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Testing „The Law of Crime Concentration at Place” and its effects by crime type, study area size, and unit of analysis - A case study in three Hungarian Cities

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LIST OF ABBREVIATIONS

FBI	Federal Bureau of Investigation
GIS	Geographic Information System
LOCC	The Law of Crime Concentration at Place
MAUP	Modifiable Areal Unit Problem
RAT	Routine Activity Theory
SPPT	Spatial Point Pattern Test
UCR	Uniform Crime Reporting

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ABSTRACT

This thesis examines whether David Weisburd's "Law of Crime Concentration at Place" can be applied in a Central European context by testing crime concentration at micro-places in three Hungarian cities: Budapest, Debrecen, and Miskolc. The study uses police-registered, geocoded crime incidents for the period 2013–2016 and applies a uniform 200 × 200 meters grid as the micro-geographic unit of analysis. Four crime categories are analyzed: simple assault, aggravated assault, residential burglary, and car break-in.

Crime concentration is assessed using cumulative percentage hypothesis measures, Lorenz curves, and Gini coefficients, including the generalized Gini coefficient to address the "more places than crimes" situation. Spatial stability over time is examined using the Spatial Point Pattern Test (SPPT), comparing the first and last year of the study period (2013 vs 2016).

The findings show that crime is highly concentrated at micro-places in all three cities. Across the different measures, a small share of grid cells accounts for a large share of crime incidents. At the same time, the comparison between cities becomes more nuanced once the generalized Gini coefficient is considered. Budapest has a broader spatial footprint of crime, with more grid cells recording incidents, while Debrecen and Miskolc have fewer active grid cells. However, Budapest cannot simply be described as less concentrated than the two smaller cities, because concentration differs by crime type and by the measure used. The cumulative percentage results and Lorenz curves suggest stronger concentration for the assault categories, while the generalized Gini coefficient shows a more differentiated picture across cities and crime types.

The SPPT results indicate substantial spatial stability between 2013 and 2016 in all three cities. At the same time, robust stability measures show that this stability is weaker when the analysis is limited to crime-relevant grid cells, particularly in Budapest. Overall, the results support the applicability of the law of crime concentration at place in a Hungarian setting and show that grid-based micro-units provide a suitable approach for studying crime concentration in European urban contexts where street-segment units may be less appropriate.

Kurzfassung

Diese Masterarbeit untersucht, ob David Weisburds „Law of Crime Concentration at Place“ in einem mitteleuropäischen Kontext anwendbar ist, indem die Kriminalitätskonzentration auf Mikroebene in den drei ungarischen Städten Budapest, Debrecen und Miskolc getestet wird. Die Studie nutzt polizeilich registrierte, geokodierte Straftaten für den Zeitraum 2013–2016 und verwendet ein einheitliches 200 × 200 Meter Raster als mikrogeografische Analyseeinheit. Analysiert werden vier Deliktskategorien: einfache Körperverletzung, schwere Körperverletzung, Wohnungseinbruchdiebstahl und Kfz-Aufbruch.

Die Kriminalitätskonzentration wird anhand von Hypothesen des kumulativen Prozentsatzes, Lorenzkurven und Gini-Koeffizienten gemessen, einschließlich des generalisierten Gini-Koeffizienten zur Berücksichtigung der Situation „mehr Orte als Straftaten“. Die räumliche Stabilität über die Zeit wird mit dem Spatial Point Pattern Test (SPPT) untersucht, indem das Jahr 2013 mit dem Jahr 2016 verglichen wird.

Die Ergebnisse zeigen, dass Kriminalität in allen drei Städten stark auf Mikroorte konzentriert ist. Über die verschiedenen Maße hinweg vereint ein kleiner Anteil der Rasterzellen einen großen Anteil der Straftaten auf sich. Gleichzeitig wird der Vergleich zwischen den Städten differenzierter, sobald der generalisierte Gini-Koeffizient berücksichtigt wird. Budapest weist ein breiteres räumliches Kriminalitätsmuster mit mehr aktiven Rasterzellen auf, während Debrecen und Miskolc weniger aktive Rasterzellen aufweisen. Budapest kann dennoch nicht einfach als weniger konzentriert gelten, da das Ausmaß der Konzentration je nach Deliktskategorie und Maß variiert. Die kumulativen Prozentwerte und Lorenzkurven deuten auf eine stärkere Konzentration bei den Körperverletzungsdelikten hin, während der generalisierte Gini-Koeffizient ein differenzierteres Bild zwischen Städten und Deliktskategorien zeigt.

Die SPPT-Ergebnisse deuten in allen drei Städten auf eine deutliche räumliche Stabilität zwischen 2013 und 2016 hin. Gleichzeitig zeigen robuste Stabilitätsmaße, dass diese Stabilität geringer ausfällt, wenn die Analyse auf kriminalitätsrelevante Rasterzellen beschränkt wird, insbesondere in Budapest. Insgesamt stützen die Ergebnisse die Anwendbarkeit von Weisburds „Law of Crime Concentration at Place“ im ungarischen Kontext und zeigen, dass rasterbasierte Mikroeinheiten für europäische Stadträume einen geeigneten Ansatz zur Untersuchung von Kriminalitätskonzentration darstellen.

1. Introduction

In the late 1980s the study of crime at microgeographic units of analysis began to interest criminologists. In 1989 the term “criminology of place” was introduced in Criminology, which encouraged researchers to study very small units within cities, often addresses or street segments (Weisburd, 2015). Early findings showed strong concentration: about 3% of micro-places accounted for roughly 50% of police calls (Sherman et al., 1989). Later research confirmed that these concentrations can remain stable over longer periods (Weisburd et al., 2004).

Subsequently, in 2014 “the law of crime concentration at place” was proposed by David Weisburd, which states that for a defined measure of crime at a specific micro-geographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime (Weisburd, 2015). In general, Weisburd (2015) argued that the percentage of micro-geographic units accounting for 25% of crime falls within a narrow bandwidth of 0.4% to 1.6% of micro-places, whereas the percentage accounting for 50% of crime falls between 2.1% and 6.0% of micro-places. Most following studies that have tested “the law of crime concentration at place” have found similar bandwidths within their test areas (Curman et al., 2015; Steenbeek & Weisburd, 2016; Andresen et al., 2017; Hipp & Kim, 2017; Hardyns et al., 2019).

To test the law of crime concentration at place, Weisburd used the street segment as the geographic unit of analysis in order to examine whether stable spatio-temporal crime patterns exist. This geographical unit was chosen as the most appropriate unit, as US cities are commonly based on a gridiron pattern, which means that the street segments do not vary greatly in size. The geographical structure in western cities differs greatly from US cities. The gridiron pattern is mostly absent in Western cities, which is why the street segment isn’t suitable as a geographical unit to test and compare “the law of crime concentration at place” in a western setting. Therefore, to start testing the law in European cities, a grid cell was chosen as a more appropriate unit of analysis in most studies. (Khalfa et al., 2023)

Weisburd (2015) argues that proposing this law was necessary to move criminological research more strongly toward micro-level place analysis, after providing evidence, that between 1990 and 2014 only 4.3% of publications in “Criminology”, the highest impact journal in the field were examining micro-units. In other words, the “criminology of place" has received little attention in criminology until Weisburd's proposal of his law in 2014. Until then, person-focused studies, with values such as age and gender have dominated the attention of criminologists. Therefore, the examination of micro-units has tremendous potential to advance criminology as a discipline and to make criminology relevant as a policy science in the future (Weisburd, 2015). Testing "the law of crime concentration at place" will not only lead us to understanding crime and its spatiotemporal component better, but it will also lead us to positively influence such micro-places, by sharing all analysis with the relevant authorities such as the police, so these can react appropriately to reduce crime rates in the analyzed areas.

Although interest in LoCC has grown in recent years, most studies have been conducted in large US cities, with fewer studies in countries such as Israel, the UK, the Netherlands, Belgium, Italy, and Sweden (Lee, 2017).

In this thesis, "the law of crime concentration at place" will be tested in a Western-European setting. Therefore, three Hungarian cities that differ greatly in terms of size, population, location and character were selected to identify possible similarities and differences in the results obtained to better understand crime at a geographical level, especially at a micro-geographic unit of analysis. Thus, the selected cities for this work are the following: Budapest, Debrecen and Miskolc. The law is tested using the cumulative percentage hypotheses method as presented by Weisburd, and additional measures are used to strengthen the analysis, including Lorenz curves, the (generalized) Gini coefficient, and the Spatial Point Pattern Test (SPPT).

1.1. Relevance of this Work

Living in a time with many global risks such as wars, climate change, and steadily rising energy prices, which could have huge socioeconomic impact on society, we should also expect that the crime rate could possibly increase with those changes, especially in urban areas. Urban planners and police forces must use their expertise to predict and fight crimes and adapt to the numerous amounts of ever-changing complex surveillance technologies. Further techniques of crime analysis need to be developed and used to move from reactive to proactive policing (Minardi et al., 2023). This requires investing resources in analyzing crime patterns, especially at the geographic level, so that prevention and targeted responses can be planned more effectively.

This thesis contributes to that goal by studying crime concentration at micro-places and testing "the law of crime concentration at place" in a European setting. The analysis focuses on three Hungarian cities that differ strongly in size, population, location, and urban character. This design allows both an overall test of LoCC and a direct comparison of results across different city contexts.

The first major study where "the law of crime concentration at place" was tested across multiple cities using comparable methods and metrics, was performed by David Weisburd in the United States in the year 2015. In this multicity case study, eight different US cities that greatly vary in character were examined (Weisburd, 2015). Since then, many studies have tested the law (Gill et al., 2016; Braga et al., 2017; Favarin, 2018; Hardyns et al., 2019; Amemiya & Ohyama, 2019; Cummings et al., 2022; Khalfa et al., 2023). However, most tests have been conducted in the US context and often use street segments as the preferred micro-unit. In contrast, fewer studies have tested the law in a Western-European context (Favarin, 2018; Hardyns et al., 2019; Khalfa et al., 2023). This means that evidence on the generalizability of LoCC outside the United States, especially in Europe, is still limited (Favarin, 2018).

Furthermore, testing "the law of crime concentration at place" also has practical relevance for crime prevention. If crime is strongly concentrated in a small number of places, prevention resources can be targeted more efficiently. This idea supports place-based strategies such as hotspot policing: if crime is concentrated at specific locations, then policing and prevention efforts can be concentrated as well (Weisburd, 2015). Visualizing crime at the micro-place level by mapping them can also help police and local authorities decide where to focus prevention efforts (Khalfa et al., 2023).

Another reason to test LoCC in Europe concerns the choice of the spatial unit. In the United States, street segments are often used as the preferred micro-unit of analysis. However, these are less suitable in a Western-European setting because many European cities lack a consistent gridiron street pattern, leading to greater variation in street-segment length. For this reason, Khalfa et al. (2023) propose using grid cells as a more appropriate unit for Western-European settings. This thesis follows that approach by using 200×200 meters grid cells for each city.

At the same time, this thesis adds to the current state of the art by going beyond the single-city design of the Brussels study by Khalfa et al. (2023). While Khalfa et al. test LoCC in one Western-European city, this thesis applies a comparable grid-based approach to three Hungarian cities that differ strongly in size, population, location, and urban character, while remaining within the same national context and data structure. This makes it possible to compare concentration and spatial stability across cities under the same methodological conditions. In this way, the thesis does not only test whether LoCC can be observed in another European setting, but also whether similar patterns appear across different city types within one country. Finally, this thesis combines the cumulative percentage approach with Lorenz curves, the (generalized) Gini coefficient, and the Spatial Point Pattern Test to provide a broader comparison of crime concentration and spatial stability over time.

1.2. Objectives and Research Questions

The main objective of this thesis is to test "the law of crime concentration at place" in a European setting. Therefore, the analysis focuses on three Hungarian cities that differ in size, population, location, and urban character: Budapest, Debrecen, and Miskolc. Studying one large city and two smaller cities also allows a comparison across city size within the same national context. Weisburd's multi-city work suggests that crime concentration may differ between smaller cities and large metropolitan areas (Weisburd, 2015). Consequently, this thesis examines whether LoCC patterns in Debrecen and Miskolc are comparable to those in Budapest.

To test the law in a European context, the thesis uses grid cells as the micro-unit of analysis instead of street segments. In many European cities, street networks are less grid-like than in many US cities, and street segment lengths can vary substantially. This reduces comparability across cities. For this reason, grid cells have been recommended and used in European LoCC research (Khalfa et al., 2023). Following this approach, crime incidents are aggregated to 200 × 200 meters grid cells in each city.

