

Policing the future, disrupting urban policy today. Predictive policing, smart city and urban policy in Memphis (TN)

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Policing the future, disrupting urban policy today. Predictive policing, smart city and urban policy in Memphis (TN)

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Abstract

Significant resources and efforts have been devoted, especially in the U.S.A., to develop predictive policing programs. Predictive policing is, at the same time, one of the drivers of the birth, and the ultimate material enactment of, the anticipatory logics that are central to the smart city discourse. Quite surprisingly, however, critical analyses of the smart city have remained divorced from critical criminology and police studies. To fill this gap, this article sets out the first critical, in-depth empirical discussion of Blue CRUSH, a predictive policing program developed in Memphis (TN, U.S.A.), where its implementation intersects long-term austerity for urban policy. The article, first, shows that there is no evidence of Blue CRUSH's capacity to prevent crime, thus adding empirical material to skepticism over the role of predictive policing as a policy solution in the first place. And, second, it argues that, rather than making crime a matter of technological solutions, predictive policing shifts the politics therein—in short, it contributes to the expansion of policing into the field of urban policy at the same time as it disrupts present police work. These takeaways allow to further the critique of the salvific promises implicit in the smart city discourse.

Keywords

Urban security; critical urban studies; crime prevention; anticipatory logics; preemption; algorithmic governance.

Introduction: from smart city to predictive policing

This article discusses the intersection between a governmental discourse, the smart city, and a governmental practice, predictive policing, that is, “the application of statistical methods to identify likely targets for police intervention (the *predictions*) to prevent crimes or solve past crimes, followed by conducting interventions against those targets” (Hunt, Saunders & Hollywood, 2014, p. iii; emphases in the original). Predictive policing, which works with the same anticipatory logics that have been shown to be crucial to the smart city discourse (White, 2016), is particularly relevant to explore and further unpack these very logics: in general, because crime control and prevention are interconnected with virtually every domain of urban policy, thus working as a synecdoche for urban policy more generally (cf. Garland, 2001; Tulumello, 2018b); and, in particular, because predictive policing makes the clash between technical “solutions” and the political nature of social “problems” (cf. Gusfield, 1981) particularly evident, allowing for a critical discussion of the rationale of technical neutrality of the smart city discourse.

Joh (2019) has recently argued that policing is “inherent” to the smart city: as cities become smarter, the practice of policing is embedded within the socio-technical infrastructure of the city. And yet, scant empirically-grounded conversation exists among, on the one hand, critiques of the smart city and its governance (found above all in urban studies and human geography), and, on the other, critiques of predictive policing (found above all in criminology, police studies and journalistic inquiry). The goal of this article is contributing to filling this gap by focusing on the *traits d’union* between the smart city discourse and predictive policing. In historical perspective, the two concepts emerged more or less at the same time during the second half of the 2000s: in 2008, IBM CEO Sam Palmisano gave his “smarter planet” speech at the Council on Foreign Relations; the same company had been working on Blue CRUSH, pioneer program of predictive policing, in Memphis since 2006, but would only start to consider crime detection and prevention a core business a few years later (cf. McNeill, 2015). In a nutshell, the development of predictive policing has been part and parcel of the birth of the smart city, at least as far as one of the key global actors

thereof is concerned. Indeed, the genealogy of both concepts is very much the same: that of longstanding attempts at making the city object of rational thinking, data calculation and control—see Townsend (2015) on cycles of urban science and Mattern (2015) on the history of the urban dashboard.

In substantive terms, two dimensions, which we are going to explore in this article, are common to the logics of the two concepts: the focus on anticipating and managing the future as a way to address present problems (cf. Anderson, 2010); and the conceptualization of urban problems as a matter of technological and technocratic solutions.

We present the first critical, in-depth study of Blue CRUSH (Crime Reduction Utilizing Statistical History), a predictive policing program developed by the Memphis Police Department (hereafter MPD) in cooperation with the University of Memphis and two corporations (IBM and local company SkyCop). We then discuss Blue CRUSH in light of the peculiar, though ordinary, policy and political context of Memphis, a city that we will show to be particularly interesting to cast light on the intersection between crime control, neoliberal governmentalities and long-term urban austerity (cf. Tulumello, 2018a). The discussion of Blue CRUSH will allow us to provide two main contributions: we will show that there is no evidence of Blue CRUSH's capacity to prevent crime, thus adding empirical material to existing skepticism over the role of predictive policing as a policy solution in the first place; and we will argue that, rather than making crime a matter of technological solutions, predictive policing shifts the politics therein—in short, it contributes to the expansion of policing in the field of urban policy at the same time as it disrupts police work. These takeaways on predictive policing, we conclude, are crucial to further the critique of the promises of the smart city discourse.

Before moving to the discussion of Blue CRUSH, in the next two sections we review the critical literature on the smart city and on predictive policing to emphasize the common focus, respectively discursive and practical, on the future; and raise the specific research questions that will guide the presentation of the case study.

Methodological notes

Our reconstruction of the case is based on a six-months period of research carried out in Memphis during a visiting period spent by Author 1 at the University of Memphis, Department of City and Regional Planning in 2016, that is, a few years after the period of maximum (political and economic) investment into Blue CRUSH (2006-2011). As we will see below, the fact that, during following years, a reducing number of sworn officials made it impossible to maintain Blue CRUSH into full operativity was considered by some of our informants to have reverted what they considered a positive trend in crime during 2006-2011. By making fieldwork in 2016, then, we were able to place both policy and crime trends in a longer context: with regard to policy, we could explore the long-term impacts of Blue CRUSH in the restructuring of urban policy; and, with regard to crime, we compared trends “before”, “during” and “after” the full implementation of Blue CRUSH (cf. Table 1). Our broad epistemological strategy is case study research, making use of qualitative mixed methods. Our main sources of evidence are: crime data from the FBI Uniform Crime Reporting (UCR)¹ plus other provided by MPD—further details are in section “On effectiveness”; documental analysis—policy documents, municipal decisions, institutional websites; in-depth qualitative interviews and work meetings with policymakers and experts, including some key actors in the development of Blue CRUSH;² and field notes from participant observation in the neighborhood of Klondike-Smokey City,³ and participation to “town-hall” meetings organized by the municipality or other organizations on topics linked to crime control and public safety, useful to understand the socio-political understanding of crime and safety policies.

