(No) Spillovers in reporting domestic abuse to police

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1 Introduction

Immediately after a crime, the risk of another crime in the same neighbourhood is increased (Johnson and Bowers, 2004; Short et al., 2009; Mohler et al., 2011). This triggering behaviour has been documented for a diverse range of crimes such as burglaries, homicides and robberies (Mohler, 2014; Reinhart and Greenhouse, 2018; Flaxman et al., 2019). Typically, the triggering is due to the same offender repeating their crime or other offenders learning about the promising criminal opportunity (Bernasco, 2008). However, this focus on offender behaviour as a source of triggering potentially overlooks victim behaviour as a source. Crime victims share their experiences with crime and with reporting to the police. This could influence other crime victims in their reporting decisions and imply triggering of crime reporting.

The reporting of crime depends on many factors which not only have to do with the characteristics of the crime, but with the geographic and social context of the crime victim (Bachman and Coker, 1995; Goudriaan et al., 2006). Studies have shown that some behaviours exhibit triggering behaviour: The behaviour of one person can spillover into their immediate social and spatial environment (e.g., Bayer et al., 2009; Fadlon and Nielsen, 2019). Combined with the well-documented triggering behaviour of crime on the offender side, we hypothesize that this property extends to the *reporting* of crime to police by victims. We explore this question in the context of domestic abuse.

Domestic abuse is a particularly interesting context to study spillovers effects due to four facts: 1. It is highly prevalent, 2. significantly under-reported, 3. has a high degree of social disclosure, that is many victims/survivors[1] tell a friend, neighbour or family member about the abuse and 4. typically, perpetrator and victim(s) constellations remain stable over time such that one perpetrator acts within only one household. That means that if we were to document any spillovers in reports of domestic abuse, they must be due to spillovers in victim behaviour rather than in offender behaviour.

The prevalence of domestic abuse is disconcerting: In the United Kingdom, approximately one in four adults experience domestic abuse in their adult life and an estimated 2.4 million adults have experienced some form of it in the last year (Office for National Statistics, 2019a). Domestic abuse is a complex phenomenon consisting of abusive events as well as patterns of abusive behaviours at the hands of intimate partners or family members (Kelly and Westmorland, 2016). At the same time, domestic abuse is largely hidden from public view. It is one of the most under-reported serious crimes and victims/survivors often endure abuse for many years before seeking outside institutional support with police or a support provider (SafeLives, 2015). Reporting a crime to police is a complex choice, especially in the context of domestic abuse. At the same time, the majority of survivors disclose the abuse to a friend, neighbour or family member, at a much higher rate than reporting to police (Osborne et al., 2012).

High rates of social disclosure paired with the high incidence of domestic abuse provide a context in which the disclosure of domestic abuse to police by *others* could affect an individual's decision to report. However, identifying spillovers in domestic abuse reporting is challenging because the number of calls to police about domestic abuse varies, both due to the variation in the underlying abuse and due to variation in reporting behaviour (Cohn, 1993). Furthermore, since neighbourhood characteristics have been shown to influence both the incidence of domestic abuse and the reporting of crime, we would expect both to cluster in neighbourhoods (Goudriaan et al., 2006; Beyer et al., 2015).

To separate spillover effects from spatio-temporal clustering, we model a data set of domestic abuse reports to police using a Hawkes process (Hawkes, 1971; Ogata, 1988;

[1] Often the term victim is used to describe someone who experienced domestic abuse recently, or in the criminal justice context. Some have criticized the term for assigning the person experiencing domestic abuse a passive role and prefer the term survivor. It emphasizes individuals' agency in processing and recovering from the abuse. Some people who experienced domestic abuse prefer to identify as victim, while others prefer survivor. In this chapter we use both terms interchangeably to reflect the tension between the victimisation that people experiencing abuse go through and the agency they possess to define, interpret and deal with the experience on their own terms.

Reinhart, 2018). Hawkes-type triggering spatio-temporal point processes have been an invaluable tool in identifying spillovers in criminal behaviour and disentangling them from clusters in space and time (Mohler, 2014; Reinhart and Greenhouse, 2018; Flaxman et al., 2019). The Hawkes process predicts a series of discrete events (reports) that arise from one of two intensity components: the background component which corresponds to the "typical" incidence of domestic abuse reports or the triggering component where each past event can trigger the occurrence of future events. The Hawkes process does not identify a causal link between events, as in "event i caused event j". Instead, past events increase the likelihood of future events in their spatio-temporal vicinity. Triggering is therefore the statistical quantification of said increase or spillover, not the identification of a causal relationship.

Specifying the forms of the background and triggering components is a crucial modelling choice since their shapes have important implications for inference and detection of triggering behaviour (Reinhart and Greenhouse, 2018). We employ the specification of the Hawkes process proposed by Zhuang and Mateu (2019) because it includes periodic components that account for the daily and weekly periodicity of reporting behaviour, for example if many domestic abuse reports are made Friday nights. Periodicity is predicted by criminological theories such as routine activity as well as empirical data (Cohen and Felson, 1979; Rotton and Cohn, 2001; Johnson and Bowers, 2004).

We also develop an extension of Zhuang and Mateu (2019)'s model such that reports of domestic abuse can be triggered by past reports, but also by the police response to past events. A meta-study by Davis et al. (2008) analysed the effect of police returning to the incident household to provide support to the initial responding officers or to follow-up with the victim(s). They find that such follow-up visits do not reduce future violence occurring but increase victim reporting of the violence. It stands to reason that if follow-up visits by police amplify the effects of a report to police, this effect could potentially extend beyond the reporting household. Our model extension adding an additional spillover channel tests this explicitly. With this extension that allows two types of events to trigger reports of domestic abuse (reports and follow-ups), we can statistically distinguish two channels of spillover effects: 1. report-to-report and 2. follow-up-to-report spillovers.

We test the presence of spillover effects in domestic abuse reporting on a data set of 6,084 calls for service to police. The data set covers all calls flagged as concerning domestic abuse in a major English city between January 2018 to December 2018. We find extremely limited evidence of spillover effects of domestic abuse reporting. Any such effects are limited to the first 6 days after an initial report and an area of 400m around the event. This is true for both types of spillovers tested in this study, report-to-report and follow-up-to-report. We find weak evidence that events taking place in neighbourhoods where people live closer together increase the likelihood of future events more than events in less dense areas. Taken together however, triggering in domestic abuse reporting is negligible.

Instead we document highly periodic reporting behaviour. In line with other studies, reports of domestic abuse are highest on weekends and in the evening. Our study highlights that when modelling crime contagion, it is important to carefully think about the dynamics of the reporting behaviour underlying the data.

The remainder of the chapter is structured as follows: Section 2 discusses the context of spillovers in reporting. Sections 3 and 4 introduce the data and methodology used in this study. Section 5 presents our results and we conclude by discussing the implications in Section 6.

2 Motivation

The focus of our study is on potential spillover effects of domestic abuse reporting. Section 2.1 discusses spillover effects in criminal behaviour due to offender behaviour identified using Hawkes processes. Section 2.2 examines the victim's decision to report domestic abuse to police. Section 2.3 concludes by discussing why spillover effects might exist in domestic abuse reporting and potential mechanisms. A full discussion of why we did not find any empirical evidence supporting this is postponed until Section 6.

2.1 Spillovers in crime

Spatio-temporal point processes are stochastic processes which model the occurrence of discrete events in space and time. In this study, we employ a spatio-temporal Hawkes-type point process with a triggering (or self-exciting) component (Hawkes, 1971; Ogata, 1988). Originally popular to model aftershocks of earthquakes, Hawkes processes have also been used to model crime events such as burglaries, shootings and calls for service more generally (Mohler et al., 2011; Reinhart and Greenhouse, 2018; Loeffler and Flaxman, 2018; Flaxman et al., 2019; Zhuang and Mateu, 2019). Their use is motivated by the observation that one crime tends to trigger further crimes in the same area immediately afterwards. For example, burglars often re-visit an area in the weeks after a successful score (Short et al., 2009; Bernasco et al., 2015). Such behaviour is very conveniently modelled by a Hawkes process because it can disentangle clusters from spillovers. Put differently, is the risk of burglary in an area high because few houses have alarm systems or because of a recent break-in? The Hawkes process can be understood as a model-based test of this distinction, in contrast with traditional statistics vulnerable arbitrary thresholds (Meyer et al., 2016; Loeffler and Flaxman, 2018).

The triggering behaviour of crime has been described under different names: Near-repeat victimization describes the phenomenon that a small number of victims or victims with similar characteristics account for a large number of crime offences (Farrell and Pease, 1993). Weisburd (2015) argues for a 'law of crime concentration' which states that just a few street segments account for the vast majority of crimes in a city. Such observations have led to a rich literature of the identification of crime hotspots, both stable and emerging in time (Johnson and Bowers, 2004; Gorr and Lee, 2015).

Multiple reasons have been put forward as to why crime exhibits triggering behaviour. Criminological theories such as routine activity theory analyse crimes as the intersection of a suitable target or victim, a motivated offender and a lack of supervision (Cohen and Felson, 1979). Similarly, the application of an economic or rational choice framework to crime predicts that a rational decision-maker will consider potential costs and pay-offs of a criminal opportunity (Clarke and Cornish, 1985; Sanders et al., 2017). Under both theories, a successful offender will seek to repeat their success in addition to other offenders picking up similar cues (Bernasco, 2008). Lastly, some crimes will result in retaliatory action. For example, gang violence can induce retaliatory violence, as can shootings (Ratcliffe and Rengert, 2008; Brantingham et al., 2018). These behaviours have been successfully identified using Hawkes processes (Mohler et al., 2011; Reinhart and Greenhouse, 2018; Loeffler and Flaxman, 2018).

