots x$. They suggested a right-censored likelihood taking the form of:

$$f_1 ln(p) + (n-f_1)ln(1-p).$$

They demonstrated that the MLE of the censored estimate of p is f_1/n, yielding an estimate of n_0 defined as:

$$\hat{n}_0 = n\frac{f_1/n}{1-f_1/n}$$

This latter equation can be restated as:

$$\hat{n}_0 = n\frac{f_1/n}{1-f_1/n} = n\frac{1-f_2/n}{f_2/n}$$

That is:

$$\hat{n}_0 = \sum_{i=2} \frac{1-p_2}{p_2}$$

In order to control for individual characteristics and account for extra-heterogeneity, the probability of being observed twice or more is approximated by $\hat{p}_i = e^{\alpha+\beta x_i} = \hat{\lambda}_i$, as previously. The final censored geometric regression estimator is then:

$$\hat{n}_{G\_C} = n + \hat{n}_0 \approx n + \sum_{i=1}^{n} \frac{1-\hat{\lambda}_i}{\hat{\lambda}_i}$$

Or, in an even simpler fashion:

$$\hat{n}_{G\_C} = n + \sum_{i=1}^{n}\left(\frac{1}{\hat{\lambda}_i} - 1\right) = n + \sum_{i=1}^{n}\left(\frac{1}{\hat{\lambda}_i}\right) - n = \sum_{i=1}^{n}\frac{1}{\hat{\lambda}_i}$$

This estimation allows us to control individual characteristics and account for high heterogeneity. We ran a two-level logistic regression model of individual nested in centres. We ran a full model to estimate the probability of being observed twice controlling for gender (female versus male), age, access to Health insurance (Social security versus other benefits), last month use of opioids (yes versus no), of stimulants other than crack cocaine (yes versus no), of hallucinogenics (yes versus no), and the type of treatment centre (non-ambulatory facility vs ambulatory), eliminating non-significant variables in a stepwise procedure.

We note that a three-level model was also tested, accounting for individual, centres and regional level to better control a potential geographical heterogeneity in substance use. However, the amount of variance at this additional level is very small, with poorer goodness of fit statistics. Therefore, the more parsimonious two-level model was favoured.

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