The Effect of Police Deployment Strategy on Emergency Response Times: An Agent-based Modelling Investigation

Tim Verlaan

t.v.verlaan@vu.nl

VU/NSCR https://orcid.org/0000-0002-3048-5817

Daniel Birks

University of Leeds https://orcid.org/0000-0003-3055-7398

Rob van der Mei

VU/CWI https://orcid.org/0000-0002-5685-5310

Research Article

Keywords: Rapid response, police response times, agent-based modelling, police deployment strategies, emergency response

Posted Date: November 5th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-8031427/v1

Additional Declarations: The authors declare no competing interests.

What is the Effect of Police Deployment Strategy on Emergency Response Times? An Agent-Based Modelling Investigation

Tim Verlaan[1,3], Dan Birks[2], Rob van der Mei[3,4]

[1] Netherlands Institute for the Study of Crime and Law Enforcement (NSCR), NL
[2] University of Leeds, School of Law, UK
[3] Vrije Universiteit Amsterdam, Mathematics Department, NL
[4] Centre for Mathematics and Computer Science (CWI), Stochastics group, NL

Corresponding author email address: t.v.verlaan@vu.nl

Funding: This research was carried out within the What Works in Policing research programme of the Netherlands Institute for the Study of Crime and Law Enforcement (NSCR) and funded by the Netherlands Police. The funder had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

Acknowledgements: This work benefitted from conservations with and feedback from: Stijn Ruiter, Henk Elffers, Nick Malleson, and Samuel Langton.

Abstract

Objectives: This study investigates the impact of three police deployment strategies on emergency response times using agent-based modelling (ABM). Specifically, it evaluates the effectiveness of *random patrol*, *stationary deployment* (optimal spreading), and *static deployment* (idling at last incident location). It further examines how key variables—urbanisation, call volume, and police capacity—moderate these effects.

Methods: A detailed ABM was developed using NetLogo, integrating real-world data: historical calls for service (CFS), jurisdiction shapefiles, and street network data from the Netherlands. The model simulated police travel and response dynamics across 300 runs, varying deployment strategies, urbanisation levels, call volumes, and police capacities. Outputs were analysed to assess response times, fast response rates (<3 minutes), and late response rates (>13 minutes). Methods were pre-registered at https://osf.io/yrwdp/?view_only=cb174d08e8834c579158a5c7f7fb03cb.

Results: On average, stationary deployment reduced response times by 35% (SD ±14%), increased fast responses by 74% (SD ±40%), and decreased late responses by 66% (SD ±33%) compared to random patrol. Static deployment also outperformed random patrol, reducing response times by 13% (SD ±9%), increasing fast responses by 22% (SD ±14%), and reducing late responses by 42% (SD ±36%). The advantages of stationary and static deployment were most pronounced in rural areas and at lower police capacities. Urbanisation reduced the performance gap between strategies, while higher call volumes modestly diminished the relative benefits of stationary deployment.

Conclusions: This study highlights the significant impact of police deployment strategies on response times and rapid interventions. These findings underscore the need for further research on rapid response. The modular ABM framework offers a valuable tool for adapting investigations to different policing contexts, enhancing external validity.

Keywords: *Rapid response, police response times, agent-based modelling, police deployment strategies, emergency response.*

1. Introduction

The Standard Model of Policing consists of two core activities for police officers on the street: *rapid response* and *random patrol* (National Research Council, 2004). While many different models of policing have been proposed and implemented in law enforcement agencies worldwide, these two activities still remain central to most departments. Nevertheless, their effectiveness has long been subject to scrutiny, particularly since the 1970s, when a series of landmark studies questioned the effectiveness of both of these core activities.

First of all, The Kansas City Preventive Patrol Experiment (Kelling et al., 1974) cast doubt on the efficacy of random patrol, concluding that it had minimal impact on crime or citizen perceptions of safety. Soon after, the Kansas City Response Time Analysis Study (Bieck, 1977) and its subsequent replication study in four more cities (Spelman & Brown, 1981) challenged the utility of rapid response, asserting that most crimes are either discovered long after the perpetrator has fled or are not reported quickly enough by citizens for a rapid police response to be effective at increasing the chance of apprehension.

While both pillars of the Standard Model faced substantial critique, the academic response varied widely. The Kansas City Preventive Patrol Experiment spurred a robust debate (see Farrington, 1983; Fienberg et al., 1976; Larson, 1975, 1982; Pate et al., 1975; Risman, 1980; Sherman & Weisburd, 1995; Weisburd et al., 2023; Zimring, 1978), leading to the development of innovative strategies like hot spot policing (Sherman & Weisburd, 1995) and numerous follow-up studies evaluating its deterrent effects (see Braga et al., 2019). Conversely, the critique of rapid response spurred no debate and led to a strong dismissal of rapid response and its potential benefits (Sherman et al., 1997). It was argued that rapid response does not have an effect on arrest rates and, by extension, crime levels and that response times are hard to improve as: "Cutting police travel time for such crime from 5 to 2.5 minutes could require a doubling of the police force" (Sherman et al., 1997, Chapter 8, p. 11). Moreover, further experimental investigation into the effects of rapid response was discouraged as: "… there is neither empirical nor theoretical justification for such expensive test… further tests of this theory seem to be a waste of tax dollars." (Sherman et al., 1997, Chapter 8, p. 11).

However, in a recent essay, [Author] (2025) argues that this view on rapid response is both outdated and overly simplistic. Reviewing the historical evidence demonstrates that the effectiveness of rapid response is highly conditional, with substantial benefits observed for fast responses (i.e., under three minutes). Moreover, the essay highlighted that the (historically small) proportion of crimes amenable to rapid response has likely increased due to declines in property crime rates (known as *the crime drop*), and might now even constitute the majority of crime calls. Lastly, it argues that recent advancements in communication technologies have mitigated many of the primary reasons for citizen reporting delays (such as: *finding a payphone* or *asking permission to use someone's landline*), further enhancing the potential impact of rapid response. These insights underscore the need for renewed empirical investigation.

Nevertheless, large-scale experimental research to explore police response times remains impractical due to high costs, logistical complexities, and ethical concerns. Additionally, lingering doubts persist about whether police agencies can meaningfully improve response times, further complicating the justification for such resource-intensive studies. Before embarking on large-scale experiments, it is vital to address these doubts and explore the dynamics underpinning police agency in improving response times.

To this end, computational methods provide a powerful alternative for studying emergency response times, allowing for controlled experimentation without real-world risks or costs. Over the years, various modelling approaches have been applied to different aspects of police operations, including vehicle selection (Dunnett et al., 2019); patrol beat design (Curtin et al., 2010; Kwak & Leavitt, 1984; Larson, 1974; Mitchell, 1972; Sacks, 2000; Zhang & Brown, 2012); patrol route design (Leigh et al., 2019); police station location optimization (Aly & Litwhiler, 1979; Chow et al., 2015; Larson, 1974); police staffing (Taylor & Huxley, 1989); and patrol deployment distribution over beats (Chenevoy, 2022). However, with the exception of some research into ambulance response times (Jagtenberg et al., 2015, 2017; van Barneveld et al., 2016, 2018), no computational investigation has been done into the effect of *deployment strategies* on emergency response times—while this is identified as the primary variable under police control to increase police travel time.

Moreover, with the exception of Chenevoy (2022), these studies relied on equation-based models, which, while effective for optimisation problems, often require high levels of abstraction that limit their ability to capture real-world variability. More flexible computational methods, such as agent-based modelling (ABM), allow for greater realism by explicitly simulating individual police units, emergency calls, and their interactions within a spatially explicit environment. Unlike equation-based models, ABMs can capture real-life complexity and heterogeneity as they incorporate feedback loops, non-linearity, and path dependency. While ABMs have been used to study a wide range of crime problems and responses (e.g., Birks et al., 2012, 2014; Birks & Davies, 2017; Bosse & Gerritsen, 2008; Brantingham & Tita, 2008; E. Groff & Birks, 2008; E. R. Groff, 2007, 2008; Malleson, 2012; Weisburd et al., 2017; Wooditch, 2023), they have predominantly been applied in a theory-testing framework. To assess the potential for police agencies to meaningfully reduce response times, a more decision-support approach to ABM is required.

Building on this premise, the present study employs a highly detailed ABM to investigate the effects of *police deployment strategies*—the primary variable under police influence—on emergency response times, while also considering the moderating roles of key variables. The methodology expands on the chapter "Agent-based decision-support systems for crime scientists" by Birks and Townsley (2018), who demonstrated how ABMs can simulate police response dynamics and test the impact of various interventions using the agent-based modelling software NetLogo. While their approach relied on a simplified representation, the present study enhances the realism and granularity of the simulation by integrating real historical emergency calls for service (CFS) data, police jurisdiction shapefiles, and detailed street network data. Additionally, it incorporates observed dispatch dynamics derived from ethnographic research, all within the NetLogo framework (Wilensky, 1999).

In the Netherlands, as in many other parts of the world, deployment mostly takes the form of motorized patrol carried out by a one- or two-officer team. Motorized patrol ranges from undirected (often called *random*) to fully directed, and may even include optimally timed stops in hot spots (Koper, 1995). However, sometimes more stationary forms of deployment are also used, an example is the use of temporary mobile police units in hot spots or near the house of a repeat-victim.