But this research focuses only on the offender side of crime. A phenomenon that has not yet been explored in depth is whether there are any spillovers in victim behaviour.

The context in which victims of a crime make the decision to report to police is explored in more detail in the next section. But a rich literature of behaviour in other contexts provide us with a reference frame on how crime victim behaviour might spill over: There is ample evidence that a change in a person's or household's behaviour can change the behaviour of surrounding people and households. For example, sending letters about TV licenses to households increases compliance in non-treated households in the neighbourhood (Rincke and Traxler, 2011; Drago et al., 2020). Beyond license compliance, such effects have been documented in, e.g., voting, insurance, or school performance (Nickerson, 2008; Hong and Raudenbush, 2006; Sobel, 2006; Cai et al., 2015; Halloran and Hudgens, 2016). Identifying spillovers is relatively feasible when evaluating a specific, randomized intervention (Aronow et al., 2020).

In observational studies however, one encounters a familiar issue: Is the similarity in behaviour the result of spillover or simply a concentration of behaviour? For example, Bertrand et al. (2000) demonstrate that women are more likely to use welfare when there is a local network of the same ethnic group (and the group also has a high level of welfare use). Aizer and Currie (2004) try to separate neighbourhood from network effects in the similar use of publicly funded prenatal care within ethnic groups. In contrast, they find no evidence for information sharing through networks and instead show that behaviour is highly similar in ethnic groups because of local hospital policies.

Without assumptions or explicit knowledge about the underlying structure of networks (e.g., Fadlon and Nielsen, 2019; Nicoletti et al., 2018) it is challenging to separate clusters and spillovers. It is in this precise context that the Hawkes process becomes a particularly valuable statistical model. Meyer et al. (2016) argue that Hawkes processes are a principled, model-based way of separating space-time clusters from the spread of a behaviour.

As we will argue in the next section, domestic abuse is an ideal context in which to explore the potential for reporting spillovers: It is under-reported but highly prevalent and exhibits a high degree of social disclosure while typically only having one offender/victim constellation per household. In our context, the use of a Hawkes process allows us to identify if a single report of domestic abuse to police increases the likelihood that a victim of domestic abuse in another household in the neighbourhood will also report without having to make any assumptions about the nature or structure of local networks.

2.2 Reporting domestic abuse

A persistent challenge to understanding and addressing domestic abuse is its hidden nature. It is hidden because the abuse often takes place away from the public eye in private homes, but also because domestic abuse is extremely under-reported. Many victims endure domestic abuse for a long period before disclosing their abuse to a formal institution, if at all (SafeLives, 2015). Because of this, available numbers are significant undercounts of the actual prevalence. Even large-scale surveys of the general population such as the Crime Survey for England and Wales are highly sensitive to methodological details (Ellsberg et al., 2001; Walby and Allen, 2004; Emery, 2010; Agüero and Frisancho, 2021). Further, they are most likely underestimates of the true prevalence because they often exclude people outside of stable households such as unhoused individuals or those in temporary accommodation, hospitals and refuges (Office for National Statistics, 2017).

Given its high prevalence, it is crucial to consider why victims/survivors of domestic abuse do not report to police in higher numbers (Osborne et al., 2012). In general, the decision to report a crime to the police is framed as a process of weighing potential positive outcomes to reporting and disincentives and barriers (Laub, 1981; Skogan, 1984; Gottfredson and Gottfredson, 1988). Both of these factors are particularly fraught within the context of domestic abuse since victims face significant barriers to reporting and judicial outcomes are usually poor.

Domestic abuse cases have high rates of attrition through the various stages of criminal justice system such that 96% of police-recorded cases do not result in a conviction (Hester, 2006; Her Majesty's Inspectorate of Constabulary, 2014). Agents within the system often attribute this to victims withdrawing participation (Hester, 2006; Starmer, 2011). In contrast, other work has identified insufficient evidence collection and under-charging as a significant factor in attrition (Nelson, 2013; Her Majesty's Inspectorate of Constabulary, 2014). Interviews of survivors find that participation in the criminal justice system process for them is highly dependent on their perception of the system's ability to provide safety (Felson et al., 2002; Hester, 2006). These interviews emphasize that justice goals of victims/survivors can differ from those of the criminal justice system and provide an important explanation for under-reporting (Coy and Kelly, 2011; Westmarland and Kelly, 2013).

Studies examining the challenges to reporting domestic abuse have identified a number of barriers. A crucial first step is recognizing the abuse as a serious offence worth reporting. Often, domestic abuse is considered a "private issue" which should not be publicized to the outside (Tjaden and Thoennes, 2000; Rogers et al., 2016). The recognition of abuse as such is strongly mediated by the seriousness of the abuse, where victims with more serious injuries are more likely to call the police (Bachman and Coker, 1995). Victims of other types of crimes are less likely to call the police if the offender is not a stranger (Gartner and Macmillan, 1995). Since domestic abuse by definition implies an offender intimately familiar to the victim, victims have to make a difficult choice of "handing over" a person close to them to the police. Involving the police can set into motion a series of consequences which victims may not necessarily want. For example, victims do not always want to leave the relationship or family environment due to love or family bonds (Strube, 1988). More importantly, many victims are potentially isolated or without means to leave the abusive environment. Combined with underfunded domestic abuse services, the decision to disclose domestic abuse can be existential (Walby and Towers, 2012; Sanders-McDonagh et al., 2016). Indeed, 10–40% of unhoused individuals cite domestic abuse as contributing factor to their homelessness (Cramer and Carter, 2002; Office for National Statistics, 2019b). Furthermore, victims of domestic abuse often fear retribution by the perpetrator or people close to the perpetrator and fear for the safety of their children (Strube, 1988; Greenfeld et al., 1998; Coy and Kelly, 2011).

Another important consideration is how perceptions of what constitutes "legitimate" abuse mediate reporting decisions. In the context of sexual assault, existing work has uncovered that notions of what a "real assault" looks like (e.g., a violent assault by an armed stranger) significantly affect victims' willingness to report to police (Myhill and Allen, 2002). Recent work finds that perceptions of what constitutes sexual harassment is mediated by how stereotypically feminine the female victim presents (Goh et al., 2021). While this is less well-explored in the context of domestic abuse, characteristics of the abuse and its survivor matter: For example, intoxicated victims are assigned more blame for the abuse than sober victims (Leonard, 2001).

Such perceptions of "real" or "legitimate" abuse affect police officers as well. Officers, too, operate with beliefs and stereotypes of "typical victims" of domestic abuse and sexual violence, which influence how they handle these cases (Trute et al., 1992; Robinson et al., 2018; O'Neal, 2019). Demographic groups such as sex workers, transgender people and people with disabilities are already considerably more likely to be subjected to violence due to their marginalization but often face further challenges being taken seriously by police (Nixon, 2009; Roch et al., 2010; Lombard and Scott, 2013; Phipps, 2013; Rogers et al., 2016). Some studies find that reports of domestic abuse increase as the number of female police officers in the force increases which suggests that some of these factors may be less pronounced in female officers (Miller and Segal, 2019; Kavanaugh et al., 2019).

This arbitration of legitimacy can turn police officers—who are often the first point of contact to the criminal justice system—into gatekeepers of access to said systems (Taylor and Gassner, 2010). Surveys have shown that victims fear not being believed or being taken seriously by police (Tjaden and Thoennes, 2000; Hawkins and Laxton, 2014; Her Majesty's Inspectorate of Constabulary, 2014). Indeed, there have been investigations into police mishandling of domestic abuse cases and into domestic abuse by police officers (Independent Office for Police Conduct, 2018; Centre for Women's Justice, 2020). Similarly, victims/survivors who decide to report to police affirm that their experience is not uniformly positive. In the Crime Survey for England and Wales, 72% of victims of domestic abuse stated that they found the police fairly or very helpful, while only 55% reported feeling safer after contacting police. Approximately 14% reported feeling less safe (Osborne et al., 2012). The upshot of analysing the factors influencing the decision to report domestic abuse to police is that many victims/survivors view calling the police as a last resort (Fitzgerald et al., 1995; Women's Aid, 2009).

This would leave us with a scant premise for investigating spillovers of police reports of domestic abuse. However, surveys of survivors reveal that they do disclose their abuse, even if not necessarily to police: In England, more than 73% of victims of domestic abuse told a friend or relative about the abuse, compared with only 23% reporting to police (Osborne et al., 2012). While the reporting rates to police vary (from as low as 2% to almost 50%), other work similarly finds that more than half of victims disclose their abuse to someone close to them (Greenberg and Ruback, 1992; Fisher et al., 2003; Coy and Kelly, 2011; Stark et al., 2013). Indeed, often the response by the confidant is influential in the victim's decision to end the relationship as well as report to police (Goodkind et al., 2003; Regan et al., 2007; Biaggio et al., 1991).

High rates of social disclosure paired with the high incidence of domestic abuse provide a context in which the disclosure of domestic abuse to police by others could affect the decision to report. This establishes the basis for our core hypothesis: Someone close to a victim of domestic abuse reporting their own abuse to police might induce the victim to contact police themselves.

2.3 Spillover channels

In our model, we distinguish between two channels of spillovers: Report-to-report and follow-up-to-report.