Crime concentration is first assessed using the cumulative percentage hypotheses approach, which describes how many micro-places account for 25%, 50%, 75%, and 100% of crime. Because fixed cut-offs can be limited and do not fully describe the complete distribution (Hardyns et al., 2019), this thesis also applies Lorenz curves and the (generalized) Gini coefficient (Bernasco & Steenbeek, 2017). The Lorenz curve visualizes how (un)evenly crime is distributed across places by plotting cumulative percentages of crime against cumulative percentages of grid cells. The Gini coefficient expresses this inequality as one value by quantifying the distance between the Lorenz curve and the line of perfect equality (Khalfa et al., 2023).

In addition to concentration, this thesis examines whether crime patterns are spatially stable over time between 2013 and 2016. Spatial stability is tested using the Spatial Point Pattern Test (SPPT) introduced by Andresen (2009, 2016). The Spatial Point Pattern Test compares two time periods using identical spatial units and uses a Monte Carlo resampling approach to assess whether individual grid cells show statistically significant change. This produces both global measures of similarity and local results that can be mapped (Andresen, 2016; Khalfa et al., 2023).

Overall, this thesis tests "the law of crime concentration at place" in Hungary and compares patterns across cities, crime types, and time to answer the following research questions:

<u>Main Objective:</u>

Testing „the law of crime concentration at place" at a grid cell level (200 × 200 meters grid cells) in the three Hungarian cities Budapest, Debrecen and Miskolc across multiple crime types

<u>Sub Objective (1):</u>

Measure the degree of crime concentration at micro-places in each of the three cities.

<u>Research Question (1):</u>

To what extent is crime concentrated in a small number of grid cells in each city (Budapest, Debrecen, Miskolc) for the period 2013–2016?

<u>Sub Objective (2):</u>

Compare concentration patterns across city size within the same national context.

Research Question (2):

How do concentration patterns differ between Budapest and the two smaller cities (Debrecen, Miskolc) when using the same spatial unit and the same measurement approach?

Sub Objective (3):

Compare concentration across four different crime categories.

Research Question (3):

Which of the four crime categories shows the highest concentration and which shows the lowest concentration, and are these patterns consistent across the three cities?

Sub Objective (4):

Examine spatial stability over time.

Research Question (4):

To what extent do the spatial patterns of crime remain stable over time when comparing 2013 with 2016, and which areas show statistically significant local change according to the Spatial Point Pattern Test?

Sub Objective (5):

Place the Hungarian results into the broader LoCC literature, with emphasis on Europe.

Research Question (5):

How do the levels of concentration and stability observed in the Hungarian case studies compare to existing LoCC findings, especially grid-based evidence from European studies such as Brussels?

1.3. Research Boundaries

This thesis examines how well Weisburd's "law of crime concentration at place" can be applied in a western, more specifically central-European setting, by testing crime concentration at a micro-geographic unit of analysis in the three Hungarian cities Budapest, Debrecen and Miskolc, using 200 × 200 meters grid cells as the unit of analysis. In this chapter, the research boundaries of this thesis are listed.

First, this thesis limits its empirical analysis to only three different Hungarian cities, which greatly vary in size and character. These were specifically selected to enable a comparison between a large metropolis and two smaller cities, applying the same methodological conditions. Therefore, the findings are not intended to represent all of Europe or Hungary but instead aim to provide a case-study-based test application of the "law of crime concentration at place" in the three selected Hungarian cities.

Furthermore, this thesis compares the results with previous studies which tested this law mostly in the United States and mostly used the street segment as a micro-geographic unit of analysis. This is supported by the gridiron-like street structure which is common in many US cities. In contrast, this thesis uses uniform 200 × 200 meters grid cells as micro-places, as these are a better fit for European urban morphology. Accordingly, all spatial analyses in this thesis are based on a 200 × 200 meters grid-cell fishnet, chosen to allow a consistent comparison across the three cities. Therefore, comparability with studies on a street-segment level (Weisburd, 2015) is imperfect.

Following the approach of Khalfa et al. (2023) in their Brussels LoCC study, this thesis applies the same fixed-size grid cells (200 × 200 meters), to allow cross-study comparability, especially in Europe, and to avoid relying on street segments, which are often less suitable for European urban morphology. However, using grid cells introduces methodological limitations, notably the Modifiable Areal Unit Problem (MAUP). In this context, MAUP means that spatial results can change depending on how the city is divided into spatial units. This includes the size of the grid cells (scale effect), but also the placement of the grid boundaries (zoning effect), because shifting the grid slightly can move incidents from one cell into another. Therefore, all results in this thesis are tied to the selected 200 × 200 meters grid-cell structure, and different grid sizes or grid placements may lead to different results and influence the measured crime concentration (Fotheringham & Wong, 1991; Wong, 2004; Dark & Bram, 2007; Khalfa et al., 2023).

Another limitation for this thesis is the temporal scope, as all results are restricted to the period of 2013 to 2016. As a result, this thesis cannot address long-term trends or structural breaks outside of this period. Furthermore, comparability with other studies (Weisburd, 2015; Khalfa et al., 2023) is once again imperfect, since the results originate from different time periods.

Furthermore, the provided data itself introduces boundaries, as the data comes from police-registered crime incidents, which were geocoded to point locations and later aggregated into grid cells. Therefore, the analysis can only be based on recorded crime, not the full spectrum of crime. In other words, the data can have boundaries because of factors like underreporting, differences in reporting, recording and classification practices and even the quality of the geocoding.

Another research boundary is the selection of crime types included in the analysis. This thesis does not examine the full range of crime categories but instead focuses on the following four specifically selected categories: simple assault, aggravated assault, car break-in and residential burglary. Furthermore, the categories simple assault and aggravated assault were combined to form one category named battery, to enable comparison with the Brussels study (Khalfa et al., 2023), which used battery as a single category covering bodily injury incidents. However, this combined battery category is used only for the specific cross-study comparison with Brussels. In the main analysis of this thesis, simple assault and aggravated assault are analyzed and reported separately. Consequently, findings on violent crime in this thesis should be interpreted according to the offence classification used in each section and should not be generalized to other forms of violence not included in this study.

Finally, this thesis is limited by its methodological focus. The goal of this work is to test whether the “law of crime concentration at place” can be observed in the selected Hungarian cities and how stable this concentration is over time. This thesis does not examine the causes of crime hotspots. It does not model how factors such as land use, socioeconomic conditions, guardianship, or routine activity patterns relate to hotspot locations. While these factors may help explain why hotspots form, the focus of this thesis is on measuring the existence and degree of concentration and its stability over time, rather than explaining the cause.

2. Theoretical Framework

The following chapters provide theoretical and conceptual background for the analysis in this thesis. First, chapter 2.1. defines the core concepts used throughout this work, such as police-recorded crime, micro-places, hotspots and crime concentration. Chapter 2.2. then briefly explains why crime has a geographic dimension and why incidents tend to cluster in specific places within cities. Finally, chapter 2.3. introduces crime mapping and the use of GIS in criminology, describing how crime incidents are geocoded and analyzed spatially. Chapter 2.4. then builds on these foundations by reviewing the “the law of crime concentration at place” and its relevance for this thesis.

2.1. Core concepts and definitions

In this thesis, a few key concepts are used consistently throughout the analysis.

First, “crime” refers to police-recorded crime incidents, which means offences that were reported to the police and officially registered by them. Therefore, the results obtained only describe recorded crime patterns and are influenced by reporting behavior and recording practices, and do not represent the full spectrum of crime.

Second, this thesis focuses only on selected crime types. The analysis includes simple assault, aggravated assault, residential burglary and car break-in. For comparability, simple assault and aggravated assault are merged into the combined category battery, following the Brussels study categories (Khalfa et al., 2023).

Third, “place” is used in the sense of a micro-place, meaning a small spatial unit in which incidents can be counted. While many LoCC studies use street segments, this thesis uses 200 × 200 meters unified grid cells as unit of analysis, which was used first by Khalfa et al. (2023) to test “the law of crime concentration at place” in Brussels.

Finally, “hotspots” describe micro-places with a dense concentration of crime incidents. GIS is used as a technical tool to create unified grid cells and later assign crime incidents to them, to calculate spatial patterns in the three chosen cities Budapest, Debrecen and Miskolc over the period of 2013-2016.

2.2. Geography of Crime

Crime is not distributed randomly across a city. Instead, crime tends to cluster in certain areas, as opportunities for crime are not evenly distributed and people's daily movements in different locations create entirely different risk situations. A basic explanation for this is provided by routine activity theory (RAT), which assumes that crimes are committed when a motivated offender and a suitable target meet at a specific time and place without capable guardianship (Cohen & Felson, 1979).

Furthermore, environmental criminology highlights that urban space is structured by “nodes”, “paths” and “edges” such as transport hubs, main roads or shopping areas, and that these structures heavily influence where offences are more likely to occur in space (Brantingham & Brantingham, 1993). As a result, analyzing crime at a micro-unit level of analysis is useful, because small places can differ strongly in risk even within the same neighborhood (Eck & Weisburd, 1995).

2.3. Crime Mapping and Crime-GIS

Crime mapping can be understood as the use of maps to support crime analysis, by showing where incidents occur and whether they form spatial patterns, such as clusters or hotspots. In research and policing, crime mapping is not only used for visualization purposes but is also used as a way to support practical decision-making, for example by identifying areas that may require further analysis or even targeted responses (Boba, 2001).

A key tool for modern crime mapping is Geographic Information System. GIS allows crime incidents to be linked to geographic space which allows for detailed analysis. In practice, GIS-based crime mapping usually includes two main steps. First, incidents are geocoded, meaning that address information is converted into point data with geographic coordinates (X and Y), so that each incident can be placed on a map. Second, the geocoded incident points are aggregated into spatial units and visualized or analyzed, for example to explore concentration patterns or to identify areas with high crime density (Boba, 2001; Eck et al., 2005).

In this thesis, GIS is therefore used mainly as a technical and methodological tool to prepare and analyze the received police-recorded incident data.

2.4. Literature on LoCC

The following chapters provide a literature review of “the law of crime concentration at place”. The review covers the original proposal, key developments, and the current state of the art, with a particular focus on LoCC studies in Europe, which are most relevant for this thesis. Methods used in this thesis, such as Lorenz curves, the Gini coefficient, and the Spatial Point Pattern Test are not discussed in detail in the literature review but are explained later in the methodology chapter.

2.4.1. The Initial Phase: Proposition of the Law

“The law of crime concentration at place” was proposed in 2014 by David Weisburd in Jerusalem, and one of the first published tests of the law was his case study of Tel Aviv–Jaffa in Israel (Weisburd, 2014). The main goal of the law was to encourage criminologists to study crime and other forms of anti-social behavior at very small geographic units. While the relationship between social problems and place was not a new topic, Weisburd argued that there were still relatively few approaches that directly tested theories about micro-places and anti-social behavior in practice (Weisburd, 2014).

By the time LoCC was proposed, many studies had already shown that crime is highly concentrated in cities. For example, Sherman et al. (1989) reported that 50% of police calls in Minneapolis came from only 3.5% of addresses. Later, Weisburd et al. (2004) showed that over a 14-year period (1989–2002), 50% of crimes in Seattle were concentrated in about 4% to 5% of street segments. Research also suggested that concentration can differ across offence types. For instance, Weisburd et al. (2009) examined incidents involving juvenile arrests in Seattle and found that a very small number of street segments accounted for a large share of arrests over the same 14-year period. Weisburd et al. (2012) extended the Seattle analysis by two additional years and reported that about 1% of street segments accounted for 23% of all crime incidents.

Because many studies across decades have found similar patterns of strong concentration at micro-places, researchers began to ask whether this regularity could be described as a general law. This question was raised explicitly by Weisburd, Groff, and Yang in “The Criminology of Place” (Weisburd et al., 2012). In this book, they argued that long-term studies consistently show a relatively stable pattern across cities: roughly 5% of micro-places account for about 50% of crime each year.

Although Weisburd proposed the law of crime concentration at place in 2014, the broader idea that crime follows regular patterns is not new. More than a century earlier, Émile Durkheim argued that crime is not necessarily a sign of pathology or illness in society but can be seen as a normal feature of social life (Durkheim, 1895). Durkheim suggested that cities may have a “normal level” of crime that relates to overall crime rates. Weisburd et al. (2012) engaged with this argument but suggested a different interpretation: the “normal level” is not mainly about the overall crime rate, but about the regularity of crime concentration at place, meaning that a small share of places consistently accounts for a large share of crime (Weisburd et al., 2012).

Before the proposal of his law, Weisburd’s criminology of place research was largely based on data from US cities, especially Seattle. A key motivation for his 2014 work was therefore to examine whether similar concentration patterns also exist outside the United States, where fewer comparable studies were available. For this reason, Weisburd included the Tel Aviv–Jaffa case study to test whether LoCC also applies in a different urban setting (Weisburd, 2014). Using street segments as the geographic unit, he examined whether crime concentrates strongly at very small places and whether this concentration falls within a relatively narrow bandwidth. In short, LoCC states that for a defined measure of crime at a defined micro-geographic unit, the share of places that accounts for a given cumulative share of crime will fall within a narrow range of percentages (Weisburd, 2015).