¹ Available at www.ucrdatatool.gov/.

² Five interviews and three work meetings with: academicians (University of Memphis, Criminology and Criminal Justice); municipal civil servants (MPD; Parks and Neighborhoods); a retired criminologist and former consultant of MPD; an activist from the Mid-South Peace and Justice Center; and a lawyer, chair of Memphis Crime Commission.

³ Thanks to a partnership between the University of Memphis, Department of City and Regional Planning (activities coordinated by Laura Saija and Antonio Raciti), and the local Community Development Corporation (CDC). Fieldwork consisted in the participation to monthly meetings of the CDC, and further events and activities; and the collaboration in the production of a participatory plan for community development.

Smart city and its critiques

Widely used yet poorly defined, over the last decade the term smart city has gained discursive dominance amid discussions of the interplay between technology, and urban governance and government. Although much has been said and written about it, the smart city still lacks a universally accepted definition. In recent years, however, a more or less coherent view on the smart city has emerged: its notion is commonly associated with a constellation of technologies—networked sensors, ubiquitous communications, big data analytics, algorithms—enabling real-time management and control of complex urban dynamics (Kominos, 2002; Batty et al., 2012; Manville et al., 2014; Melgaço & Willis, 2017). Grounded in positive visions of data-driven urban omniscience, the epistemological assumption behind smart urbanism is that each city functions, ideally at least, as a complex “system of systems”—including transportation, energy, education, health care, public safety, and security (cf. IBM, 2011, p. 2; Marvin and Luque-Ayala, 2017). As such, cities’ overall performance can be optimized by tackling urban problems in a holistic and coordinated fashion through the integrative analysis of geosocial data.

As a result of the widespread deployment, at the urban scale, of smart technologies, and in view of their capacity to collect, store, share and process huge amounts of data, cities have recently become ‘testbed territories’ (Halpern et. al, 2013) for new forms of data-driven, algorithmic governance—namely, “a technically-mediated means to manage a city”, whose political legitimization lies in the belief that algorithm-informed decision-making “ensures rational, logical and impartial governance and optimal performance” (Kitchin, 2018, p. 224). Thus, put into perspective, the city-scale implementation of smart solutions, including predictive policing, as tools to solve otherwise intractable problems can be understood as part of a broader trend towards algorithm-based policymaking, and must be framed within the context of the smart city’s global discourse and imaginary (White, 2016; Sadowski & Bendor, 2019).

As its advocates maintain, the rationale underpinning the smart city, and algorithmic governance more generally (cf. Coletta & Kitchin, 2017; Danaher et al., 2017), rests upon two partially overlapping, mutually reinforcing logics: anticipating uncertain futures as a way to shape today's policy; solving actual and potential urban problems by means of (supposedly) objective, politically-neutral, technological fixes. Shaped through business reports and promotional materials, the smart city's global imaginary, which "consists of a general but flexible narrative and a common set of logics for anticipating future crises" (White, 2016, p. 3), is inherently appealing. Whereas in response to impending yet unavoidable "crises" (e.g. mass urbanization), "the smart city seeks to prepare for [them] by pre-empting [their] anticipated effects on infrastructure and resource management" (White 2016, p. 9), in the domain of public safety/security the smart city's anticipatory logics (Anderson, 2010; Amoore, 2013) are pushed to extremes: predictive models promise to prevent crime and violence from happening in the first place.

Critical urban scholarship has shown how multinational private vendors have been "selling smartness" to local governments by disseminating narratives of crisis—demographic, ecological, financial—and thereby proposing their own technological solutions for securing the present against those same crises (Sadowski & Bendor, 2019). In other words, as cities are portrayed both as the sites where problems emerge and solutions are to be found, the salvific rhetoric implicit in the smart city imaginary, while enabling its global circulation and reach, has served as discursive device to justify neoliberal strategies of urban entrepreneurialism (Hollands, 2008; Rossi, 2016) and technocratic configurations of urban governance (Raco & Imrie, 2000; Kitchin, 2014; Greenfield, 2013). The smart city, in this sense, can be understood as the ultimate attempt at deploying technology as ideology (cf. León & Rosen, 2020), an ideology that is typical of the neoliberal(izing) city: corporatization of urban services (Hollands, 2008; Kitchin, 2014; Vanolo, 2014); dismantling of welfare programs; and over-securitization of public space (Armao, 2013; Hoover, 2013). Complementary to such criticisms are concerns, which we will discuss further in the next section, associated with the "black box" opacity of algorithms (Shuppli, 2014; Pasquale, 2015; AI Now

Institute, 2019; Amoore & Raley, 2017), especially considering the troublesome involvement of private companies in their design and implementation, and as they often conceal, if not amplify, societal biases embedded in their inner workings.

Predictive policing and its critiques

Predictive policing is the ultimate, algorithm-based version of an evidence-informed approach to policing based on the systemic use of statistical methods for crime mapping and analysis. The genealogy of predictive policing can be traced back to the 1960s (Hinton, 2016, p. 91), with experiences in Philadelphia, Cleveland and California—the latter promoted by the RAND corporation, a major player in this field (see Perry, McInnis, Price, Smith & Hollywood, 2013; Hunt et al., 2014). An important moment for the popularization of crime mapping techniques is to be found in New York City Police Department's CompStats (short for Compare Statistics), launched in 1994. Though CompStats was above all designed to be an accountability instrument, useful to hold precinct commanders to account for crime spikes, in fact, crime statistics were discussed on weekly meetings where georeferenced patterns and regularities were identified, high-crime areas (also known as "hot-spots")⁴ mapped, and a "rational distribution" of patrols sought (Jefferson, 2018, p. 1254). The innovative aspect of predictive policing is the combined use of GIS, software technology provided by hi-tech corporations, and algorithmic analytics to support (near) real-time crime data analysis, mapping and visualization (see, e.g., Fittered, Nelson & Nathoo, 2015). Blue CRUSH and PredPol—this latter developed by criminologist P. Jeffrey Brantingham and mathematician and computer scientist George Mohler, and launched in Los Angeles—pioneered the development of predictive policing. PredPol has become the most popular technology, used by some 60 police departments all around the U.S.A. (Hvistendahl, 2016). Another, less common

⁴ Hot-spot policing is grounded on the evidence of concentration of crimes, in U.S. cities, in "very small places": "the appeal of focusing limited resources on a small number of high-activity crime places is straightforward. If we can prevent crime at these hot spots, then we might be able to reduce total crime" (Braga, Papachristos & Hureau., 2014). See Hope (2017) for a compelling critique of the very roots of this understanding.

version of predictive policing assesses risks associated with individuals considered to be likely to be involved in criminal activity—see, e.g., the Strategic Subject List created in 2013 by the Chicago Police Department (Saunders, Hunt & Hollywood, 2016) and the system developed by Palantir in New Orleans (Winston, 2018).

