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The (In)Stability of Residential Burglary Patterns on Street Segments: The Case of Antwerp, Belgium 2005–2016

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Abstract
Objectives To examine the spatial concentration and spatial stability of residential burglary at micro places in the context of a substantial city-level burglary drop in Antwerp, Belgium.
Methods 51,337 police recorded home burglary incidents for the period 2005–2016 are geo-referenced to 26,875 street segments. Longitudinal trends in spatial concentrations of burglary are considered using descriptive statistics, generalized Gini coefficients, and local Getis–Ord statistics. Andresen's (Appl Geogr 29(3):333–345, 2009) non-parametric spatial point pattern test (SPPT) is used to identify spatial stability in burglary point patterns and evaluate the ubiquity of a city-level burglary drop across street segments. A longitudinal extension of the SPPT is implemented.
Results Residential burglary is substantially concentrated in street segments. Burglary point patterns exhibit a moderate to high degree of spatial stability over time. Local analyses show that 91% of street segments with burglary experienced a net decrease in crime and under 1% of street segments with burglary experienced a net increase. Absolute spatial stability over time is found for just 1.43% of street segments with burglary and minor increases are consistently observed for as few as 11 street segments with burglary.
Conclusions The citywide home burglary drop manifested itself uniformly across street segments with burglary and the majority of street segments that experienced burglary contributed relatively equally to the crime drop. In other words, we find no strong evidence

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that the city-level crime drop can be tied to substantial decreases in a few specific places, nor do we find that the reductions in burglary are spatially concentrated.

Keywords Spatial point pattern test · Spatial stability · Crime trends · Street segment

Introduction

Over the past two decades, property crime in general and burglary in particular has been decreasing in volume in most advanced countries. First observed in North American cities for burglary and theft in the early 1970s (Farrell 2013), this crime drop was subsequently established for other crime types in different cities and other countries as well prompting some authors to suggest there may have been a global drop in crime in general (Tseloni et al. 2010). For example, residential burglary, theft, and motor vehicle theft fell by over − 60% from 1993 to 2014 in the US (Truman and Langton 2015). Similar declines were observed for burglary and motor vehicle theft in Canada (Hodgkinson et al. 2016; Ouimet 2002), and for property crimes in New Zealand and Australia (Mayhew 2012). Most European countries saw reductions in property crime as well (Van Dijk et al. 2008, 2012). In Belgium, for example, residential burglary dropped nationwide by a quarter between 2000 and 2016 (Belgian Federal Police 2017).

Numerous theories and hypotheses have been advanced to explain these declining property crime volumes (for reviews, see Blumstein and Rosenfeld 2008; Farrell 2013; Levitt 2004). In Western Europe, recent reductions in property crime have repeatedly been linked to reductions in crime opportunities triggered by increased and improved household security (see inter alia Tseloni et al. 2017; Vollaard and van Ours 2011). Despite our growing understanding of the processes that may underlie property crime reductions, there have been relatively few investigations of the changing *spatial crime patterns* associated with falling crime in general, and property crime and burglary in particular. As such, it remains unclear to what extent a global burglary reduction is a widespread spatial process that manifests itself across many micro places, or instead a spatially concentrated process limited to sharp reductions in burglary in just a few micro crime concentrations. Identifying changing micro-spatial patterns of crime is a first step towards a better understanding of the mechanics behind a drop in any particular crime (Farrell et al. 2014), because the causal processes behind a widespread reduction in crime across micro places may be entirely different from those behind a crime drop that is concentrated in a small number of places (see, e.g., Fujita and Maxfield 2012; Mielke and Zahran 2012).

Thus, before addressing explanatory questions in detail or developing crime prevention strategies, the focus should arguably be on careful description of how a reduction in any particular crime impacts the associated spatial concentrations of that crime and their stability over time. In this study, we examine the spatial dynamics associated with a burglary reduction and do so in an international context. Like many other Western countries, the number of reported burglaries dropped nationwide in Belgium in the past two decades. Residential burglary reduced by an estimated − 30% over a 12-year period (from 2005 to 2016) in Antwerp, Belgium's second-largest city. This citywide reduction in burglary was possibly one of the most pronounced burglary drops in any of Belgium's largest cities. In this study, we focus on the 12-year residential burglary decline in Antwerp and examine how the citywide burglary reduction affected spatial burglary patterns. We extend the study of spatial processes of the crime drop and crime concentrations to a particular crime type and an international context that has hitherto received limited attention in the criminology-of-place literature. In addition, we apply a longitudinal extension of the spatial point pattern test (Andresen 2016) that allows us to examine longitudinal patterns of spatial stability of crime patterns globally as well as locally.

Spatial Dynamics of a Crime Drop

Despite overall reductions in crime, crime is strongly concentrated in a few micro places and crime concentrations are stable over time (Andresen et al. 2017; Andresen and Malleson 2011; Curman et al. 2015; Hodgkinson et al. 2016; Weisburd et al. 2004; Wheeler et al. 2016). There are less consistent findings, however, about the *spatial patterns* of crime concentration. Some authors suggest that strong reductions in relatively few micro-places are responsible for the overall crime drop (Andresen et al. 2017; Groff et al. 2010; Weisburd et al. 2004), whereas others find evidence of a more widespread phenomenon, with many places experiencing relatively similar crime reductions (Andresen and Malleson 2011; Curman et al. 2015; Hodgkinson et al. 2016; Wheeler et al. 2016).

In their seminal effort to investigate the stability of crime concentrations in Seattle over time, Weisburd et al. (2004) concluded that half of all crime[1] was concentrated in 4–5% of Seattle street segments and that the 24% citywide crime reduction which occurred during the 14-year study period was a spatially concentrated process. Just 14% of street segments generated the citywide trend and had a strong declining crime trend over time. Conversely, 84% of street segments exhibited stability and saw no meaningful changes in their crime trajectories (see also, e.g., Groff et al. 2010; Weisburd et al. 2009). Recently, the Seattle study (Weisburd et al. 2004) was replicated in Vancouver (Curman et al. 2015) and Albany (Wheeler et al. 2016), where crime decreased in recent years (− 40% in Vancouver[2] and − 35% in Albany[3]). Similar to Seattle, half of all crime in Vancouver was stably clustered in about 8% of street segments (Curman et al. 2015) and 241 street segments (5%) in Albany remained consistent high-crime clusters (Wheeler et al. 2016).

In contrast to Weisburd et al. (2004), both Curman et al. (2015) and Wheeler et al. (2016) found that crime was decreasing across most street segments. In fact, a large number of micro places in Vancouver (30%) and Albany (40%) followed the citywide declining trend and contributed to the observed crime reduction throughout the study period. Further contrasting with Seattle, where 2% of street segments saw a relatively large increase in crime during the study period, no increasing crime trajectories were identified at all in both cities prompting the researchers to note for Vancouver that "this decline in criminal activity was more widespread […] and almost all street blocks would have played a role in this change over time" (Curman et al. 2015, p. 142).

[1] Crime includes incident reports of property crime, disorder, drugs, and prostitution offences, violent personal crime, a range of various non-traffic crime related events such as domestic disputes and missing persons, traffic-related events, and unknown events.

[2] Curman et al. (2015) combine 22 incident categories into a single crime measure: arson, assault, assault in progress, attempted break and enter, attempted theft, break and enter, break and enter in progress, drug arrest, fight, alarm, holdup, homicide, purse snatching, robbery, robbery in progress, shoplifting, stabbing, stolen vehicle, sexual assault, theft from vehicle, theft and theft in progress.

[3] Wheeler et al. (2016) analyze Part 1 and Part 2 UCR crime. Part 1 crimes include homicide, rape, robbery, aggravated assault, burglary, larceny, theft of a motor vehicle, and arson. Part 2 crimes include all criminal law crimes not listed under Part 1 crimes.