2.4.2. The case study of Tel Aviv-Jaffa

The case study of Tel Aviv–Jaffa was one of the first large-scale studies that tested crime concentration at micro-places outside of the United States. The purpose of the study was to provide evidence consistent with the law of crime concentration at place and to examine whether similar concentration patterns can be found in a non-US urban setting (Weisburd, 2014).

Tel Aviv–Jaffa is the economic and cultural center of Israel. In 2010, it had a population of about 404,000 and was the second largest city in Israel after Jerusalem. The wider metropolitan area had around 3.3 million inhabitants, which represented roughly 43.4% of Israel’s total population at the time. Tel Aviv–Jaffa also recorded high crime rates in 2010, including a property crime rate of 54 incidents per 1,000 persons and a violent crime rate of 10.8 incidents per 1,000 persons. In total, 43,258 crimes were recorded in the year of study. These characteristics made Tel Aviv–Jaffa a suitable case for testing crime concentration at place in a large urban area (Weisburd, 2014).

As in much of the U.S. literature, Weisburd used street segments as the unit of analysis. In this study, a street segment is defined as the two block faces on both sides of a street between two intersections (Weisburd, 2014). This unit was considered appropriate because Tel Aviv–Jaffa is a relatively modern city designed with a street-grid model, which results in street segments that are more similar in length than in many older cities (Weisburd, 2014). It is repeatedly argued in literature that street segments are a particularly useful unit for analyzing places, as they present regularly recurring rhythms of activity (Taylor, 1997; Taylor, 1998).

Using this definition, the street network of Tel Aviv–Jaffa was divided into 17,160 unique street segments, with an average length of 62 meters. Around 75% of segments were between 50 and 67 meters long, and fewer than 3% exceeded 101 meters (Weisburd, 2014). Because the analysis focused on street segments, some locations were excluded from the study, including crimes that occurred on the beach, in the central station area, and on non-residential or business roads such as highways or regional roads. According to Weisburd (2014), the excluded incidents represent about 9% of all crimes, meaning that 91% of crimes remained in the analysis. The final dataset contained 39,392 incidents.

The results follow the general pattern reported in many studies of criminology of place, where a small share of places accounts for a large share of crime. Weisburd (2014) reports that in Tel Aviv–Jaffa in 2010, 4.5% of street segments accounted for 50% of all crime (Table 1). This is highly consistent with findings from other cities, including long-term analyses in Seattle where roughly 4.7% to 6% of street segments accounted for 50% of crime over a 16-year period (Weisburd et al., 2012). The Tel Aviv–Jaffa results therefore provide support for the idea that crime concentration at micro-places is a common feature of urban crime patterns (Weisburd, 2014).

Table 1: Percentage of street segments accounting for cumulative shares of crime in Tel Aviv–Jaffa, adopted from Weisburd (2014)

Cumulative share of crime	Percentage of street segments
25%	0.9%
50%	4.5%
75%	12.1%
100%	36.8%

Furthermore, Table 1 also shows that 0.9% of street segments accounted for 25% of crime, and 12.1% accounted for 75% of crime. In addition, crime was recorded in only 36.8% of all street segments in Tel Aviv–Jaffa in 2010, meaning that 63.2% of segments were crime-free in that year. Compared to findings from Seattle, this suggests an even larger share of crime-free segments in Tel Aviv–Jaffa for the study year (Weisburd, 2014).

This method is known as the cumulative percentage hypotheses and is used to determine how much of the micro-places account for 25%, 50%, 75%, and 100% of crime in a study area. Using this method alone to analyze the concentration of crime at place will be criticized at a later stage, with the argumentation that cut-off values do not provide a complete picture of the entire cumulative distribution (Hardyns et al., 2019). For this reason, this thesis also uses additional measures to supplement the interpretation of concentration.

Finally, the Tel Aviv–Jaffa study also considers whether crime concentration at micro-places is linked to larger spatial patterns. This relates to the distinction between hot spots and hot neighborhoods. The idea of hot neighborhoods became more prominent in the early 1980s (Greenberg et al., 1982), because some studies found that high-crime streets are often located close to each other in the same parts of a city. This implies that micro-place hotspots can cluster into larger hotspot areas (Weisburd, 2014).

Overall, the Tel Aviv–Jaffa case study was an important early test of crime concentration outside the United States. Its results are consistent with earlier US findings and provide further evidence that crime in modern cities often concentrates at a small number of micro-places. Weisburd (2014) concludes that because similar concentration patterns appear in different cities, there are likely common processes that lead crime to concentrate in a small number of places.

2.4.3. The first large-scale multi-city LoCC study

Shortly after the Tel Aviv–Jaffa case study, Weisburd (2015) published the first large-scale multi-city study designed to test "the law of crime concentration at place" across different urban contexts. The study included eight cities: seven in the United States and Tel Aviv–Yafo in Israel. The aim was to apply comparable methods and metrics across cities that vary strongly in size and other characteristics.

Weisburd (2015) grouped the cities into two categories. Five were treated as large cities, with populations ranging from roughly 300,000 to more than 8 million: Cincinnati, Seattle, Tel Aviv–Yafo, New York, and Sacramento. Three were treated as smaller cities, with populations between about 70,000 and 108,000: Brooklyn Park, Redlands, and Ventura. Beyond population size, the cities also differed in features such as the number of street segments and their average length, as shown in Table 3. The study's goal was to examine whether crime concentration follows a similar "bandwidth" despite these differences. Tables 2 and 3 provide selected information from Weisburd's (2015) multi-city study that is most relevant for the discussion in this thesis. Both tables are adapted versions of the original tables and include only the variables referred to in the text.

Table 2: Selected characteristics of the crime concentration data in Weisburd's multi-city study, adapted from Weisburd (2015)

City	Time period	Yearly crime incidents on street segments	Percentage of crime at intersections
Cincinnati, OH	2009	34,006	6.9%
Seattle, WA	1989–2004	106,076	15.7%
Tel Aviv–Yafo	1990–2010	32,361	0.0%
New York, NY	2004–2012	376,856	20.2%
Sacramento, CA	2012	33,196	16.9%
Brooklyn Park, MN	2000–2013	14,327	5.9%
Redlands, CA	2012–2013	5,841	33.2%
Ventura, CA	2011	14,299	11.0%

Table 2 describes the crime concentration data used in Weisburd's multi-city study, including the observation periods, which differ strongly across cities. The three smaller cities provide the most recent data, covering periods between 2000 and 2013. The longest time series is for the Israeli city Tel Aviv–Yafo, which covers 21 years (1990–2010). The Tel Aviv–Yafo data were collected from the Ministry of Public Security's

Index of Serious Crimes and were provided by the Israeli Ministry (Weisburd, 2015). This dataset includes offence categories such as murder, assault, manslaughter, attempted assault, and serious injury, which differ from the crime categories used for the US cities.

The US data was provided through the US Department of Justice and collected via the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) system. The offence categories include murder, forcible rape, robbery, and aggravated assault (Weisburd, 2015). Table 3 also includes a variable labelled "percentage of African American". For Tel Aviv–Yafo, this variable reflects the percentage of the Arab population rather than African Americans. Because the offence categories and some demographic measures are defined differently for Tel Aviv–Yafo compared to the US cities, Weisburd (2015) notes that direct comparisons between Tel Aviv–Yafo and the seven US cities should be interpreted with caution.

Table 3: Selected city characteristics in Weisburd's multi-city study, adapted from Weisburd (2015)

City	Population	Number of street segments	Average length of Street segment	Violent crimes per 1,000 population	Percent African American	Poverty level
Cincinnati, OH	296,204	13,550	445 ft	9.7	44.8%	30.4%
Seattle, WA	626,865	24,023	387 ft	6.0	7.9%	13.6%
Tel Aviv–Yafo	414,600	14,149	183 ft	3.61	4.2%*	14.0%
New York, NY	8,289,415	87,279	393 ft	6.4	25.5%	20.3%
Sacramento, CA	476,577	22,867	416 ft	7.4	14.6%	21.9%
Brooklyn Park, MN	77,346	2,937	596 ft	3.4	24.4%	12.3%
Redlands, CA	70,399	4,674	678 ft	3.1	5.2%	12.5%
Ventura, CA	108,511	4,568	681 ft	2.9	2.2%	11.1%

Population size is one dimension in which the eight cities in Weisburd's study vary strongly, but they also differ in several other characteristics. These include the number of street segments and the average street-segment length, which ranges from 183 feet in Tel Aviv–Yafo to much longer segment lengths in the smaller cities, with the highest average length reported for Ventura with 681 feet (Table 3).

In addition to these physical characteristics of the street network, Table 3 also reports social and crime-related indicators, such as the violent crime rate per 1,000 residents, the percentage of the population living below the poverty line, and the percentage of African

American residents (for Tel Aviv–Yafo this variable reflects the percentage of the Arab population). Overall, these characteristics vary widely across the eight cities. For example, violent crime rates in the larger US cities range from 6.0 to 9.7 per 1,000 residents, whereas violent crime rates are lower in the three smaller cities, ranging from 2.9 to 3.4 per 1,000 residents (Table 3).

In Weisburd's multi-city study, the geographic unit of analysis is the street segment, defined as both faces of a block between two intersections (Weisburd, 2015). Street segments are a widely used micro-geographic unit in US criminology of place research because they reflect meaningful units of everyday city life. They often capture regularly recurring rhythms of activity and shared norms and behaviors, and their historical development makes them a stable and practical unit for analysis (Weisburd, 2015).

A key limitation of street segments is the handling of crimes recorded at intersections. Incidents located at an intersection cannot be uniquely assigned to one street segment, because an intersection is shared by multiple connected segments. This makes it difficult to analyze the full crime pattern across a city using street segments alone. In Weisburd's study, the share of crimes tied to intersections varies widely between cities: for example, 7% in Cincinnati and 20% in New York (Weisburd, 2015). Among the three smaller cities, the differences are even larger: 6% in Brooklyn Park, 11% in Ventura, and 33% in Redlands. Weisburd (2015) suggests that these differences may partly reflect local recording practices, which can reduce comparability across cities. To avoid this issue in the present thesis, crime is analyzed using grid cells of identical size as the micro-unit of analysis. This supports direct comparison across cities with different street structures and different data recording practices.

In the next step of the multi-city LoCC study, Weisburd (2015) applies the cumulative percentage hypotheses method to show what percentage of street segments accounts for a given percentage of crime. In practical terms, this calculation describes how strongly crime is concentrated in a small number of street segments. Because the study includes eight cities, Weisburd first compares the five larger cities (population roughly 300,000 to 8.3 million). Figure 1 shows that concentration falls within a relatively tight bandwidth across these cities. For the large-city group, 25% of crime is concentrated in about 0.8% of street segments in Sacramento up to 1.6% in Cincinnati. For 50% of crime, the range is about 4.2% of street segments in Sacramento up to 6% in Cincinnati. Despite clear differences in city characteristics, the results are very similar across the five large cities, supporting the idea of a consistent bandwidth of crime concentration (Weisburd, 2015).