As such, this paper evaluates the impact of three distinct police deployment strategies— *random patrol deployment, stationary deployment, static deployment*—on police response times through simulation. In the random patrol strategy, police units sequentially and randomly select nodes within their jurisdiction's street network, travel to these nodes via the shortest path, and idle for 15 minutes before repeating the process unless dispatched to an emergency call. The stationary deployment strategy involves clustering nodes within a jurisdiction and assigning each police unit to the most central node in its cluster; when not responding to incidents, the units return to and remain at their designated (optimally distributed) stations. The static deployment strategy positions police units at the location of their most recently handled emergency call. This approach assumes that recent incidents serve as a reasonable predictor for future calls, as crime and emergency events often exhibit spatiotemporal patterns.

Besides the effect of these three different police deployment strategies, we also investigate the effect of three variables suggested by Verlaan & Ruiter (2023) to moderate the effect between these police deployment strategies and police response time. These moderating variables are: *police capacity*, *call volume* and *degree of urbanization of the "Basisteam"*, the lowest level geographical unit of the Dutch police with a police station; analogous to the US *precinct*.

This aim leads to the development of the following research questions:

1) What is the impact of police deployment strategies on emergency response times?
    a) How do *urbanisation*, *call volume*, and *police capacity* moderate these effects?

To systematically address these questions, we have developed six falsifiable hypotheses. These hypotheses are as follows:

(1) *Stationary deployment* yields better response times than *random patrol deployment* operationalized as lower average response time, higher percentage fast responses *(i.e. < 3 minutes)* and lower percentage late responses *(i.e. > 13 minutes).*
(2) S*tatic deployment* yields better response times than *random patrol deployment* operationalized as lower average response time, higher percentage fast responses *(i.e. < 3 minutes)* and lower percentage late responses *(i.e. > 13 minutes).*
(3) Stationary deployment yields better response times than s*tatic deployment* operationalized as lower average response time, higher percentage fast responses *(i.e. < 3 minutes)* and lower percentage late responses *(i.e. > 13 minutes*).
(4) As *police capacity* increases, operationalized as the number of virtual police response units serving each Basisteam, the relative effect on *average response time*, percentages of *fast responses* and percentages *late responses* within *stationary* -, *static* -, and *random patrol deployment* decreases.
(5) As the *urbanization* of the Basisteams increase, operationalized based on its street length in meters per square kilometres, the relative difference in *average response time*, *percentages fast responses* and *percentages late responses* within *stationary* -, *static* -, and *random patrol deployment* decreases.
(6) As *call volume* increases, operationalized as high call volume shift or normal call volume shift, the relative difference in *average response time*, percentages of *fast responses* and percentages *late responses* within *stationary* -, *static* -, and *random patrol deployment* decreases.

In answering these questions and testing these hypotheses, this research aims to provide actionable insights for both academic and practical contexts. By leveraging real-world data, including historical priority 1 CFS, jurisdictional shapefiles, and detailed street network data, the study seeks to bridge the gap between theoretical exploration and practical application. Furthermore, it aligns with recent calls to revisit long-standing assumptions about rapid response and its role in modern policing.

Importantly this study focuses specifically on how deployment strategy and moderating variables influence outcomes in reactive policing, while acknowledging that officers on the street engage in a range of other activities, including proactive patrol—an area that has received comparatively greater empirical attention in recent years (Braga et al., 2019). We argue that the simulation approach used here is particularly well suited to studying reactive policing, as empirical experimentation in this area would require direct manipulation of police responses to real incidents, presenting significant practical and ethical challenges. Moreover, a key strength of the simulation method is its ability to isolate reactive policing from other core activities, something that would also be exceptionally difficult using traditional empirical approaches. Future research could of course apply similar approaches to explore proactive policing strategies and further models could combine simulation of additional police activities to better understand the relative opportunity cost impacts of each on the others. For instance, integrating models of proactive patrol, community engagement, or investigative work could provide a more holistic view of how police resources are allocated and the trade-offs involved.

2. Methodology

This study follows a data-driven simulation approach, integrating real-world police data, geographical information, and agent-based modelling to assess the impact of deployment strategies on response times. The ABM developed simulates daily police incidents and responses in the District Oost-Utrecht over a full year, operating on a second-by-second basis. Using real-world police data on incident timing, location, and recorded response actions, the model replicates observed response patterns while systematically varying police deployment strategy and capacity. By doing so, it generates synthetic counterfactuals that allow for a structured evaluation of different strategies under controlled conditions. This approach enables direct comparisons of response effectiveness across key performance metrics, such as average response time and the proportion of rapid responses

The methodology first describes the primary data sources, including police incident and dispatch records alongside geographical data used to simulate police movement. Next, it details the ABM environment, specifying agent behaviour, deployment strategies, and dispatch dynamics. The simulation design is then outlined, including variations in police capacity and strategy. Finally, the data extraction and analysis section explains how response time metrics are generated within the ABM, extracted, and analysed using descriptive statistics and regression models.

2.1 Primary Data

The GMS data used in the ABM is obtained from the Dutch Police and covers the whole of District Utrecht-Oost for the year 2019. The data is spread over two databases. The first database contains information about the incident, the second contains information about the police dispatches to these incidents; one incident can have multiple units dispatched to it. Table 1 and Table 2 represent the relevant pseudonymized variables which are used from each data frame.

Table 1: GMS calls-for-service data

Variable name	Description
Incident ID	Unique identifier of each incident
Dispatch ID	Unique identifier of each dispatch
Call_sign	Unique identifier of police response unit vehicle
Incident_start_timestamp	Timestamp of when the call was received.
Incident_closure_type	Captures whether the incoming call was dispatched a response unit or whether it was considered, for example, a "fake call"
Incident_priority_level	Priority level of call – range: 5 Levels (1,2,3,4,5)
T_x_coord_aanrij	X coordinate of the location
T_y_coord_aanrij	Y coordinate of the location

Table 2: GMS dispatch data

Variable name	Description
Incident ID	Unique identifier of each incident
Dispatch ID	Unique identifier of each dispatch
Timestamp	Timestamp of status logging (Format: yyyy-mm-dd hh:mm:ss)
Status	Status logged by unit (4 Levels: dispatched, on-way, arrived, cleared)

In addition to police records, geographical data was incorporated to ensure realistic simulation of police movement and response times. Jurisdiction shapefiles were used to define the boundaries of each Basisteam, while street network data was retrieved from OpenStreetMap (OSM) via OSMnx (Boeing, 2017). The road network was filtered to include only drivable roads, with travel speeds and road restrictions applied accordingly. Table 3 details the characteristics of the street network data.

Table 3: OSM "drive" street network data within District Oost-Utrecht

Variable name	Description
Road_ID	Unique identifier for each road segment within the network
Average_Speed	Average travel speed for cars on the road segment (km/h)
Directionality	Indicates whether the road is one-way or two-way
Length	True length of the road segment (meters)

2.1.1 Primary data pre-processing

The pre-processing code is openly available on the open GitHub page: [anonymized]. Here, we provide a short summary of the pre-processing. We begin with a number of filtering steps in order to obtain a representative sample of incidents, and all individual dispatches to these various incidents. First, we exclude incidents that were initiated by the police (as this constitutes proactive policing). Second, we remove incidents which did not receive a physical dispatch, but were, for example, handled over the phone or considered *false alarm*. Third, we remove dispatches to incidents by non-standard response units, e.g. helicopter, military police units etcetera. These steps leave 34,593 incidents and 50,694 individual dispatches to model in the ABM. However, there are a few more filtering steps needed to ensure data quality and representativeness: Fourth, we exclude dispatches that contain timestamp logs in the hour in which, in the Netherlands, the clock is set to daylight-saving hours: *2019-10-27 02:00:00* until *03:00:00*. Fifth, we exclude dispatches for which no *cleared* timestamp is present in the data. Sixth, we exclude dispatches for which the duration between being dispatched to a call and clearing a call is less than five minutes, as these are often false alarms, resolved before police arrival, or otherwise erroneous. Seventh, we exclude dispatches which last longer than the duration of a shift; eight hours. Eighth, we exclude dispatched which arrive within one minute of being dispatched to a call. Lastly, we exclude calls for which the duration between arrival and clearing is less than one minute. After these last filtering steps, we are left with 30,380 (88%) incidents and 38,893 (77%) individual dispatches to these incidents. Table 4 summarizes these steps, together with the reason behind each filtering step and its effect on the size of the data frame. Lastly, we took steps to infer missing data in the *arrived* timestamp, see the open code for details.

Table 4: Pre-processing steps and their impacts on incidents and dispatches

Filter	**Incidents**	**Dispatches**	**Rationale for filtering step**
District Oost-Utrecht 2019	72,649 (100%)	113,959 (100%)	The dataset encompasses four Basisteams, both rural and urban
Reactive calls	56,118 (77%)	90,695 (80%)	This ABM focuses exclusively on reactive policing, necessitating the exclusion of proactive or preventive calls
Received dispatch	38,457 (53%)	67,983 (60%)	Certain CFS are false alarms or are resolved without police dispatch
Received police response unit	34,593 (48%)	50,694 (44%)	Some CFS are handled by nonstandard units, such as Military Police, which fall outside the scope of this study.
Summer-time	34,573 (48%)	50,664 (44%)	The transition from summer to wintertime results in clock adjustments that create timestamp inconsistencies; these cases were removed to prevent data integrity issues.
"cleared" missing	33,664 (46%)	45,426 (40%)	Incidents lacking a *cleared* timestamp were excluded, as the duration of police presence at the scene could not be determined.
"dispatched" to cleared" > 5 min	32,882 (45%)	43,687 (38%)	Calls with a very short duration often lack complete timestamps and are likely false alarms, resolved before police arrival, or otherwise erroneous.
"dispatched" to "cleared" < 8 hrs	32,880 (45%)	43,682 (38%)	A police shift lasts eight hours, this step removes only a minimal number of cases (five dispatches and two incidents).
"dispatched" to "arrived" > 1 min	32,099 (44%)	41,990 (37%)	These cases are likely instances of cars already at the scene or other unrepresentative events.
"arrived" to "cleared" > 1 min	30.380 (42%)	38.893 (34%)	These cases are likely the result of data entry errors or are otherwise unrepresentative of typical police responses.