Instead of using trajectory analysis to investigate crime trajectories of micro places (see, e.g., Curman et al. 2015; Weisburd et al. 2004; Wheeler et al. 2016), some authors have relied on a non-parametric area based spatial point pattern test (Andresen 2009, 2016) to explicitly study changes in the actual spatial patterns of crime (see Andresen et al. 2017; Andresen and Malleson 2011; Hodgkinson et al. 2016). This approach has the advantage over trajectory analysis that it allows to formally test the assumption of spatial stability of spatial crime patterns and that it may detect small but meaningful changes in spatial crime patterns over longer periods that could otherwise go undetected in a trajectory analysis (Andresen et al. 2017, pp. 4, 6).

Initially, applications of the spatial point pattern test to study changes in spatial patterns of crime over time were restricted to pairwise comparisons of discrete time points that span longer periods. Andresen and Malleson (2011) investigated changes in spatial patterns of a variety of crime types[4] in Vancouver over a 10-year period by comparing data at three time points (1991, 1996, 2001). In the context of substantial overall reductions in crime volume (− 12% for robbery and up to − 54% for assault), the authors found moderate to strong support of spatial stability of crime patterns over time suggesting that the crime drop occurred evenly across Vancouver street segments. Like Weisburd et al. (2004), they identified a small (4%) group of street segments where robbery actually increased and found that these streets were spatially clustered. Hodgkinson et al. (2016) analyzed two years (2003, 2013) of data that span an 11-year period to investigate how an 84% citywide reduction in automotive theft impacted spatial patterns of this crime in Vancouver. They found that 65% of street segments that had crime exhibited stability over this 11-year period, whereas 35% saw statistically significant changes in relative crime volume.

Most recently and most relevant for this study, Andresen et al. (2017) considered the long-term stability of crime concentrations in Vancouver from 2003 through 2013. Instead of comparing crime patterns at two or more discrete time points, Andresen et al. (2017) rely on a longitudinal extension of Andresen's non-parametric spatial point pattern test to investigate how micro level concentrations of various property crimes[5] changed over an 11-year period while Vancouver crime levels dropped by 47% citywide. They found that the number of street segments with any crime declined from 35% in earlier years to 25% in later years of their study period. However, crime concentrations in micro places remained stable with approximately 3–4% of Vancouver street segments accounting for half of all crimes in any given year. Finding moderate to high degrees of spatial stability, the results of the longitudinal spatial point pattern test generally supported the conclusion that the observed crime drop manifested itself evenly across Vancouver street segments during the entire study period. However, once Andresen et al. (2017) limited their analysis to street segments with any crime, the conclusion of a uniform crime drop across Vancouver seems no longer warranted. They found considerably lower degrees of spatial stability suggesting that the crime drop did not occur evenly across micro places, as initially thought. In fact, about half of the street segments with any crime exhibited statistically significant changes in relative crime volume. In this study, we build on this earlier research in which the spatial point pattern test was applied to study changes in spatial crime patterns over time in the context of a substantial crime reduction. We extend those studies by applying the

[4] Andresen and Malleson (2011) analyze calls for service for assault, burglary, robbery, sexual assault, theft, theft from vehicle, and theft of vehicle.

[5] Andresen et al. (2017) use incident data for commercial break and enter, mischief, theft from vehicle, and theft of vehicle.

longitudinal extension of Andresen's (2009) spatial point pattern test and expanding it to the local level, as discussed in detail below.

Data and Methods

Antwerp Burglary Data

We use 12 years of georeferenced residential burglary data for the city of Antwerp, Belgium.[6] Burglary data for the period 2005 through 2016 were made available by the Antwerp Local Police Department (ALPD). The burglary data include the date and time of the incident and the address of the burglarized house. 96.25% of the available burglary data were geocoded with 1 m precision, which is well above suggested minimum acceptable geocoding hit rates (Ratcliffe 2004). Conversely, 3.75% of the burglary data could not be geocoded because the available address information was insufficiently precise. In total, 51,337 burglary incidents were included in the analyses reported here.

During the study period, burglary declined by an estimated − 30%[7] from 4628 incidents in 2005 to 2674 burglaries in 2016, notwithstanding substantial fluctuations in burglary levels during the study period (shown in Fig. 1). This downward trend is primarily driven by two steep declines from 2012 to 2013 and from 2015 to 2016.[8] In previous years,

[6] The decision to focus on residential burglary data was motivated by two arguments. Since we are interested in studying changes in spatial patterns of crime over time, we required the offence category under study to be a high volume crime with little or no spatial bias in recorded incidents. Residential burglary has a high citizen reporting and police recording rate, ensuring a comprehensive overview of burglary incidents. In part, this is due to most common Belgian fire insurance policies covering material damages caused by (attempted) burglaries provided that the victim files a police report. Furthermore, unlike for other crime types such as robbery, vehicle theft, or personal violence, precise address information is generally available for residential burglary since these incidents take place at a specific residential unit. This ensures high geocoding hit rates and aggregating burglary incidents to the correct street segments thereby minimizing the bias in the spatial patterns under study. The decision to focus on Antwerp was pragmatic more than anything else. The city's population size and the presence of the largest Belgian local police force ensures having a sizeable number of offences to study. In addition, the ALPD was motivated to collaborate and provided access to the recorded crime data. Finally, international contexts have received little attention in the criminology-of-place literature so far. The external validity of some of the key findings from the criminology-of-place literature may therefore be limited requiring additional studies in different contexts. We acknowledge, however, that our focus on a particular crime type, burglary, in a particular context, Antwerp, limits the focus of our study and, to an extent, the implications of our result.

[7] To take all available burglary data into account and correct for fluctuations in burglary levels over time, a linear trend line was estimated through an ordinary least squares regression model with burglary count as a function of time. A simple comparison of 2005 and 2016 would lead to an even stronger conclusion, namely a burglary decline of − 42%. In addition, we point out that even disregarding 2016, the percentage decline predicted by a linear time trend is − 19%, and disregarding 2013 *and* 2016 the time trend predicts a − 15% crime reduction. This indeed shows a long-term trend of crime decrease.

[8] An anonymous reviewer suggested we offer potential explanations for the 2012–2013 and 2015–2016 burglary reductions. While identification of the cause(s) of a substantial crime reduction is an interesting question in its own right, we wish to emphasize that this is not the objective of our study. Independently of what may have triggered the burglary reduction, we aim to study to what extent a reduction in burglary volume is a widespread spatial process that manifests itself proportionally across micro places or instead a spatially concentrated process shaped by sharp reductions in just a handful of street segments. In the event of a widespread reduction across many micro places, the factors affecting the Antwerp burglary reduction would be likely rooted in changes in systemic causes that occur across all street segments. A spatially concentrated burglary reduction would be likely due to one or more micro-place processes that are specific to a limited number of street segments. Finally, although we do not wish to suggest causality, we are aware that in 2012 a new local government coalition came into power in Antwerp. The new local coalition quickly

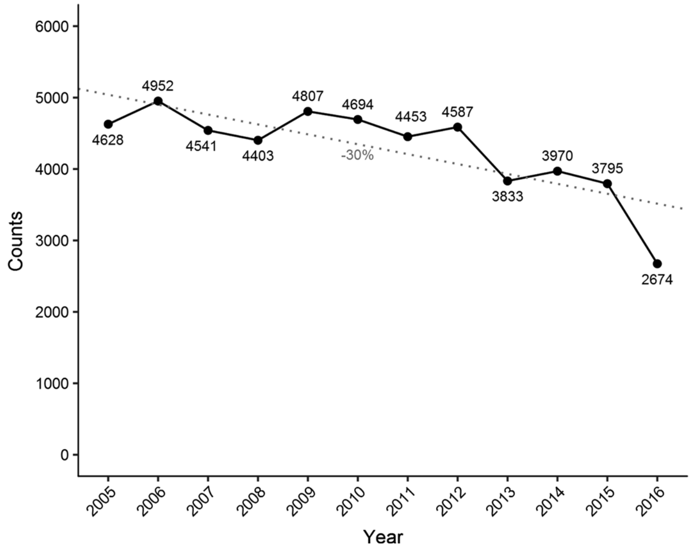

Fig. 1 Yearly residential burglary counts (OLS estimated 12-year change in residential burglary counts (dotted line): − 30%)

consecutive smaller declines are observed as well though followed by a temporary increase. Overall, however, burglary volumes declined during the study period and burglary spatial patterns may have been impacted considerably.