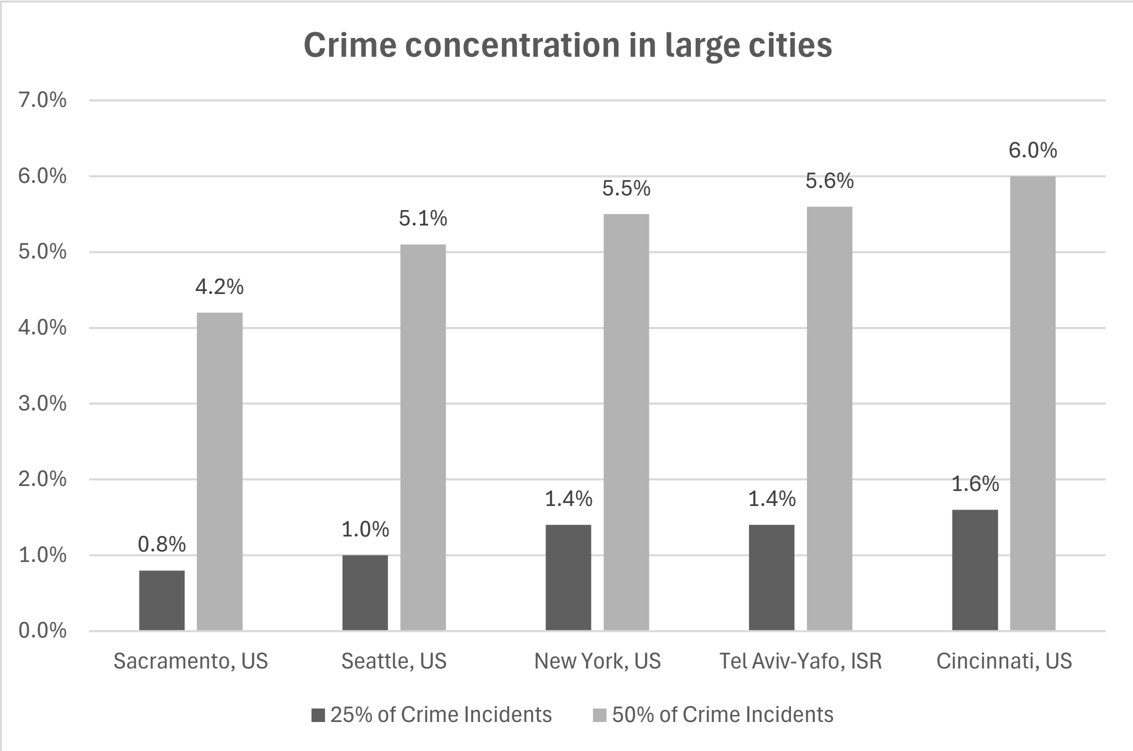

Figure 1: Percentage of street segments accounting for 25% and 50% of crime in the five larger cities, adapted from Weisburd (2015)

Weisburd (2015) then compared the three smaller cities (population roughly 70,000 to 110,000) to examine whether crime concentration looks different in smaller cities than in large metropolitan areas. Figure 2 shows that crime is also concentrated within a tight bandwidth in these smaller cities. For 25% of crime, the share of street segments ranges from about 0.4% in Brooklyn Park and Redlands to 0.7% in Ventura. For 50% of crime, the range is about 2.1% of street segments in Brooklyn Park and Redlands to 3.5% in Ventura. Overall, the pattern is similar to the large-city results, but concentration is even stronger in the smaller cities. Weisburd (2015) argues that higher concentration in smaller cities may occur because a small number of street segments have unusually high crime levels. For example, in Brooklyn Park, particular streets associated with public housing developments account for a large share of citywide crime.

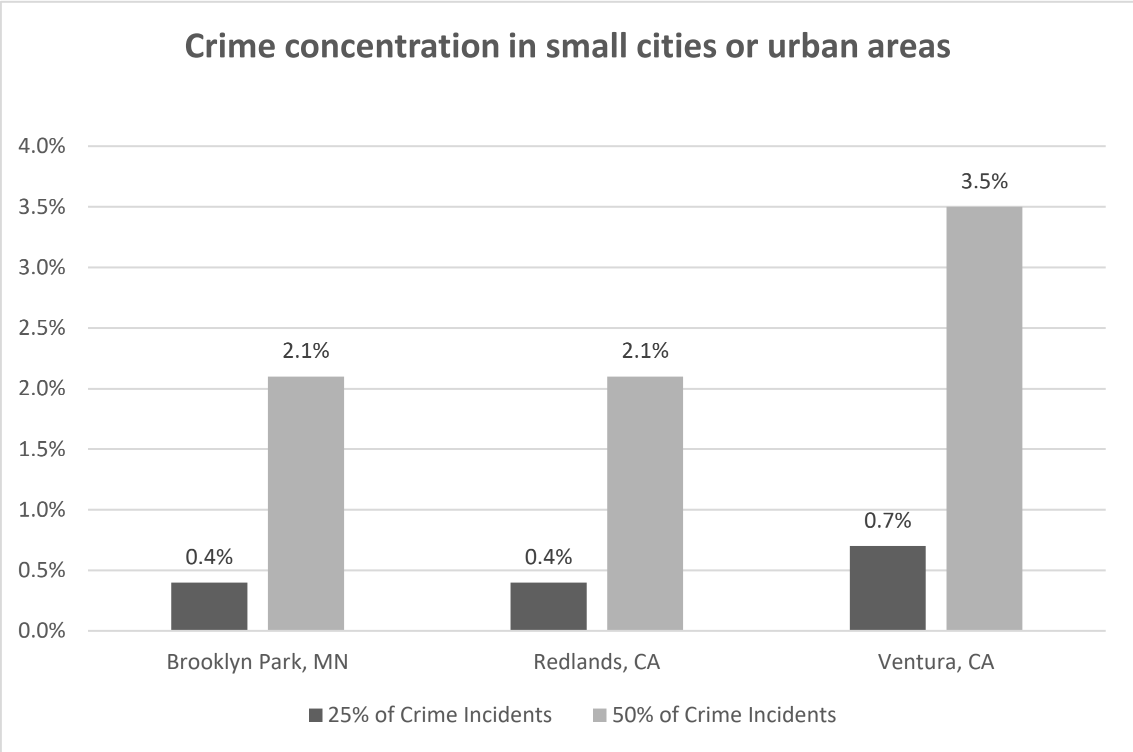

Figure 2: Percentage of street segments accounting for 25% and 50% of crime in the three smaller cities, adapted from Weisburd (2015)

Furthermore, Weisburd (2015) examined whether this tight bandwidth of crime concentration applies not only across different cities, but also across time within the same city. For this part of the analysis, he selected four cities with longer time series: Tel Aviv–Yafo (21 years), Seattle (16 years), Brooklyn Park (14 years), and New York (9 years).

Overall, Weisburd finds a general pattern of stability over time in all four cities, meaning that the percentage of places accounting for 25% and 50% of crime stays within relatively narrow ranges even across many years. Tel Aviv–Yafo shows the longest time period (21 years). For Tel Aviv–Yafo, the share of street segments accounting for 50% of crime ranges from 3.9% (1990) to 6.5% (2003), while the share accounting for 25% of crime ranges from 0.8% (1990) to 1.8% (2003).

In Seattle (16 years), the share of street segments accounting for 50% of crime ranges from 4.6% (2000) to 5.8% (1992), while the share accounting for 25% of crime ranges from 0.9% (2004) to 1.2% (1989). In Brooklyn Park (14 years), the 50% bandwidth ranges from 1.5% (2000) to 2.6% (2008), and the 25% bandwidth ranges from 0.3% (2000) to 0.5% (2003). In New York (9 years), the share of street segments accounting for 50% of crime ranges from 4.7% (2012) to 6.0% (2011), while the 25% bandwidth ranges from 1.1% (2012) to 1.5% (2007) (Weisburd, 2015).

Furthermore, Table 4 shows that the number of crimes per year fluctuates both within cities over time and between cities. These changes reflect periods of rising and falling crime, often described as crime “waves” and “drops”, in the studied cities. At the same time, the concentration ranges reported by Weisburd (2015) remain relatively narrow across the study periods, which supports the argument that crime concentration at place can remain stable even when the total number of crimes changes over time. For example, Tel Aviv–Yafo shows a clear increase in crime between 1992 and 1998, followed by a decline between 2007 and 2010. Seattle shows a more gradual and almost continuous decrease in crime incidents between 1989 and 2004. Brooklyn Park shows a decline between 2001 and 2004, followed by an increase between 2004 and 2007, and then a strong decline between 2007 and 2013. New York shows a short increase between 2005 and 2006, followed by a pronounced decrease over the later years reported by Weisburd (2015).

Table 4: Crime concentration across time in four cities, adapted from Weisburd (2015)

City	Study period	25% concentration range	50% concentration range	Main crime trend described by Weisburd
Seattle, WA	1989–2004	0.9%–1.2%	4.6%–5.8%	Overall crime drop across the study period
New York, NY	2004–2012	1.1%–1.5%	4.7%–6.0%	Mixed trend between 2004 and 2006, then decline
Brooklyn Park, MN	2000–2013	0.3%–0.5%	1.5%–2.6%	Crime drop, then increase, then stronger drop
Tel Aviv–Yafo	1990–2010	0.8%–1.8%	3.9%–6.5%	Crime wave in the 1990s, then decline after 2004

This first large-scale multi-city LoCC study by Weisburd (2015) provides strong evidence that crime concentration follows a relatively tight bandwidth across cities, which supports the idea of a “law of crime concentration at place”. The study also shows that concentration tends to remain within a narrow range over time within the same city, which further strengthens the argument that these patterns are not random and can be relatively stable.

From a practical perspective, these findings are relevant for police and local authorities because they suggest that a large share of crime occurs in a small number of locations. This supports place-based approaches, where prevention and policing resources are focused on the most affected places. At the same time, Weisburd (2015) emphasizes that evidence alone is not enough. Further theoretical and methodological development is needed to improve how crime-at-place data are collected, measured, and compared across contexts.

Several key questions therefore remain important for future research. For example, does “the law of crime concentration at place" apply in the same way when identical measurement approaches are used across different countries and cities outside the United States? Are there contexts where the expected bandwidth does not hold? Addressing such questions requires more consistent sampling and measurement strategies that can be applied across different cities, so results can be compared more reliably and used to advance criminology and crime prevention.

2.4.4. Further Development and State of the Art

After Weisburd’s (2015) multi-city study, several authors developed the LoCC discussion further by addressing open questions about the law and by refining how concentration should be measured and compared. Hipp and Kim (2017), for example, point out that LoCC describes concentration as falling within a “narrow bandwidth”, but that it is not always clear what counts as narrow in practice. They also highlight that concentration levels may differ depending on city size and crime type, which makes comparisons across different cities and different crime types more complex. To examine these issues, Hipp and Kim (2017) analyzed street-segment crime data from 42 cities in southern California for the period of 2005–2012. They found that crime is highly concentrated in all cities, but also that the degree of concentration varies across cities and across crime categories (Hipp & Kim, 2017).

Later research also emphasized that the choice of measurement approach matters, especially in datasets where many micro-places record zero incidents. This situation is common when there are many spatial units but relatively few crimes. Bernasco and Steenbeek (2017) argue that standard Lorenz curves and Gini coefficients can be biased under these conditions and can become difficult to compare across cities and crime types. They therefore propose generalized versions of these measures to reduce bias and improve comparability (Bernasco & Steenbeek, 2017).

A further important development in the LoCC literature is the growing focus on spatial stability. This means examining whether the same parts of a city remain the most affected over time, or whether crime shifts to other places. Andresen et al. (2017), for example, study property crime in Vancouver and use the Spatial Point Pattern Test to compare crime patterns between years and to assess how stable spatial distribution is over time (Andresen et al., 2017).

2.4.5. LoCC in Europe

Even though most early LoCC research was conducted in the United States, a growing number of studies has tested "the law of crime concentration at place" in a European setting. Overall, these studies provide confirmation that crime is also highly concentrated at micro places in Europe, but they also highlight that the choice of micro-units can differ from the US context, because European urban morphology is often less suitable for street-segment approaches as it is more heterogeneous across cities (Khalfa et al., 2023).

A first example is Steenbeek and Weisburd (2016) testing "the law of crime concentration at place" in The Hague. The results showed that the observed level of concentration can vary depending on the spatial unit used, which underlines that the unit of analysis matters when comparing results across different countries and city types. Another example is the study of Milan, where Favarin (2018) tested "the law of crime concentration at place" at the street segment level. Results showed high concentration patterns, with only a small share of street segments accounting for a large share of crime. Another European example is where Hardyns et al. (2019) tested crime concentration at a micro-unit level of analysis in two Belgian cities using a 200 × 200 meters grid approach, reporting high concentration patterns and differences across various crime types.

The most relevant European study for this thesis is the Brussels LoCC study by Khalfa et al. (2023), which tested "the law of crime concentration at place" in Brussels at a grid-cell level (200 × 200 meters) and furthermore examined the spatial stability of crime concentrations over time.

Finally, some European studies also suggest that the strength of concentration may depend on local context. For example, Šimon and Jíchová (2022) report a post-socialist city case (meaning a city in a former socialist country in Central and Eastern Europe) in the Czech Republic where crime and harm were less spatially clustered than expected, suggesting that European contexts are not always identical and should be tested empirically.

These European findings support the relevance of LoCC beyond the US context and motivate testing whether similar concentration patterns can also be observed in Hungary under comparable methodological conditions.

3. Case Study

This chapter introduces the case study design of this thesis. First, the three selected study areas, Budapest, Debrecen and Miskolc, are described and the reasons for their selection are explained. Then, the chapter presents the crime data used for the analysis, including the spatial unit of analysis.

3.1. Study Areas

This thesis focuses on three Hungarian cities: Budapest, Debrecen and Miskolc. The cities were selected because they strongly differ in size and character. This allows a comparison between a large metropolis and two smaller cities under the same methodological conditions, which is relevant for testing crime concentration at micro-places.

Budapest is the largest city and capital of Hungary, with an official administrative area of 525.1 km^2. Debrecen is a major regional city in eastern Hungary with an official administrative area of 462 km^2. Miskolc, the smallest city analyzed in this work, is a city in northeastern Hungary with an official administrative area of 236.68 km^2.

For the spatial analysis, all three cities are analyzed using the same 200 × 200 meters grid. Further details on the unit of analysis and the number of grid cells are provided in chapter 3.2.3.