From a theoretical perspective, predictive policing builds on the “criminologies of everyday life” (see Garland, 2001, p. 127ff) and situational crime prevention (see Brantingham, Brantingham & Taylor, 2005), themselves grounded on rational choice theories of crime.⁵ The specificity of predictive policing is that it adopts an anticipatory logic to disrupting criminal activity thus understood, coherently with the recent emergence of preemption as a mode of governing in the field of security and beyond (Anderson 2010; Amoore 2013). More specifically, two excerpts from testimonials on PredPol’s website show the centrality of the two-fold rationale of the smart city’s anticipatory discourse for predictive policing:

The theory is that you prevent them from committing the crime to begin with... Burglars and thieves work *in a mathematical way, whether they know it or not.*

We probably *disrupted* criminal activity eight to 10 times a week...⁶

First, crime is a matter of mathematics, hence it can be addressed through technological means, as long as one is able to reverse-engineer its working from its spatio-temporal distribution. And,

⁵ Theories such as routine activity (Brunet, 2002) or opportunity (Felson & Clarke, 1998), which explain crime as the result of the encounter of a rationally motivated criminal with a potential victim in a favourable time/space context. If truth be said, Brantingham (2013; see also Maguire, 2018) has theorized a more complex rationale of car thieves, who would follow sub-optimal choices guided by evolutionary patterns. But, first, other crimes, for instance burglary, have long been discussed by positivist criminology as following rational choice patterns; and, second, the idea of police patrols as preventative means nonetheless builds on a paradigm of situational prevention (see also the “Crime Prediction and Prevention” page on IBM’s website: www.ibm.com/industries/government/public-safety/crime-prediction-prevention; accessed 15 November 2019).

⁶ Our emphases. Modesto Police Chief Galen Carroll and LAPD Foothill Division Captain Sean Malinowski, quoted in www.predpol.com/testimonials/ (accessed 15 November 2019). See also the case for predictive policing made by Los Angeles chief of detectives in three arguments (Beck, 2009): first, predictive policing improves efficiency by reducing costs; second, evidence-based policing makes a neutral and technical issue of crime; and, third, by emulating forecasts used in distribution and retail operations, it allows public policy to be managed like a business.

second, once reverse-engineering is completed, one can predict future crimes from past ones and hence disrupt them in the present. By using technology intensively, and by putting governments in partnership with private companies, predictive policing offers a future-oriented, “technically neutral” solution to crime and violence, the ultimate intractable problem of urban imagination—particularly in U.S. cities, where they are deeply entrenched with socio-economic relationships, and racial and class strife (Friedson & Sharkey, 2015; Tulumello, 2018a).

Against this backdrop, two questions arise. First, is predictive policing a (future-oriented) “solution”? (That is, does it reduce crime in the first place?) And, second, is it a “neutral” solution that neutralizes the complex politics of crime control?

With regard to the first issue, predictive policing has been advertised as a successful experience and a recent review (Meijer & Wessels, 2019) found two works that had backed up those claims: one carried out by the developers of PredPol (Mohler et al., 2015) and another one on NYPD’s Domain Awareness System, carried out by members of the same department (Levine et al., 2017). In short, these works have been produced by practitioners invested in the development of the programs they evaluated—see Benbouzid (2015) on the epistemological problems of connecting crime science to the commercialization of crime software. Indeed, independent research has produced quite different findings. Two RAND Corporation’s evaluations—of the predictive policing program used by the Shreveport Police Department (Louisiana) and of Chicago’s Strategic Subject List—found no significant effect in reducing crime (Hunt et al., 2014; Saunders et al., 2016). In summary, empirical evidence of the effectiveness of predictive policing is basically missing (Moses & Chan, 2018; Meijer & Wessels, 2019). Theoretically, it is reasonable to believe that predictive policing may have some impact on property crimes, where the rational decision of the offender plays a role, but definitely not on violent crimes (see Ferguson, 2012).

With regards to the second issue, advocates of predictive policing have been arguing that it is a neutral and bias-free instrument:

PredPol uses only three data points in making predictions: past type of crime, place of crime and time

of crime. It uses no personal information about individuals or groups of individuals, *eliminating any personal liberties and profiling concerns*.⁷

The idea that the use of crime data would prevent bias or profiling is fascinating, but it has been proven false by research on the relation between scientific evidence and racialization of policing—see, among others, Hinton (2016, pp. 17-26) on scientific data in the history of mass incarceration and Jefferson (2016; 2018a) on racialization of CompStats. Recently, academia and the press have put forward four main critical arguments (see Ferguson, 2012; Vlahos, 2012; Stroud, 2014; Townsend, 2015; Luum & Isaac, 2016; O’Neil, 2016; Shapiro, 2017; Jefferson, 2018b; Moses & Chan, 2018; Munn, 2018; Winston, 2018). First, the fact that algorithms are systematically protected by copyrights eliminates accountability, transparency, and the possibility to actually verify claims about neutrality and objectiveness—moreover, police departments throughout the U.S.A. have tended to implement predictive policing secretly, in some cases even without the knowledge of city governments (for instance in New Orleans). Second, it is nonetheless quite obvious that the collection of massive data about crime raises problems of privacy and data handling, particularly when data are shared among governmental agencies and corporations. Third, predictive policing is heavily shaped by the data it uses; and in contexts where enforcement, hence reporting, is influenced by class and racial biases (the U.S.A. being the quintessentially problematic case), it cannot help but reproduce those same biases through its algorithmic elaboration.⁸ This tends to worsen when police decides to focus, and predictive policing incorporates data about, misdemeanors and nuisance crimes, which are not directly connected to individual safety and tend to be “endemic” to impoverished neighborhoods (O’Neil, 2016, p. 86). Hence, last, the scientific elaboration over geographic concentration of reported crimes, itself influenced by police biases,

⁷ Our emphasis. Quoted by Lum and Isaac (2016, p. 18) and originally found on PredPol website (www.predpol.com/about/), but not available at the time of writing.

