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ORIGINAL PAPER

The Burglary Boost: A Note on Detecting Contagion Using the Knox Test

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Abstract
Objectives A large body of literature in quantitative criminology finds that the spatio-temporal clustering of burglary is greater than one would expect from chance alone. This suggests that such crimes may exhibit a "boost" effect, wherein each burglary increases the risk to nearby locations for a short period. In this study, we demonstrate that standard tests for spatio-temporal dependence have difficulty distinguishing between clustering caused by contagion and that caused by changing relative risks. Therefore, any estimates of the boost effect drawn from these tests alone will be upwardly biased.
Methods We construct an agent-based model to generate simulated burglary data, and explore whether the Knox test can reliably distinguish between contagion (one burglary increases the likelihood of another burglary nearby) and changes in risk (one area gets safer while another gets more dangerous). Incorporating insights from this exercise, we analyze a decade of data on burglary events from Washington, DC.
Results We find that (1) absent contagion, exogenous changes in relative risk can be sufficient to produce statistically significant Knox ratios, (2) if risk is changing over time, estimated Knox ratios are sensitive to one's choice of time window, and (3) Knox ratios estimated from Washington, DC burglary data are sensitive to one's choice of time window, suggesting that long-run changes in relative risk are, in part, driving empirical estimates of burglary's boost effect.
Conclusions Researchers testing for contagion in empirical time series should take precautions to distinguish true contagion from exogenous changes in relative risks. Adjusting the time window of analysis is a useful robustness check, and future studies should be supplemented with new approaches like agent-based modeling or spatial econometric methods.

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Introduction

Measuring the extent to which crime exhibits contagion is an important research effort in quantitative criminology, both for understanding of the determinants of crime and informing policy to combat it. Recent work (Townsley et al. 2003; Johnson et al. 2007) has made use of statistical techniques drawn from infectious disease epidemiology to study the phenomenon, and these studies provide compelling evidence that burglary is highly clustered in both space and time. This finding was motivated by theory on criminal foraging behavior and analyzed using the Knox test (Knox and Bartlett 1964).

In this paper, we discuss the implementation of the Knox test for analyzing data on crime events, and demonstrate using a computational model of burglary contagion that such statistical methods are likely to overestimate burglary's "boost" effect.[1] We then use this insight to analyze a decade of burglary data from Washington, DC, and discuss how researchers and policymakers can better implement and interpret such analyses.

Numerous empirical studies (Farrell 1995; Townsley et al. 2003) suggest that burglary victims face a substantial risk of re-victimization, and that nearby homes face increased risk of "near-repeat" victimization in the weeks following a burglary event. For researchers, the difficulty lies in determining whether this relationship is causal (Johnson 2008). Are near-repeats the result of unobserved heterogeneity in risk (the "flag" hypothesis) or does one burglary actually increase the risk that nearby homes will be burgled in the near future (the "boost" hypothesis)?

Such a boost effect could emerge for a number of reasons. According to optimal foraging theory (Johnson et al. 2009), criminals who commit a burglary gain information about the vulnerabilities and expected payoffs of other targets in the area, and use this information to exploit susceptible homes nearby. Indeed, Bowers and Johnson (2004) find that pairs of burglaries close in space and time are more likely to share a modus operandi (point of entry, tools used, etc.) than those that are close in space or time alone. Studies of repeat offenders find that they will often burgle nearby houses within a very short period of time (Bernasco 2008). Routine activity theory suggests that burglars often select their targets during the course of legitimate activities (Townsley et al. 2003), so a burglary at one location reflects an increased likelihood that a burglar is operating nearby.