The first channel, report-to-report, accounts for spillovers due to information passing through social peer networks. As established, victims of domestic abuse often fail to identify criminal abuse as such because of their close relationship with the perpetrator. Knowing that others in their vicinity reported abuse might affect how victims perceive and frame their abuse. While this has not yet been explored in the context of domestic abuse, some studies have examined the effects of information transmission on the reporting of sexual violence: Cheng and Hsiaw (2020) develop a formal model of reporting sexual misconduct in the workplace. The context of workplace harassment differs from domestic abuse: Mainly, their work centres on corroboration, that is multiple individuals need to report misconduct before action against an offender is taken. As a consequence, individuals subjected to sexual harassment face strategic uncertainty and a coordination problem around reporting: If they report misconduct and no one else has, they may face retaliatory penalties. If instead multiple individuals have come forward and a substantive record can be corroborated, then an outside party can sanction the harasser. Corroboration is difficult to translate to the context of domestic abuse (where a perpetrator typically only abuses within their immediate household). Still, Cheng and Hsiaw (2020)' model illustrates that individuals face information frictions about how wide-spread a behaviour is, which affects their propensity to report.

Levy and Mattsson (2020) study the effect of the #MeToo movement on reporting behaviour and find that it resulted in a persistent increase of reports of sexual violence. They argue that their results are plausibly explained by a rapid change in social norms and information. Similarly, Iyer et al. (2012) and McDougal et al. (2018) find that visible social changes (the election of female politicians and a highly publicized case of sexual violence) lead to a large increase of reports of sexual violence.

The second channel of spillovers, follow-up-to-report, accounts for the effects of police intervention. Intervention by police in cases of domestic abuse is not uncontroversial: Historically, police departments tended to follow an under-enforcement policy which meant they rarely intervened and even less frequently arrested the perpetrator. Only after public pressure by activists did the policy response change (Fagan, 1996; Erwin, 2006). In the United States, police departments' non-arrest policies were subjects of lawsuits which argued that the (lack of) intervention did not provide women victims with equal protection of the law. As a result, many police departments in the United States implemented mandatory arrest policies, meaning that one person, the perpetrator, is to be arrested at the scene of the domestic abuse incident (Fagan, 1996). Multiple studies have since demonstrated that such mandatory arrest policies do not create deterrent effects and may lead to increased arrest rates of victims of abuse (Hoppe et al., 2020). Mandatory arrest policies were never formally implemented in the United Kingdom, but actively encouraged. Today, policing is an integral part of the United Kingdom's policy response to domestic abuse (Walklate, 2008; Matczak et al., 2011).

Some studies have investigated the effects of police intervention on future violence within the same household, with mixed results (Hoppe et al., 2020; Hanmer et al., 1999). A meta analysis by Davis et al. (2008) of ten studies investigates a specific type of police intervention: follow-up visits which they call "second responder visits". These in-person visits are part of specific programmes which aim to intervene in the cycle of domestic abuse. When victims notify police about an incident, a lot of time may pass before they call police again. This may be due to a cessation of the abuse or reflective of victims' reluctance to report to police. Crisis theory predicts that there may be a "window of opportunity" immediately after an incident of domestic abuse during which the victim might be interested in leaving the environment and/or pursue legal options because the usual coping strategies are not working (Kelly et al., 1999; Mickish, 2002). Therefore, the programmes evaluated in Davis et al. (2008) send a police officer and, depending on the programme, police officer together with a victim advocate to follow up on the initial report within a few days.

Each study in the meta analysis considered recidivism as a primary outcome, with most studies using both police reports and victim surveys to measure the incidence of repeat violence. Half the studies were a fully randomized experimental design, half were quasi-experimental. All studies took place in the United States. Results from the victim surveys indicate that the follow-up visits had no significant effect on repeat violence (standardized difference in group means: -0.01, $p = 0.82$). Instead, there is a modest positive increase in reports to police (standardized difference in group means: 0.12, $p = 0.01$). The results suggest that while the follow-up visits do not reduce the likelihood of abuse, victims seem more confident about reporting the violence to police.

Our study tests an extension of this effect: Do police visits following an incident have an effect outside the directly affected household? The mechanism of this effect links back to the notion that victims of domestic abuse often do not recognize their abuse as such. Repeat visits by police to another call can then serve as validation and amplification: Police are taking the incident seriously and paying attention.

We would expect any spillover effects to be more prevalent in areas with strong social networks. Unfortunately, we do not have any measure of local social cohesion available (as in, e.g., Goudriaan et al., 2006). As a proxy, we use the share of households living in detached houses in the area since individuals living closer together are also closer to the goings-on of their neighbours (see also Ivandic et al., 2020).

3 Data

Our data set covers all 6,084 calls to police about an incident of domestic abuse between 01/01/2018 to 31/12/2018 in a city with over 300,000 inhabitants in England.

When someone calls the police for service, the call will be picked up by a call handler in the police contact centre. The handler will ask a series of questions to evaluate the situation and decide on an appropriate police response. If the call handler at this point assesses the situation to take place in the context of domestic abuse, he or she raises a flag in the system which notifies the responding officer of that context.

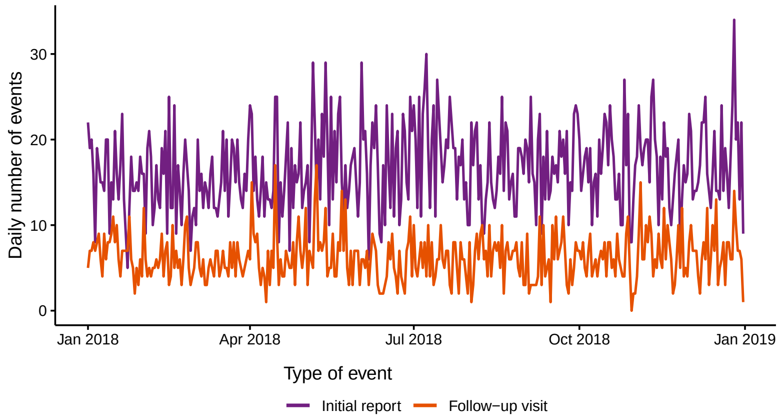
In the United Kingdom, there is no statutory crime of domestic abuse. But many forms of domestic violence constitute criminal offences such as assault, sexual offences, stalking or criminal damage. Police forces in the UK classify such incidents as domestic abuse if they meet the cross-government definition: “Any incident or pattern of incidents of controlling, coercive or threatening behaviour, violence or abuse between those aged 16 or over who are or have been intimate partners or family members regardless of gender or sexuality. This can encompass but is not limited to the following types of abuse: psychological, physical, sexual, financial, emotional." (Home Office, 2013).

In the past, English police forces have been criticized for not supplying responding officers with sufficient information. For example, officers may often not have any information on the perpetrator or know that the victim/survivor may be a repeat victim (Her Majesty's Inspectorate of Constabulary, 2014). Similarly, the initial call handler may not identify a situation as domestic abuse but the police responders at the scene may do so.

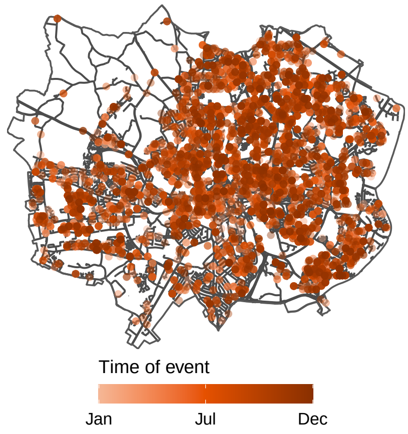
A call enters our data set when either the handler or the responders classify the call as domestic abuse. Research conducted in the UK finds evidence that there is variation between call handlers and officers in their handling of domestic abuse: Female call handlers result in faster police response and cases handled by response teams with more female officers have lower legal attrition (Hawkins and Laxton, 2014).

For each call in our data set, we know the time when the call was placed and the location of the incident. A key feature of our analysis is the question of police follow-ups where officers return to places of domestic abuse. A key challenge here, however, is that we cannot consistently check *why* police officers return: Is it for a scheduled routine visit or is it because the domestic situation escalated and requires intervention? This reason for this inconsistency is inconsistent police record keeping. Some officers who return to the scene will link their new visit to the old case identifier which means that we can follow this link. However, some officers will also create a new case identifier unconnected to the original case. Is this because there is a new incident of domestic abuse at the house, therefore necessitating the creation of a new case file? Or is this simply an oversight on the officer's part?

While more than two thirds of return visits happen between business hours, suggestive of scheduled visits, our approach to this issue is conservative: Every return visit by police officers to the same address within two weeks of the initial call is classified as a follow-up visit, without distinction as to why the officers might have returned. If officers return after more than 15 days of the initial call we consider it a new incident of domestic abuse due to escalated violence. This concerns only 29 calls in our data set. Choosing 15 days as the cutoff is motivated by two factors: 1. Police aim to respond to non-urgent incidents



(a) Time series of events



(b) Event locations

Figure 1: Time and location occurrence of events

within 5 days (and within 15-60min to urgent incidents, depending on the urgency) which means that there is a reasonable range of days after an initial incident during which officers might follow-up and 2. our model uses an explicit cutoff at 30 days after which we no longer expect triggering of domestic abuse reports and classifying into this scheme implicitly prevents reports of domestic abuse in a household from apparently "triggering" further reports in the same household which are in reality the fallout from the initial report.

Taken together, this results in 6,084 initial calls for service and 2,286 follow-up visits by police. Figure 1a and Figure 1b show the temporal and spatial dimension of the raw data.