Antwerp is Belgium's second largest city with a growing population of approx. 458,000 in 2005 and 517,000 in 2016 and is policed by Belgium's largest local police force.[9] The city is located in the northern part of Belgium and covers about 204 square kilometers. A third of Antwerp's surface area is covered by the Port of Antwerp, Europe's second-largest sea port, which isolates a smaller residential area in the north of the city from the main city center.

Spatial Units of Analysis

Street segments, or the section of a street between two intersections, are the primary spatial units of analysis in this study. We chose street segments because of their relevance in organizing the daily lives of city dwellers and because they are a small enough spatial unit of analysis to minimize aggregation bias while large enough to ensure having a measurable number of burglaries and detecting meaningful changes in spatial patterns of burglary (Groff et al. 2010; Taylor 1998; Weisburd et al. 2004). Street segments are extracted from

Footnote 8 continued
implemented a 'tough-on-crime' policy. The number of a variety of offences, including burglary, reduced and remained low in comparison to the previous coalition period (Antwerp Local Police Department 2017). While these events may offer context, we encourage readers not to infer causality. Indeed, the largest decline occurred from 2015 to 2016, several years after this event.

[9] Strictly speaking, Antwerp is Belgium's largest city but the Brussels metropolitan area, which consists of 19 municipalities policed by six different police forces, is the most populous area and is considered Belgium's largest 'city' despite not being an actual city.

the Flemish Road Registry.[10] Contrary to many North American cities, Antwerp does not have a grid-based street network layout. Instead, the street network has an irregular pattern typical for European cities with a medieval city center. There are 26,875 street segments in Antwerp with a mean length of 97.73 meters (SD = 141.77). In addition, the study area is overlaid with a grid of 200 by 200 m cells. These cells are determined independently of street segments and serve to compute relevant exploratory spatial data analysis statistics.

Analytic Strategy

We apply four complementary methods to summarize the spatial concentration and spatial stability of burglary events in Antwerp longitudinally, and to study how these processes changed from 2005 through 2016 across street segments.

Descriptive Statistics and Generalized Gini Coefficient

First, we provide summary statistics of the spatial crime concentration across street segments for each year of the study period separately. We compute standard summary statistics of crime concentration, including the percentage of units that account for 50% of all burglaries and Gini coefficients. The Gini coefficient is a measure of the concentration of a distribution and varies between 0 and 1, with 0 indicating minimal concentration (all crime is equally distributed across all spatial units) and 1 indicating maximal concentration (all crime is concentrated within one spatial unit). Because the standard Gini coefficient overestimates the degree of concentration when the number of crime events is smaller than the number of units of analysis,[11] we use the recently introduced generalized Gini coefficient (Bernasco and Steenbeek 2016). The generalized Gini has the desirable property that it is equal to the original coefficient when the number of crimes is equal to or larger than the number of units of analysis thus allowing for direct comparisons of the degree of concentration across years, even when crime declines over time.

*Hot Spot Mapping: Local Gi**

Second, we apply exploratory spatial data analysis (ESDA) techniques to identify where burglary events cluster in Antwerp over time. For each of the 200 by 200 m grid cells, we estimate local Getis–Ord (Gi*) statistics to distinguish between clusters of statistically significant high and low values of burglaries (Chainey and Ratcliffe 2005). As suggested by Greiling et al. (2005, pp. 72–73), statistical significance is determined through a Monte Carlo simulation process that involves generating a reference distribution against which the observed burglary patterns are compared (instead of complete spatial randomness). For each grid cell, local Gi* statistics are generated using 999 conditional Monte Carlo permutations of the burglary values. Statistical significance is assessed by comparing the reference distribution of Gi* statistics obtained through this conditional randomization process with the observed distribution in the data. A correction (Simes 1986) is then

[10] The street segments shapefile (Vlaams Wegenregister, downloaded on 3 June 2016) is available for download at the product catalogue of the Flemish Geographical Information Agency (FGIA) [https://download.agiv.be/] and can be accessed online through the FGIA's online geoportal [http://geopunt.be].

[11] For example, in our data there are six to ten times more street segments than yearly burglary events. Standard measures of concentration, including the standard Gini coefficient, do not account for the fact that the data imposes structural constraints on the maximally possible degree of crime concentration.

applied to the p values of the local Gi* statistics to account for the dependency in statistical testing arising out of computing Gi* statistics for adjacent areas and introduced by the Monte Carlo simulation process. This analysis is repeated for the first and last years of our data and discussed in the results section.

Andresen's Spatial Point Pattern Test (SPPT): Global Patterns

Third, the *changes* in burglary spatial patterns in Antwerp street segments are gauged using Andresen's (2009) non-parametric spatial point pattern test (SPPT; for details, see Andresen, 2016). This test was purposely developed by Andresen (2009) to quantify the degree of similarity of point patterns in two datasets for a given spatial unit of analysis. It works by pairwise comparing the relative event counts aggregated to a specified spatial resolution in a reference dataset against another dataset.[12] Confidence intervals are obtained through a Monte Carlo simulation process that involves repeated random sampling of 85% of the test data (200 permutations are recommended, see Andresen 2016). Similarity is assessed by verifying that the observed relative event count in the base dataset falls within the corresponding confidence interval in the test data. This procedure is repeated for each areal unit in the data.

The outcome of the SPPT yields a *Local Similarity Index*—one for each spatial unit—that specifies whether the event count is similar (0) in both datasets or whether it was lower (1) or higher ($-$ 1) in the base dataset compared to the test dataset. These local S-indices can be mapped to visualize where and how event patterns significantly changed and serve as input for computing the global S-Index. The *global S-Index* expresses the degree of similarity between two point patterns. It is the percentage of units that have a Local Similarity Index of 0 and varies between 0 (no similarity) and 1 (perfect similarity) Although the global S-index can be interpreted directly as the percentage of units that have a similar event percentages in both datasets, a global S-Index $\geq$ 0.80 has been recommended as cut-off to decide if two point patterns are similar (Andresen 2009, 2016).

While the SPPT is primarily applied to investigate point pattern spatial stability, it can be used to gauge the ubiquity and concentration of changes in crime levels across micro places as well (see, e.g., Andresen and Malleson 2014). Remember that Andresen's spatial point pattern analysis compares spatial changes in relative event counts. Thus, if the total volume of crime decreases citywide and this pattern scales proportionally to the local level then this test would find that there is stability in burglary spatial patterns across these localities (corresponding to a moderate to high global S-Index).[13] Conversely, a spatially uneven decline in residential burglary will result in low global S-Indices for some or all yearly comparisons, because a low global S-Index indicates that a large number of areas saw changes in relative event volume at significantly different rates.

An application of the SPPT to a multiyear comparison requires extension into a multivariate context (Andresen 2016; Andresen et al. 2017). Andresen et al. (2017) proposed to compare all time periods under consideration against a static reference year of the study period. Longitudinal stability trends are studied by identifying predefined similarity

[12] Relative event counts ensure that datasets with different event volumes can be compared. Since total burglary volume declined during the study period, this is an appealing and appropriate analytical approach to study burglary spatial patterns independently from yearly fluctuations in total burglary volume.

[13] Of course, stability in spatial patterns does not exclude the possibility that a small number of high crime localities contribute substantially to the observed crime decline. Spatial patterns are considered globally stable if no more than 20% of spatial units exhibit significant spatial change. As such, considerable spatial change could still underlie global stability of spatial patterns.

patterns or aggregating yearly global S-Indices into a summarized, multiyear global S-Index (for details, see Andresen et al. 2017). However, the multiyear global similarity indices proposed by Andresen et al. (2017) yield a single value for the entire study period.[14] In doing so, their longitudinal extension of the SPPT loses some of the appeal and versatility offered by the bivariate version of the test: the underlying local similarity indices cannot be plotted straightforwardly to contextualize the qualitative processes underlying spatial (in)stability, and the focus on year-to-year comparisons. To address this, we implement an alternative longitudinal extension of Andresen's (2009) SPPT. Instead of defining a static reference base dataset against which multiple test datasets are compared, this particular longitudinal extension allows for multiple, dynamically changing base and test datasets. All time periods in the entire study period are consecutively considered base and test datasets and all possible pairwise comparisons are computed simultaneously.