2.2 Agent-based Model Development

This section describes the development of the ABM, including the model environment, agent behaviour, deployment strategies, dispatch dynamics, and experimental setup.

2.2.1 Model environment

The agent-based model is built in NetLogo 6.2.2 (Wilensky, 1999) and simulates traversable street networks for the four Basisteams within District Oost Utrecht. Shapefiles of police districts and Basisteams were sourced from the Dutch Police, while street network data was retrieved from OpenStreetMap using OSMnx (Boeing, 2017). The network was constructed with the "drive" specification, ensuring only drivable roads and paths were included. Each road segment in the network is characterised by parameters such as average travel speed for cars, directional flow, and true length in meters. The temporal dimension of the simulation is structured in ticks, where each tick corresponds to one real-world second. A graphical representation of the model is shown in Figure 1.

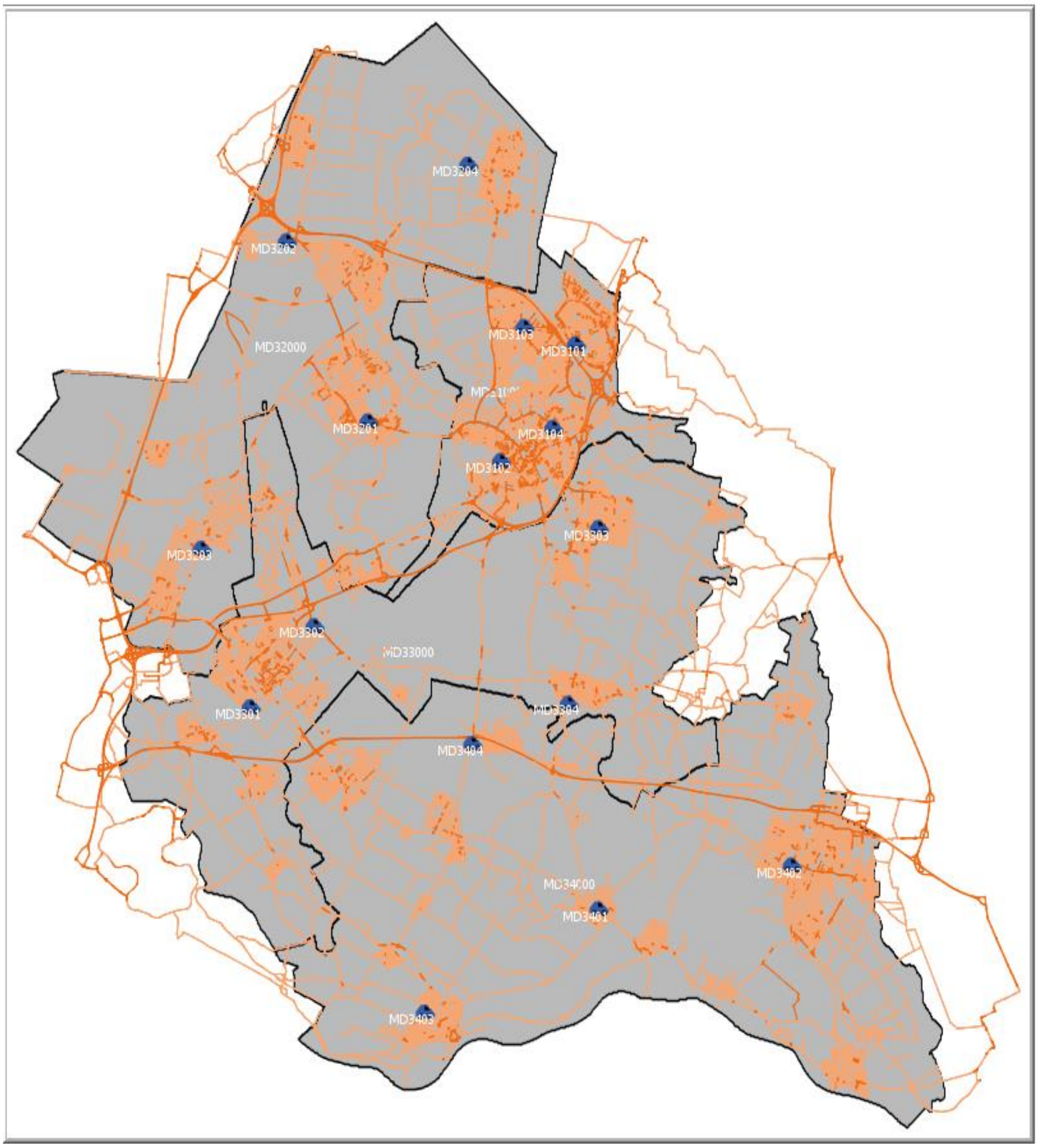

Figure 1: Graphical representation of the ABM model - instantiated with police capacity = 4

2.2.2 Agents: calls-for-service

The model incorporates real historical calls-for-service (CFS) data from the year 2019 within the jurisdiction of District Oost-Utrecht, which includes the four *Basisteams*. These calls provide the foundation for simulating police response dynamics and are pre-processed to ensure representativeness and compatibility with the ABM framework. The details of the CFS data are summarised in Table 5.

Each CFS is assigned a pseudonymized incident ID, enabling linkage with the original data while ensuring privacy. Incidents are also categorised by their priority level as assigned at the time of the call. To simplify the simulation, calls with lower priority levels (3, 4, and 5) are re-coded as priority level 2 due to their low frequency in the dataset. This adjustment maintains model efficiency without compromising realism.

CFS timestamps, indicating when the call was received by the dispatch centre, are operationalised as seconds elapsed since the start of 2019. This conversion aligns the data with the temporal structure of the ABM, where each tick corresponds to one second in real-world time.

The model further integrates operational details to accurately simulate resource allocation. This includes the number of police units deployed to each incident (*reactive_supply*) and a list of on-scene durations (*on_scene_times*), capturing the time each unit remains engaged with the incident. Additionally, spatial precision is ensured by mapping each incident to specific x and y coordinates (*Xcor* and *Ycor*) within the NetLogo world, aligning the incidents with the simulated street network.

Table 5: Pre-processed CFS data input in the ABM

Variable name	**Description**
Incident_id	Unique incident identifier
Priority_level	Priority level of the incident
Start_incident	Timestamp of incident recorded by dispatch centre, operationalized as seconds since start of the year 2019
Reactive_supply	Number of virtual police units to respond to the incident
On_scene_times	List of on-scene times (*arrived_cleared*)
Xcor	Integer representing the x coordinate of the incident on the street network, in the format of the NetLogo world
Ycor	Integer representing the y coordinate of the incident on the street network, in the format of the NetLogo world

2.2.3 Agents: virtual police response units

The agent-based model simulates a population of virtual police response units to represent the operational capabilities of law enforcement within each Basisteam. These agents act as individual police units, dynamically responding to CFS and interacting with the simulated environment in real time.

The number of virtual police units per Basisteam varies between 1 and 10, depending on the instantiation of the simulation run. This variation allows for an exploration of the moderating effects of differing police capacities on the relationship between police strategy and response times. At the start of the simulation (tick = 0), all agents are instantiated and deployed within the street network of their respective Basisteam jurisdictions.

For simplicity and to focus on response dynamics, the model does not include mechanisms for returning police units to their stations at the end of shifts. Additionally, the size of the police force remains constant throughout the simulation, irrespective of typical fluctuations in staffing levels during day and night shifts. While these simplifications may reduce fidelity in certain contexts, they allow for a controlled examination of deployment strategies and response outcomes without the added complexity of shift-based staffing adjustments.

Each virtual police unit is equipped with a set of behavioural rules that govern their movement, response to dispatches, and idle behaviour. These rules vary depending on the active deployment strategy, ensuring the agents accurately represent the operational logic of different patrol methods. By incorporating individual decision-making processes and interactions with the environment, the agents are capable of capturing emergent patterns in response times and resource allocation under various scenarios.

2.2.4 Model Dynamics: Call and Agent Behaviour

Call Behaviour

The behaviour of CFS is driven by real-world historical data. Each call becomes active at the simulation tick corresponding to its *start_incident* timestamp, representing the time the call was received by the dispatch centre.

When a call becomes active, the model assesses the availability of the required number of police units (*reactive_supply*) within the Basisteam. If sufficient units are available, they are dispatched to the incident. When fewer units are available than required, the maximum number of available units is dispatched, and the remaining demand is added to a dispatch queue. Calls in the queue are prioritised by urgency (priority level), with waiting time determining the order of dispatch for calls of the same priority. This queuing system follows a first-in, first-out strategy for calls of equal priority.

Once dispatched, police units travel along the shortest path to the incident location, observing road speed limits and restrictions. Upon arrival of the first unit, the response time is recorded as the elapsed time since *start_incident*. The units then remain on scene for the duration specified in the call data (*on_scene_times*), during which they are unavailable to respond to other calls. However, units can be redirected mid-response to handle higher-priority incidents. In such cases, the interrupted call re-enters the dispatch queue, and the interrupted on-scene time is preserved for completion in the future.