However, distinguishing between the boost and flag hypotheses empirically poses a vexing statistical problem. Knox and Bartlett (1964) propose a solution in the context of infectious disease, which has recently been adopted by criminologists. Let each burglary event in the data be denoted by a time t and its x- and y-coordinates. The Knox statistic is the number of "close" pairs of events that occur within T days and D meters, where T and D are selected by the researcher. To determine whether the number of close pairs is greater than we would expect if the timing and location of events were independent, the Knox test permutes the dataset, assigning a random time t to each location. Repeating this process a large number of times (conventionally 99 or 999) generates a Monte Carlo distribution of the expected Knox statistic under the assumption of independence. By using the actual data to construct the null distribution, the Knox test incorporates observed variation in spatial

[1] Although we focus in this paper on the Knox Test, our critique applies more generally to any test of spatio-temporal interaction on individual-level data (e.g. the Mantel test or Jacquez's k-nearest neighbor method).

and temporal clustering into its expected number of close pairs. If the estimated Knox statistic is greater than a statistically significant proportion of Monte Carlo-generated Knox statistics, we can reject the null hypothesis that the spatio-temporal clustering in the data was due to spatial clustering or temporal clustering alone.

Johnson et al. (2007) reviews results from Knox tests of residential burglary in ten cities, demonstrating that the observed spatio-temporal clustering of burglary could not be generated by the flag hypothesis alone. This result has been replicated in a number of different cities (Bowers and Johnson 2005; Grubesic and Mack 2008; Townsley et al. 2003), for different types of crime (Ratcliffe and Rengert 2008; Wells et al. 2012; Youstin et al. 2011), and for other types of violence, like piracy (Marchione and Johnson 2013) and insurgency in war zones (Braithwaite and Johnson 2012; Townsley et al. 2008). Several authors approach the question using agent-based modeling (Johnson 2008; Pitcher and Johnson 2011), further demonstrating that the results from the statistical test are not "fooled" by unobserved heterogeneity in risk.

There is, however, an important caveat that goes unmentioned in much of this research. Spatio-temporal clustering in data can be generated by two processes: the boost effect and exogenous changes in relative risk. The former is a micro-level phenomenon, in which one offense increases the probability of a repeat or near-repeat offense. The latter is an aggregate phenomenon, as particular regions become safer over time while others become more dangerous. The Knox test is a test of spatio-temporal dependence, and a statistically significant Knox ratio indicates that the number of close pairs exhibited in the data was unlikely to have been generated by a process in which time and location of events are independent. However, this does not necessarily imply that the process was driven by contagion. Schmertmann et al. (2010) note in their study of fertility transition in Brazil that the Knox test alone cannot distinguish between spatio-temporal clusters that are generated by contagion and those that are generated by exogenous changes in relative risks. Such changes in relative risks may be present in crime data as well.

For example, residential burglary tends to occur on weekdays, during the hours when residents are away from the home at either work or school (Ratcliffe 2001; Weisel 2002). Meanwhile, non-residential burglary is more likely to occur on nights and weekends, when employees are away (Ratcliffe 2001). Because there is heterogeneity in residential/workplace density across cities, this fact alone implies that we should not expect the timing and location of burglary events to be independent of one another. Even absent a boost effect, we should observe more close pairs than expected if these relative risks were held constant. This distinction between the boost effect and exogenous changes in relative risks is important to recognize, because clustering driven by the latter may be generated by very different mechanisms and have different implications for policy. In the next section, we present a computational model to help clear up this distinction, and to provide recommendations for researchers hoping to distinguish between the two.

The Model

In what follows, we construct an agent-based computational model (ABM) similar to that in (Johnson 2008; Pitcher and Johnson 2011).[2] This allows us to control the mechanisms that generate our simulated burglary data, and to explore the Knox test's ability to

[2] The model is implemented in NetLogo (v 5.2) and analyzed using R. Replication code will be made available at the first author's website.

distinguish among them. First, we use this model to replicate earlier work, demonstrating that the Knox test can reliably distinguish between data generated with and without a boost effect. Next, we add exogenous changes in relative risks, showing that this alone can be sufficient to produce statistically significant Knox ratios. Finally, we demonstrate that, in the presence of changing relative risks, the estimated Knox ratio is highly sensitive to one's choice of time window, a fact underemphasized in the literature.