One further complication needs to be addressed. Areas with zero events in both datasets will be classified as having similar patterns by the SPPT. This is undesirable for areas that cannot experience a certain crime type by definition (e.g., residential burglary along a stretch of motorway). To overcome this, Andresen and Malleson (2011) proposed what we will call a *bivariate robust global S-Index*. The bivariate robust version of the global S-Index only considers areas with at least one event in either datasets under consideration. Under sparse crime data that contain a large number of zero event spatial units, this may adjust similarity estimates considerably downwards. However, while the standard global S-Index is straightforward to apply in a multiyear comparison—in which multiple point patterns are subsequently compared independently of each other—the bivariate robust version is not, because the robust index may consider different study areas for different pairwise comparisons.

We implement and extend a *multivariate robust global S-Index* that uses the same units of analysis for all comparisons, discussed as a sensitivity analysis by Andresen et al. (2017, p. 268). We identify all areal units where at least one event occurred in *any* of the time periods under study and include these areal units in *all* comparisons. Similar to the robust version of the bivariate S-Index, areas that did not experience any crime in any time period are excluded from the calculation of the multivariate robust global S-Index. As such, this multivariate index seeks to find a balance between calculating a spatial stability S-Index for an invariant set of relevant non-zero event areas over a longer time period while avoiding inflation of the values of this S-Index that is caused by including zero event areas. This approach yields a robust multivariate global S-Index that is accurate in a longitudinal context and ensures that the same set of relevant non-zero event areas are consistently compared longitudinally, even though some of these areas may not have experienced crime at all considered time points.

SPPT: Local Change in Crime Concentration

An overall reduction in crime may occur relatively evenly distributed across space, or it could be concentrated on some street segments but not others. Of course, both processes could occur simultaneously as well with a majority of places exhibiting stability and a small number of areas experiencing greater variation in their crime patterns. Investigating this thoroughly requires analysis of the local similarity indices. To this end, we investigate

[14] Instead of describing one of the three patterns chosen a priori by Andresen et al. (2017), our approach allows to describe any longitudinal pattern by combining the local similarity sum scores and the associated volatility scores (see below).

the multivariate robust local S-Indices: these are the local S-Indices—one for each spatial unit—from which the multivariate robust global S-Index was calculated as explained above. For each area and across all eleven sequential pairwise comparisons, we summarize the multivariate robust local similarity indices into a single *local similarity sum score* that expresses the degree to which an area was stable over time or saw multiple increases or decreases in crime. This sum score has a range from − 11 to + 11, with negative values indicating that an area experienced a net decrease in crime and positive values signaling that an area experienced a net increase.[15] Note that the minimum and maximum on this score can only be obtained if an area exclusively experienced crime decreases or increases.

Importantly, a zero value on the local similarity sum score could signal that relative residential burglary counts were stable over time but could mask a random pattern of consecutive increases and decreases in crime. To gauge the degree of volatility underlying this sum score, we compute how many other changes occurred in the local S-Index across all time comparisons. High values indicate many other changes during the period under study, signaling that an area had greater volatility in its local crime pattern. Using this measure of volatility, we are able to gauge the degree of stability in micro-level crime concentrations over the entire study period and identify to what extent qualitatively different processes impacted the observed local stability patterns.[16]

Results

Residential Burglary Concentration Over Time

We begin by examining the degree of concentration in our burglary data for each year separately. For each year of our study period, Table 1 presents the percentage of street segments that account for 50% of all burglaries (Column A) and the percentage of street segments where at least one burglary occurred (Column B). A small number of street segments experience the majority of burglaries in Antwerp, a finding in line with the law of crime concentration (Weisburd 2015) and previous research on this topic in North America and Europe (see, e.g., Andresen et al. 2017; Steenbeek and Weisburd 2015). Burglary is strongly clustered at the street segment level with 50% of all burglaries occurring in

[15] Since there are 12 time periods in our study period, there are 11 consecutive pairwise comparisons that are relevant to gauge the stability of burglary patterns longitudinally (i.e., 2005–2006, 2006–2007, …, 2015–2016).

[16] The following example is instructive to understand how we define volatility. Consider three street segments in a 12-year study period each with a sum score of − 7 but with different associated volatility scores. First, assume a street segment with the following local similarity index values: (− 1, − 1, − 1, − 1, − 1, − 1, − 1, 0, 0, 0, 0). This street segment experienced seven consecutive burglary decreases and no significant change thereafter, receiving a volatility score of 0 because no changes other than a consecutive decrease occurred. A second street segment is characterized by (− 1, − 1, − 1, − 1, − 1, − 1, − 1, 0, 1, 0, − 1). Next to the seven decreases, this segment also experienced one increase and one decrease. The sum score is − 7 but the associated volatility score is 1 because one increase is offset by one decrease. Finally, consider a street segment with an even higher degree of volatility: (− 1, − 1, − 1, − 1, − 1, − 1, − 1, 1, − 1, 1, − 1). With a sum score of − 7, this street segment has a volatility score of 2 because next to seven decreases, two increase/decrease changes also occurred. Coincidentally, a volatility score of 2 is also the maximum possible volatility score associated with a sum score of − 7 and twelve time periods.

Table 1 Percentage of street segments (N = 26,875) that cluster 50% of residential burglary

	(A) Percentage of street segments responsible for 50% of all residential burglaries	(B) Percentage of street segments where at least one residential burglary occurred
2005	2.55	9.82
2006	2.41	9.94
2007	2.28	9.30
2008	2.39	9.29
2009	2.24	9.51
2010	2.30	9.42
2011	2.53	9.73
2012	2.50	9.78
2013	2.22	8.51
2014	2.08	8.47
2015	2.05	8.08
2016	1.83	6.59

approximately 2% of all street segments.[17] Despite the citywide burglary reduction, the percentage of street segments that account for 50% of burglaries remains stable throughout the entire study period and no particular trend can be discerned.

The *entire* burglary concentration distribution over time is summarized through the generalized Gini coefficient (Bernasco and Steenbeek 2016). Figure 2 shows that residential burglary is substantially concentrated at the street segment level. Furthermore, the degree of burglary concentration is relatively stable over time for Antwerp street segments.

Spatial Location of Burglary Concentration

To identify where burglary is concentrated in our study area and to what extent burglary concentration spatially shifted during the 12-year study period, we estimate (Monte Carlo simulated, Simes corrected) local Getis–Ord (Gi*) statistics to distinguish between clusters of statistically significant high and low concentrations of home burglaries in Antwerp. The output of the Gi* statistic for 2005 and 2016 is displayed in Fig. 3. Initially, the hot spot procedure identifies a large significantly high cluster of residential burglary in Antwerp's city center and a smaller significantly high cluster of residential burglary southwest of Antwerp's city center. In 2016, both high burglary clusters persist and a number of smaller clusters have emerged. Given the citywide burglary drop, the comparison of hot spot maps between 2005 and 2016 may indicate a locally slower burglary decrease in some grid cells (see Hodgkinson et al. 2016). However, this could also signal that some cells saw a continued increase in burglary volume despite a global burglary reduction 2005 through 2016. We investigate this in detail in the next two sections.

[17] However, note that 50% of all home burglaries in 2005 (= 4628/2 = 2314) can only occur in about (2314/26,875 × 100% =) 8.6% of all street segments under maximum spatial dispersion, i.e., when every event occurs on a different street segment. In 2016, this percentage of *possible* street segments is further reduced to 5.0%. These structural constraints to the maximally possible degree of burglary concentration help put the reported concentrations in perspective, and are also accounted for in the generalized Gini calculations.