Agent Behaviour

The actions of virtual police response units are divided into two phases: their behaviour during response to active calls and their behaviour during idle periods.

When responding to a call, agents traverse the street network to reach the incident location via the shortest possible route, calculated based on road speed and travel time. Upon arrival, agents remain at the scene for the allocated time before becoming available for new assignments. During this response phase, agents can be dynamically reallocated if a higher-priority call arises. This ensures that police response prioritises the most urgent incidents.

During idle periods, the behaviour of agents is determined by the deployment strategy assigned in the simulation. Under the *random* deployment strategy, agents sequentially and randomly select nodes within their Basisteam jurisdiction and travel to these nodes, idling at each location for 15 minutes before repeating the process. This pattern mimics undirected patrol operations commonly observed in real-world policing.

The *stationary deployment* strategy assigns agents to optimally distributed locations within their Basisteam. Street network nodes are divided into clusters using k-means clustering, and agents are stationed at the node with the highest closeness centrality within each cluster. When not responding to incidents, agents return to their designated stations via the shortest path and remain there until dispatched to another call. This strategy reflects a more structured and centralised approach to resource deployment.

Under the *static deployment* strategy agents remain idle at the location of their most recently handled call for service. This approach seeks to leverage the temporal and spatial clustering of incidents by assuming that recent call locations serve as effective predictors for future demand, and provides an alternative to centralised or random patrol patterns.

2.3 Experimental setup

Each experiment simulates the same calls-for-service within District Utrecht-Oost for the exact same 365 days (in 2019) on a minute-by-minute basis. The simulation experiments systematically vary the key independent variables: *police deployment strategy* and *police capacity*. Each experiment is run under a combination of these conditions, allowing for a structured assessment of their effects on response times. Police deployment strategy has three levels (random patrol, stationary deployment, and static deployment), while police capacity varies from one to ten units per Basisteam. These two parameters result in thirty unique simulation scenarios. The full set of simulation parameters is summarized in Table 6. The *static* and *stationary* deployment models are fully deterministic, and the *random* deployment models is highly deterministic with only minor influences of stochasticity. Hence, multiple random seed reruns of the models was found to be unnecessary.

Table 6: Simulation parameters

Simulation parameters	description	operationalization
Police deployment strategy	A navigation strategy for police units not currently responding to a call	random patrol deployment; stationary deployment; static deployment
Police capacity	The number of virtual police response units per Basisteam in the simulation	1-10 (increment: 1)

2.4 Model Outputs and Data Analysis

2.4.1 Model Output Data

Each simulation run generates a dataset capturing all dispatch-level events, structured similarly to the original police dispatch input data (see Table 2). This generated data includes a record of each dispatch event, capturing the police unit involved, the corresponding incident, a unique dispatch and key time stamps. This results in 30 output datasets, each corresponding to one of the unique simulation runs. Table 7 details this output data.

Table 7: Structure of ABM dispatch level output data

Call sign	Incident ID	Dispatch ID	Timestamp	Status
Police call sign	Unique ID	Unique ID	In ticks (seconds since start 2019)	Levels = dispatched, arrived, cleared, cancelled

2.4.2 Data Analysis Approach

The analysis focuses on quantifying response times and evaluating the effects of different deployment strategies under varying conditions. Following Verlaan & Ruiter (2023), response time is operationalised as the elapsed time (in seconds) between the dispatch timestamp and the arrival of the first unit on the scene. To test the hypotheses, response times are analysed using descriptive statistics and visualised per Basisteam and police capacity level. As preregistered, falsification of the hypotheses is attempted based on mean and median response times, as well as distributions of fast responses (under three minutes) and late responses (over 13 minutes). The results are compared across deployment strategies, while controlling for urbanisation level, call volume, and police capacity. The variables included in the analysis and their sources are detailed in Table 8.

Table 8: Dependent and independent variables

Variables	Operationalization	Source
Response time	(s)	ABM
Deployment strategy	Random/Stationary/Static	ABM
Urbanization rank	standardized (0-100) Basisteam rank: *meters of streets/km²*	GIS
Police capacity	Police units/shift	ABM
Call volume	Calls for service/shift	GMS

2.4.3 Hypothesis Testing and Exploratory Analysis

The results section systematically attempts falsification of the hypotheses using descriptive plots and statistical summaries. The analysis first examines response time distributions for each strategy per Basisteam and police capacity level. Following Verlaan & Ruiter (2023), and in order to ensure comparability, findings are only interpreted for priority 1 calls, where all independent variables can be considered limiting factors.

Falsification of hypotheses 1–3 is conducted under all conditions of police capacity and per Basisteam but only within the "normal" call volume condition. Hypothesis 4 is tested across all deployment strategies and Basisteams but again restricted to normal call volumes. Hypothesis 5 is evaluated across all strategies and police capacities, while hypothesis 6 is tested under all strategy and Basisteam conditions. Since different scenarios may yield different results, hypotheses may be falsified under some conditions but not others.

All simulation code, pre-processing scripts, and output visualisations will be made openly available on the project's GitHub repository.

3. Results

The results presented below are based on Figures 2 to 5 in Appendix A. These figures provide insights into the outcome metrics of mean response time, percentage of fast responses (< 3 minutes), and percentage of late responses (> 13 minutes) for each of the scenarios (combination of jurisdiction and initialized police capacity level). Figure 2 shows the response time distribution for each scenario, Figure 3 details the mean response time, percentage fast responses, and percentage late responses per scenario, and Figure 3 investigates the relative impact of incremental increases call volume.

To provide context to these results, we first examine the distribution of priority 1 call volume per shift and police capacity per shift for each Basisteam, as presented in Figures 5 and 6 (Appendix B). A substantial proportion of shifts—approximately a quarter to a third—receive no priority one calls. Among shifts that do, most shifts receiving around six calls per shift (SD = 5). Meanwhile, police capacity per shift shows minimal variation within each Basisteam, with most shifts operating at five police units (SD = 2). These distributions inform the conditions under which different deployment strategies are evaluated in the subsequent analyses.

3.1 Average Effect of Deployment Strategies

Across all scenarios, stationary deployment consistently outperformed both static and random patrol strategies in terms of mean response time, percentage of fast responses (< 3 minutes), and percentage of late responses (> 13 minutes). As detailed in Figure 2, on average, stationary deployment reduced mean response times by 35% (± 14%) compared to random patrol. Similarly, it achieved substantially higher rates of fast responses (74% ± 40%) and reduced late responses by 66% (± 33%). Static deployment also exhibited substantial improvements over random patrol, particularly in scenarios with higher police capacity. Mean response times were reduced by 13% (± 9%), with fast response rates increasing by 22% (± 14%) and late response rates decreasing by 42% (± 36%).

Figure 3 illustrates the potential of stationary deployment in absolute terms: in the urban context of Basisteam Amersfoort, under the average capacity of 5 police units, *stationary* deployment enables police to (theoretically) respond to 75% of all priority 1 calls in under 3 minutes—approximately twice as many as under *static* deployment (38%) or random patrol (32%). Even with police capacity doubled to 10 units, *static* deployment would barely be able to respond to 65%, and *random* patrol would still fail to reach 50% of such calls within the same timeframe.

3.2 Moderating Effect of Police Capacity

As police capacity increased, mean response time and the percentage of fast and late responses improved in absolute terms across all deployment strategies. However, in line with hypothesis 4, both the relative as well as the absolute marginal improvement per additional police unit diminished. Nevertheless, as is evident from Figure 3, the marginal benefit of each additional police unit is larger under *stationary* deployment than under *static* and *random* deployment for all three measures.

For *percentage of late response*, we observe saturation (meaning all calls are serviced with the timeframe of 13 minutes) across all Basisteams within the currently tested levels of police capacity. For *percentage of fast response*, this saturation does not yet take place, although it is close from Basisteam Amersfoort under stationary deployment. In contrast, for *random patrol*, it is not clear if it will ever reach saturation, as the curve appears to asymptote below the 50% line.

Ultimately, across virtually scenarios and metrics, stationary deployment with a police capacity of four outperforms static and random with a police capacity of ten.

3.3 Moderating Effect of Urbanisation

Across the board, it is evident that the more rural a jurisdiction is (all else being equal), the higher the response times and higher the percentage of late responses. However, this is mainly due to having a higher baseline, the marginal effects per additional police capacity does not appear to vary per Basisteam over any of the strategies. It is noteworthy that we do not witness the same dynamic for fast response. In fact, while we do observe substantially higher percentages of fast response in the urban jurisdiction of Basisteam Amersfoort, the difference between the other more rural jurisdiction is for similar police capacity levels is not distinguishable.

3.4 Moderating Effect of Call Volume

Figure 4 details the effect of call volume on the three outcome metrics. The effect of call volume on response metrics is not strictly monotonic across strategies and jurisdictions. While mean response time and late response rates show some discernible increases as call volume rises, the relationship is less clear for fast responses. The impact is also more pronounced under stationary deployment, likely because its efficiency depends on pre-positioning, which becomes less relevant when calls accumulate, forcing units into a queue. As queueing increases and units have reduced idling time, deployment strategy plays a diminishing role in performance, effectively eroding the advantage of better strategies.

As such, at higher call volumes, the differences between deployment strategies diminish, as reduced idle time and increased queuing constrain the advantages of more effective strategies.