⁸ Aradau and Blanke suggest that, “through the featurization of time and space, PredPol has, for example, pre-emptively dis-activated accusations of discrimination” (2017, p. 386). This argument is theoretically intriguing, but is nonetheless problematized by the fact that, as shown by the literature here reviewed, discrimination has been proven virtually every time predictive policing has been empirically scrutinized.

ends up furthering processes of territorial stigmatization.⁹ Indeed, a leaked PredPol report demonstrates that the company considers predictive policing a contemporary form of “broken windows”, a deeply racialized approach to policing (e.g. Jefferson, 2016; Camp & Heatherton, 2016).¹⁰ As recently summarized by Shapiro (2019: abstract): “the ambiguities and contradictions of the patrol are not resolved through algorithmic remediation. Instead, they lead to new indeterminacies, trade-offs, and experimentations based on unfalsifiable claims.”

Against this backdrop, in what follows we will set out the first critical, in-depth study of Blue CRUSH, to further the critique of predictive policing and bridge it to the critique of the discourse of the smart city.

Predictive policing in Memphis: Blue CRUSH

Blue CRUSH was developed in Memphis (Tennessee; 650,000 inhabitants), central city of one of the most unequal and poor metros in the U.S.A. (EIG, 2018), undergoing processes of turbulent change. In line with broader trends of the U.S. South, Memphis has been experiencing with globalization and neoliberalization (Rushing, 2009; Lloyd, 2012; Tulumello, 2018a), in a rush to attract corporate investment and creative classes, and compete with other emerging cities. Regarding the participation of the city in smart city trends, Memphis stays in a paradoxical position as an early adopter and, together, a laggard. As already mentioned, Blue CRUSH, whose development started in 2006, pioneered predictive policing and was one of the earliest attempts by IBM in this field. However, the explicit adoption of a grammar of “smart city” was never part of Blue CRUSH, and only recently have city leaders been interested in catching up on global trends of smart city development: in 2016, Memphis applied to the federally funded Smart City Challenge for

⁹ If truth be said, one study authored by the developers of PredPol found no evidence of racial bias in arrests made through predictive policing in Los Angeles (Brantingham, Valasik & Mohler, 2018).

¹⁰ The report is available at www.muckrock.com/foi/elgin-7770/foia-elgin-police-dept-predpol-documents-51858/#file-190432 (accessed 15 November 2019) and was made public by Lucy Parsons Labs, a Chicago-based project that focuses on the intersection between digital rights and “on-the-streets issues” (see <https://lucyparsonslabs.com/>).

integrated smart transportation system (see Office of the Mayor, no date); and in 2017 a partnership between the city and the University of Memphis (sponsored by Memphis-based logistic giant FedEx) launched a research cluster on smart cities—including attempts at predicting crimes using Twitter data (Venugopal, 2018).¹¹ But the biggest investment in this field made by the city has been in partnership with IBM itself, plus Oracle, to develop smart solutions for human resources management and services such as the emergency call system (Post, 2018). In this sense, Memphis is a perfect example of the way predictive policing has been one of the drivers of those logics widely understood to be typical of the smart city.

The cooperation between the city and IBM started precisely with Blue CRUSH. Launched as a pilot in 2006 and implemented city-wide in 2007, Blue CRUSH is a typical example of GIS based predictive policing program that makes use of real time data from reports by police officers and intelligent CCTV with plate recognition software.

Blue CRUSH is data-driven policing. This is a trademark, a name that was put on data-driven policing. [...] Data-driven policing [is] putting resources in the right place, at the right time, looking for very specific things (high-ranking MPD official, interview).

Patterns are going to be good at forecasting where you're gonna have your crime problems. If you put officers in the right place, at the right time, on the right day, things are gonna happen (former MPD consultant, interview).

Investment into Blue CRUSH peaked in 2011. Afterwards, because of the shrinking number of sworn officers (mostly due to attrition) and cuts in overtime funding,¹² predictive policing had to be reduced in scope. In the remainder of this section, we will question the effectiveness of Blue

¹¹ See www.memphis.edu/fedex/SmartCities/ (accessed 15 November 2019).

¹² Blue CRUSH was heavily reliant on overtimes, as we heard from two interviewees (former MPD consultant and activist of Mid-South Peace and Justice Center) and a document made available by a local councilman confirmed (www.memphistn.gov/Portals/0/pdf_forms/bluecrushanalysis1.pdf; available through Internet Archive, <https://archive.org/>).

CRUSH in addressing crime and discuss its alleged neutrality.

On effectiveness

The full implementation of Blue CRUSH between 2007 and 2011 was accompanied by triumphalist discourses. A high-ranking MPD official, a former MPD consultant and the former chief of Memphis Crime Commission, interviewed, declared that Blue CRUSH had brought crime down. Blue CRUSH was awarded locally (in 2010 by newspaper Commercial Appeal) and internationally—the MPD was the recipient of the 2009 award for Excellence in Law Enforcement Communications and Interoperability (Large Cities) by the International Association of Chiefs of Police.

On what grounds was Blue CRUSH considered successful? In 2012, the MPD announced a 26% drop of serious property and violent crimes in comparison with 2006 (Vlahos, 2012)—according to another source, MPD reported in 2010 a 31% reduction of serious crime and 15.4% reduction of violent crime (Smith, 2010). Almost all the few academic or journalistic works on Blue CRUSH have reported those data, providing no empirical discussion (Hickman, 2013; Perry et al., 2013, pp. 67-69; Dinale, 2014, p. 28; Djukanovic, Harrison & Randjelovic, 2015, p. 103).