4 Method

We formally introduce our specification of the Hawkes process in Section 4.1 and our inference procedure in Section 4.2.

4.1 Model

We use a self-exciting point process model to describe reports of domestic abuse to police. Consider a set of observed realizations from a Hawkes process (Hawkes, 1971; Ogata, 1988), where $\{t_1, t_2, \ldots, t_n\}$ denotes the time-ordered sequence of event times and and

$\{s_1, s_2, \ldots, s_n\}$ denotes the time-ordered sequence of event locations. The conditional intensity of this spatio-temporal point process defined on time $t \in [0, T)$ and location $s \in X \subseteq \mathbb{R}^d$ is then given by

$$\begin{aligned} \lambda(t, s|\mathcal{H}_t) &= \mu(t, s) + \int_0^t \int_X f(t-u, s-v)\mathrm{d}N(u \times v) \\ &= \mu(t, s) + \sum_{j:t_j<t} f(t-t_j, s-s_j), \end{aligned} \tag{1}$$

where $N(\cdot)$ counts the number of events in an interval and $\mu(t, s)$ describes the background rate. Because of the self-exciting component f, the intensity is conditioned on the history of the process up to and including t, $\mathcal{H}_t$. The shape of f determines if, by how much and for how long past events can trigger events in addition to the base background rate. Because we need $\lambda(t, s|\mathcal{H}_t) \geq 0$, we set $\mu(t, s) \geq 0$ and $f(t, s) \geq 0$ for all t, s. For ease of notation, we will omit the explicit conditioning on $\mathcal{H}_t$ from now on, but the reader should keep in mind that $f(t, s)$ depends on all past events $\mathcal{H}_t$, for all spatial locations s.

The specification of the background and triggering component depend on the application context (Reinhart, 2018). Our specification of the background component follows Zhuang and Mateu (2019), who consider a periodic decomposition of the background as follows:

$$\mu(t, s) = m_0 \mu_{\text{trend}}(t)\mu_{\text{weekly}}(t)\mu_{\text{daily}}(t)\mu_{\text{area}}(s), \tag{2}$$

where $\mu_{\text{trend}}(t)$, $\mu_{\text{weekly}}(t)$ and $\mu_{\text{daily}}(t)$ represent the trend term over the whole study window, the weekly and daily periodicity in the time dimension of the background rate, respectively. $\mu_{\text{area}}(s)$ is an estimate of the background spatial intensity in the study area. These terms are normalized to have mean 1. As a consequence, m_0, which is a non-negative weighting term attains the role of weighting the entire background component (Loeffler and Flaxman, 2018; Zhuang and Mateu, 2019).

We take the triggering component f to be separable in time and space such that $f(t, s) = \theta g(t)h(s)$. Again we normalize g and h to integrate to 1 such that θ gives the average number of events coming from the trigger component. Furthermore, we extend the approach of Zhuang and Mateu (2019) by not only allowing past events in the trigger, but also additional event types. Here, we explicitly consider the effect of follow-up visits by police, in addition to the self-exciting effect of reporting domestic abuse itself. Doing so requires us to consider additional event times and locations, those of police follow-ups. This results in an additional sequence of event times $\{t'_1, \ldots, t'_k\}$ and of locations $\{s'_1, \ldots, s'_k\}$, where (t'_j, s'_j) give time and location of a follow-up event j. These different event types are distinguished by a sequence of length $n+k$ of labels M_j, where $M_j = 0$ if event j is a report of domestic abuse to police and $M_j = 1$ if event j is a follow-up.

Note that despite the introduction of additional events, we are still only modelling the intensity of domestic abuse reports (events for which $M_j = 0$). Allowing police follow-ups ($M_j = 1$) to induce additional reports of domestic abuse does not change the outcome event of interest. However, its introduction creates a notational challenge: The number of events to sum over differ between the background which only depends on the reports and the trigger which depends on outcome events (reports) and additional events (follow-ups). If we wanted to be absolutely precise in our notation, we would have to distinguish two sequences of event times: t^{reports} which holds the event times of our outcome event of interest and t^{all} which is the time-ordered sequence of *all* events in $t^{\text{reports}} \cup t^{\text{followups}}$. To then denote the total triggering probability mass on event i, we would need to write:

$$\sum_{\substack{j:t_j<t_i \\ t_j \in t^{\text{all}}}} \theta_{M_j} g(t_i - t_j) h(s_i - s_j).$$

In an attempt to avoid such cumbersome indexing, we abuse notation and assume that anytime we index over j, we are implicitly indexing over all events in t^{all}. Using this shortcut, we instead rewrite the last equation to:

$$\sum_{j:t_j<t_i} \theta_{M_j} g(t_i - t_j) h(s_i - s_j),$$

where the initial

$$g(t_i - t_j) = \frac{1}{(t_i - t_j)/24 + 1/24}, \qquad t_i > t_j$$

$$h(s_i - s_j) = \frac{1}{1 + (s_i - s_j)^2}.$$

We measure distance in kilometres and time in days, such that $t_i = 1.5$ denotes the time of an event i that took place 1.5 days (= 36 hours) since the beginning of the study window. In contrast with e.g., Kalair et al. (2020), we do not enforce monotonicity of $g(t)$ and $h(s)$ since we might expect the social dynamics of reporting to be non-monotonic.

Together, we finally have the conditional intensity function:

$$\lambda(t, s) = m_0 \mu_{\text{trend}}(t)\mu_{\text{weekly}}(t)\mu_{\text{daily}}(t)\mu_{\text{area}}(s) + \sum_{j:t_j<t} \theta_{M_j} g(t - t_j)h(s - s_j). \tag{3}$$

4.2 Inference

Performing inference for this model is challenging: The estimation of the background component requires that one can distinguish events coming from the background and triggered events (Reinhart, 2018). This paper follows the inference procedure first proposed in Zhuang et al. (2002) and applied in the context of crime in Zhuang and Mateu (2019). While full details are available in these references, the following section provides a brief overview over the inference procedure's key steps. We begin with stochastic declustering, which gives the answer to the question of why an iterative procedure allows us to obtain estimates for our model components. We then explain how the exact estimates for the model components are derived and then put forward our extension of the model.

4.2.1 Stochastic declustering

When the background component contains a non-parametric element estimated from data, we need to be able to separate out the events coming from the background to properly estimate it. Zhuang et al. (2002) propose the following basic approach: With the observed realizations of the point process and the conditional intensity as defined in Equation (1), we can define two quantities of interest from this setup.

1. the probability that an event came from the background, rather than the trigger component

$$\varphi_i = \text{P}(\text{event } i \text{ came from background}) = \frac{\mu(t_i, s_i)}{\lambda(t_i, s_i)} \tag{4}$$

2. the probability that an event was triggered by a past event

$$\rho_{ij} = \mathrm{P}(\text{event } i \text{ was triggered by } j,\, j < i) = \frac{f(t_i - t_j, s_i - s_j)}{\lambda(t_i, s_i)}. \tag{5}$$

By the law of total probability, it is clear that

$$\varphi_i + \sum_{j=1}^{i-1} \rho_{ij} = 1. \tag{6}$$

One way to interpret Equation (6) is that all events $j = 1, \ldots, i-1$ preceding event i added probability mass ρ_{ij} on the event i, which allows us to decompose event i into background and trigger.

We can now begin to address our problem: In order to estimate the background, we need to determine whether an event came from the background (φ_i), which in turn depends on f (to obtain λ). The procedure is therefore iterative, beginning with an initial guess for μ, f and λ and iterating until convergence.

A very naive first guess at an estimator for μ would be a histogram estimator. For a spatio-temporal point process with conditional intensity as in Equation (1), we can subdivide the spatial study area into K subdivisions S_k and assume that the background is piece-wise constant in each subdivision. A histogram estimator for subdivision k is then given by (compare Equation (31) in Zhuang, 2020):

$$\hat{\mu}_k = \frac{1}{\|S_k\|} \sum_i \hat{\varphi}_i \mathbb{I}((t_i, s_i) \in S_k),$$

where $\mathbb{I}$ is the indicator function. While instructive, this estimator is always coarser than and therefore inferior to a kernel density estimator:

$$\hat{\mu}(s,t) = \sum_i \varphi_i Z(t - t_i; b_t) Z(s - s_i; b_i),$$

where

$$Z(x; b) = \frac{1}{\sqrt{2\pi} b} \exp\left(-\frac{x^2}{2b^2}\right)$$

is a Gaussian kernel with bandwidth b. b_t denotes the bandwidth for the temporal kernel and b_i is an event-specific bandwidth for the spatial kernel. This adaptive bandwidth accounts for the fact that a single bandwidth is often a poor choice with clustered point processes because it oversmooths some areas while being too noisy in other areas (Reinhart, 2018). Instead, b_i is set such that a spatial disk centred on event i with radius b_i contains n_p other events (Zhuang et al., 2002; Zhuang, 2011).

In much the same way, we can construct an estimator for f based on the triggering probabilities ρ_{ij}:

$$\hat{f}(t, s) = \sum_{i,j} \rho_{ij} Z(t - (t_i - t_j); b_g) Z(s - (s_i - s_j); b_h),$$

where b_g and b_h are the bandwidths for the temporal kernel and the spatial kernel, respectively. With these estimators in hand, we can in principle define an iterative procedure: With an initial guess for μ and f, we calculate φ and ρ. Then we update our estimates for μ and f, update φ and ρ until convergence.