For realistic policing conditions—where Basisteams typically operate with three to seven units per shift (see Figure 6) and priority 1 call volumes rarely exceed fifteen per shift (see Figure 5)—the overall effect of call volume is limited:

Under random patrol, mean response time increases 10-20 seconds from low to high call volume, 20-30 seconds under static deployment, and up to 40 seconds under stationary deployment, where high demand weakens its advantage. Fast responses decline 10-15 percentage points for random patrol, 7-12 percentage points for static, and 5-10 percentage points for stationary. Late responses increase 3-5 percentage points under random patrol, 2-4 percentage points for static, and only 1-3 percentage points for stationary, reinforcing its resilience.

Crucially, stationary deployment at the highest observed call volumes still outperforms random and static deployment at the lowest call volumes. Even when facing the most demanding conditions, stationary deployment achieves substantially lower response times, higher fast response rates, and fewer late responses than the other strategies under optimal conditions. This highlights that deployment strategy is a far greater determinant of performance than variations in call volume, reinforcing the importance of an effective positioning approach.

4. Conclusion

The findings strongly support hypotheses 1–3: stationary deployment consistently outperforms both static and random patrol across all response metrics. Even under the highest call volumes, it achieves faster response times, more fast responses, and fewer late responses than static and random patrol under optimal conditions.

Hypothesis 4 is also confirmed, as marginal gains from additional police capacity diminish across all strategies, though stationary deployment benefits most. Hypothesis 5 receives partial support—while urban areas see lower response times and fewer late responses, the effect on fast response rates is less clear.

The results for hypothesis 6 (call volume effects) are mixed. While response times and late responses increase with more calls, the effect remains relatively minor within realistic policing conditions. More importantly, as call volume rises, differences between strategies narrow, particularly for stationary deployment, where its effectiveness is increasingly nullified by workload saturation.

Ultimately, deployment strategy is the dominant factor in determining response times, outweighing the effects of urbanization, call volume and police capacity.

5. Discussion

This study set out to investigate the impact of police deployment strategies—stationary deployment, static deployment, and random patrol deployment—on emergency response times and to examine how these effects are moderated by police capacity, urbanisation, and call volume. By employing a detailed ABM that integrates real-world CFS data, geographical information, and dispatch dynamics, we have provided actionable insights into the dynamics of police response times under varying conditions.

The findings reveal that stationary deployment—whereby response vehicles relocate themselves to a central location within their respective jurisdiction after resolving each incident—consistently outperforms both static deployment and random patrol across all key metrics of response time, percentage of fast responses (< 3 minutes), and percentage of late responses (> 13 minutes). This superiority is particularly evident in fast responses, where it produces a large and decisive impact.

These findings contribute to the reinvigorated academic debate surrounding rapid response in modern policing. The results demonstrate a substantial potential for the Police to reduce response times and increase fast responses through the selection of deployment strategies. This challenges Sherman's (1997, Chapter 8, p. 11) conjecture that cutting response times in half may require doubling the police force. Instead, the choice of deployment strategy shows a much larger effect size, underscoring the agency that police departments have in improving response times without significant increases in resources. Coupled with rapid response literature on the effect of fast responses on on-scene arrests (see Bieck, 1977; Blanes i Vidal & Kirchmaier, 2018; Cihan et al., 2012; Clawson & Chang, 1977; Isaacs, 1967; Spelman & Brown, 1981; Tarr, 1978), these findings indicate that police departments can substantially improve their arrest and clearance rates through their deployment strategy.

Beyond theoretical contributions, these findings also hold direct implications for practice. Stationary deployment is particularly effective for either increasing fast responses or limiting late responses, making it valuable in understaffed conditions where meeting on-time response quotas—such as the 95% threshold mandated in countries like the Netherlands—is critical.

From an academic perspective, the study underscores the potential of ABM as a decision-support tool for exploring complex policing dynamics. By explicitly simulating individual police units, CFS, and their interactions within a spatially explicit environment, the ABM provides a level of granularity and realism that is difficult to achieve with traditional equation-based models.

A final theoretical insight emerged from the performance of static deployment—whereby officers remain at the location of the most recently resolved incident until they are required to respond to the next. While this deployment strategy performs poorly under low police capacities, it demonstrates increasing effectiveness as capacity rises. To us, this pattern suggests a fundamental misalignment between the cyclical nature of hotspots—where recent incidents predict future activity—and the sequential nature of police response. The assumption that the location of the last call serves as an effective predictor of the next call breaks down when intervening calls from other hotspots redirect police units. This sequential reality introduces delays that disrupt the predictive power of the strategy. However, as police capacity increases, this misalignment diminishes, as more units are available to simultaneously address calls from multiple hotspots.

Limitations

While this study provides valuable insights, several limitations should be acknowledged. First, like all models, the ABM's external validity is inherently constrained by the context of its design. The simulation focuses on Dutch Basisteams, with specific geographic, demographic, and operational characteristics. While these findings may generalise to similar contexts, their applicability to other policing systems (e.g., in the US or UK) requires further exploration.

Second, the model incorporates several simplifying assumptions to enhance computational efficiency and isolate the effects of deployment strategies. For instance, the model does not account for shifts or the practice of returning police units to stations at the end of a shift. Similarly, non-reactive policing activities, such as proactive patrols or community engagement, are not simulated, potentially limiting the holistic applicability of the findings. Future research should address these dynamics to provide a more comprehensive view of policing operations.

Future Research and Broader Implications

The demonstrated influence of deployment strategies on response times underscores the need for renewed empirical investigations into rapid response, a topic long side-lined in policing research. While randomised controlled trials (RCTs) may remain impractical due to cost and ethical concerns, quasi-experimental and observational studies offer viable alternatives to advance this line of inquiry. As [Author] (2025) highlights, these methods provide rigorous and actionable insights, addressing many of the constraints associated with large-scale experimentation.

Additionally, the modular nature of the ABM developed in this study allows for its adaptation to diverse policing contexts. Future applications in different geographical and operational settings, such as urban US precincts or rural UK constabularies, would enhance the external validity of the findings and identify context-specific dynamics. By extending the model's scope, we hope to support a broader understanding of rapid response and inform evidence-based strategies for improving public safety.

In conclusion, this study demonstrates the substantial potential for police agencies to influence response times through strategic deployment, challenging longstanding assumptions and providing a strong foundation for further research and policy development. The findings emphasise that renewed focus on rapid response is not only feasible but overdue, offering a clear opportunity to bridge the gap between theoretical insights and practical advancements in policing.