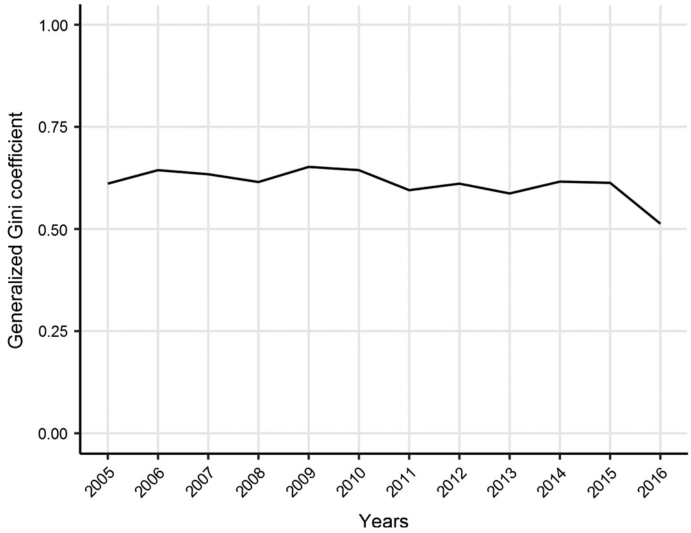

Fig. 2 Generalized Gini coefficients for residential burglary concentration in street segments (2005–2016)

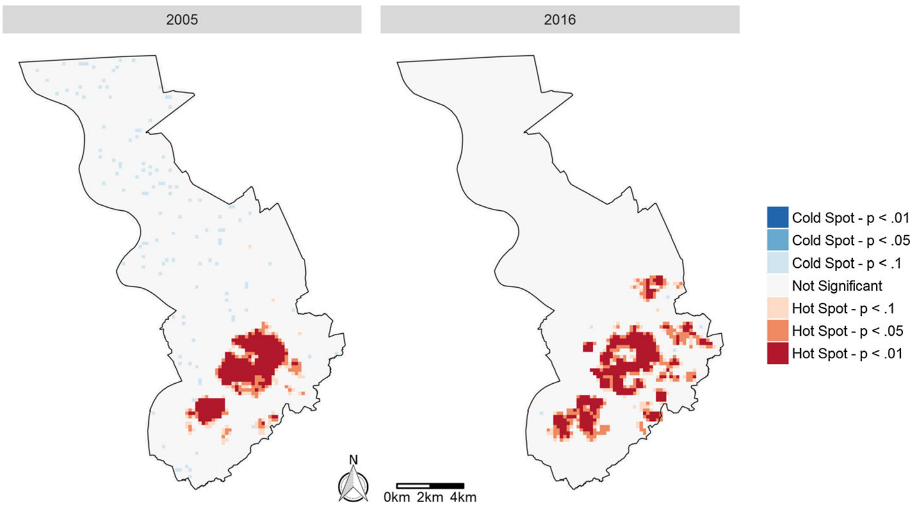

Fig. 3 Map of local Getis–Ord (Gi*) statistics output for Antwerp overlaid with 200 by 200 m grid cells (Monte Carlo simulated and Simes corrected)

Spatial Point Pattern Test: Global (In)Stability

We assess the extent of the burglary drop in our study area globally for street segments using Andresen's (2009) SPPT. The top right parts of Tables 2 and 3 show the result of the bivariate comparisons of the SPPT for all street segments and for non-zero event street segments respectively. The bottom left part of Table 3 shows the multivariate version of the robust similarity index for non-zero event street segments in any year of our time series.

Table 2 Bivariate global similarity S-Indices (2005–2016) for all street segments

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
2005		0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
2006			0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
2007				0.92	0.91	0.91	0.91	0.92	0.91	0.91	0.91	0.92
2008					0.92	0.91	0.91	0.91	0.92	0.92	0.91	0.92
2009						0.91	0.91	0.91	0.91	0.91	0.91	0.92
2010							0.91	0.91	0.91	0.91	0.91	0.92
2011								0.91	0.91	0.91	0.91	0.91
2012									0.91	0.91	0.91	0.91
2013										0.92	0.92	0.92
2014											0.92	0.92
2015												0.93
2016												

Table 3 Bivariate robust global similarity S-Indices (2005–2016) for non-zero event street segments (top right), and Multivariate robust global similarity S-Indices (2005–2016) for non-zero event street segments (bottom left)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
2005		0.41	0.40	0.39	0.39	0.37	0.41	0.40	0.38	0.37	0.35	0.35
2006	0.67		0.39	0.39	0.39	0.38	0.40	0.39	0.37	0.36	0.35	0.34
2007	0.67	0.67		0.40	0.40	0.39	0.41	0.43	0.39	0.38	0.36	0.34
2008	0.67	0.67	0.69		0.41	0.40	0.42	0.41	0.39	0.39	0.36	0.34
2009	0.66	0.66	0.68	0.68		0.39	0.41	0.41	0.37	0.37	0.35	0.35
2010	0.66	0.66	0.68	0.68	0.67		0.42	0.41	0.39	0.38	0.36	0.37
2011	0.67	0.66	0.68	0.68	0.67	0.68		0.41	0.38	0.37	0.36	0.33
2012	0.66	0.66	0.69	0.68	0.67	0.68	0.67		0.38	0.38	0.35	0.35
2013	0.67	0.66	0.68	0.69	0.67	0.68	0.67	0.67		0.41	0.38	0.37
2014	0.67	0.66	0.68	0.68	0.67	0.68	0.66	0.67	0.71		0.39	0.36
2015	0.66	0.66	0.68	0.67	0.66	0.67	0.66	0.66	0.70	0.71		0.38
2016	0.68	0.67	0.68	0.68	0.68	0.69	0.67	0.68	0.71	0.71	0.73	

The bivariate global similarity indices in Table 2 indicate extremely high spatial stability in burglary concentration in the 26,875 street segments. On average, < 9% of street segments saw a significant change in burglary concentration. This suggests that, for each two-year comparison, burglary volume decreased very uniformly across Antwerp street segments. However, these results are in stark contrast with the results of the *bivariate robust* global similarity index, which addresses potential bias towards identifying stability due to the high number of zero event areas. These indices printed in the top right part of Table 3 indicate low spatial stability. For street segments where any burglary occurred (in each two-year comparison), about 60% of these street segments saw significant change suggesting that burglary declined more pronouncedly in some street segments but not others.

As discussed, the standard and the robust bivariate global S-Index have their disadvantages when studying longitudinal patterns of spatial stability. On the one hand, the values of the bivariate global similarity index displayed in Table 2 are consistently computed for the same set of areas but overestimate the degree of spatial stability due to the inclusion of zero event areas. On the other hand, the robust version of this index displayed in the top right part of Table 3 only considers non-zero event areas but in doing so is not computed for an invariant set of areas invalidating longitudinal comparisons. Non-zero event areas change over time, implying that the areas included in the computation of the bivariate robust global similarity index for 2005–2006 are not the same as the areas included in the computation of the 2006–2007, and so on.

To overcome this, we identified all spatial areas that had any burglary during any moment over the entire study period, and computed the global similarity index based on these units for every two-year comparison. The results of this *multivariate robust global similarity index* are shown in the bottom left part of Table 3. In contrast to the Bivariate Robust Global Similarity Index (top right, Table 3), the results suggest moderate to high spatial stability of residential burglary concentration. About 67% of street segments (that had at least one burglary at any time during the study period) experience the same percentage of home burglaries for each two-year comparison. This offers evidence that the burglary drop was relatively uniformly distributed across Antwerp street segments with at least one burglary once during the study period.[18]

Spatial Point Pattern Test: Micro-spatial (In)Stability

As discussed in the Analytical Strategy, the global S-Indices discussed above are calculated using the *Local Similarity Index*—one for each spatial unit—that specifies whether the proportion of crime in that spatial unit is similar, lower, or higher, in the base dataset as compared to the test dataset. For each of the 7192 street segments that experienced at least one residential burglary event in the study period, eleven local similarity indices are calculated (one for each time comparison 2005–2006; 2006–2007; …; 2015–2016). We summarize the pattern across these eleven comparisons first by calculating a sum score per street segment.