An exception is Vlahos (2012), who noticed that comparing crime rates with 2006, a year characterized by a crime peak, could prove misleading and suggested comparing the average of 2001-2005 with 2006-2010—comparing longer periods of time, by reducing the effect of sudden yearly oscillations, is a more sensible choice than comparing single years. Vlahos found, for 2006-2010, a slight drop of total crime (-8%) but a rise of violent crime (+14%). However, we suggest that including 2006 (the year of the crime peak) in the period of implementation may be misleading in turn because Blue CRUSH was not yet deployed city-wide.

We have therefore compared the period 2002-2006 (hereafter “before”) with 2007-2011 (“during”)—by attributing the crime peak of 2006 to “before”, we are conceding Blue CRUSH the

best possible case for comparison. We broke down the analysis for the most important categories available in the FBI UCR. We did not consider homicide and rape (and hence the total volume of violent crimes), whose (reported) numbers are too small to create geographically significant patterns—the creators of Blue CRUSH indeed claimed they were not expecting the program to affect those crimes (former MPD consultant and high-ranking MPD official, interviews). We also verified the claim by MPD that, after 2011, once the number of sworn officials started to shrink and Blue CRUSH was scaled down, crime went up again (high-ranking MPD official, interview). For this purpose, we compared the period “during” with 2012-2014 (“after”; 2014 is the most recent comparable year).¹³ The results are in Table 1. Let us remind that reported crime rates are influenced heavily by police priorities, the likeliness that victims report crimes and even reporting systems—see the difference between UCR and MPD data (Table 1; Figures 1 and 2). Our goal is therefore not seeking “the truth” about crime trends in Memphis, but rather questioning whether official data support policymakers’ claims.

The comparison of 2006 with 2011 confirms the drop of crime reported by policymakers. However, the comparison of “before” with “during” shows that, during the years of full implementation of Blue CRUSH, *some crimes* were reported to be dropping. Property crimes and robbery went down—robbery is categorized as a violent crime, but it can be associated to property crime because the role of the rational decision plays a more important role than in other violent crimes. Aggravated assault, the most frequent and problematic violent crime in the city (as we heard in all interviews), on the contrary, grew quite significantly (+13.6%)—“we have very little if any effect, for example, on aggravated assault”, admitted a former MPD consultant, interviewed.

When we compare “during” with “after”, we see property crime and robbery still going down, and aggravated assault still growing: in plain contradiction with MPD allegations, UCR data show that trends did not change after the reduction of Blue CRUSH. Indeed, the only crime that went up after the scaling down of Blue CRUSH, aggravated assault, is the one that we expected to be

¹³ More recent UCR crime data are provided in different formats and may be not comparable.

influenced the least. Data provided by MPD¹⁴ show that the total volume of reported violent crime (therefore, above all, robberies and aggravated assaults), despite seasonal variations, kept decreasing (Figure 1) and the volume of solved crimes decreased too. A simple correlation of the monthly number of sworn officers with the number of violent crimes shows a dispersed graph (the dispersion is above all due to seasonal variations), with a very slight positive correlation (Figure 2). Of course, we are not suggesting that less sworn officers should be associated causally with decreasing crime, but probably that less crimes are reported with less active officers; and of course less crimes are solved by less officers. At any rate, there is no ground to MPD's claim that crime "went up" once Blue CRUSH was scaled down.

TABLE 1, FIGURES 1 and 2 ABOUT HERE

These data make more sense once they are put into context and considered in the long run.¹⁵ In the long term, almost all property crimes, with the exception of larceny theft, have been decreasing in Memphis, in line with the national "crime drop" (Baumer & Wolff, 2014). Robbery is in line with property crime, having dropped since the mid-1990s—a peak happened in 2005 and 2006, followed by a decline back to pre-2005 levels. This seems to suggest that, yearly variations notwithstanding, Blue CRUSH accompanied the longstanding trend of reduction of property crimes and robbery. Aggravated assault had been growing since the 1980s and stabilized, though with oscillations, since 2006, right before Blue CRUSH was implemented city-wide. Crucially, around half of the crimes reported as aggravated assault are due to domestic violence, which happens where Blue CRUSH has no role to play (as many of our interviewees admitted). All in all, official crime data do not offer any empirical ground to conclude that Blue CRUSH may have had any impact on crime.

¹⁴ Monthly number of violent crimes, violent crimes solved and sworn officers, January 2012 to June 2016. MIMEO (we can share the files upon request). We are grateful to MPD's Office of Public Relations.

¹⁵ The following claims are based on our elaboration of UCR data, available since 1985, and, again, should be considered with a pinch of salt, like all reported crime data (for some series of data, see Tulumello, 2018b).

On territorial discrimination, transparency and privatization

Similarly to other predictive policing programs, Blue CRUSH raised concerns about the way increased police presence associated with the program was felt in minority-majority neighborhoods. The Mid-South Peace and Justice Center¹⁶ has denounced that the deployment of preventative patrols in certain areas, together with the concurrent dissolution of pre-existing proximity policing¹⁷ units (cf. Tulumello, 2018b), resulted in “harassment” of, and feelings of fear and distress by, many communities, and especially Black and Brown youths and young adults (Mid-South Peace and Justice Center, 2013). An activist, interviewed, considered that, in African-American communities, “now everyone’s being treated like a criminal;” and defined Blue CRUSH a process of “occupation” (see also Garner, 2019). Indeed, also a former chief of the Crime Commission and advocate of Blue CRUSH, interviewed, argued that “you’ve got to really *saturate* an area to improve... to prevent bad stuff from happen” (our emphasis).

While Blue CRUSH policing is concentrated in minority-majority neighborhoods, Blue CRUSH cameras “leave many neighborhoods in the dark” (Poe, 2016), being concentrated in affluent and touristic areas. Moreover, the city has encouraged neighborhoods to fundraise to install cameras¹⁸—considering that each camera costs around 15 thousand dollars, this is increasing the disparities among wealthy and poor neighborhoods (cf. Corbet, 2016). In Memphis, the geography of predictive policing, and of the security apparatus in general, seems to have a double nature: “reassuring the rich, policing the (racialized) poor” (Tulumello, 2018a, p. 193).