Yet, this precise inference procedure does not actually work for the concrete model proposed: The iterative procedure can only recover a single temporal component applied to the entire period. However, in our specification of $\mu(t, s)$ in Equation (2), we specified multiple periodic components to account for periodicity. To obtain estimates for all background components, we need to modify our inference procedure.

4.2.2 Estimating periodic non-parametric background

To do that, we rely on the Georgii-Nguyen-Zessin formula (Georgii, 1976; Nguyen and Zessin, 1979) developed in the context of spatial and spatio-temporal point processes by Baddeley et al. (2005) and Zhuang (2006):

$$\mathbb{E}\left[\int_{[T_1,T_2]\times X} \gamma(t, s) \mathrm{d}N(t \times s)\right] = \mathbb{E}\left[\int_{T_1}^{T_2} \int_X \gamma(t, s)\lambda(t, s) \mathrm{d}t \mathrm{d}s\right], \tag{7}$$

for a time interval $[T_1, T_2]$, area X and a non-negative function γ. Equation (7) is not trivial. Briefly, say we would like to know the value of the function γ over the entire space over which our point process is defined. Equation (7) states that we can evaluate the function γ over all observed points and the expectation of this (i.e., the left-hand side of Equation (7)) is equivalent to the expectation of that function over the entire space weighted by the intensity of the point process. This allows us to then rearrange terms and obtain the expectation of the function over the entire space.

Going back to our inference problem, recall that we are still trying to estimate the model components. For each of these components, we can construct a non-negative function w which is the component's contribution to the overall intensity. As an example, take the trend component:

$$w^{\text{trend}}(t, s) = \frac{\mu_{\text{trend}}(t)\mu_{\text{area}}(s)}{\lambda(t, s)}. \tag{8}$$

Now we can substitute w for γ in Equation (7), by considering the time interval $[t-\Delta_t, t+\Delta_t]$, where Δ_t is a small positive number, and the whole of domain X to obtain:

$$\begin{aligned}
\sum_i w^{\text{trend}}(t_i, s_i)\mathbb{I}(t_i \in [t-\Delta_t, t+\Delta_t]) &\approx \int_{T_1}^{T_2}\int_X w^{\text{trend}}(u, v)\lambda(u, v) \\
&\quad \mathbb{I}(u \in [t-\Delta_t, t+\Delta_t])\mathrm{d}u\mathrm{d}v \\
&= \int_{t-\Delta_t}^{t+\Delta_t} \mu_{\text{trend}}(u)\mathrm{d}u \int_X \mu_{\text{area}}(v)\mathrm{d}v \\
&\propto \int_{t-\Delta_t}^{t+\Delta_t} \mu_{\text{trend}}(u)\mathrm{d}u \\
&\approx \mu_{\text{trend}}(t)2\Delta_t.
\end{aligned} \tag{9}$$

We can then rearrange the last expression to

$$\hat{\mu}_{\text{trend}}(t) \propto \sum_i \underbrace{\frac{\mu_{\text{trend}}(t_i)\mu_{\text{area}}(s_i)}{\lambda(t_i, s_i)}}_{:= w_i^{\text{trend}}} \mathbb{I}(t_i \in [t-\Delta_t, t+\Delta_t]). \tag{10}$$

Finally, we can smooth our estimates by using kernel density estimates which replace the indicator function in Equation (10) to obtain:

$$\hat{\mu}_{\text{trend}}(t) \propto \sum_i w_i^{\text{trend}} Z(t - t_i; b_{\text{trend}}) \tag{11}$$

In a similar fashion to Equation (8), we can define functions w and then estimators for all background components:

$$\hat{\mu}_{\text{daily}}(t) \propto \sum_i w_i^{\text{daily}} \sum_{k=0}^{T} Z(t - (t_i - \lfloor t_i \rfloor + k); b_{\text{daily}}) \tag{12}$$

$$\hat{\mu}_{\text{weekly}}(t) \propto \sum_i w_i^{\text{weekly}} \sum_{k=0}^{\lfloor T/7 \rfloor} Z(t - (t_i - 7\lfloor t_i/7 \rfloor + 7k); b_{\text{weekly}}) \tag{13}$$

$$\hat{\mu}_{\text{area}}(s) \propto \sum_i \varphi_i Z(s - s_i; b_{\text{area}}), \tag{14}$$

where $\lfloor x \rfloor$ denotes the largest integer smaller than or equal x. The periodicity in μ_{daily} and μ_{weekly} comes from mapping the input event time t into the periodic domain. For the daily component, we simply subtract the day on which the event took place and are left with the time of day on which the day took place $(t_i - \lfloor t_i \rfloor)$. For the weekly component, we subtract the week from the event time $(t_i - 7\lfloor t_i/7 \rfloor)$.

For the triggering components, we obtain very similar expressions. As before, we can define a function

$$w^f(t, s, u, v) = \begin{cases} g(u - t)h(v - s)/\lambda(u, v) & \text{if } u > t, \\ 0 & \text{otherwise.} \end{cases}$$

We can then substitute w^f for γ into Equation (7) for a fixed t_i and s_i by considering the time interval $[t - \Delta_t, t + \Delta_t]$ to obtain

$$\begin{aligned} \sum_i w^f(t_j, s_j, t_i, s_i)\mathbb{I}(t_i - t_j \in [t - \Delta_t, t + \Delta_t]) &\approx \int_0^T \int_X w^f(t_j, s_j, u, v) \\ &\qquad \mathbb{I}(u - t_j \in [t - \Delta_t, t + \Delta_t])\lambda(u, v)\mathrm{d}u\mathrm{d}v \\ &\approx \int_{t-\Delta_t}^{t+\Delta_t} g(u - t_j)\mathrm{d}u \int_X h(v - s_j)\mathrm{d}v \\ &\propto g(t) \end{aligned}$$

To now obtain a more stable estimate for $g(t)$, we can additionally sum over the left-hand side for all j and obtain

$$g(t) \propto \sum_{i,j} w^f(t_j, s_j, t_i, s_i)\mathbb{I}(t_i - t_j \in [t - \Delta_t, t + \Delta_t]).$$

Now it is clear that $w^f(t_j, s_j, t_i, s_i)$ is just ρ_{ij}, which means that we can rewrite the last line to obtain an estimate for $g(t)$:

$$\hat{g}(t) \propto \sum_{i,j} \rho_{ij} \mathbb{I}(t_i - t_j \in [t - \Delta_t, t + \Delta_t]). \tag{15}$$

Similarly, we can obtain an estimate for $h(s)$:

$$\hat{h}(s) \propto \sum_{i,j} \rho_{ij} \mathbb{I}(s_i - s_j \in [s - \Delta_s, s + \Delta_s]), \tag{16}$$

where Δ_s is a small positive number. In addition, we apply a repetition correction which counts how often the triggering effect is observed at a specific time or space distance (Zhuang and Mateu, 2019):

$$\hat{g}(t) \propto \frac{\sum_{i,j} \rho_{ij} Z(t - (t_i - t_j); b_g)}{\sum_j \mathbb{I}(t_j + t \leq T)} \tag{17}$$

$$\hat{h}(s) \propto \frac{\sum_{i,j} \rho_{ij} Z(s - (s_i - s_j); b_h)}{\sum_j \mathbb{I}((s_j + s) \in X)}. \tag{18}$$

4.2.3 Estimating the weighting terms and including additional event types

With the estimators for all background and triggering components, we can now turn to estimating the weighting terms m_0 and θ_M from Equation (3). The original paper by Zhuang and Mateu (2019) does not consider additional event types which is why we extend their model to accommodate the effect of follow-up visits by police.

The model defined in Equation (3) with complete parameter vector $\Theta = \{m_0, \theta_0, \theta_1\}$ has the following log-likelihood (Daley and Vere-Jones, 2003):

$$\ell(\Theta) = \sum_i \log \lambda(t_i, s_i) - \int_0^T \int_X \lambda(t, s) \mathrm{d}t \mathrm{d}s. \tag{19}$$

For the interested reader, we write out the full likelihood in Section A but for brevity, we set the derivative of Equation (19) with respect to m_0 and θ_0 to zero (the derivative for

θ_1 is analogous):

$$\begin{aligned}\partial\ell(\Theta)/\partial m_0 &= 0\\ &= \sum_i \frac{\mu_{\text{trend}}(t_i)\mu_{\text{weekly}}(t_i)\mu_{\text{daily}}(t_i)\mu_{\text{area}}(s_i)}{\lambda(t_i,s_i)}\\ &\quad - \int_0^T\int_X \mu_{\text{trend}}(t)\mu_{\text{weekly}}(t)\mu_{\text{daily}}(t)\mu_{\text{area}}(s)\mathrm{d}t\mathrm{d}s \qquad (20)\end{aligned}$$

and

$$\begin{aligned}\partial\ell(\Theta)/\partial\theta_0 &= 0\\ &= \sum_i \frac{\sum_{j:t_j<t_i}\mathbb{I}(M_j=0)g(t_i-t_j)h(s_i-s_j)}{\lambda(t_i,s_i)}\\ &\quad - \int_0^T\int_X \sum_{j:t_j<t}\mathbb{I}(M_j=0)g(t-t_j)h(s-s_j)\mathrm{d}s\mathrm{d}t. \qquad (21)\end{aligned}$$

Similar to Zhuang and Mateu (2019), this system of equations can be solved by basing the estimates for m_0, θ_0 and θ_1 in inference round $(k+1)$ on estimated quantities from round (k).