3.2. Data

The analysis in this thesis is based on official police-registered crime incidents from Hungary for the period of 2013 to 2016 in Budapest, Debrecen and Miskolc. The data was received in an already geocoded format, meaning that each crime incident record was already linked to a geographic point location (X and Y coordinates). Therefore, no additional geocoding was required for this work.

Overall, the dataset contains n = 48,815 incidents for the period 2013–2016 across all three cities. Budapest accounts for the largest share with 43,580 incidents, followed by Miskolc with 2,676 incidents and Debrecen with 2,559 incidents in total. The geocoded incident points were assigned to the 200 × 200 meters grid cells to analyse crime concentration at a micro-geographic level.

3.2.1. Types of Crime

This thesis does not analyze all recorded offence categories, but focuses on four selected crime types: simple assault, aggravated assault, residential burglary and car break-in. These categories were selected because they cover both violent and property crime and are available in a comparable form across the three cities. Furthermore, these specific categories were selected because they allow a direct comparison with a major LoCC-focused study in Europe, the Brussels study by Khalfa et al. (2023), which uses comparable crime incident categories.

For the period 2013 to 2016, the incidents in the dataset are distributed as follows:

Table 5: Number of police-registered crime incidents by city and offence type, 2013–2016

City	Aggravated assault	Simple assault	Car break-in	Residential burglary	Total
Budapest	6,232	3,392	13,987	19,969	43,580
Debrecen	814	263	488	994	2,559
Miskolc	394	420	363	1,499	2,676
Total	7,440	4,075	14,838	22,462	48,815

Across all three cities combined, this results in a total of 48,815 crime incidents for the period of 2013–2016.

To improve comparability across cities of different sizes, Table 6 reports the average annual crime rates per 1,000 inhabitants for each offence type in Budapest, Debrecen, and Miskolc. Rates are calculated as the average annual number of incidents per 1,000 inhabitants for the period 2013–2016, using the average annual city population for 2013–2016 based on official KSH population figures (KSH, 2016).

Table 6: Average annual crime rates per 1,000 inhabitants by city and offence type (2013–2016)

City	Aggravated assault	Simple assault	Car break-in	Residential burglary	Total
Budapest	0.89	0.48	2.00	2.85	6.23
Debrecen	1.00	0.32	0.60	1.22	3.14
Miskolc	0.61	0.65	0.57	2.34	4.17

Reporting the data as rates shows more clearly that residential burglary has the highest average annual rate in Budapest and Miskolc, while aggravated assault has the highest rate in Debrecen.

3.2.2. Classification

To enable comparison with the Brussels LoCC study (Khalfa et al., 2023), simple assault and aggravated assault are additionally combined into one category labelled battery, because the Brussels study uses battery as a single category covering bodily injury incidents. This combined category is only used for the specific cross-study comparison with Brussels. In the main analysis of this thesis, simple assault and aggravated assault are still analyzed and reported separately. Therefore, results labelled "battery" should be interpreted only as a comparison measure and not as the primary offence classification used in this thesis. Across all three cities and the study period of 2013–2016, the battery category includes 11,515 incidents.

3.2.3. Unit of Analysis

The unit of analysis in this thesis is the grid cell. A uniform grid of 200 × 200 meters is used across all three cities to keep the spatial unit the same in all three cities and make the results comparable. Because the incident data were already geocoded when received, each crime incident was available as point data (X and Y coordinates) and could directly be assigned to the corresponding grid cell. After applying the grid and clipping it to the official city boundaries, the number of grid cells used for the analysis is:

- Budapest: 13,610 grid cells
- Debrecen: 11,971 grid cells
- Miskolc: 6,224 grid cells

To support the comparison between the three study cities, Table 7 summarizes key indicators such as area size, population, population density, total number of recorded incidents, and the average annual crime rate per 1,000 inhabitants. Population figures are reported as the average annual city population for the period 2013–2016 based on official KSH data. Population density is calculated using the official administrative area of each city. Crime rates are calculated as the average annual number of police-registered incidents per 1,000 inhabitants for the four offence categories included in this thesis.

Table 7: Comparative characteristics of the three study cities

City	Area size (km²)	Average population (2013–2016)	Population density (per km²)	Total incidents (2013–2016)	Average annual crime rate per 1,000 inhabitants
Budapest	525.10	1,749,350	3,350.51	43,580	6.23
Debrecen	462.00	203,703	440.92	2,559	3.14
Miskolc	236.68	160,456	677.95	2,676	4.17

4. Methodology

To test "the law of crime concentration at place", all point data were imported into ArcGIS. Then, a grid of 200 × 200 meter cells was created for the three selected cities. This cell size proved to be the most suitable for all three Hungarian cities studied in this thesis. Using the same cell size for all three cities allowed a direct comparison. In the next step, the point data were aggregated to the grid, which made it possible to examine the crime data at a micro-unit level of analysis.

The cumulative percentage hypotheses, as presented in Weisburd's proposal (2015), were used to determine what share of micro-places accounted for 25%, 50%, 75%, and 100% of all crime incidents in an area. Following the argument that cut-off values do not provide a complete picture of the entire cumulative distribution (Hardyns et al., 2019), this study also applied a generalized version of the Lorenz curve and Gini coefficient to measure and report crime concentration. The Lorenz curve was used to describe crime concentration, while the (generalized) Gini coefficient was used to summarize it (Bernasco & Steenbeek, 2017).

Furthermore, the spatial stability of crime concentrations was examined using the Spatial Point Pattern Test developed by Andresen (2009, 2016), a method that makes it possible to quantify and identify the stability of crime counts across spatial micro-units by calculating the similarity of crime points between multiple spatial crime point pattern datasets (Andresen, 2016).

4.1. Defining Cumulative Percentage Hypotheses

In criminology of place, cumulative percentage hypotheses translate the general statement that "a small percentage of micro-places accounts for a large percentage of crime" into testable and comparable hypotheses. They do this by choosing a fixed cumulative share of crime (most commonly 25% and 50%) and asking what percentage of micro-places accounts for that share (Weisburd, 2015).

In his test of "the law of crime concentration at place", Weisburd applied this approach to a defined micro-geographic unit (in his work, mainly street segments). The procedure is straightforward: all micro-units in the study area are included (including units with zero crime), and they are ranked from the highest to the lowest number of incidents. Based on this ranking, the cumulative distribution can be calculated. The output is then a simple concentration statement, such as: "x% of micro-places account for 25% (or 50%) of all crime." This cumulative approach is consistent with classic hotspot findings showing that a small fraction of addresses can account for a large fraction of calls for service (Sherman et al., 1989). It also reflects Weisburd's general claim that for a defined measure of crime at a defined micro-geographic unit, concentration falls within a relatively narrow bandwidth for a defined cumulative proportion of crime (Weisburd, 2015).

At the same time, cumulative percentage hypotheses can be criticized because the choice of cut-offs (such as 25% and 50%) can be somewhat arbitrary (Lee, 2017). A highly skewed distribution is reduced to one or two points, and this can hide important differences in the overall shape of the distribution. Two cities (or two crime types) can produce the same result (e.g., "50% of crime occurs in x% of places") while still differing substantially in how the remaining crime is distributed across other places. Cut-off values only tell us what share of places produce 25% or 50% of crime, but they do not describe how the rest of crime is distributed. In other words, cut-off values do not provide a complete picture of the cumulative distribution (Hardyns et al., 2019).

For this reason, many studies now also report the full cumulative curve, typically by plotting a Lorenz curve, and using summary measures that reflect the entire distribution, such as the (generalized) Gini coefficient. This is especially important in settings with many zero-crime units and in situations where there are more places than crimes (Bernasco & Steenbeek, 2017).

4.2. Lorenz Curve and Gini Coefficient

Although "the law of crime concentration at place" is an important milestone in the crime and place literature, the field still lacks common standards for how crime concentration should be reported and summarized in a way that allows direct comparison across studies (Bernasco & Steenbeek, 2017). LoCC is usually tested by relating cumulative percentages of places to cumulative percentages of crime. In practice, many studies report concentration using statements such as: "Y% of crime occurs in the X% most affected places." However, there is no widely accepted standard for which values of X or Y should be reported. As a result, studies often choose different cut-offs and reference points, which makes results harder to compare across cities, crime types, and datasets (Bernasco & Steenbeek, 2017).

To address this issue, Bernasco and Steenbeek (2017) argue that the Lorenz curve is a strong tool for describing crime concentration because it presents the entire cumulative distribution rather than only a few selected cut-offs. They also argue that the Gini coefficient is a useful summary measure because it captures the overall degree of inequality in one value. At the same time, they note an important limitation in crime-at-place data: many micro-units often have zero incidents, especially for rare crimes or very small spatial units. In these situations, standard Lorenz curves and Gini coefficients can be biased and harder to compare. For this reason, Bernasco and Steenbeek (2017) propose generalized versions to reduce this problem and improve comparability.

4.2.1. Defining the Lorenz Curve

The Lorenz curve is a graphical tool that represents the cumulative distribution of a variable. In criminology of place, the variable of interest is usually crime, and the observational units are places. While the Lorenz curve was originally developed to visualize inequality in income distributions, it is now widely used to describe inequality or concentration in many different fields, including crime concentration at place (Bernasco & Steenbeek, 2017).

To study how crime is distributed across places, the Lorenz curve plots the cumulative percentage of crimes on the vertical axis against the cumulative percentage of places on the horizontal axis. The places are ordered by the number of crimes (typically from the most crimes to the fewest). Each point on the curve therefore corresponds to a cumulative statement such as: "Y% of crimes occurs in the X% most affected places." The advantage of the Lorenz curve is that it includes all such cumulative percentage statements in one diagram. This means that it is not necessary to select a single cut-off value for X or Y in advance, because the full cumulative distribution is already shown (Bernasco & Steenbeek, 2017).

For illustration, this thesis follows the fictitious example provided by Bernasco and Steenbeek (2017), which uses simplified values to make the steps easier to follow. In Table 8, 100 crimes are distributed across 10 places. The first column lists the places, and the second column shows the number of crimes per place. The places are sorted in descending order by crime count. In this example, place G has the highest number of crimes (22), while place B has the fewest (1). The third column shows the cumulative percentage of places: place G represents 10% of all places; places G and A represent 20%; places G, A, and D represent 30%; and so on until all 10 places represent 100%. The fourth column shows the cumulative percentage of crimes: place G accounts for 22% of all crimes; places G and A together account for 40%; places G, A, and D account for 57%; and so on until all places together account for 100% of crimes.

Table 8: Fictitious distribution of crime across places, adapted from Bernasco & Steenbeek (2017)

Place label	Number of crimes	Cumulative percentage of places	Cumulative percentage of crimes	Proportion of crime y_i	Ranking (by y_i) i	$i \times y_i$
G	22	10	22	0.22	10	2.20
A	18	20	40	0.18	9	1.62
D	17	30	57	0.17	8	1.36
J	12	40	69	0.12	7	0.84
C	11	50	80	0.11	6	0.66
E	8	60	88	0.08	5	0.40
I	6	70	94	0.06	4	0.24
F	3	80	97	0.03	3	0.09
H	2	90	99	0.02	2	0.04
B	1	100	100	0.01	1	0.01
Σ	100					7.46

Figure 3 shows the Lorenz curve based on the values in Table 8. The dashed diagonal line represents perfect equality, meaning a situation where crime is distributed evenly across places. In this case, perfect equality would mean that each of the 10 places has exactly 10 crimes. If crime were distributed perfectly equally, the Lorenz curve would lie directly on this diagonal line. The more the Lorenz curve bends away from the diagonal line, the more concentrated crime is in a smaller number of places (Bernasco & Steenbeek, 2017; Khalfa et al., 2023).