Blue CRUSH shows further problems concerning transparency and privatization. First, in 2012,

¹⁶ An organization with the mission to “engage, organize and mobilize communities to realize social justice through nonviolent action” since 1982. See <https://midsouthpeace.org/about-us/history/> (accessed 15 November 2019).

¹⁷ We do not use the term “community policing” because in Memphis, and in the U.S.A. more generally, the ideal type of the latter—which is characterized by co-decisional practices—has never been achieved, and the label has been used to refer to proximity practices such as aggressive order maintenance and nuisance abatement (Goetz & Mitchell, 2003; Tulumello, 2018b).

¹⁸ Mayor’s Weekly Digest Bulletin, 17 June 2016.

following the change of the police chief, a local newspaper reported an internal governmental audit that had discovered 79,000 police memos not included in official statistics over the previous five years, those of full implementation of predictive policing (Maki, 2012; *The Commercial Appeal*, 2012), when, Blue CRUSH advocates argue, the program was being a success (see above).¹⁹ Second, allegations of conflict of interest and revolving doors have been made with regard to the contract awarded to local corporation SkyCop for intelligent CCTVs (Perrusquia, 2010)—the current vice-president of sales at SkyCop was among those in the MPD who assembled the bid and selected the winner.²⁰ Third, Blue CRUSH is a trademark, a simple fact that shows the existence of important economic interests around this theoretically public program²¹ and makes it almost impossible to scrutinize in-depth its technological rationale.

Placing predictive policing in context: discussion

Predictive policing, quite obviously, does not happen in a vacuum, especially in institutional contexts, like the U.S.A., where the competence for policing is coupled, at the local level, with that for urban and social policy (see Tulumello, 2018b). Investing in policing and deciding what types of policing are to be prioritized are political decisions driven, on the one hand, by public pressures for “doing something about crime”, and, on the other, the hegemony of neoliberal ideas about, and trends for, public policy (idem; Garland, 2001). Predictive policing, in resonance with smart city discourses, is based on arguments of efficiency and technological-intensive neutrality. And yet, our empirical discussion of Blue CRUSH adds to the literature that problematizes those very arguments.

¹⁹ *The Commercial Appeal* did not follow up on the topic and our requests of information were never answered by the newspaper.

²⁰ Ken Shackleford is listed in the page “About SkyCop” of the company website at the time of writing: www.skycopinc.com/index.php?p=about. In a document (without data) available on SkyCop website, Shackleford is quoted as MPD Lieutenant, explaining the decision to buy SkyCop equipment: www.skycopinc.com/assets/sitemedia/PDFs/SkyCopMemphis.pdf (accessed 15 November 2019). Our requests of interview were not answered by SkyCop.

²¹ In 2008, a firm of lawyers, representing the City of Memphis and MPD, sent a takedown notice to an online shop, for the selling of t-shirts and bumper stickers with Blue CRUSH logo. See www.citizen.org/documents/MemphisTakedownNoticetoZazzle.pdf (accessed 15 November 2019).

If predictive policing does not prevent crime and does not neutralize the politics therein, what is its role in the urban realm? By widening the discussion of Blue CRUSH to the political and institutional context of Memphis, we can provide some answers to this question—in what follows, we will focus on how predictive policing contributes to restructuring urban policy and police job.

To begin with, let us note that there was not much public debate at the time when Blue CRUSH was launched. According to a high-ranking MPD official, interviewed, the decision to launch Blue CRUSH was the police department's.

There isn't a lot of public discussion about [Blue CRUSH]. It's like the public has not been given a lot of thought for the most part. Why that is? I guess we could probably speculate, I think some of it because it is technical, some of it because... at a certain level the public is actually comfortable with it as the technology has sort of expanded (former MPD consultant, interview).

Though Blue CRUSH was developed independently by MPD, the city government was happy to follow through, providing the budgetary resources to hire more sworn officials (which grew from 2,000 in 2006 to 2,450 in 2011) and pay the necessary overtimes. There was a generalized consensus around the implementation of predictive policing in Memphis, which is explicable in light of this city's particularly high crime rates. Analyses of media and political discourses show how crime is an extremely hot topic in Memphis and how generalized is, among policymakers and most citizens alike, the idea that policing is the most appropriate means to prevent it (Tulumello, 2018a; 2018b). Indeed, during our participant observation in Klondike-Smokey City, in the monthly partnership meetings convened by the local Community Development Corporation, crime and violence were systematically the main topics of discussion; and one of the recurring arguments was the possibility to install Blue CRUSH cameras in the school campus, where a shooting took place in November 2015. Against this background, the creators of Blue CRUSH were able to convince policymakers that “the chaos can be controlled with information and technology” (Rosin, 2008).

Predictive policing was not object of political discussion, but it had policy impacts, as evident

once we consider it against the background of the long-term austerity characterizing urban policy in the U.S.A. (Golsmith & Blakely, 2010[1992]). Austerity, in Memphis and many other U.S. cities, is at the same time low-intensity and permanent (Tulumello, 2018a; Saija, Santo & Raciti, 2020): rather than characterized by sudden cuts to public expenditure as a response to economic crises, U.S.-style local austerity is more often a cycle through which public action is restructured, by shifting resources from social programs toward other policy areas; and from the public sphere toward circuits of accumulation. Since Blue CRUSH was launched in 2006, the budget of the City of Memphis has remained overall stable; but while funding for the MPD has been growing steadily, virtually all other policy areas have been cut (Tulumello, 2018a, pp. 179-180). MPD budget also increased in the years when the number of officers was going down, as the City of Memphis allocated massive resources to technological equipment, including a “\$3 million state-of-the-art crime monitoring and analysis hub” (the Real Time Crime Center purchased from IBM),²² body-wear cameras, in-car viewing systems and a radio system (high-ranking MPD official, interview). When questioned on the reasons for this budget growth, and on the role of technology in the process, a high-ranking MPD official argued that, on the one hand, technology had helped “offset[ting the] reduction in personnel;” but, on the other, “it is not that we are reducing the force to bring in more technology.” Part of the investment in technology is “kinda mandated, we have to update things that are going off their service life.” But, overall, technology is purchased “because smart policing is the way the law enforcement kinda does business now.”