4.2.4 Kernel bandwidths and edge correction

Throughout the previous sections, we introduced several kernel bandwidths b_{daily}, b_{trend}, b_{weekly}, b_g and b_h. Typically, we would use cross-validation to choose values for those bandwidths. Given the computational complexity of the model however, this is not feasible. One alternative would be using a rule of thumb or other heuristic choice, but we can actually do better than that. Because the kernels governed by b_{daily}, b_{trend} and b_{weekly} are defined on a timeline, they are univariate. This means that the bandwidths for our Gaussian kernels retain an interesting interpretation: We can choose bandwidths with respect to the temporal range that we want the kernel to smooth over. For example, we set $b_{\text{daily}} = 1/24 \approx 0.04$ such that one standard deviation corresponds to 1 hour. That implies that 99.7% (= 3 standard deviations) of the contributions to our kernel density estimate come from events within 3 hours of the event. Similarly, we set $b_{\text{weekly}} = 1/3 \approx 0.33$ which corresponds to 99.7% of the contributions to the weekly kernel density estimate to come from events within 24 hours around our event. Lastly, we select $b_{\text{trend}} = 10$ which implies that 99.7% of the contributions to the trend kernel density estimate come from events within 30 days of our event.

As already discussed in Section 4.2.1, b_{area} is set to be adaptive so it does not require an explicit choice. However, it does depend on choice of n_p, the number of neighbours to the event. Zhuang (2011) propose setting n_p between 3 and 6, and our model uses $n_p = 5$.

Lastly, we have to choose b_g and b_h. Since the kernels are not Gaussian, the straightforward interpretation of the previous bandwidths does not work. Still, we set the bandwidth for the temporal distance between events to $b_g = 1$, corresponding to one day and $b_h = 0.2$, corresponding to 200m in spatial distance.

Because kernel density estimates are well-known to behave poorly around the edges, an edge correction is necessary. For the periodic and area kernels and the kernel smoothing $g(t)$ and $h(s)$, we use a truncated kernel which normalizes the kernel density estimator by its integral over the support (Hall and Turlach, 1999). For example, the estimator for μ_{daily} from Equation (12) is modified to:

$$\hat{\mu}_{\text{daily}}(t) \propto \sum_i w_i^{\text{daily}} \frac{\sum_{k=0}^{T} Z(t - t_i + \lfloor t_i \rfloor - k; b_{\text{daily}})}{\int_0^T Z(u - t_i; b_{\text{daily}}) \mathrm{d}u}. \tag{22}$$

This modification was not sufficient to ensure sensible edge behaviour for the trend kernel. That is because the support for the trend kernel is bounded between $[0, T]$. Instead, we apply an edge correction proposed by Schuster (1985) called boundary folding where the density "leaking" outside the support is mirrored or folded back onto the support. For a kernel with support in $[a, b]$, we correct the standard kernel density estimator $f_h(x) = \frac{1}{nh} \sum_i K(\frac{x - x_i}{h})$ to

$$f_h(x) = \frac{1}{nh} \sum_i K\left(\frac{x - 2a + x_i}{h}\right) + K\left(\frac{x - x_i}{h}\right) + K\left(\frac{x + 2b - x_i}{h}\right). \tag{23}$$

5 Results

With this inference procedure, we can now fit our model to the data. The model was implemented in `R` and is publicly available at `https://github.com/laravomfell/reporting_spillovers`, together with a file that generates synthetic data since the original data cannot be provided publicly.

Besides the full model in Equation (3), we also estimated a model without the periodic components in the background specification. However, the AIC of the full model was considerably smaller (20,392 compared to 21,735) so in what follows, we only consider the full model.

In Figures 2a through 2e we visualize the estimated intensities coming from the background components. As shown in Equation (2), these estimated intensities are multiplied together and then weighted by m_0. We estimate $m_0 = 0.1689$.

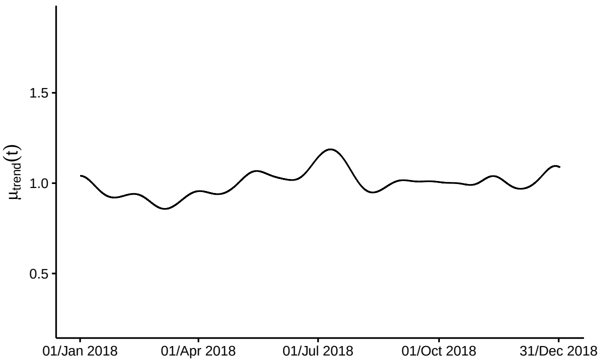
The trend component in Figure 2a demonstrates that there is no dominant trend in domestic abuse reports over our study period since most of the normalized Kernel density lies between 0.9 and 1.1, i.e., close to the mean of 1. We observe an increase in domestic abuse reporting, however, in the summer months of July and August.

We document strong time of day and day of week effects. There are remarkably few calls between the hours of midnight and 4am with the estimated intensity increasing during the day. We observe two peaks of intensity, one between 12:00 and 13:00 and another one between 20:00 and 21:00 before calls drop off at night again. Looking at the weekly periodicity, we observe a strong weekend effect as calls begin to pick up from Friday onwards throughout the weekend. Together, the daily and weekly periodicity visualized in Figure 2d show that Friday evenings, Saturday evenings and Sunday mornings are particularly high-intensity periods for reports of domestic abuse.

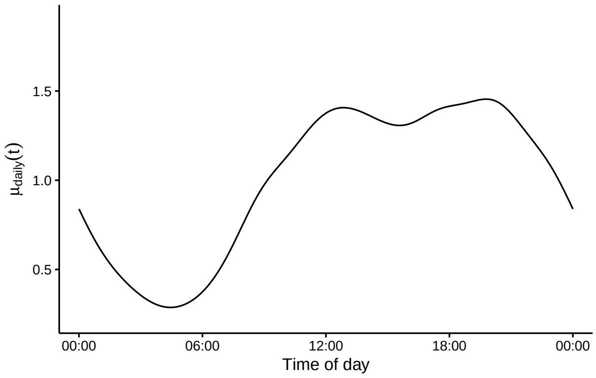
These findings mirror those found in other studies: Reports of domestic abuse are lowest during the week and strongly increase on the weekend with Sunday being the peak day (Rotton and Cohn, 2001; Brimicombe and Cafe, 2012).

Lastly, we find that there is marked variation in space. Specifically, we find that for some locations, the estimated spatial intensity of the background is particularly pronounced. This is clear from the small, dark spots in Figure 2e.

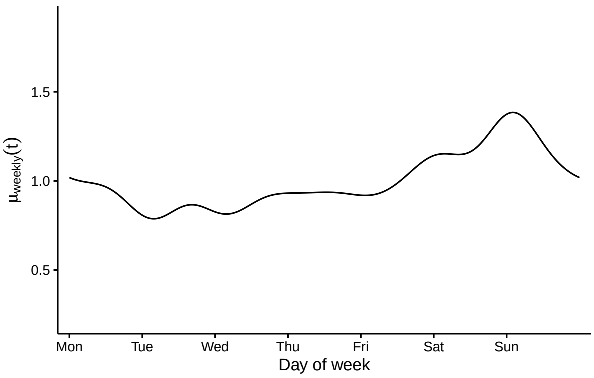
This raises a question of why these areas might see such high levels of domestic abuse reporting. A number of studies predict and confirm a relationship between levels of domestic abuse and deprivation (e.g., Gracia et al., 2015). In Figure 2f, we show the spatial background intensity at event locations against local deprivation. Deprivation is measured using the 2015 index of multiple deprivation, a composite index combining measures of deprivation from seven domains such as income, employment, education and health (Office for National Statistics, 2015). Overall the relationship between abuse reporting and