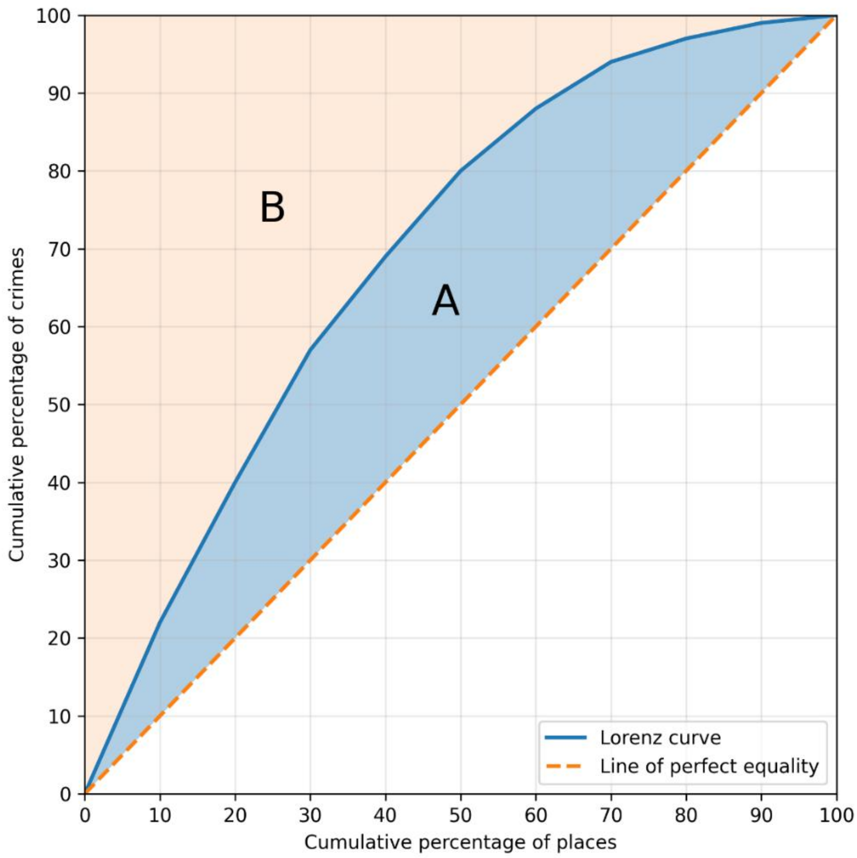

Figure 3: Lorenz curve based on the fictitious crime distribution shown in Table 8, adapted from Bernasco & Steenbeek (2017)

4.2.2. Defining the Gini Coefficient

The Gini coefficient was developed by Corrado Gini in 1912 as a measure of income inequality. Today, it is widely used as a single number that summarizes how strongly a variable is concentrated in a distribution. In geometric terms, the Gini coefficient is defined using the Lorenz curve: it is the ratio of the area between the Lorenz curve and the line of perfect equality to the total area under the line of perfect equality (Bernasco & Steenbeek, 2017; Khalfa et al., 2023).

In Figure 3, the area between the Lorenz curve and the line of perfect equality is indicated as area *A* and the area above the Lorenz curve is indicated as area *B*. The Gini coefficient equals *A / (A + B)*. The Gini coefficient normally represents a value between 0 and 1. If the Gini coefficient equals 0, this means that the Lorenz curve and the line of perfect equality coincide with each other, which means that crime concentration is very minimal to non-existent. All crimes are committed in all places. If the Gini coefficient equals 1, this means that crime concentration is concentrated as high as possible, which means that all crimes occur in a single place. (Bernasco & Steenbeek, 2017; Hardyns et al., 2019).

When calculating the Gini coefficient in terms of crime concentration at place, the following formula is used as non-generalized Gini coefficient in this work. *G* is the Gini coefficient, *n* is the total number of places, *yi* is the proportion of crimes occurring in place *i*, and *i* is the rank order of the place when places are ordered by the number of crimes *y* (Bernasco & Steenbeek, 2017; Khalfa et al., 2023).

$$G = \left(\frac{1}{n}\right)\left(2\sum_{i=1}^{n} i\, y_i - n - 1\right)$$

Equation 1: Formula for calculating the Gini coefficient for crime concentration at place (Bernasco & Steenbeek, 2017)

4.2.3. Limitation of the Lorenz Curve and Gini Coefficient

Both the Lorenz curve and the Gini coefficient have limitations when they are applied to crime-at-place data. A key issue occurs when there are more places than crimes, which is common for rare crime types or when very small spatial units are used. In this situation, interpretation becomes less straightforward because the standard Lorenz curve and Gini coefficient rely on the line of perfect equality as a benchmark.

However, when places outnumber crimes, perfect equality is not logically possible. Crime incidents are discrete events, meaning one incident cannot be split across multiple places. As a result, some places must have zero crimes, even under the most equal possible distribution. In this case, the boundary condition of maximum equality is no longer represented by the standard 45-degree line with slope 1. Instead, Bernasco and Steenbeek (2017) define a different benchmark: a line of maximal equality, which is steeper than the line of perfect equality and reflects the most equal distribution that is possible given the number of crimes and the number of places (Bernasco & Steenbeek, 2017; Khalfa et al., 2023).

4.2.4. Generalization of the Lorenz Curve and Gini Coefficient

To avoid overstating how strongly crime is concentrated at the micro-place level in situations where places outnumber crimes, Bernasco and Steenbeek (2017) propose a generalised version of the Lorenz curve and the Gini coefficient.

The Lorenz curve hasn't changed, but the line of perfect equality is replaced by a line of maximal equality. This line is to serve as a reference line and should represent the boundary condition of maximal equality. Unlike the standardized Lorenz curve, it should only have a slope of 1 if the total number of crimes c is larger than or equal to the total number of places n. In every other case, the slope should be n / c, where n is the ratio of the number of places and c is the number of crimes. The slope of the line of maximal equality is therefore defined as follows (Bernasco & Steenbeek, 2017):

$$\frac{n}{min(c,n)} = max\left(\frac{n}{c},1\right)$$

Equation 2: Formula for calculating the slope of the generalized Lorenz curve (Bernasco & Steenbeek, 2017)

To visually explain the generalized Lorenz curve, Figure 4 shows a simple example with 10 places and 5 crimes in total. One place has 3 crimes, two places have 1 crime each, and the remaining seven places have 0 crimes. The solid line shows the Lorenz curve. The dashed line shows the line of perfect equality, and the dotted line shows the line of maximal equality. In this example, the slope of the line of maximal equality is $n/c = 10/5 = 2$.

The standard plot, which shows only the Lorenz curve and the line of perfect equality, can be misleading in this situation. It hides that the correct boundary condition is the line of maximal equality, not the line of perfect equality (Bernasco & Steenbeek, 2017).

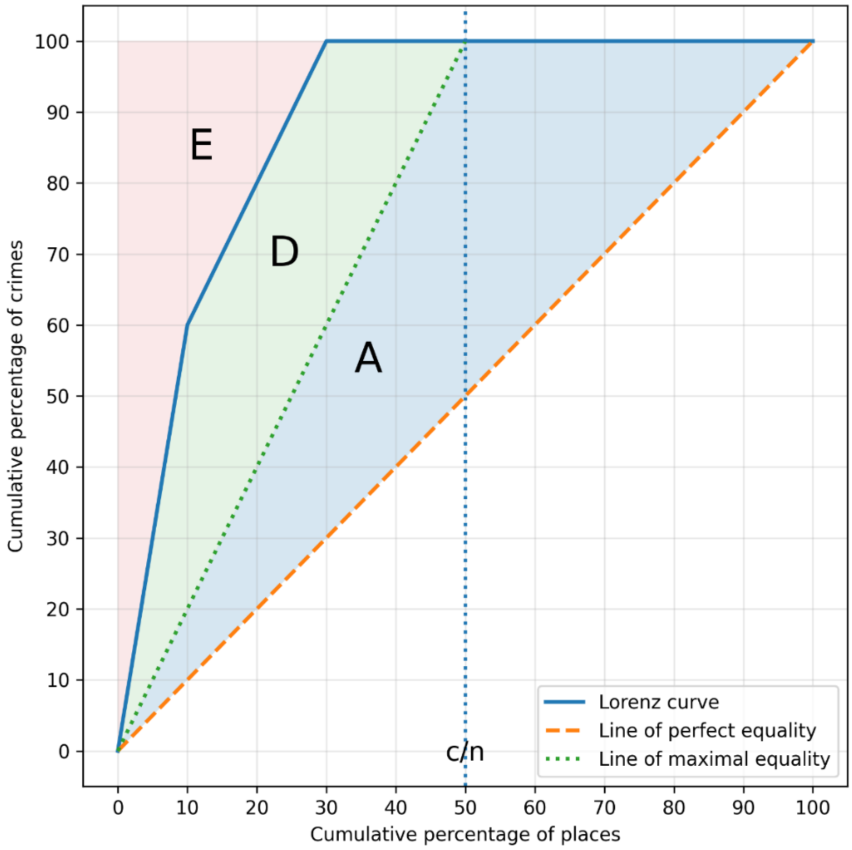

Figure 4: Generalized Lorenz curve illustrating the line of maximal equality in a setting with more places than crimes, adapted from Bernasco & Steenbeek (2017)

When there are fewer crimes than places, perfect equality is logically not possible, because crime incidents are discrete and many places must have zero crimes. For this reason, Bernasco and Steenbeek (2017) introduce a generalized Gini coefficient that uses the line of maximal equality, shown as the dotted line in Figure 4 as the reference line.

While the standard Gini coefficient G refers to the line of perfect equality, the generalized Gini coefficient *G'* refers to the line of maximum equality. When the number of crimes is lower than the number of places, the standard Gini coefficient is calculated as *(A + D) / (A + D + E)*, whereas the generalized Gini coefficient is calculated as *D / (D + E)*. The generalized Gini coefficient can therefore be expressed with the following formula (Bernasco & Steenbeek, 2017):

$$G' = \max\left(\frac{n}{c}, 1\right)(G - 1) + 1$$

Equation 3: Formula for the generalized Gini coefficient *G'* (Bernasco & Steenbeek, 2017)

4.3. Spatial Point Pattern Test

This thesis examines not only whether crime is concentrated at micro-places, but also whether these concentrations are spatially stable over time. Spatial stability means that the overall pattern remains similar across years, so that the same small areas keep the same relative importance in the citywide distribution of crime. To test this, the thesis applies the Spatial Point Pattern Test (SPPT) developed by Andresen as an area-based, nonparametric approach to compare two spatial point patterns across time (Andresen, 2009).

SPPT is useful in the criminology of place literature because it goes beyond concentration measures (such as the Lorenz curve and Gini coefficients). Concentration measures describe how strongly crime is clustered, but they do not directly test whether the same micro-places remain the most affected. SPPT addresses this by comparing two time periods cell-by-cell and summarizing how similar the spatial distributions are (Andresen, 2016).

4.3.1. Unit of analysis and core comparison

The Spatial Point Pattern Test requires that incidents are aggregated to the same spatial units in both time periods. In this thesis, incidents are aggregated to a fixed 200 × 200 meters grid for each city. A consistent grid and consistent cell IDs across years are essential, because SPPT evaluates similarity at the level of each individual spatial unit (Andresen, 2016).

The comparison is based on relative event counts (proportions), not raw counts. For each cell, SPPT uses the percentage (share) of all incidents in that year that fall into the cell. Using proportions is important because total crime volumes can differ between years; SPPT is therefore a test of whether a place keeps a similar share of citywide crime, not whether the absolute number of incidents is identical (Khalfa et al., 2023).

4.3.2. SPPT procedure

In the standard bivariate SPPT setup, one period is defined as the base dataset and the other as the test dataset. The procedure then uses a Monte Carlo resampling approach to create a confidence interval for the test dataset in each spatial unit, and checks whether the base value falls within that interval.

In this thesis, the SPPT is implemented as follows:

1. Choose the base year and test year.

   The base year represents the reference pattern, and the test year represents the pattern being compared.

2. Calculate base-year proportions.

   For the base year, the proportion for each cell i is computed as the number of incidents in cell i divided by the total number of incidents in the city for that year.

3. Create a confidence interval for the test-year proportions using a Monte Carlo simulation.

   For the test year, a Monte Carlo simulation is performed by repeatedly drawing random samples of incidents from the test dataset. A common setup is to draw 85% of incidents per replicate and repeat this procedure many times (e.g., 200). Each replicate produces a test-year proportion for every cell, and these simulated values form a distribution per cell (Andresen, 2016).

4. Derive a 95% confidence interval for each cell.

   From the simulated distribution of test-year proportions for each cell, a 95% confidence interval is constructed (commonly by removing the lowest 2.5% and the highest 2.5% of simulated values) (Khalfa et al., 2023).

5. Classify each cell as similar or different.

   A cell is classified as similar if the base-year proportion falls within the 95% confidence interval derived from the test year simulation. If the base year proportion falls outside the interval, the cell is classified as different. A base proportion below the interval suggests the cell's share increased in the test year, while a base proportion above the interval suggests the cell's share decreased in the test year.

This classification is made for every cell, which allows both local and global interpretations.

4.3.3. Local and global S-index

The SPPT provides both local and global measures of similarity.

<u>Local S-index (cell-level similarity)</u>

For each grid cell, SPPT decides whether the cell behaves similarly across the two years. A cell is similar if its share of citywide crime in the base year is within the 95% confidence interval estimated for the test year. If it falls outside the interval, the cell is different. These cell-level results identify where the spatial pattern is stable and where it changes (Andresen, 2016).

<u>Global S-index (overall similarity)</u>

The global S-index summarizes the local results in one number: it is the share of cells that are classified as similar. If $s_i = 1$ when cell i is similar and $s_i = 0$ otherwise, then:

$$S = \frac{\sum_{i=1}^{n} s_i}{n}$$

Equation 4: Formula for calculating the global S-index (Andresen, 2016)

where n is the total number of cells. An S close to 1 means most cells are stable; a lower S means more cells changed (Khalfa et al., 2023).