The sum scores of the local S-Indices provide the ‘net effect’ of the relative burglary increase or decrease over the entire study period (Table 4, right most totals). Table 4 shows that across the entire study period, 6554 (91%) street segments showed a net *decrease* in the burglary proportion, with three-quarter of those street segments (75%) experiencing one or two significant declines in relative burglary volume. Only 69 street segments experienced a significant net increase in relative burglary over the 12-year period. 569 street segments (7.91% of the 7192 significantly changing segments) experienced a zero net effect: the relative occurrence of burglary on these street segments neither

[18] Reviewing an earlier version of this paper, an anonymous reviewer suggested to verify whether the two steepest reductions (2012–2013, 2015–2016) are distributed proportionally across Antwerp street segments similarly to the overall reduction (2005–2016). The multivariate robust global similarity indices (top right, Table 3) for the 2012–2013 (.71) and the 2015–2016 (.73) comparison suggest moderate to high spatial stability of residential burglary concentration. In line with the general pattern, just over seven out of ten street segments (that had at least one burglary at any time during the study period) experience the same percentage of home burglaries from 2012 to 2013 and from 2015 to 2016. This indicates that both burglary changes indeed scale proportionally across street segments.

Table 4 Volatility of the net increasing or decreasing residential burglary pattern

		Volatility of increase/decrease						Total	
		Consistent (0)	(1)	(2)	(3)	(4)	Volatile (5)	Freq.	Perc.
Burglary increase–decrease sum score	− 6	3	1	2	–	–	–	6	0.08
	− 5	37	20	5	0	–	–	62	0.86
	− 4	186	116	51	4	–	–	357	4.96
	− 3	591	371	182	56	1	–	1201	16.70
	− 2	1132	622	372	141	29	–	2296	31.92
	− 1	1580	525	300	161	63	3	2632	36.60
	0	103	213	95	100	42	16	569	7.91
	1	11	12	11	14	11	2	61	0.85
	2	0	0	1	5	2	–	8	0.11
Total	Freq.	3643	1880	1019	481	148	21	7192	
	Perc.	50.65	26.14	14.17	6.69	2.06	0.29		100

Dashes indicate that volatility score cannot be attained for the corresponding sum score

increased nor decreased, or these street segments experienced exactly as many increases as decreases.[19]

Figure 4 maps the sum scores of the local similarity indices for all street segments that experienced at least one burglary. Red shaded street segments experienced a net increase in relative burglary volume. Blue shaded street segments experienced a net decrease in burglary. Green street segments experienced a zero net effect. Inspection of Fig. 4 does not reveal a particular pattern although it is apparent that the burglary reduction was widespread across Antwerp street segments.

We next turn to the volatility of the multivariate robust Local Similarity Index sum score. While a negative or positive sum score indicates the net change in relative burglary volume over the 12-year period, the underlying pattern may be much more volatile than the sum score suggests at face value. Similarly, street segments with a zero sum score are 'on average' stable but may actually have experienced a volatile trajectory of repeated decreases, increases and stability. Table 4 also shows the volatility of the net increasing or decreasing pattern of burglary concentration.

At least three important conclusions can be drawn from Table 4. First, just 103 street segments exhibited absolute stability in their burglary patterns. That is, burglary patterns did not change once at statistically significant rates in those street segments between 2005 and 2016. Note, however, that 19,683 street segments were excluded from analysis because these segments never had any burglary during the entire study period. Thus, an alternative conclusion is that 19,786 (or 73.62% of all 26,875 street segments) experienced no change in relative residential burglary concentration. The remaining 7089 street segments experienced at least one significant relative residential burglary increase or decrease.

[19] The observed negative correlation between number of burglaries in 2005 and size of proportional reduction 2005–2016 indicates that, generally, the highest burglary count street segments exhibited the greatest changes. The Spearman correlation between 2005 burglary count and size of proportional reduction 2005–2016 is − .85 (N = 3581; $p < .001$) for street segments with any local change in burglary volume and − .85 (N = 2319; $p < .001$) for streets with significant local change in burglary volume.

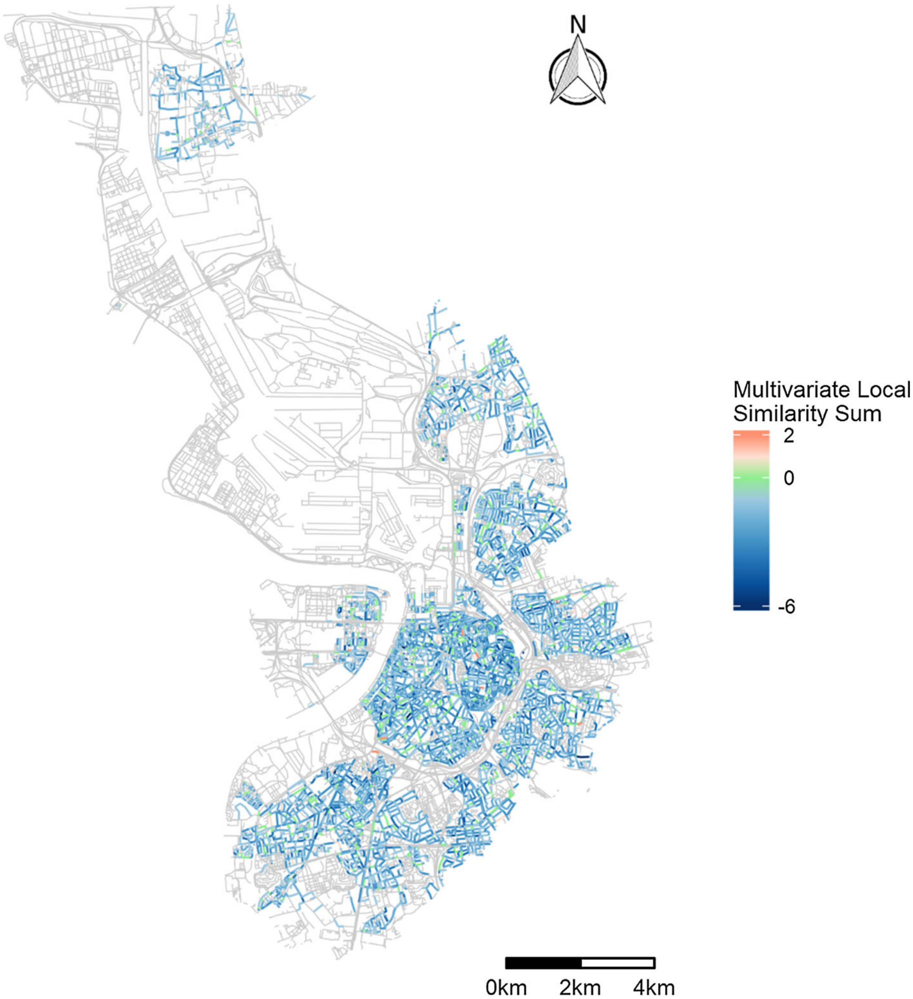

Fig. 4 Map of Local Similarity Index sum scores for all Antwerp street segments with residential burglary in the period 2005–2016. Blue shaded street segments experienced a net decrease with darker blue shades indicating a greater net decrease. Green street segments experienced a zero net effect. Red shaded street segments experienced a net increase with darker red shades indicating a greater net increase (Color figure online)

Second, while about half of all street segments with any burglary incident (N = 3540, or 49.22%) experienced monotonous burglary increases or decreases, the bulk of those street segments (N = 3303) experienced up to three significant decreases in burglary percentage between 2005 and 2016. A very small number (N = 40) of street segments saw five or six statistically significant reductions in relative residential burglary volume. These street segments in particular may prove interesting study grounds to gain a better understanding of the place-specific factors that drive local burglary drops in Antwerp. In combination with the moderately high values for the multivariate robust global similarity index reported earlier, this finding offers evidence for a widespread and relatively uniform burglary decline across Antwerp street segments and suggest that this decline was driven by a much larger number of places (up to half of all street segments with any burglary) than hitherto reported in research. Despite the widespread nature of the process, these results also highlight that it was a relatively rare process since most street segments saw relative burglary decrease just once or twice during the 12-year observation period.