In the model, ten thousand computational agents, each of which may represent a city block, are situated on a 100 by 100 lattice. Each time period, agents are burgled with probability λ. To simulate contagion, whenever an agent is burgled, all nearby agents receive a boost in their probability of burglary, represented by parameter α (unless otherwise noted, the boost lasts two periods and affects agents up to five lattice spaces away from the index case). Let K_i be an indicator variable equal to 1 if a nearby agent was recently burgled and 0 otherwise. Each agent i has a per-period probability of burglary equal to

$$P_i = (1 - K_i + aK_i)\lambda$$

For our first computational experiment, we let $\lambda = 0.0005$ and vary the size of the boost effect. The simulation runs for 90 periods, and we compute Knox ratios from 50 simulations for each parameterization (letting $T = 2$ and $D = 5$). As is clear from Fig. 1, the Knox test can reliably distinguish between data generated with a boost effect ($\alpha > 1$) and data not generated with a boost effect ($\alpha = 1$). However, note that the estimated Knox ratios do not have a linear relationship with the underlying boost effect (the ratio between Knox ratio and alpha is not constant), which implies that researchers should take care when interpreting such ratios. A Knox ratio measures the excess number of close *pairs* of events, relative to what we would expect under the assumption of independence, not the excess *risk* associated with a nearby crime event (as suggested in Ratcliffe and Rengert 2008; Wells et al. 2012; Youstin et al. 2011).

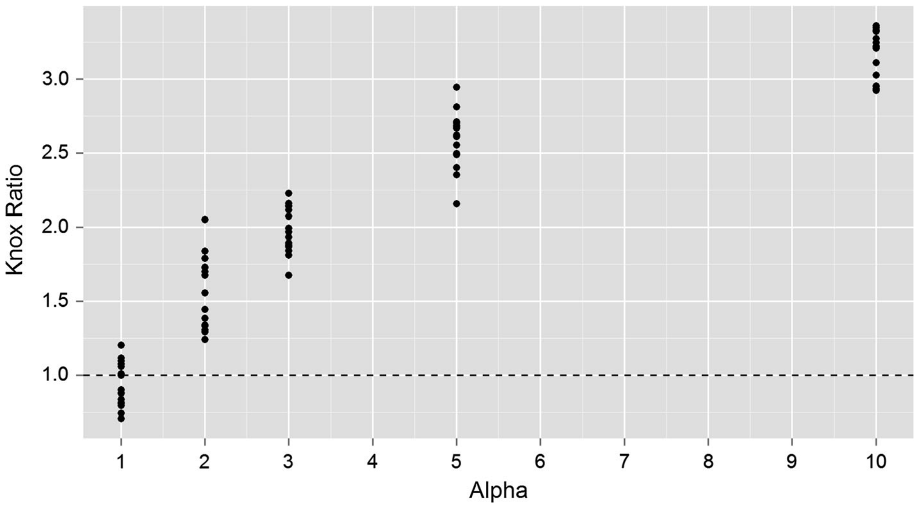

Fig. 1 Estimated Knox ratios varying alpha. 3 month time window (permutations = 99, T = 2, D = 5)

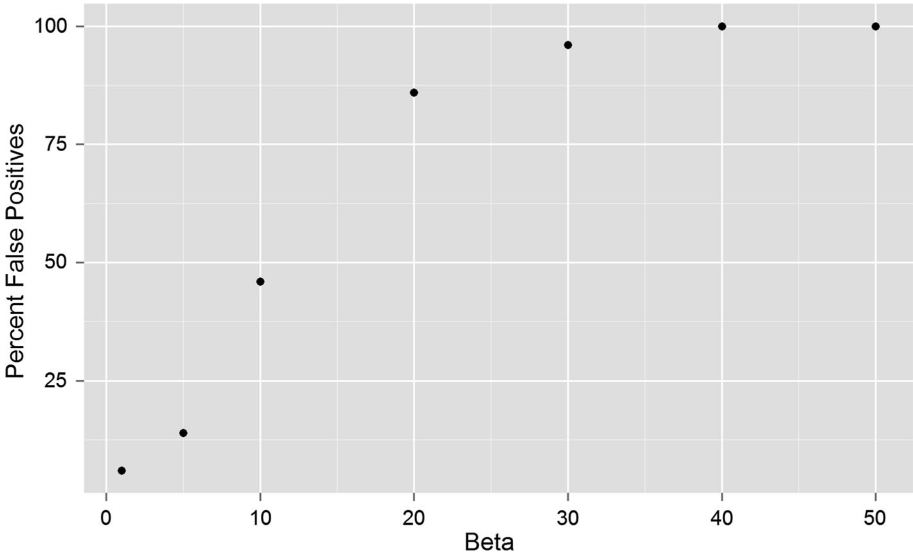

Fig. 2 Percent false positives from ABM, varying β (permutations = 99, T = 2, D = 5)