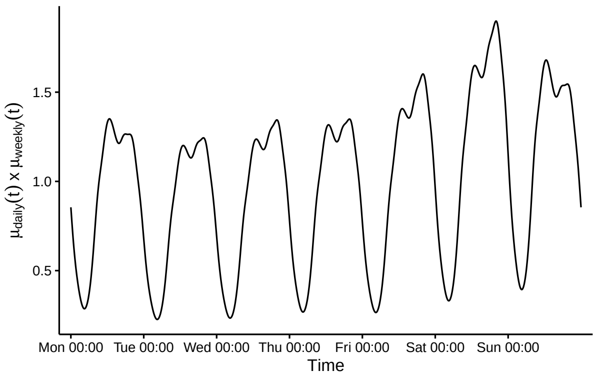
(a) Temporal trend



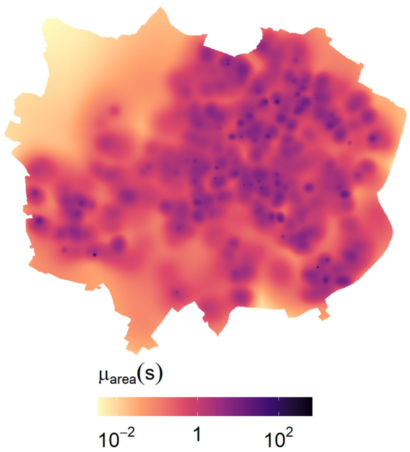
(b) Daily periodicity



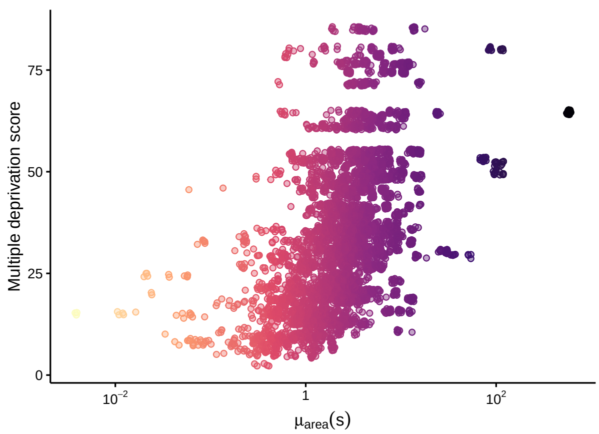
(c) Weekly periodicity



(d) Daily and weekly periodicity



(e) Spatial background intensity



(f) Spatial intensity at locations against deprivation

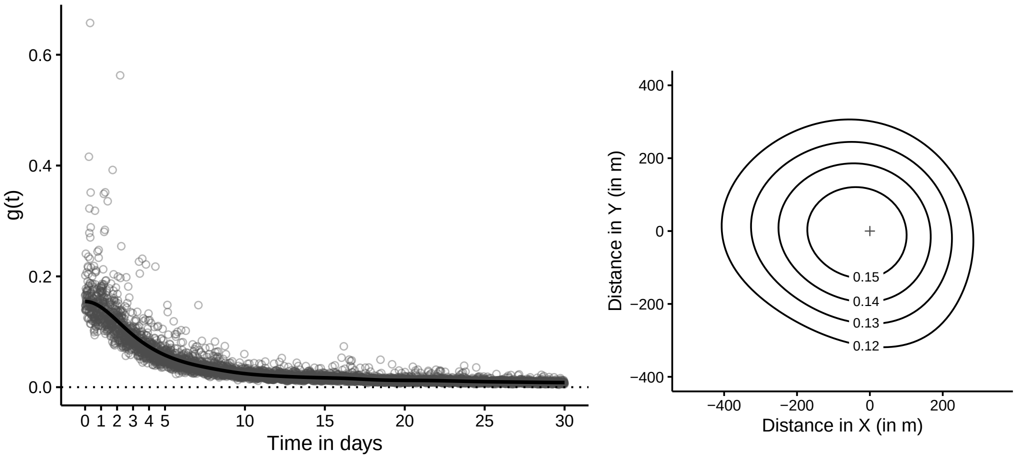
Figure 2: Estimated background components

deprivation is not straightforward: We see high levels of reporting in areas with high and low levels of deprivation. However, event locations with very high spatial background intensity (points in darker colours) are consistently in areas with high levels of deprivation. Regarding the triggering component, we visualize the estimated triggering functions $g(t)$ and $h(s)$ in Figure 3a and 3b. As shown in Equation (3), these functions are weighted by θ_M. Our estimated θ_M both for reports and for follow-ups are essentially zero: 1.52×10^{-9} for report-to-report and 2.19×10^{-8} for follow-up-to-report. Those numbers mean that one report of domestic abuse triggers, on average, 1.52×10^{-9} further reports. Similarly, one follow-up by police triggers, on average, 2.19×10^{-8} reports of domestic abuse. Together, the model implies that of the 6,084 initial reports of domestic abuse, 9.75×10^{-7} % reports were triggered by other events. In other words, there is very little evidence to support the notion of spillovers in domestic abuse reporting.

Furthermore, Figure 3a and 3b demonstrate that even before the weighting with θ, the estimated triggering functions imply very little triggering: The temporal range of triggering is very small to begin with and limited to the first 6 days after an event. Similarly, the spatial range of triggering is limited to an area of 400×400m around an event. In summary, our model finds no evidence of spillovers in domestic abuse reporting.

Since Hawkes processes are complex statistical objects with challenging inference procedures, it is important to validate the plausibility of model outputs. For example, Reinhart and Greenhouse (2018) show that when the background component does not provide a good fit to the data, the triggering component is inflated. In other words, one typically over-estimates the triggering component. This is not the case for our model since our estimates of the triggering component are negligibly small. Still, we perform two additional plausibility checks to ensure that the quantities produced by our model are sensible.

First, we check for the plausibility of our triggering findings: We expect spillover effects to be stronger in areas where people are more aware of what is happening in their neighbours' households. Since no data on this is available, we use the share of households living in non-detached houses in the neighbourhood as a proxy instead (Office for National Statistics, 2011). People living in terraced houses or flats are much closer to any issues in their neighbours' domestic life (Ivandic et al., 2020). We define neighbourhood as 2011 Census Output areas with, on average, 300 usual residents in 150 households (Office for National Statistics, 2016). For each event, we then evaluate how many other reports it



(a) Temporal excitation

(b) Spatial excitation

Figure 3: Estimated triggering components

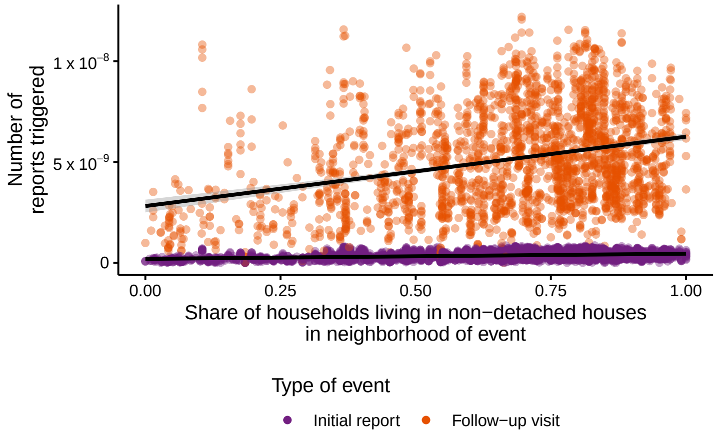


Figure 4: Share of households in neighbourhood living in non-detached houses against the mean number of reports triggered. Black lines show separate regression fits with 95% confidence intervals shown in gray.

triggered according to our model by calculating $\theta_{M_j} \sum_i \rho_{ij}$ for each event j. This gives us a quantification of how much an event j increases the likelihood of further reports of domestic abuse around itself.

In Figure 4 we show the share of households living in non-detached houses in the area against the mean number of reports triggered. Indeed, we find weak evidence that follow-up events taking place in neighbourhoods where people live closer together exert more triggering pressure than events taking place in areas where houses are more spread out. While this effect is very small, it demonstrates that the quantities produced by our model are plausible.

As a second step, we check the model fit. A useful way of checking if the model is

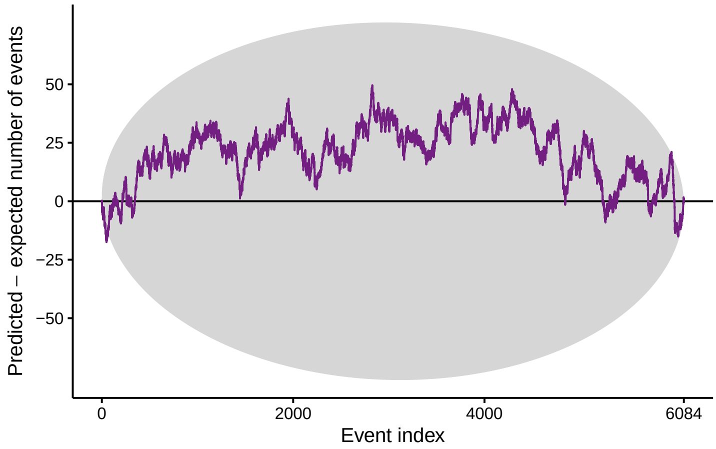


Figure 5: Deviation of the transformed time sequence (purple) from the theoretical (black) sequence with 95% confidence bands (grey).

well-calibrated is a temporal residual plot. To do so, we calculate the following function of event times t_i

$$t_i \rightarrow \tau_i = \int_0^{t_i} \int_X \lambda(u, v) \mathrm{d}u \mathrm{d}v, \tag{24}$$

such that τ_i is the expected number of events in the time interval $[0, t_i)$ or the cumulative number of events by event time t_i. This simple transformation makes use of the time-rescaling theorem: If the model is correct, the sequence of τ_i is a stationary Poisson process with unit rate (Ogata, 1988; Brown et al., 2002). Accordingly, a plot of the event index i against τ_i should form a 45 diagonal line. This property can be used to assess model fit: If $\hat{\lambda}$ is a good approximation of the true model, then its sequence of $\hat{\tau}_i$ will behave similarly to the sequence of theoretical τ_i (Schoenberg, 2002). For the theoretical τ_i we can construct confidence intervals for each τ_i by taking the $\frac{\alpha}{2}$ and $1 - \frac{\alpha}{2}$ quantiles of a Beta distribution with parameters $(i + 1, n - i + 1)$ and then multiply by n (Zhuang and Mateu, 2019). We set α at the usual 0.05 level.

In Figure 5 we plot the deviation of $\hat{\tau}_i$ from the diagonal against the event index i to verify how far away from the diagonal our model deviates. Indeed, we find that $\hat{\tau}_i$ is within the 95% confidence bounds of the true model and that our model is therefore a reasonable approximation.

6 Discussion

This paper studies if—like the criminal behaviour of offenders—the reporting of crime by victims exhibits triggering behaviour. We particularly investigate whether there are any spillover effects in the reporting of domestic abuse to police.

Analysing data from one year of calls for service concerning domestic abuse in a large English city, we find no convincing evidence for spillover effects. Spillover effects are limited to a very short time frame (within 6 days) and very short distances (400m around the event). These effects do not plausibly account for spillovers due to information sharing by victims in a social or neighbourhood network. We find some very weak evidence that events taking place in more densely populated neighbourhoods increase the likelihood of further reports of domestic abuse slightly more than events taking place in less dense neighbourhoods Overall, reporting of domestic abuse by victims does not appear to exhibit any triggering behaviour since only 9.75×10^{-7} % of the reports in our sample are predicted to have been triggered.