Technology is “mandated”—much like smartness has become a mandate (Halpern, Mitchell & Geoghehan, 2017)—, it is the way “business” goes on. And, in the field of crime control, it is a pivotal component of the transference of resources from all sectors of public policy toward policing; and from the latter toward private actors: an activist of the Mid-South Peace and Justice Center reminded us in an interview that “there’s a lot of people who make a lot of money off of building the infrastructure around the science of data.” Beyond reminding us of the problems interlinked

²² See www-03.ibm.com/press/us/en/pressrelease/32169.wss#release (accessed 15 November 2019).

with the very nature of public-private-partnerships crucial to the smart city, the case of predictive policing is paradigmatic of the power that the intersection of discourses about crime control and smart governance has in deepening austerity and neoliberalization of public policy (cf. Pollio, 2018).

At the same time, predictive policing restructures police priorities. Before the launch of Blue CRUSH, Co-Acts proximity units were deployed throughout the city. During participant observation in Klondike-Smokey City, the elderly residents we met remembered the Co-Acts unit as an important presence, in terms of creation of trustworthy relationships between police and local community. With the full deployment of Blue CRUSH, with its heavy request in terms of manpower, Co-Acts units were discontinued and replaced by the pilot program Community Outreach (active in three precincts), whose objective is to “communicate to community in general that you’re changing the strategy in general and, then, what the results [are] on an ongoing basis” (former MPD consultant, interview). Community Outreach, which included the organization of town-hall meetings, was intended to reduce the risk of “pushbacks” (idem). It is quite intuitive to infer that the downscaling of proximity policing may have played a role in the perception of Blue CRUSH as “occupation” (see previous section).

More generally, predictive policing, because of its quintessentially anticipatory logics, transforms the nature of proactive police work qualitatively. In models such as proximity and community policing, the preventive role of police is considered to stem above all from the engagement of police in fields other from policing, like social work, mental health care and community building (see Goetz & Mitchell, 2003; Tulumello, 2018b). Within predictive policing, instead, the ambition is preventing by deploying police patrols to anticipate specific threats forecasted by technological, intensive surveillance. As evidence of the effectiveness of the latter approach is missing, then, the trend toward predictive policing may also result in a worsening of police work more generally: as we saw, the investment in Blue CRUSH brought to a reduced attention by MPD into building relationships of trust with communities, which are themselves crucial to investigating crime. In other words, by following delusional dreams of situational prevention, not only does predictive policing makes social

prevention harder; but at the same time it may even jeopardize good police work, that is, to *solve* crime in the first place.²³

Conclusion: beyond (smart) solutions

These tech advances are sold as morally superior because they purport to rise above human bias, even though they could not exist without data produced through histories of exclusion and discrimination (Benjamin, 2019, p. 15).

We repeatedly see reform agendas framed in terms of beautification and optimization which tend to distract us from what they ultimately are, namely the expression of underlying political and social transformations, and the reproduction of the same problems in new guises (Angelo & Vormann, 2018, p. 16).

The empirical discussion of Blue CRUSH allowed us to further the deconstruction of the idea that predictive policing is a “solution” to crime and violence. If we cannot understand Blue CRUSH as an instrument to *reduce* crime, what is predictive policing about in the first place? Let us come back to issues long known to critical criminology. Predictive policing can hardly be much better than the data it is fed with, data which have always been problematic to begin with. This is to say, if police data describe police priorities more accurately than crime (Sutherland & Cressey, 1978, p. 30), how could the algorithmic, real-time analysis of those very data do anything else than reproducing the priorities police has already set for itself? At the same time as it projects an aura of scientific truth and neutrality, predictive policing above all reproduces the ways crime and criminalization, far from being neutral concepts, are shaped by power relationships, represent the purview and interests of dominant groups (see Gusfield, 1981; Hulsman, 1986; Reiner, 2016)—an

²³ This is a topic that deserves further specific empirical investigation. For an early example, see Sanhu and Fussey’s ethnography (2020) in police agencies that make use of predictive policing in the UK, which has emphasized a tendency by police officers to be reluctant in following software’s instructions.

argument made by Ruha Benjamin (2019; see quotation above) with regard to technology and racial injustice more widely.

We suggested, then, the need to open up to other dimensions, showing the role of predictive policing in shaping urban policy, and police job as well, in Memphis, a city under long-term austerity rule. By doing so, we have shown that predictive policing contributes to the expansion of policing at the expenses of urban policy, at the same time as it disrupts police work. In other words, predictive policing pushes in the same direction—more police, more aggressive policing, and less social prevention and intervention—of many decades of neoliberalization in U.S. cities (cf. Tulumello, 2018a).

Our goal was to discuss a policy instrument that has been part and parcel of the emergence and success of the smart city discourse: the problems we have emphasized in the field of predictive policing may not be generalized to the entire field of the smart city; and yet, our case study gives empirical evidence to Angelo and Vormann's hypothesis (2018; see quotation above) that, once explored as the irruption of a long wave of urban reform and historicized, the smart city argument tastes quite like the proverbial old wine in new bottles.

This is an argument that has been recently problematized by Mark Maguire in relation, precisely, to predictive policing. For Maguire, by “simply engag[ing] with new policing and security technologies in terms of their possible nefarious uses, we will lose the possibility of genuine critique, by which I mean an understanding of the core assumptions from which those technologies emerged and the alternatives available at root” (2018, p. 154). Maguire starts his essay by reflecting on the killing of Michael Brown in Ferguson (Missouri) by a police officer, asking us to think beyond the problem of the encounter of the Black body with the agent of his death, and consider the nature of that encounter—and possible alternatives—to begin with. Maguire then asks: “even if we distrust technological governance and despise the advocates of predictive solutions, we must ask ourselves this: what if the robbery in the Ferguson Market and Liquor had never occurred?” (idem: *ibidem*). Blue CRUSH may well have flagged the “Ferguson Market and Liquor” store at the

particular moment when Michael Brown was to be there—once again, that would not really be any news, as liquor stores at night have been considered “hot spots” in the U.S.A. long before predictive policing was invented. As we know by now, it is unlikely that this would have reduced the possibility of the encounter—no available evidence backs the idea that Blue CRUSH and predictive policing do reduce the risk of crime to happen. In other words, Michael Brown and the police officer may have encountered there even if the latter had been deployed by an algorithm rather than following an emergency call. Would this have been enough for that particular encounter to happen differently? In fact, this may even have increased the suspicion of the officer while stepping into an area defined by the software to be at high risk (cf. Benjamin, 2019, pp.88-89).