Third, further corroborative evidence that the burglary drop in Antwerp impacted most street segments is found in the absence of a large number of street segments with increasing relative burglary volume. In fact, the bulk of the increasing relative burglary volume can be attributed to 61 street segments that had on average just one statistically

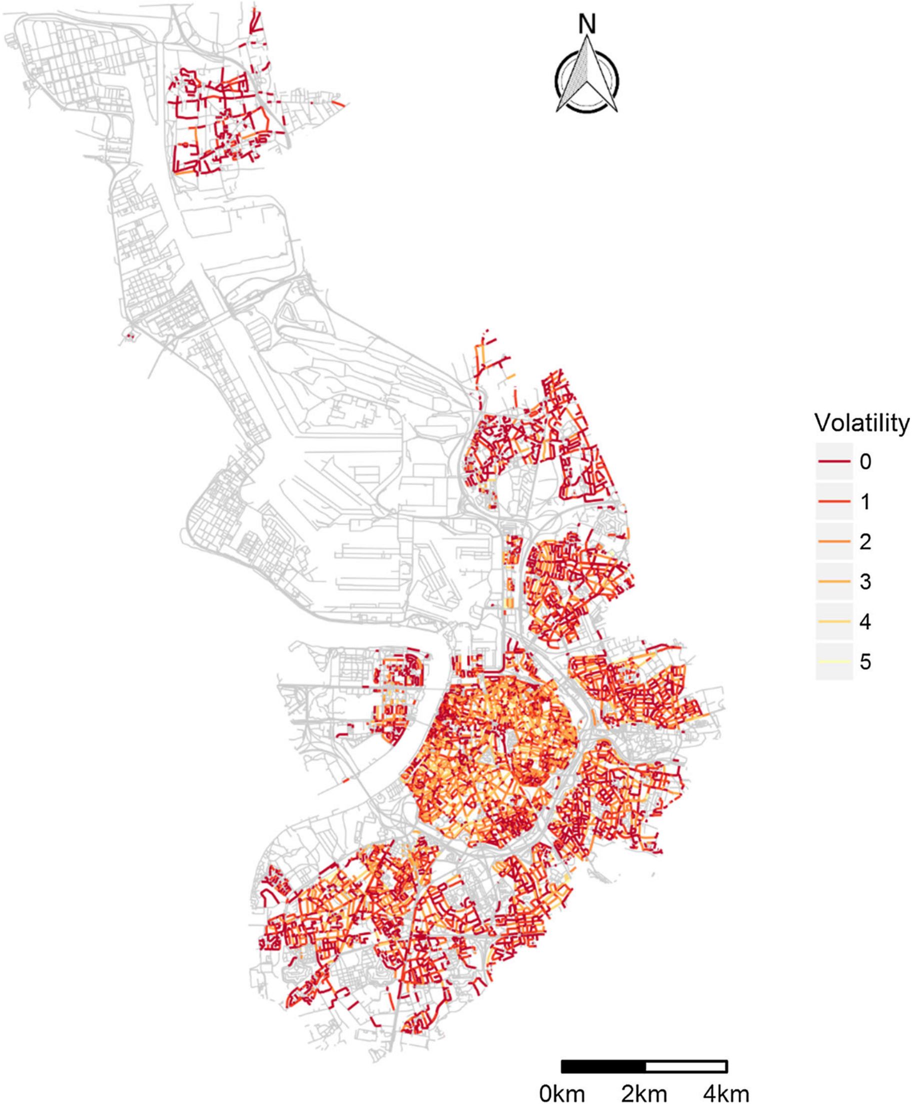

Fig. 5 Map of volatility scores associated with Local Similarity Index sum scores for all Antwerp street segments with residential burglary in the period 2005–2016. Red shaded street segments have a low volatility score. Yellow shaded street segments have a high volatility score (Color figure online)

significant increase in burglary percentage over time. Moreover, just 11 of those segments experienced a non-volatile single increase in relative burglary, meaning that the other street segments experienced a mixture of stability, decreases and increases but on average saw a net increase.

All street segments with burglary and their associated volatility scores are displayed in Fig. 5. Red shaded street segments have low volatility scores, while yellow shaded street segments have high volatility scores. Inspection of Fig. 5 reveals that street segments with volatile longitudinal changes seem somewhat more clustered in Antwerp's city center.

Conclusion and Discussion

In this study, we set out to examine how a reduction in burglary at the city-level was related to the changing burglary concentration at micro-places in Antwerp, Belgium between 2005 and 2016. To what extent is an overall reduction in residential burglary a widespread spatial process that manifests itself across many micro places, or instead a spatially concentrated process limited to sharp reductions in burglary in just a few micro burglary concentrations? Our results suggest, in fact, that both processes occurred simultaneously. Results of simple descriptive statistics and Gini coefficients show that despite a citywide reduction in burglary volume by an estimated − 30%, the degree of concentration remained stable during the 12-year study period: a remarkably similar number of street segments experience a similar percentage of residential burglary events across the entire study period.

Andresen's (2009) spatial point pattern test (SPPT) was used to determine whether spatial shifts in residential burglary point patterns were statistically significant and to evaluate the ubiquity of a city-level burglary drop across street segments. We implemented an extension of the SPPT in which only spatial units of analysis are investigated where any burglary occurred during the study period. This index avoids overestimating the degree of spatial stability of spatial crime patterns caused by including consistent zero event areas. Disregarding street segments where no burglary ever occurred, about 67% of street segments experience similar relative residential burglary levels over time. In other words, these outcomes indicate that the global spatial pattern of residential burglary was quite consistent over time.

Results at the micro-spatial level showcase in the first place that the city-level decline scaled rather proportionally across street segments. Half of all street segments with burglary experienced substantially larger declines in burglary percentages but these were infrequently observed across the entire study period. Burglary spatial point patterns were stable in most street segments and decreased just once or twice at significantly higher rates. Interestingly, relative burglary volume was found to increase in just a handful of street segments but the majority of those street segments were at some point in time also affected by the burglary drop in Antwerp. Finally, we do not see strong evidence that street segments that experienced (stronger) burglary declines also cluster spatially.

Undeniably, burglary is strongly concentrated in Antwerp street segments. Under 10% of Antwerp street segments experienced burglary at least once during the study period and fewer than 3% of all street segments produced the majority of burglaries. Because of this high degree of spatial concentration, the burglary reduction across Antwerp was ultimately a spatially concentrated process as well occurring in just a few street segments. Although most street segments with residential burglary were affected by the declining trend, the burglary reduction could not have played out in more than 10% of all Antwerp street segments due to the high degree of spatial concentration and had its most pronounced effect in just a small number of streets responsible for the majority of burglaries. Nevertheless, we have established that street segments that experienced at least one burglary at any time during the study period were affected proportionally by the citywide burglary decline. As such, the burglary reduction was widespread across Antwerp street segments with burglary despite it being spatially concentrated as well.

This paper makes a number of contributions to the existing literature. Theoretically, this paper contributes to our understanding of the stability of burglary patterns over time, and especially in the context of an overall burglary decline. Our finding of moderate to high spatial stability in burglary spatial patterns year after year suggests there is little evidence of temporal fluctuations in burglary spatial patterns (cf. Andresen and Malleson 2013; but see Linning 2015). At first glance, our results do not confirm the importance of micro-level or place-specific processes in our understanding of the observed macro burglary trends. In contrast, one apparent conclusion may be that the underlying factors driving the observed burglary decline in Antwerp are rooted in systemic causes that are shared across all street segments with burglary and impact these streets similarly, such as socio-demographic and macro-economic changes or overall improved household security (e.g., Blumstein and Rosenfeld 2008; Farrell 2013; Levitt 2004), rather than place-specific processes that affect only some street segments with burglary but not others. Our data, however, does not allow us to precisely define the changes in root causes across Antwerp street segments that may have played a role in the widespread burglary decline but, given the strong evidence in prior research (see Farrell et al. 2014), improved household security across the board may well have played a role in the Antwerp burglary reduction.