6. Appendix A

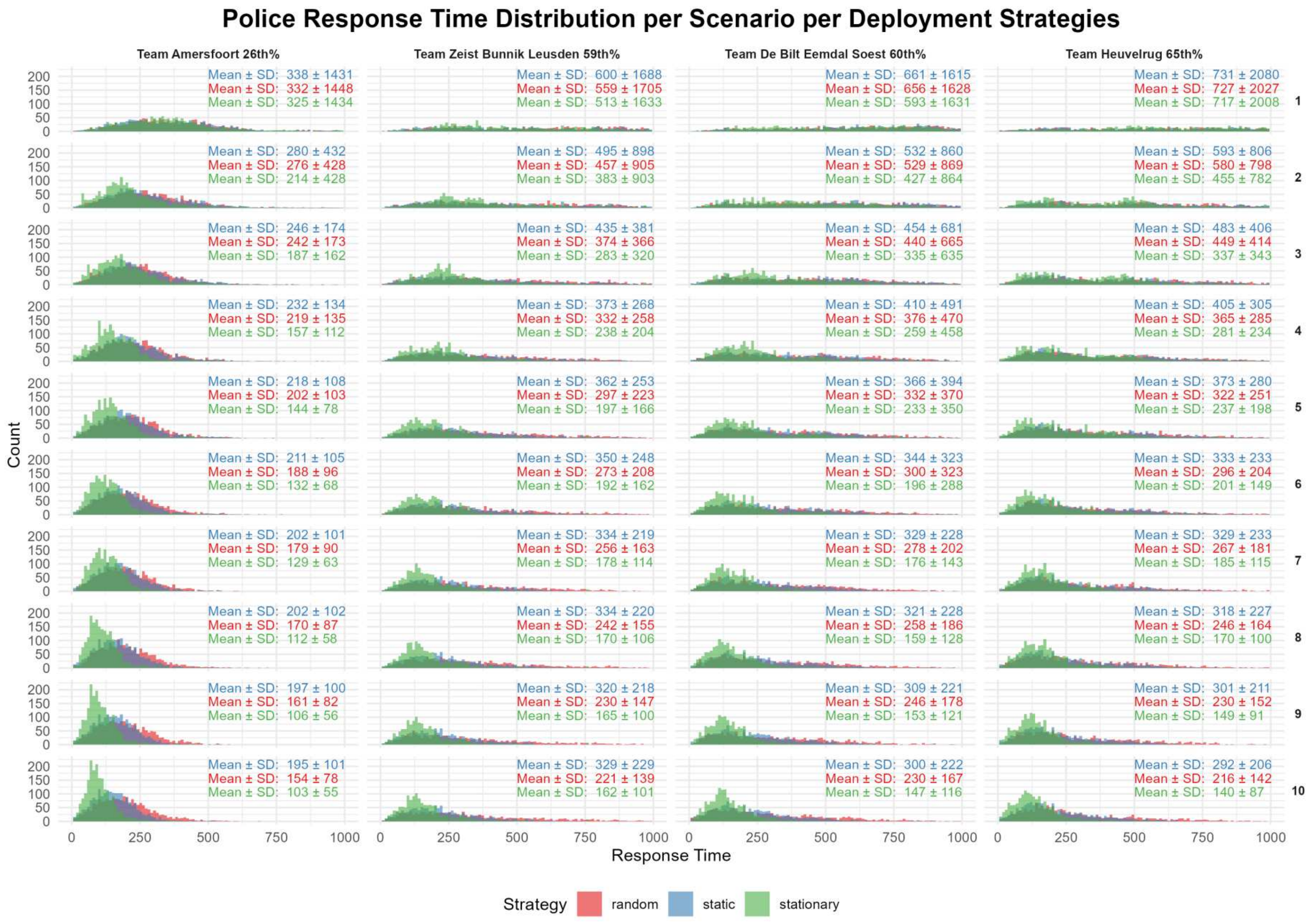

Figure 2: Police Response Time Distribution per Deployment Strategy

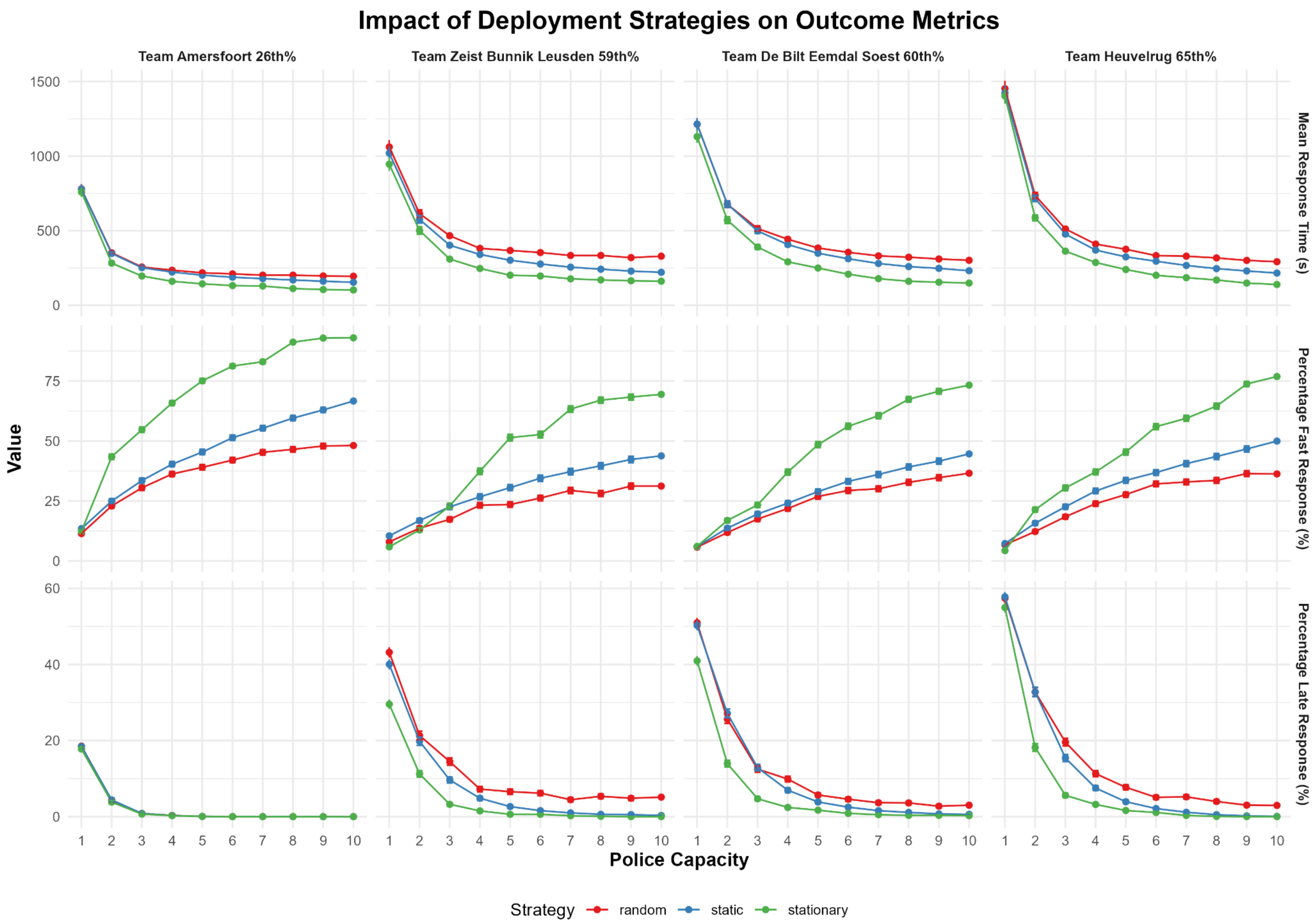

Figure 3: Impact of Deployment Strategies on Outcome Metrics

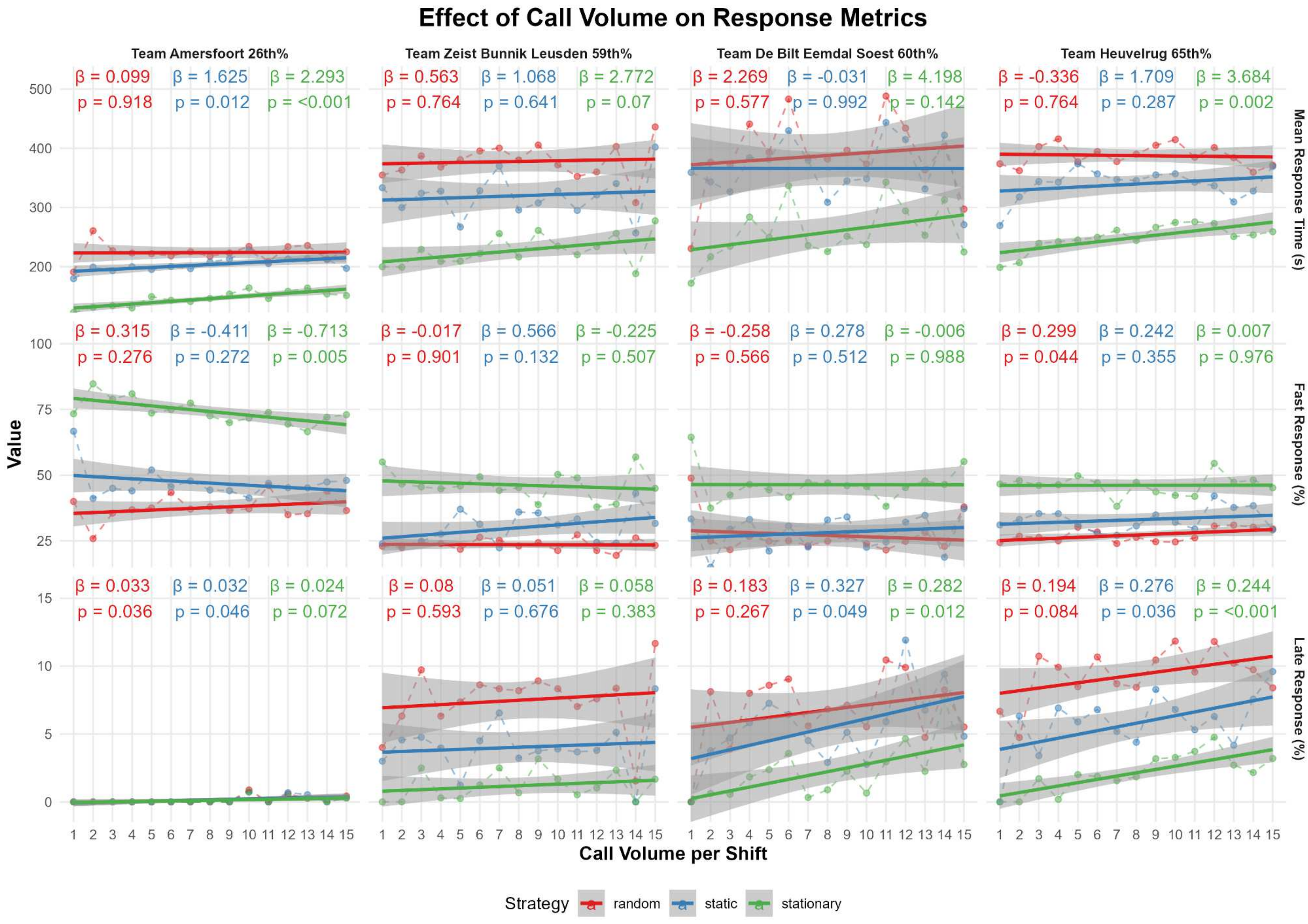

Figure 4: Impact of Call Volume per Basisteam per Deployment Strategy (for police capacity 3 - 7)