Still, it seems to us that Maguire’s proposal for a different critique of predictive policing is still fruitful for reflecting on the smart city, but once applied to the *promises* of the latter as an ideal construct rather than to the “actually-existing smart city”. Indeed, it is in their promises, in their “mundanely predictable hopes” (Datta & Odenaal, 2019, p. 392), that we find the power of predictive policing and smart city. The promise is the depiction of an ideal—the safe/smart city—against which the messy present is projected as problematic and in need to be aggressively enforced. Paraphrasing Pavoni and Tulumello’s discussion (2020) of the way the (neoliberal) promise to “secure” the city shapes the form of violence that we call urban violence, our discussion shows that it is because of the smart city’s promise to solve all urban problems that (instruments like) predictive policing end(s) up disrupting urban policy by contributing to progressively replace it with policing *lato sensu*—aspects that may be less visible when theoretically reflecting on the discourse of the smart city, but that surface when connecting the empirical investigation of specific technologies to the political economy of urban government in times of late neoliberalism.

And yet, it is precisely here that the potential for a transformative critique can be found. The deconstruction of predictive policing, the ultimate attempt at “solving” urban problems—one that was envisioned by sci-fi well before its technological actualization²⁴—, ultimately opens up to the

²⁴ Quite interestingly, some of the most poignant critiques of predictive technologies have been made by former data scientists become novelists (cf. Lepore, 2020).

understanding that the problem is the “problem” in the first place; that only by giving up the illusion that urban problems can be “solved” merely by means of technical and technological management we may find more just ways to draw paths to navigate this messy world of ours.

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²⁵ When not available online, articles from *The Commercial Appeal* have been downloaded from NewsBank online resource (subscription required).

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Table 1. Variations of main crime categories (rates), “before”, “during” and “after” the full implementation of Blue CRUSH. Source: own elaboration of data FBI UCR.					
	Violent crimes		Property crimes		
	<i>Robbery</i>	<i>Aggravated assault</i>	<i>Burglary</i>	<i>Larceny-theft</i>	<i>Motor vehicle theft</i>
2006	780.4	1125.2	2417.2	4962.0	989.1
2011	472.3	1032.3	2030.6	3932.3	526.1
<i>Δ 2006-2011</i>	-39.5	-8.3	-16.0	-20.8	-46.8
Average “before” (2002-2006)	662.9	959.1	2410.4	4766.3	1207.3
Average “during” (2007-2011)	606.6	1089.1	2138.7	4397.1	699.3
<i>Δ “before”/“during”</i>	-8.5	+13.6	-11.3	-7.7	-42.1
Average ‘after’ (2012-2014)	497.5	1128.0	1821.3	3863.8	438.6
<i>Δ “during”/“after”</i>	-18.0	+3.6	-14.8	-12.1	-37.3

Figure 1. Violent crimes reported and sworn officers in Memphis, monthly, trend. Our elaboration on data MPD [MIMEO].

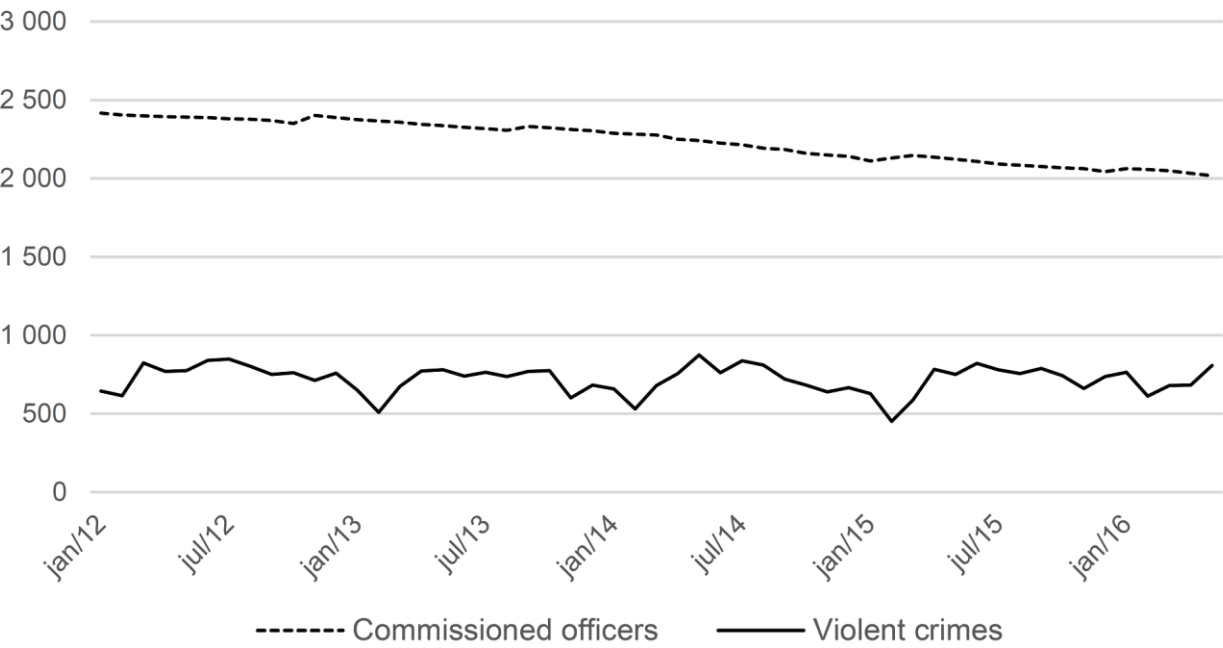


Figure 2. Violent crimes reported and sworn officers, monthly, scatterplot. Our elaboration on data MPD [MIMEO].