However, as our study is aimed at more a precise description rather than advancing causal inference, we are very hesitant in making definitive claims about systemic versus place-specific causes of (un)changing burglary patterns and we would urge readers to equally refrain from extrapolating descriptive results to causal explanations. Our finding of a uniform burglary decline across Antwerp street segments where at least one burglary occurred once during the study period may seem to imply that local law enforcement agencies had a limited deterrent effect on burglary and were only a minor driver of the change in burglary volume across Antwerp. However, an alternative and equally valid interpretation of the empirical results may well be that law enforcement agencies have consistently targeted specific places with burglary which would have experienced burglary increases in absence of such efforts but developed similarly to the rest of the city because of continued law enforcement efforts. In addition to targeted law enforcement deployment to certain areas (e.g., Andresen and Malleson 2014), other smaller-scale processes may include changes in the environmental backcloth in which burglaries are situated such as the (temporary) closure of streets or nearby crime generating facilities (e.g., Beavon et al. 1994). To identify the causal effects of such processes, for example fine-grained spatial data on police patrol intensity and form need be collected (e.g., Davies and Bowers 2014). Interestingly, our finding of high volatility at certain street segments, especially in the city center, may suggest that burglary there could have been affected by smaller scale, place-specific processes. In summary, explanations of the observed stability of burglary patterns should be made with a healthy dose of caution because the counterfactual outcome is unknown. Nevertheless, we encourage future researchers to pursue such *explanations* of micro-spatial burglary changes, for which the current study provides a toolbox to *identify* such changes.

A methodological contribution was made by implementing a multivariate extension of the spatial point pattern test and expanding it to the micro-level. In previous studies

(Andresen and Malleson 2011), a 'robust' version of the SPPT has been proposed in which only areas are compared that experience any crime. However, in multiyear comparisons a consistent set of units of analysis across all comparisons must be ensured. The multivariate robust S-Index we implement allows to meaningfully quantify similarity in a longitudinal context and can be used to identify the global degree of similarity with regard to a reference base dataset for an entire study period or for one or more pairwise year-to-year comparisons while still accounting for relevant information in the preceding and subsequent years in the data under study (see also Andresen et al. 2017). In addition, we demonstrated how the multivariate local similarity indices can be visualized and analyzed to understand how global stability patterns manifest themselves locally within individual spatial units of analysis. We recommend this particular multivariate extension of the spatial point pattern test if the interest lies with quantifying and visualizing longitudinal similarity patterns.

From a practical perspective, our study could improve the efficiency and effectiveness of law enforcement agencies by prioritizing their deployment to those places that saw relative burglary volume increasing despite the citywide burglary reduction and to the most chronic burglary concentrations. First, analyzing local (multivariate) outcomes enables law enforcement to identify those places where the proportion of burglary increased (or decreased) significantly, focusing their deployment to where it is needed most. In this study, we identified 69 street segments out of more than 25,000 street segments (just 0.25% of all Antwerp street segments) where, on average, relative burglary volume increased over the 12-year period. Arguably, such a small number of street segments could be targeted effectively by increased police patrol or other burglary prevention initiatives. Still, patrolling 1% of street segments with burglary requires substantial resources and police cannot discontinue patrolling other street segments with or without burglary. Instead, a limited but possibly more realistic effort might be to increase police patrol dosage in just those 11 street segments where the burglary percentage increased consistently at a statistically significant different rate. At the suggestion of a reviewer, however, it is important to qualify these statements by differentiating between operational (real-time) and strategic (long-term) recommendations. While real-time analysis is important to timely address emerging crime hot spots and changes in crime patterns, other more appropriate techniques are available to assist police crime analysts in achieving this objective, especially considering the SPPT approach used here to identify long term (in)stability of spatial patterns. Instead, the value of our analysis lies primarily in analyzing historical trends to inform longer term police strategies. The (multivariate) local SPPT outcomes help to identify the places with *long-term persistent* burglary concentrations, i.e., street segments with low volatility over time.

A number of qualifications must be made with regard to our study. While each 2-year comparison uses a Monte Carlo procedure to generate 95% non-parametric confidence intervals, over a 12-year study period 66 bivariate tests are needed to statistically test all changes (e.g., see the top right part of Table 2). These multiple tests may result in too often unduly rejecting the null hypothesis (of no change) and lead to the (incorrect) conclusion that meaningful changes occurred in spatial point patterns. A correction for the number of bivariate comparisons, however, is outside the scope of this contribution. While it is important to address this methodological limitation in future research, the substantive implication of this limitation is straightforward and does not invalidate the conclusion of our study: a Bonferroni-type correction for multiple testing would result in fewer rejections of the null hypothesis—i.e., higher S-Indices—and thus strengthen our conclusion that the burglary drop occurred quite uniformly across most street segments.

For our analysis, we relied on the SPPT. This test works by pairwise comparing relative event counts in two datasets and applies a Monte Carlo procedure to identify significant proportional change. While comparing relative event volume is analytically appropriate given our research question, it could lead to two misleading interpretations. First, comparing relative event counts may confuse one into thinking that absolute event counts did not change if the SPPT supports the conclusion of spatial similarity. Under a global burglary reduction, spatial similarity may be attained as long as the spatial distribution of burglaries did not change, even though absolute burglary counts may have dropped in the areas under consideration. Of course, this is not a limitation of our method and study per se since the SPPT is designed to work with relative event counts to facilitate comparisons between different-sized datasets (see Andresen 2016). However, it may be meaningful to reiterate this and ensure that stability of spatial patterns is not erroneously associated with similarity of local burglary counts. Second and relatedly, one may erroneously equate the sign and significance of change over time with the magnitude of change. This interpretation is incorrect as the Local Similarity Index provides information on the change of burglary proportion rather than an estimate of change in absolute event counts. Some streets will have seen greater declines in event counts than others, thus having a larger contribution to the global burglary reduction. Again, the SPPT is not designed to quantify the extent of local changes in burglary patterns and it was not our goal to determine how *much* burglary changed within street segments. There exist other methods, for example group-based trajectory models, to address this (e.g., Curman et al. 2015; Wheeler et al. 2016). Instead, we were interested in describing the changing global spatial pattern of burglary over time and which street segments contributed to these global spatial pattern differences, a goal for which the SPPT is well-suited.

Furthermore, the police recorded burglary data may be sensitive to citizen reporting and police recording bias. As a result, the spatial burglary patterns under study may misrepresent the true spatial patterns of burglary in Antwerp. However, we have no reasons to believe that this poses a threat to the validity of our analysis. Most common fire insurance policies in Belgium cover material damages to the house as a result of an (attempted) burglary. Prior to making an insurance claim, home owners are required to file a burglary report at their local police department. As such, we are confident that the police recorded burglary data offers a comprehensive view of burglary events in Antwerp.

Finally, the generalizability of our results may be limited. The conclusions we draw here are based on a study of spatial burglary patterns in a single European city. However, similarly to our results, previous authors found in different cities and for other crime types that citywide crime drops were relatively widespread with many small places experiencing similar reductions in crime (see, e.g., Andresen and Malleson 2011; Curman et al. 2015; Hodgkinson et al. 2016; Wheeler et al. 2016). We now extend those studies by considering the spatial crime patterns associated with a drop of a particular crime type, burglary, in an international context and by studying longitudinal changes in spatial stability of burglary patterns in individual spatial units of analysis.

Notwithstanding these limitations, we show that although burglary is strongly concentrated in a few street segments, the observed citywide burglary reduction in Antwerp, Belgium manifested itself quite uniformly across street segments with burglary. Although more than half of all street segments with burglary experienced one or two declines in relative burglary volume at some point in the study period, burglary declined most of the time gradually and uniformly.

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