7. Appendix B

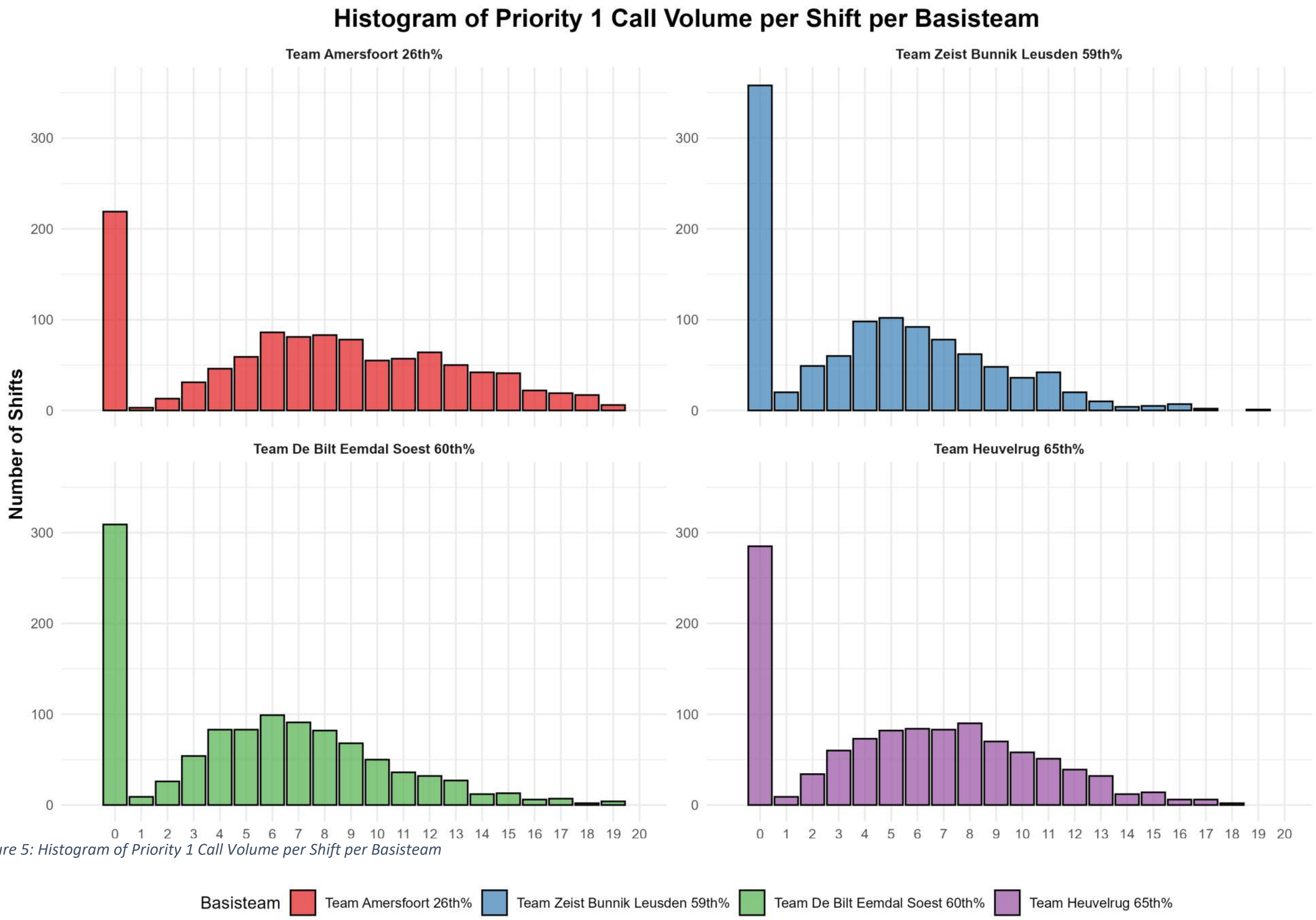

Figure 5: Histogram of Priority 1 Call Volume per Shift per Basisteam

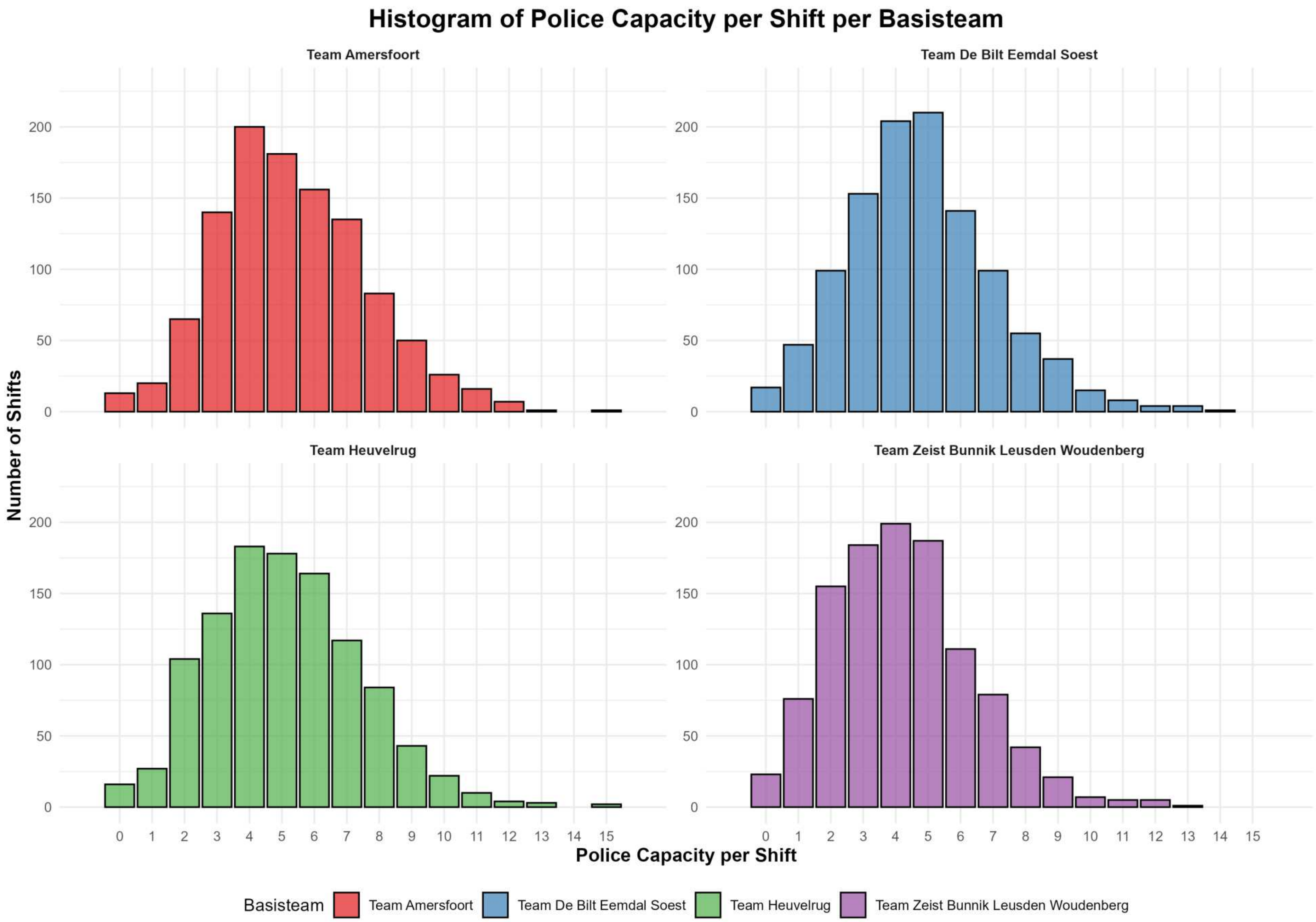

Figure 6: Histogram of Police Capacity per Shift per Basisteam (only including police units active within the shift)

References

Aly, A. A., & Litwhiler, D. W. (1979). Police Briefing Stations: A Location Problem. *A I I E Transactions*, *11*(1), 12–22. https://doi.org/10.1080/05695557908974395

Bieck. (1977). *Response Time Analysis: Executive summary*.

Birks, D., & Davies, T. (2017). Street Network Structure and Crime Risk: An Agent-Based Investigation of the Encounter and Enclosure Hypotheses. *Criminology*, *55*(4), 900–937. https://doi.org/10.1111/1745-9125.12163

Birks, D., & Townsley, M. (2018). Agent-based decision-support systems for crime scientists. In R. Wortley, A. Sidebottom, N. Tilley, & G. Laycock (Eds.), *Routledge Handbook of Crime Science* (pp. 334–349). Routledge.

Birks, D., Townsley, M., & Stewart, A. (2012). Generative Explanations of Crime: Using Simulation to Test Criminological Theory*. *Criminology*, *50*(1), 221–254. https://doi.org/10.1111/J.1745-9125.2011.00258.X

Birks, D., Townsley, M., & Stewart, A. (2014). Emergent Regularities of Interpersonal Victimization. *Journal of Research in Crime and Delinquency*, *51*(1), 119–140. https://doi.org/10.1177/0022427813487353

Blanes i Vidal, J., & Kirchmaier, T. (2018). The Effect of Police Response Time on Crime Clearance Rates. *The Review of Economic Studies*, *85*(2), 855–891. https://doi.org/10.1093/restud/rdx044

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, *65*, 126–139. https://doi.org/10.1016/j.compenvurbsys.2017.05.004

Bosse, T., & Gerritsen, C. (2008). Agent-based simulation of the spatial dynamics of crime: on the interplay between criminal hot spots and reputation. In L. Padgham, D. C. Parkes, J. Mueller, S. Parsons, & L. Cao (Eds.), *Proceedings of the Seventh International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS'08)* (pp. 1129–1136). ACM Press. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=76df8bb2916d7e48e8acf7436ad0ebbf38655ab6

Braga, A. A., Turchan, B. S., Papachristos, A. V., & Hureau, D. M. (2019). Hot spots policing and crime reduction: an update of an ongoing systematic review and meta-analysis. *Journal of Experimental Criminology*, *15*(3), 289–311. https://doi.org/10.1007/s11292-019-09372-3

Brantingham, P. J., & Tita, G. (2008). Offender Mobility and Crime Pattern Formation from First Principles. In *Artificial Crime Analysis Systems* (pp. 193–208). IGI Global. https://doi.org/10.4018/978-1-59904-591-7.ch010

Chenevoy, N. L. (2022). *Determining optimal police patrol deployments: a simulation-based optimisation approach combining agent-based modelling and genetic algorithms*. University of Leeds.