The estimation of the background intensity of domestic abuse reporting shows that reporting follows highly periodic patterns. Calls for service of domestic abuse increase on the weekend and particularly in the evening. We also find that the reporting of domestic abuse is highly clustered and some locations in our study area see very high levels of reported domestic abuse.

A natural question arising from our work is if our estimates of the background intensity are also modelling the spatio-temporal intensity of domestic abuse itself. Certainly, in some instances the timing of a report of domestic abuse will coincide with the timing of the domestic abuse itself. A range of models of domestic abuse, from ecological to feminist to economic models, make predictions about when violence is likely to break out in the abuse cycle (Heise, 1998; Bobonis et al., 2013; Lombard and McMillan, 2013; Leonard and Quigley, 2017). However, we cannot meaningfully separate the incidence of domestic abuse from the incidence of domestic abuse reporting, especially because many survivors of domestic abuse will have experienced multiple abuse incidents before alerting the police, if at all (SafeLives, 2015).

There is good reason to believe that making the decision to report domestic abuse to police would also influence others suffering from abuse in their reporting decision. However, our study documents that none of these hypotheses are confirmed in the reporting of domestic abuse.

There are a few reasons why we did not find an effect: The functional form of the triggering component of the Hawkes process might not be able to accommodate the shape of spillover effects. In their study of the effect of the #MeToo movement, Levy and Mattsson (2020) find that the effect is largest on crimes reported a month after they took place. Therefore, it is possible that assuming temporal spillovers in such a limited time frame is an ill fit to the nature of spillovers in reporting.

It may also be that expecting reporting to police to affect further domestic abuse reporting is overly optimistic. Studies consistently show that victims have quite heterogeneous preferences and justice goals in mind when they approach formal institutions (Rajah et al., 2006; Kelly et al., 2014). Evidence has shown that survivors of domestic abuse are most satisfied with approaches that provide them with options (Ellsberg et al., 2015). Police officers without special training may not be sufficiently attuned to respond to victims/survivors' agency. This is actually partially reflected in the studies in Davis et al. (2008)' meta analysis: The programmes where only a police officer (i.e., not a social worker and a police officer together) visited the household did not have a significant effect of the reporting of future violence (e.g., Davis et al., 2010; Pate et al., 1992). If such visits already do not encourage victims in the treated households to turn to police again, the likelihood that such visits would have any effect outside those households is low.

Lastly and perhaps most important, it is worth examining the differences between crimes that exhibit strong triggering behaviours and domestic abuse. Clearly, the offender side is different: Unlike burglars, perpetrators of domestic abuse do not choose the geographic location of their crimes. This was an explicit reason for choosing domestic abuse for our investigation. But the nature of the crime is also different: Burglaries, homicides and shootings are all discrete events with a distinct time and place of offence. This gives crime victims a concrete event to report. In contrast, domestic abuse consists of both discrete events such as assaults but more so of patterns of abusive behaviour. With this combination, domestic abuse cannot be thought of as a sequence of individual criminal offences (Hawkins and Laxton, 2014). The discretisation of a latent, on-going phenomenon such as domestic abuse into reports may not capture if and when victims' share information about domestic abuse and the police response to it.

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Appendix A Likelihood

We did not write out the full log likelihood in Equation (19). We do this here, but for simplicity, we simplify the background to be denoted by $m_0\mu(t,s)$ and the trigger by $\theta_M f(t,s)$. Altogether, our model in Equation (3) with parameter vector $\Theta = \{m_0, \theta_0, \theta_1\}$

has the following log likelihood:

$$
\begin{aligned}
\ell(\Theta) &= \sum_i \log \lambda(t_i, s_i) - \int_0^T \int_X \lambda(t, s) \mathrm{d}t\mathrm{d}s \\
&= \sum_i \log \left(m_0 \mu(t_i, s_i) + \sum_{j:t_j<t_i} \theta_{M_j} f(t_i - t_j, s_i - s_j) \right) \\
&\quad - \int_0^T \int_X \left(m_0 \mu(t, s) + \sum_{j:t_j<t} \theta_{M_j} f(t - t_j, s - s_j) \right) \mathrm{d}t\mathrm{d}s \\
&= \sum_i \log \left(m_0 \mu(t_i, s_i) \right) + \sum_i \log \left(\sum_{j:t_j<t_i} \mathbb{I}(M_j = 0) \theta_0 f(t_i - t_j, s_i - s_j) \right) \\
&\quad + \sum_i \log \left(\sum_{j:t_j<t_i} \mathbb{I}(M_j = 1) \theta_1 f(t_i - t_j, s_i - s_j) \right) - \int_0^T \int_X m_0 \mu(t, s) \mathrm{d}t\mathrm{d}s \\
&\quad - \int_0^T \int_X \sum_{j:t_j<t} \mathbb{I}(M_j = 0) \theta_0 f(t - t_j, s - s_j) \mathrm{d}t\mathrm{d}s \\
&\quad - \int_0^T \int_X \sum_{j:t_j<t} \mathbb{I}(M_j = 1) \theta_1 f(t - t_j, s - s_j) \mathrm{d}t\mathrm{d}s.
\end{aligned}
$$

We can now take the derivative of Equation (A.1) with respect to m_0, using the chain rule:

$$
\begin{aligned}
\partial \ell(\Theta)/\partial m_0 = 0& \\
&= \sum_i \frac{\mu_{\text{trend}}(t_i) \mu_{\text{weekly}}(t_i) \mu_{\text{daily}}(t_i) \mu_{\text{area}}(s_i)}{\lambda(t_i, s_i)} \\
&\quad - \int_0^T \int_X \mu_{\text{trend}}(t) \mu_{\text{weekly}}(t) \mu_{\text{daily}}(t) \mu_{\text{area}}(s) \mathrm{d}t\mathrm{d}s.
\end{aligned} \tag{A.1}
$$

Again, using the chain rule we can now take the derivative of Equation (A.1) with respect to θ_0 (the derivative with respect to θ_1 is analogous) and obtain:

$$
\begin{aligned}
\partial \ell(\Theta)/\partial \theta_0 = 0& \\
&= \sum_i \frac{\sum_{j:t_j<t_i} \mathbb{I}(M_j = 0) g(t_i - t_j) h(s_i - s_j)}{\lambda(t_i, s_i)} \\
&\quad - \int_0^T \int_X \sum_{j:t_j<t} \mathbb{I}(M_j = 0) g(t - t_j) h(s - s_j) \mathrm{d}s\mathrm{d}t.
\end{aligned} \tag{A.2}
$$

Appendix B Inference algorithm

We can write out the inference procedure for the model explained in Section 4.2 in algorithmic form. The procedure consists of two main steps: The initialisation and the inference loop.

In the initialisation stage, we obtain initial values for the daily, weekly, trend, area and triggering components. We then use those to calculate the entire background component $\mu(t, s)$. We need to do this calculation twice: Once to obtain $\mu(t_i, s_i)$, that is the background value at all events i and once more to obtain $\int \mu(t, s)\mathrm{d}t\mathrm{d}s$, that is the background integrated over the entire study area. We then repeat this step to obtain the trigger at all events i $f(t_i, s_i)$ and integrated over the study area $\int f(t, s)\mathrm{d}t\mathrm{d}s$.

With those quantities in hand, we then update m_0 and θ_M from some initial guesses and then calculate the intensity λ, again at all events i and integrated over the study area.

We then enter the inference loop where essentially the procedure repeats: We obtain updated values for the daily, weekly, trend, area and triggering components; we calculate the background and triggering components at the events and integrated over the study area. We update m_0 and θ_M, and calculate λ at all events i and integrated over the study area. When m_0 and θ converge, we break the inference loop.

More formally, we write:

Algorithm 1 Inference algorithm

Input: n_p, b_{daily}, b_{weekly}, b_{trend}, b_{area}, b_g, b_h, m_0 and θ_M
Initialisation
Initialise components μ_{daily}, μ_{weekly}, μ_{trend}, μ_{area}, $g(t)$, $h(s)$,
Calculate background $\mu(s_i, t_i)$ and $\int_0^T \int_X \mu(s, t)\mathrm{d}t\mathrm{d}s$
Calculate trigger $g(t - t_i)h(s - s_i)$ and $\sum_i \int_{t_i}^T \int_X g(t - t_i)h(s - s_i)\mathrm{d}t\mathrm{d}s$
Update m_0 and θ_M
Calculate intensity $\lambda(t_i, s_i)$ and $\int_0^T \int_X \lambda(t, s)\mathrm{d}t\mathrm{d}$
while not convergence **do**
  Update components μ_{daily}, μ_{weekly}, μ_{trend}, μ_{area}, $g(t)$, $h(s)$
  Calculate background $\mu(s_i, t_i)$ and $\int_0^T \int_X \mu(s, t)\mathrm{d}t\mathrm{d}s$
  Calculate trigger $g(t - t_i)h(s - s_i)$ and $\sum_i \int_{t_i}^T \int_X (t - t_i)h(s - s_i)\mathrm{d}t\mathrm{d}s$
  Update m_0 and θ_M
  Calculate intensity $\lambda(t_i, s_i)$ and $\int_0^T \int_X \lambda(t, s)$
  Check convergence of m_0 and θ_M