Next, we demonstrate that, absent a boost effect, exogenous changes in relative risk can yield Knox ratios consistently greater than one. For this experiment, we let $\lambda = 0.0001$ and $\alpha = 1$ (no boost effect). Every thirty periods, agents on a random 20 by 20 subsection of the lattice are selected to experience an increase in their exogenous risk of burglary. Let β represent the increased risk that these agents face during the random shocks, such that their per-period probability of burglary is $\beta\lambda$ for those thirty periods. Again, the simulation runs for 90 periods, and we compute Knox ratios from 50 simulations for each parameterization. Figure 2 demonstrates how the percentage of false positives (Knox ratios with associated *p* value <0.05) increases with the magnitude of these changes in relative risk.

As β increases, so does the likelihood of observing a significant Knox ratio (despite the absence of a boost effect). This is not to imply that such exogenous shifts in crime risk are the only dynamics driving the Knox ratios in empirical crime data (indeed, this example is highly stylized). Rather, it is most likely that the boost effect and changing relative risks co-occur, and this combination of effects produces the observed spatio-temporal clustering. Given this, it is likely that any estimate of the boost effect using Knox ratios alone will overstate its true magnitude.

Often, researchers conducting the Knox test will not choose a single set of thresholds, but will perform multiple Knox tests, varying their definition of a “close pair”. In empirical work, the estimated Knox ratio will typically increase in magnitude and statistical significance as these thresholds get smaller. To demonstrate that changes in relative risks produce a similar pattern, we repeat the computational experiment, setting $\beta = 30$ and varying the time and distance thresholds as shown in Table 1. The Knox table generated by this mechanism is quite similar to those from empirical patterns of burglary. As we decrease the thresholds for *T* and *D*, the estimated magnitude of the Knox ratio increases.

One would be mistaken to infer from this table that the strength of contagion is strongest at 1 day and 2 blocks, and that increased monitoring within that area during that period is likely to deter crime. As constructed, the exogenous boost occurs within a much larger area (20 by 20 blocks), and out of the 347 simulated burglary events, only 11 pairs were ever that close to one another!

Finally, the agent-based model demonstrates that, in the presence of changes in relative risk, the estimated Knox ratio is highly sensitive to the size of the test's time window (the amount of data used to compute the Knox ratio). Typically, researchers estimate a single Knox ratio using the entire data set (often 6–12 months of data at a time). However, in the presence of changing relative risks this is not an innocuous decision. To demonstrate, we first hold exogenous risk constant ($\lambda = 0.0005$) and set the boost effect to $\alpha = 2$, running the simulation for 1460 time periods. Figure 3 shows that when relative risks are held constant, restricting the time window of analysis increases the variance of the Knox ratio estimates (due to a decreased sample size), but does not affect the mean estimate. In Fig. 4, we repeat the test, varying the exogenous risk in random subspaces as before (setting

Table 1 Knox table: $\beta = 30$, $\lambda = 0.0001$, permutations = 99 (all entries except bottom-right significant at $p < 0.05$)

Distance	Time				
	1	7	14	28	56
2	4.71	3.60	2.84	2.16	1.36
5	3.17	3.05	2.81	2.02	1.30
10	2.70	2.64	2.43	1.81	1.24
20	2.02	1.93	1.79	1.44	1.11
30	1.51	1.43	1.35	1.19	1.02
40	1.26	1.23	1.16	1.09	0.99