4.3.4. Robust global S-index and the zero-cell problem

A known issue in grid-based SPPT applications is that many cells can have zero incidents in both periods, especially for rarer crime types. These zero–zero cells are almost always classified as similar and can inflate the global S-index, giving the impression of strong stability even when the pattern among active cells changes. To address this, Khalfa et al.

(2023) report a robust global S-index that excludes cells with zero incidents in both periods and restricts the calculation to non-zero cells, meaning cells with at least one incident in either the base year or the test year (Dewinter et al., 2021; Khalfa et al., 2023). In this thesis, both global S-index and robust global S-index are reported. The standard global S-index for comparability with earlier SPPT applications, and the robust S-index to describe stability among the spatial units where crime is actually observed.

4.3.5. Application in this thesis

In this thesis, the Spatial Point Pattern Test is applied to yearly crime patterns in the three Hungarian cities Budapest, Debrecen, and Miskolc. Incidents are aggregated to 200 × 200 meters grid cells, and SPPT is computed for the four crime types simple assault, aggravated assault, car break-in and residential burglary, by comparing 2013 as the base year with 2016 as the test year. Local similarity outcomes are joined back to the grid to identify where spatial stability and change occur, and global and robust S-indices are reported to summarize overall similarity between 2013 and 2016.

5. Results

This chapter presents the results obtained from the application of the different methods described in chapter 4 Methodology. The data are organized and analyzed to highlight major trends, compare results across different methods, and provide a basis for further interpretation in the following discussion.

5.1. Cumulative Percentage Hypotheses

This section presents the results for all three cities using the cumulative percentage hypotheses method. To show the full picture, the figures in this section display the results separately for each year (2013–2016) and for each crime type. The figures report how many micro-places account for 25%, 50%, 75%, and 100% of recorded crime in each city.

In the later parts of this chapter, smaller and more focused figures are used to highlight specific patterns and to support comparisons with other studies. Although the figures also report on the 75% and 100% values, the interpretation mainly focuses on 25% and 50%, since these cut-offs are the most commonly reported in LoCC research and allow the best comparison with the existing literature.

For comparison with the Brussels study by Khalfa et al. (2023), this thesis also reports a combined offence category labelled battery, which merges simple assault and aggravated assault. This mirrors the Brussels data structure, where "battery" covers both minor and more serious physical assaults.

Before discussing each crime type in detail, the overall results already show a clear difference between the capital Budapest and the two smaller cities Debrecen and Miskolc. In the cumulative percentage results, concentration is consistently higher in Debrecen and Miskolc than in Budapest. This pattern is in line with Weisburd's (2015) multi-city findings, which suggest that crime concentration can be stronger in smaller cities than in large metropolitan areas.

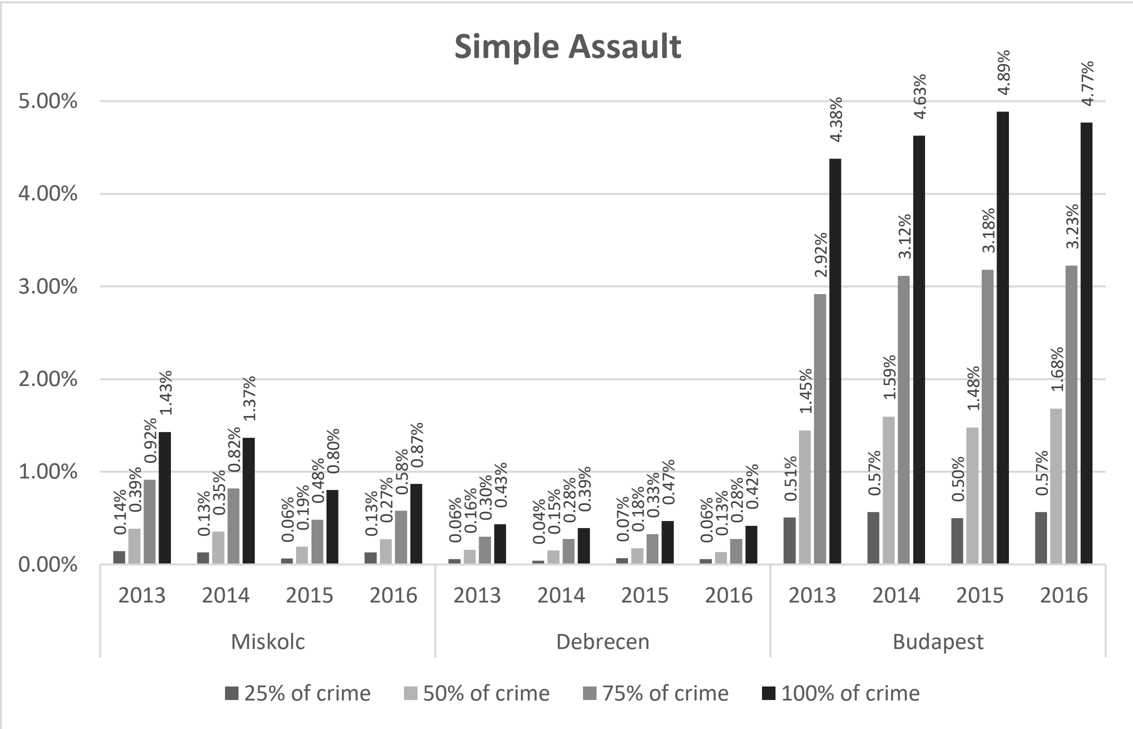

Figure 5: Percentage of grid cells responsible for 25%, 50%, 75% and 100% of simple assault crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

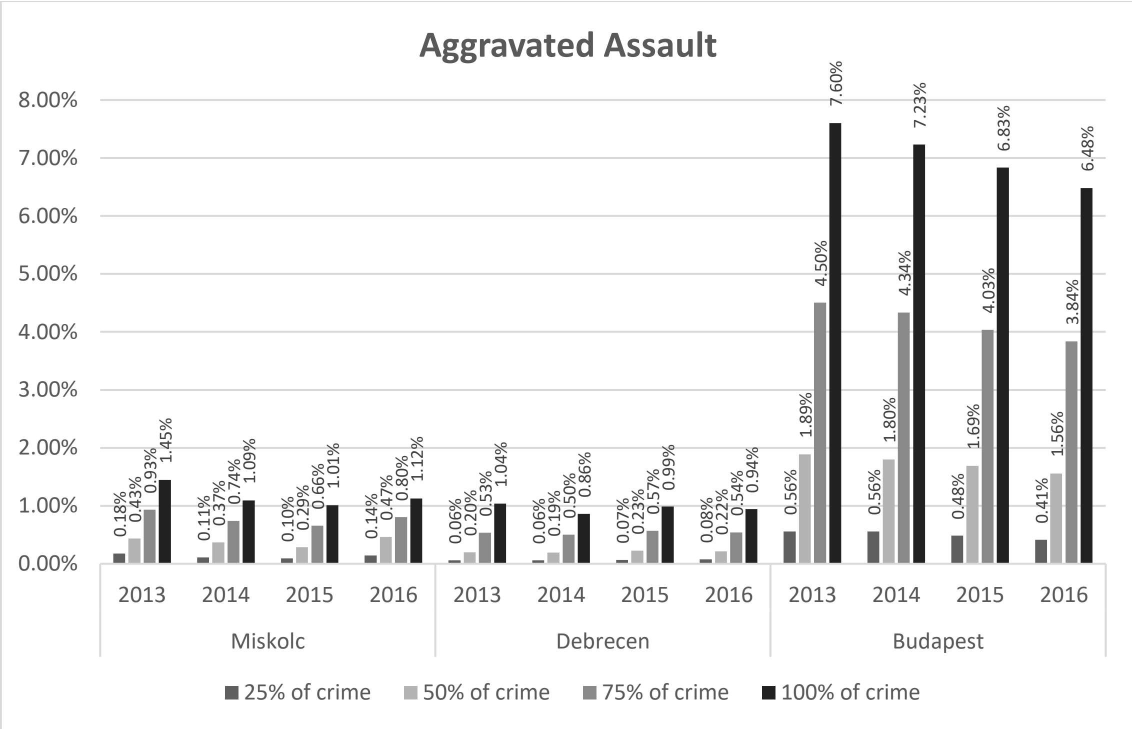

Figure 6: Percentage of grid cells responsible for 25%, 50%, 75% and 100% of aggravated assault crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

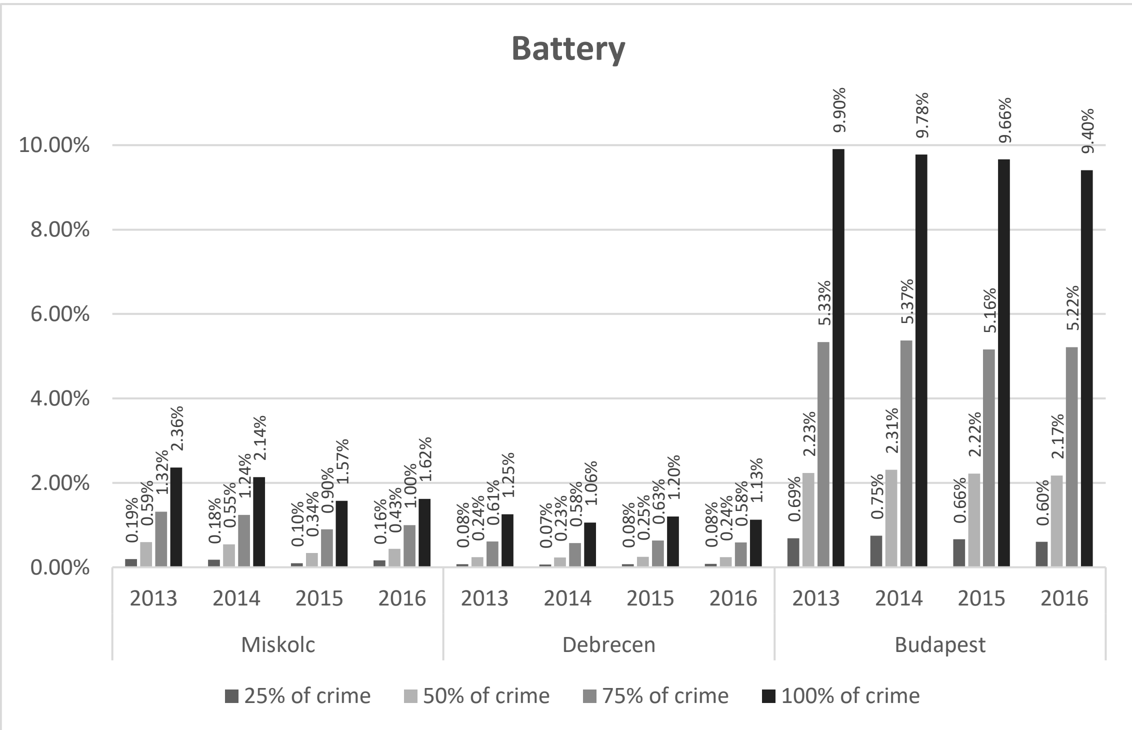

Figure 7: Percentage of grid cells responsible for 25%, 50%, 75% and 100% of battery crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

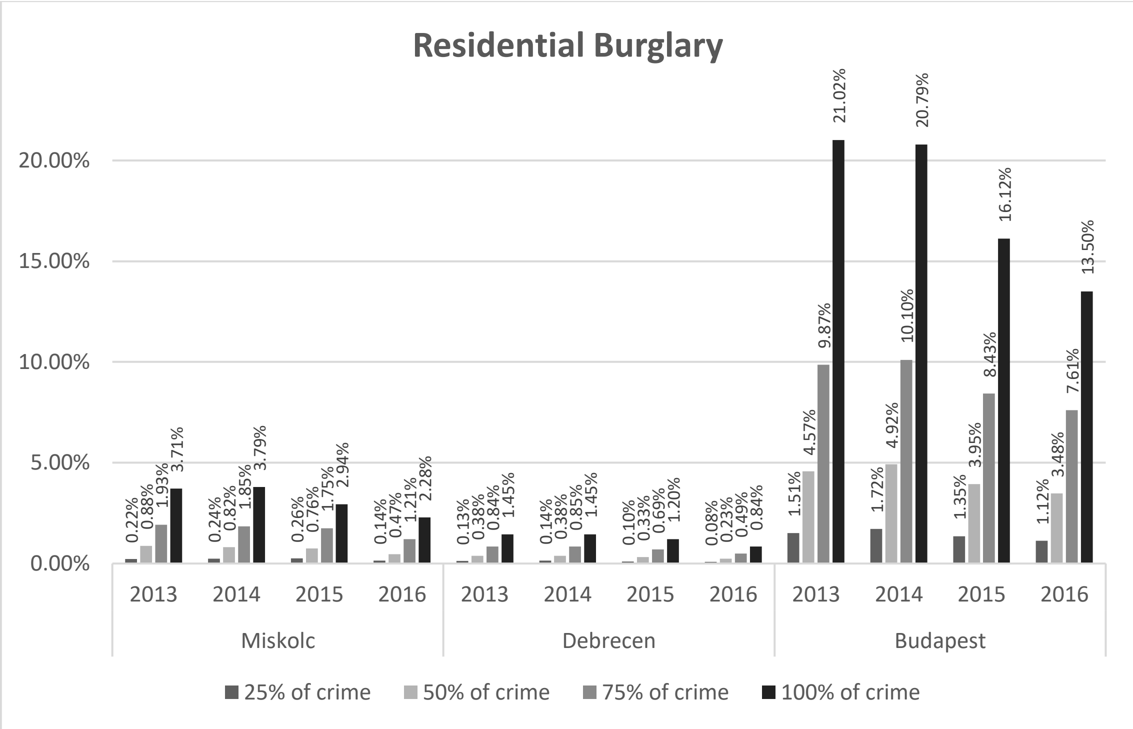

Figure 8: Percentage of grid cells responsible for 25%, 50%, 75% and 100% of residential burglary crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