Chow, A. H. F., Cheung, C. Y., & Yoon, H. T. (2015). Optimization of Police Facility Locationing. *Transportation Research Record: Journal of the Transportation Research Board*, *2528*(1), 60–68. https://doi.org/10.3141/2528-07

Cihan, A., Zhang, Y., & Hoover, L. (2012). Police Response Time to In-Progress Burglary. *Police Quarterly*, *15*(3), 308–327. https://doi.org/10.1177/1098611112447753

Clawson, C., & Chang, S. K. (1977). The relationship of response delays and arrest rates. *Journal of Police Science and Administration*, *5*(1), 53–68.

Curtin, K. M., Hayslett-McCall, K., & Qiu, F. (2010). Determining optimal police patrol areas with maximal covering and backup covering location models. *Networks and Spatial Economics*, *10*(1), 125–145. https://doi.org/10.1007/S11067-007-9035-6/METRICS

Dunnett, S., Leigh, J., & Jackson, L. (2019). Optimising police dispatch for incident response in real time. *Journal of the Operational Research Society*, *70*(2), 269–279. https://doi.org/10.1080/01605682.2018.1434401

Farrington, D. P. (1983). Randomized Experiments on Crime and Justice. *Crime and Justice*, *4*, 257–308. https://doi.org/10.1086/449091

Fienberg, S., Larntz, K., & Reiss Jr, A. J. (1976). Redesigning the Kansas City preventive patrol experiment. *Evaluation*, *3*(1–2), 124–131.

Groff, E., & Birks, D. (2008). Simulating Crime Prevention Strategies: A Look at the Possibilities. *Policing*, *2*(2), 175–184. https://doi.org/10.1093/police/pan020

Groff, E. R. (2007). Simulation for theory testing and experimentation: An example using routine activity theory and street robbery. *Journal of Quantitative Criminology*, *23*(2), 75–103. https://doi.org/10.1007/S10940-006-9021-Z/TABLES/6

Groff, E. R. (2008). Adding the Temporal and Spatial Aspects of Routine Activities: A Further Test of Routine Activity Theory. *Security Journal*, *21*(1–2), 95–116. https://doi.org/10.1057/palgrave.sj.8350070

Isaacs, H. H. (1967). *A Study of Communications, Crimes and Arrest in a Metropolitan Police Department. Appendix B of Science and Technology Task Force Report.*

Jagtenberg, C. J., Bhulai, S., & van der Mei, R. D. (2015). An efficient heuristic for real-time ambulance redeployment. *Operations Research for Health Care*, *4*, 27–35. https://doi.org/10.1016/j.orhc.2015.01.001

Jagtenberg, C. J., Bhulai, S., & van der Mei, R. D. (2017). Dynamic ambulance dispatching: is the closest-idle policy always optimal? *Health Care Management Science*, *20*(4), 517–531. https://doi.org/10.1007/s10729-016-9368-0

Kelling, G. L., Pate, A. M., Dieckman, D., & Brown, C. (1974). The Kansas City Preventive Patrol Experiment: A Summary Report. In *Washington, DC: Police Foundation.* https://blueravenintelligence.com/wp-content/uploads/blue-raven-intelligence-patrol-document-compressed.pdf

Koper, C. S. (1995). Just enough police presence: Reducing crime and disorderly behavior by optimizing patrol time in crime hot spots. *Justice Quarterly*, *12*(4), 649–672. https://doi.org/10.1080/07418829500096231

Kwak, N. K., & Leavitt, M. B. (1984). Police Patrol Beat Design: Allocation of Effort and Evaluation of Expected Performance. *Decision Sciences*, *15*(3), 421–433. https://doi.org/10.1111/j.1540-5915.1984.tb01227.x

Larson, R. C. (1974). A hypercube queuing model for facility location and redistricting in urban emergency services. *Computers & Operations Research*, *1*(1), 67–95. https://doi.org/10.1016/0305-0548(74)90076-8

Larson, R. C. (1975). What happened to patrol operations in Kansas city? A review of the Kansas city preventive patrol experiment. *Journal of Criminal Justice*, *3*(4), 267–297. https://doi.org/10.1016/0047-2352(75)90034-3

Larson, R. C. (1982). Critiquing Critiques. *Evaluation Review*, *6*(2), 285–293. https://doi.org/10.1177/0193841X8200600209

Leigh, J., Dunnett, S., & Jackson, L. (2019). Predictive police patrolling to target hotspots and cover response demand. *Annals of Operations Research*, *283*(1–2), 395–410. https://doi.org/10.1007/S10479-017-2528-X/TABLES/1

Malleson, N. (2012). Using Agent-Based Models to Simulate Crime. In *Agent-Based Models of Geographical Systems* (pp. 411–434). Springer Netherlands. https://doi.org/10.1007/978-90-481-8927-4_19

Mitchell, P. S. (1972). Optimal Selection of Police Patrol Beats. *The Journal of Criminal Law, Criminology, and Police Science*, *63*(4), 577. https://doi.org/10.2307/1141814

National Research Council. (2004). Fairness and Effectiveness in Policing. In K. Frydl & W. Skogan (Eds.), *Fairness and Effectiveness in Policing*. National Academies Press. https://doi.org/10.17226/10419

Pate, T., Kelling, G. L., & Brown, C. (1975). A response to “what happened to patrol operations in Kansas City?” *Journal of Criminal Justice*, *3*(4), 299–320. https://doi.org/10.1016/0047-2352(75)90035-5

Risman, B. J. (1980). The Kansas City Preventive Patrol Experiment: A Continuing Debate. *Evaluation Review*, *4*(6), 802–808. https://doi.org/10.1177/0193841X8000400605

Sacks, S. R. (2000). Optimal Spatial Deployment of Police Patrol Cars. *Social Science Computer Review*, *18*(1), 40–55. https://doi.org/10.1177/089443930001800103

Sherman, L. W., Gottfredson, D., MacKenzie, D., Eck, J., Reuter, P., & Bushway, S. (1997). *Preventing Crime: What Works, What Doesn’t, What’s Promising: A Report to the United States Congress*. https://nij.ojp.gov/library/publications/preventing-crime-what-works-what-doesnt-whats-promising-report-united-states

Sherman, L. W., & Weisburd, D. (1995). General deterrent effects of police patrol in crime “hot spots”: A randomized, controlled trial. *Justice Quarterly*, *12*(4), 625–648. https://doi.org/10.1080/07418829500096221

Spelman, W., & Brown, D. K. (1981). *Calling the Police: Citizen Reporting of Serious Crime*.

Tarr, D. P. (1978). Analysis of response delays and arrest rates. *Journal of Police Science & Administration*, *6*(4), 429–451.

Taylor, P. E., & Huxley, S. J. (1989). A Break from Tradition for the San Francisco Police: Patrol Officer Scheduling Using an Optimization-Based Decision Support System. *Interfaces*, *19*(1), 4–24. https://doi.org/10.1287/inte.19.1.4

van Barneveld, T., Bhulai, S., & van der Mei, R. D. (2016). The effect of ambulance relocations on the performance of ambulance service providers. *European Journal of Operational Research*, *252*(1), 257–269. https://doi.org/10.1016/j.ejor.2015.12.022

van Barneveld, T., Jagtenberg, C., Bhulai, S., & van der Mei, R. (2018). Real-time ambulance relocation: Assessing real-time redeployment strategies for ambulance relocation. *Socio-Economic Planning Sciences*, *62*, 129–142. https://doi.org/10.1016/j.seps.2017.11.001

Verlaan, T., & Ruiter, S. (2023). Predictors of police response time: a scoping review. In *Crime Science* (Vol. 12, Issue 1). BioMed Central Ltd. https://doi.org/10.1186/s40163-023-00194-3

Weisburd, D., Braga, A. A., Groff, E. R., & Wooditch, A. (2017). Can Hot Spots Policing Reduce Crime in Urban Areas? An Agent-based Simulation*. *Criminology*, *55*(1), 137–173. https://doi.org/10.1111/1745-9125.12131

Weisburd, D., Wilson, D. B., Petersen, K., & Telep, C. W. (2023). Does police patrol in large areas prevent crime? Revisiting the Kansas City Preventive Patrol Experiment. *Criminology & Public Policy*, *22*(3), 543–560. https://doi.org/10.1111/1745-9133.12623

Wilensky, U. (1999). *Netlogo* (6.4.0). Center for Connected Learning and Computer-Based Modeling, Northwestern University.

Wooditch, A. (2023). The Benefits of Patrol Officers Using Unallocated Time for Everyday Crime Prevention. *Journal of Quantitative Criminology*, *39*(1), 161–185. https://doi.org/10.1007/S10940-021-09527-4

Zhang, Y., & Brown, D. E. (2012). Police patrol district design using agent-based simulation and GIS. *2012 IEEE International Conference on Intelligence and Security Informatics*, 54–59. https://doi.org/10.1109/ISI.2012.6284091

Zimring, F. E. (1978). Policy Experiments in General Deterrence: 1970-1975. In *Deterrence and Incapacitation Estimating the Effects of Criminal Sanctions on Crime Rates* (pp. 140–186). The National Academies Press. https://doi.org/10.17226/18561