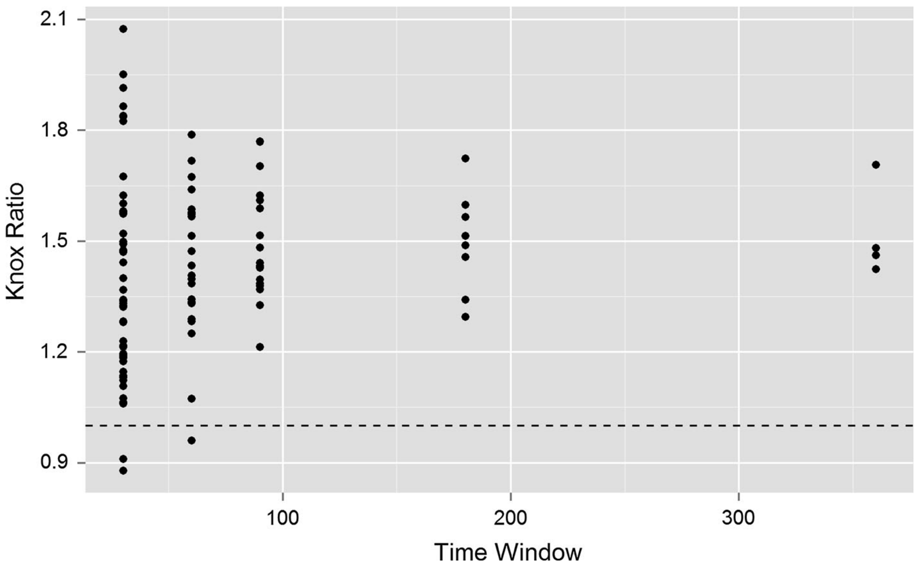

Fig. 3 Estimated Knox ratios from ABM with $\alpha = 2$, varying the time window (simulated for 1460 days, permutations = 99, T = 2, D = 5)

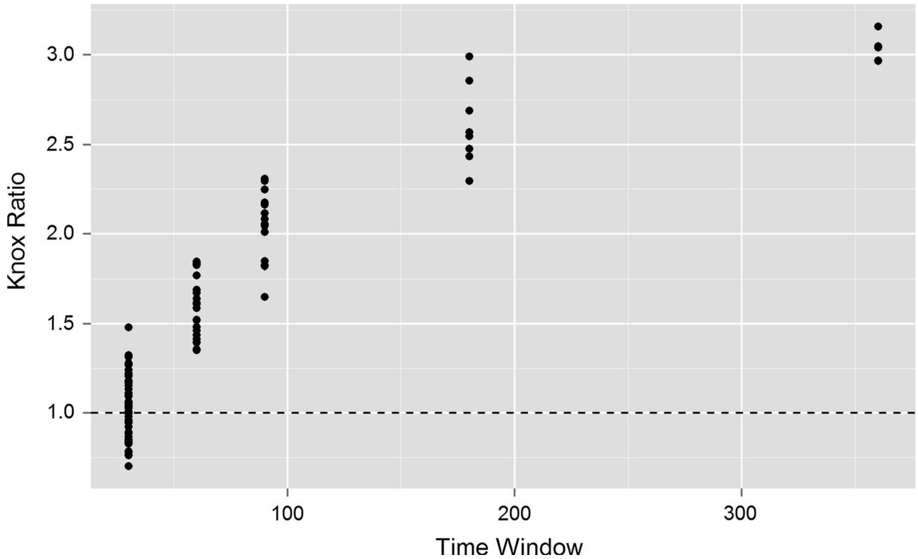

Fig. 4 Estimated Knox ratios from ABM with $\beta = 20$ ($\alpha = 1$), varying the time window (simulated for 1460 days, permutations = 99, T = 2, D = 5)

$\alpha = 1$, $\lambda = 0.00025$ and $\beta = 20$). When relative risks are not held constant, a larger time window picks up more variation over time, and increases the estimate of the Knox ratio accordingly. In the next section, we will see that Knox ratios from burglary in Washington, DC display a similar pattern.

Empirical Analysis

To explore these questions empirically, we use records of burglary in the city of Washington, DC from 2000 to 2012 (this includes only the first 6 months of data from 2012). These records include date, approximate time, and coordinates of the victim's location, and there are a total of 52,757 unique events. Plotting the coordinates of all burglaries yields Fig. 5.

Clearly, the risk of burglary clusters in space, corresponding with population density and topographical features. Additionally, burglary risk clusters by time, following the seasonal pattern shown in Fig. 6 and the weekly pattern in Fig. 7. Over the course of the data, the average monthly burglary rate decreased substantially.

However, this aggregate-level analysis obscures changing relative risks at the neighborhood level. Between 2000 and 2012, the burglary risk in the areas northwest of the Anacostia River decreased, while those areas southeast of the Anacostia River remained the same or became slightly riskier (Fig. 7). Like the weekend/weekday trends discussed in the introduction, this long-term change in relative risks was likely driven by exogenous factors (e.g. gentrification, the late-2000s economic recession, etc.). Therefore, a standard Knox test on all 12 years of data would yield upwardly biased estimates of the boost effect for Washington, DC burglary. Restricting the time window of analysis may be a useful safeguard against such changes in relative risk. As we see in Fig. 1, for instance, a time

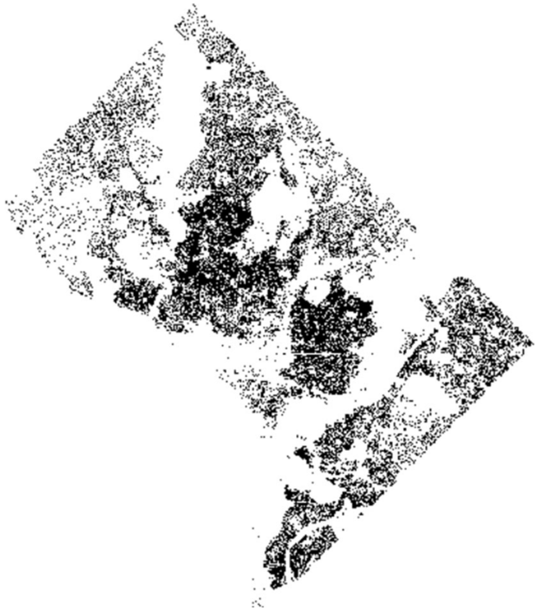

Fig. 5 Locations of burglaries in Washington, DC (2000–2012)

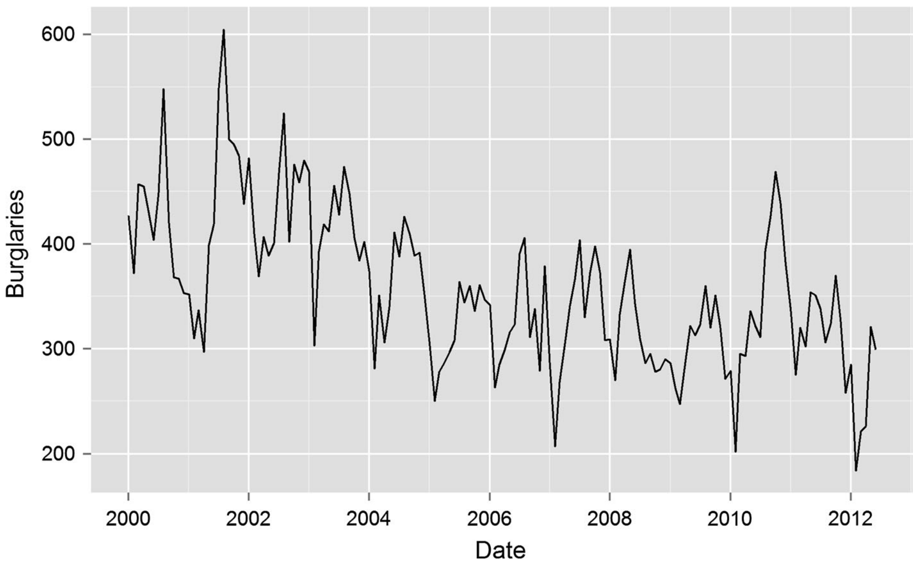

Fig. 6 Burglaries in Washington, DC by month (2000–2012)

window as small as 90 days can still reliably distinguish between data generated by a boost effect and data generated without a boost effect.

Following (Johnson et al. 2007) we define a "close" pair as a pair of burglaries that occur within 1 week and 200 m of each other, and we conduct several variants of the Knox test on Washington, DC burglary data using these values. Figure 8 plots the Knox ratios

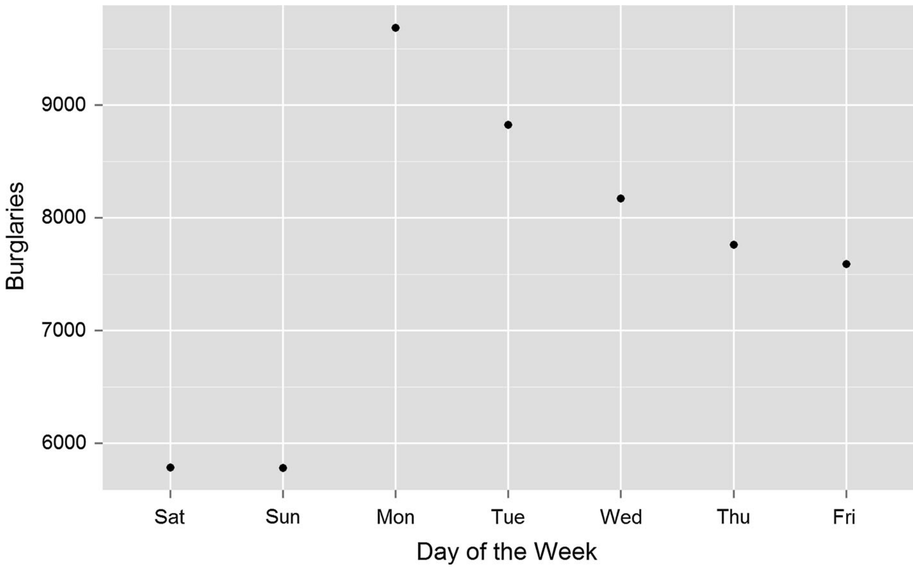

Fig. 7 Total burglaries in DC by day of the week (2000–2012)

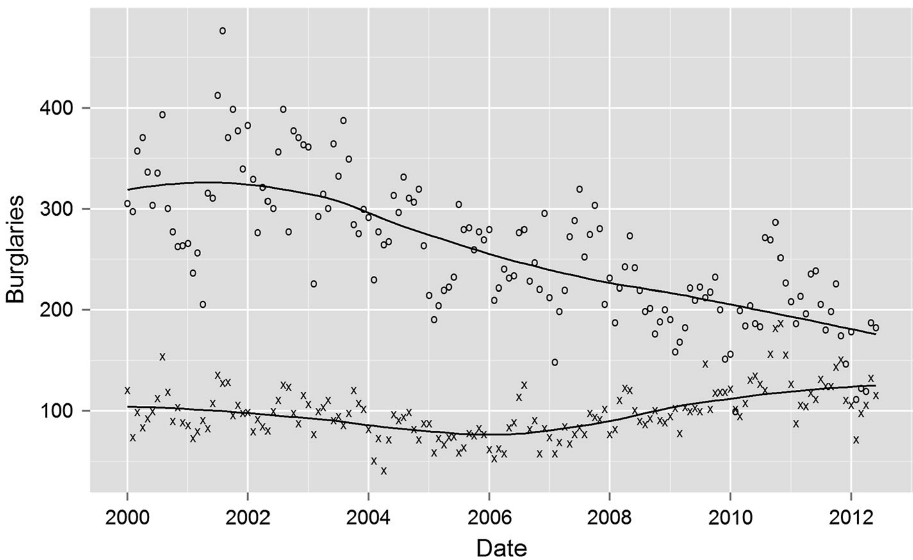

Fig. 8 Neighborhood risk over time. Northwest and southeast of the Anacostia River (*circles* = NW, *exes* = SE)

observed in the DC data as we change the time window of analysis (i.e. splitting the data into 1, 2, 3, 6, or 12 month intervals and analyzing these one at a time). Only 1/3 of the Knox ratios observed when the time window is restricted to 1 month were statistically significant at conventional levels ($p < 0.05$). However, every test at the 6 and 12 month

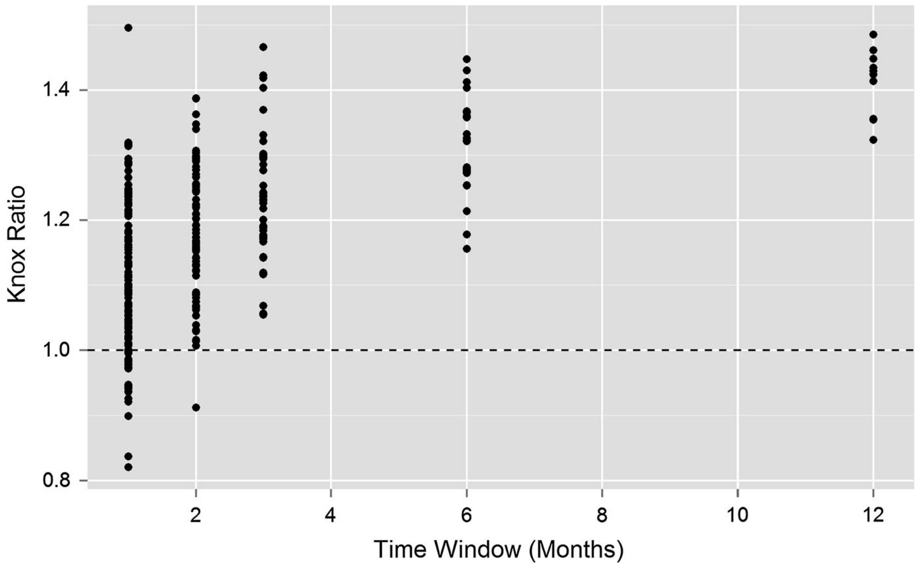

Fig. 9 Knox ratios from DC burglary data as we vary the window of analysis (T = 7, D = 200)

windows passed this statistical significance threshold. Additionally, the average estimated Knox ratio increases as the time window increases (from about 1.1 at 1 month to 1.4 at 1 year). If the Knox ratio reflects the magnitude of the boost effect, then we should not expect to see this pattern. Rather, as the agent-based model suggests, this is a signature of changing relative risks (Fig. 9).

Conclusion

Given these results, what is the proper way forward? Spatio-temporal clustering is ubiquitous in burglary, and it is clear both from theory and evidence on repeat offenders that this clustering is driven in part by contagion. Roughly 27 % of burglaries in Washington, DC between 2000 and 2012 were followed by another burglary within 200 meters and 7 days. Such information about spatio-temporal clustering could be useful for law enforcement even absent knowledge about the mechanism producing it, and can provide a tool for deploying law enforcement resources to prevent repeat and near-repeat victimization. However, if our standard tools for detecting spatio-temporal clustering cannot distinguish between contagion and exogenously-driven changes in relative risks, then estimating the size of the boost effect, and its implications for policymakers, becomes much more difficult.

In light of our findings, we have two recommendations for researchers. First, it is clear that the Knox test can only provide an unbiased test of contagion if there is good reason to believe that relative risks in the data are constant over time. Because this is a more plausible assumption over shorter time periods, restricting the window of analysis can be a useful robustness check, and the results from the agent-based model suggest that the Knox test can distinguish between data with and without contagion even using time windows as small as 3 months. Second, researchers should consider augmenting tests for spatio-temporal clustering with additional theoretical/empirical tools. As we demonstrate here, agent-based modeling provides a useful tool for matching observed Knox ratios to those simulated with known boost effects (recognizing that such estimates will be sensitive to parameters like population size and density). Similarly, spatial econometric methods that control for exogenous changes in relative risks may be appropriate (e.g. Glaeser et al. 1996; Morenoff et al. 2001). However, by necessity such techniques require neighborhood-level data rather than individual-level data. Contagion across neighborhoods is a phenomenon worth studying, but may reflect a different mechanism than is the focus of contagion research using the Knox test.

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