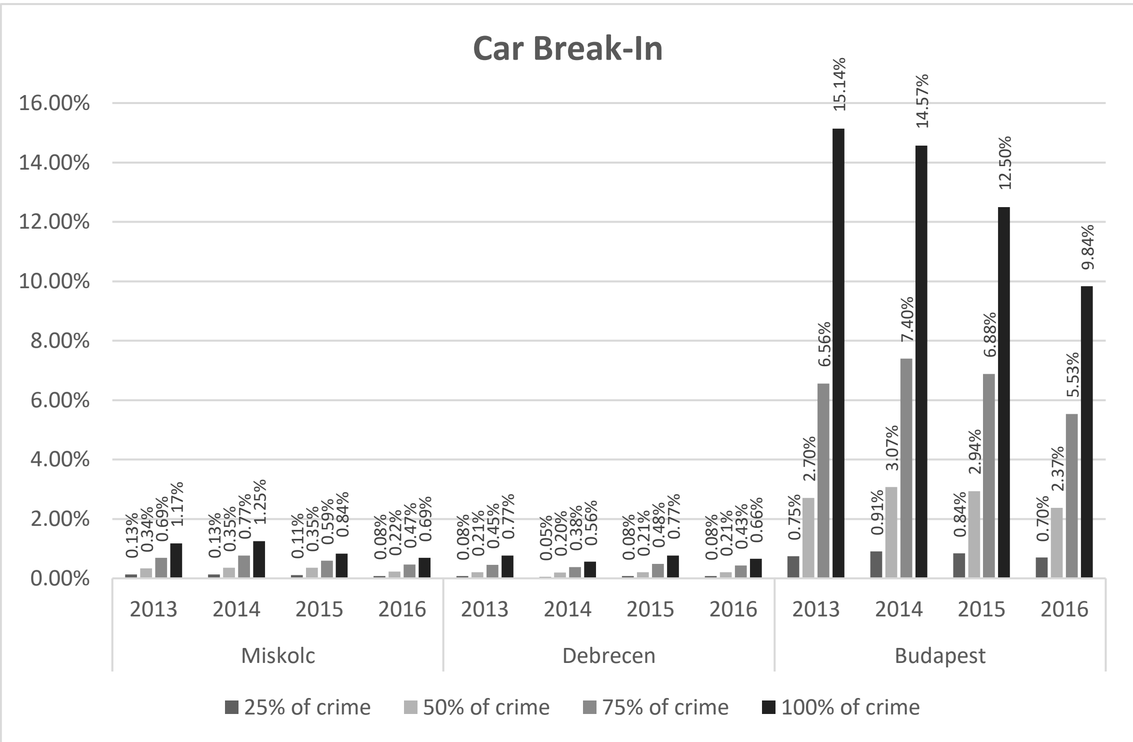

Figure 9: Percentage of grid cells responsible for 25%, 50%, 75% and 100% of car break-in crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

Figures 5-9 indicate that simple assault and aggravated assault are more strongly concentrated in Miskolc and Debrecen than in Budapest. Simple assault shows noticeably higher concentration in Debrecen than in Miskolc, whereas aggravated assault is only slightly more concentrated in Debrecen.

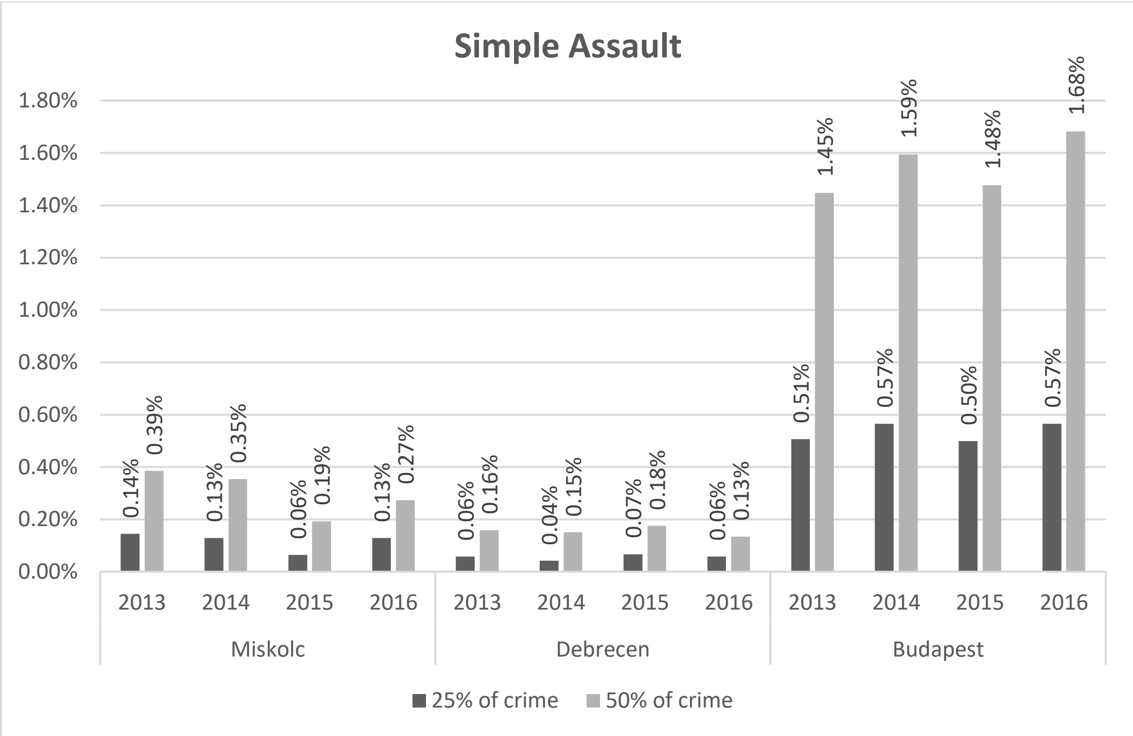

Figure 10: Percentage of grid cells responsible for 25% and 50% of simple assault crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

Starting with Miskolc, both simple assault and aggravated assault are highly concentrated across the study period (2013–2016). Lower percentages mean higher concentration, because fewer grid cells account for the same share of crime. For simple assault, the percentage of grid cells accounting for 25% of incidents is 0.14% in 2013 and 0.13% in 2016, with the strongest concentration in 2015 (0.06%). For 50% of simple assault incidents, the percentage is 0.39% in 2013 and 0.27% in 2016, again with the strongest concentration in 2015 (0.19%).

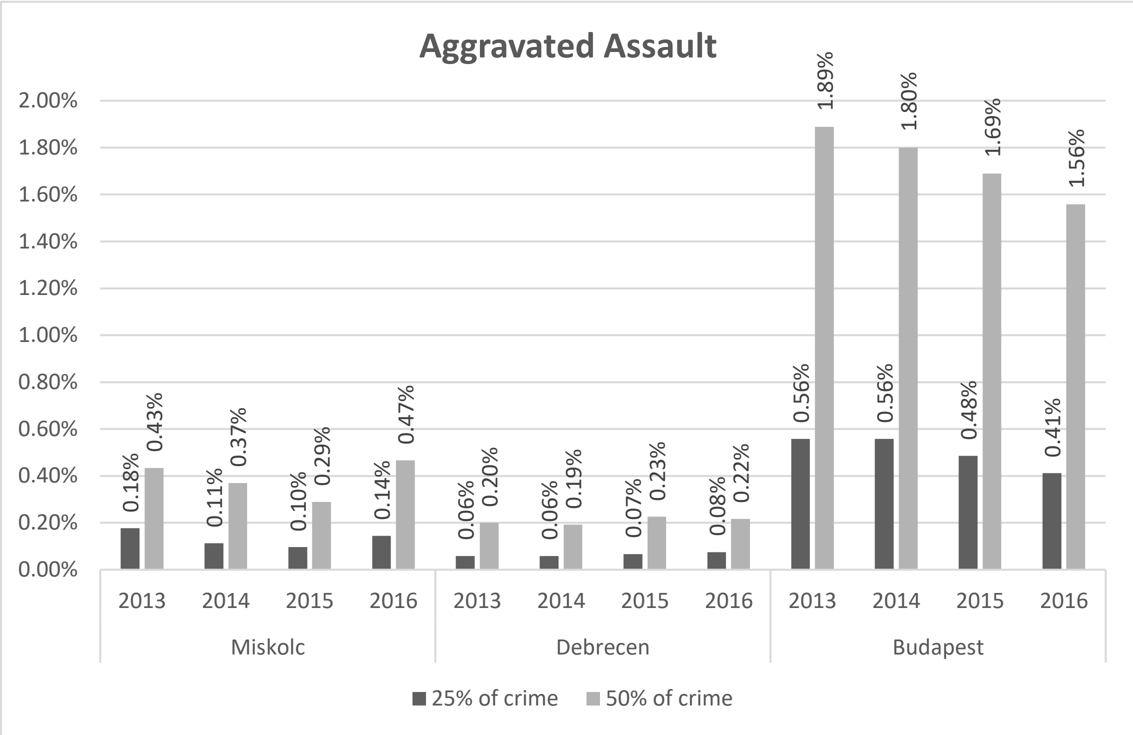

Figure 11: Percentage of grid cells responsible for 25% and 50% of aggravated assault crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

For aggravated assault, the pattern is similar. For 25% of incidents, 0.18% of grid cells account for that share in 2013, decreasing to 0.14% in 2016, with the strongest concentration in 2015 (0.10%). For 50% of incidents, 0.43% of grid cells account for that share in 2013, dropping to 0.29% in 2015. In 2016, this increases to 0.47%, meaning aggravated assault becomes slightly less concentrated in that year compared to the earlier years.

In Debrecen, concentration is even stronger for both assault categories. For simple assault, only 0.06% of grid cells account for 25% of incidents in 2013, and this remains 0.06% in 2016. For 50% of incidents, the value is 0.16% in 2013 and decreases to 0.13% in 2016, indicating slightly stronger concentration over time. Debrecen also shows a clear exception in 2015, where the values rise to 0.07% for 25% and 0.18% for 50%, which means concentration is lower in 2015 than in the surrounding years.

For aggravated assault in Debrecen, concentration changes only slightly. The percentage of grid cells accounting for 25% of incidents increases from 0.06% in 2013 to 0.08% in 2016, indicating a small decrease in concentration. For 50%, the value increases from

0.20% in 2013 to 0.22% in 2016, showing the same direction, where aggravated assault becomes slightly less concentrated over time.

Compared to the two smaller cities, Budapest shows much lower concentration across both assault categories. For simple assault, the share of grid cells accounting for 25% of incidents increases from 0.51% in 2013 to 0.57% in 2016, which means concentration slightly decreases over time, with 2015 showing the strongest concentration at 0.50%. For 50% of simple assault incidents, 1.45% of grid cells account for that share in 2013, increasing to 1.68% in 2016, again indicating lower concentration in the later year.

For aggravated assault in Budapest, the pattern is different. The share of grid cells accounting for 25% of incidents decreases from 0.56% in 2013 to 0.41% in 2016, meaning aggravated assault becomes more concentrated over time. For 50%, the share decreased from 1.89% in 2013 to 1.56% in 2016, showing the same trend.

Overall, the assault results show two main patterns. First, concentration is consistently stronger in Debrecen and Miskolc than in Budapest when the same 200 × 200 meters grid-cell unit is applied in all three cities. This means that the difference cannot be explained by using different units of analysis across cities, although the measured level of concentration is still shaped by the chosen grid-cell approach. Second, the time trends differ by city and crime type. In the smaller cities, simple assault generally becomes slightly more concentrated (with a clear Debrecen exception in 2015), while aggravated assault changes only modestly. In Budapest, simple assault becomes slightly less concentrated over time, whereas aggravated assault becomes more concentrated over the same period.

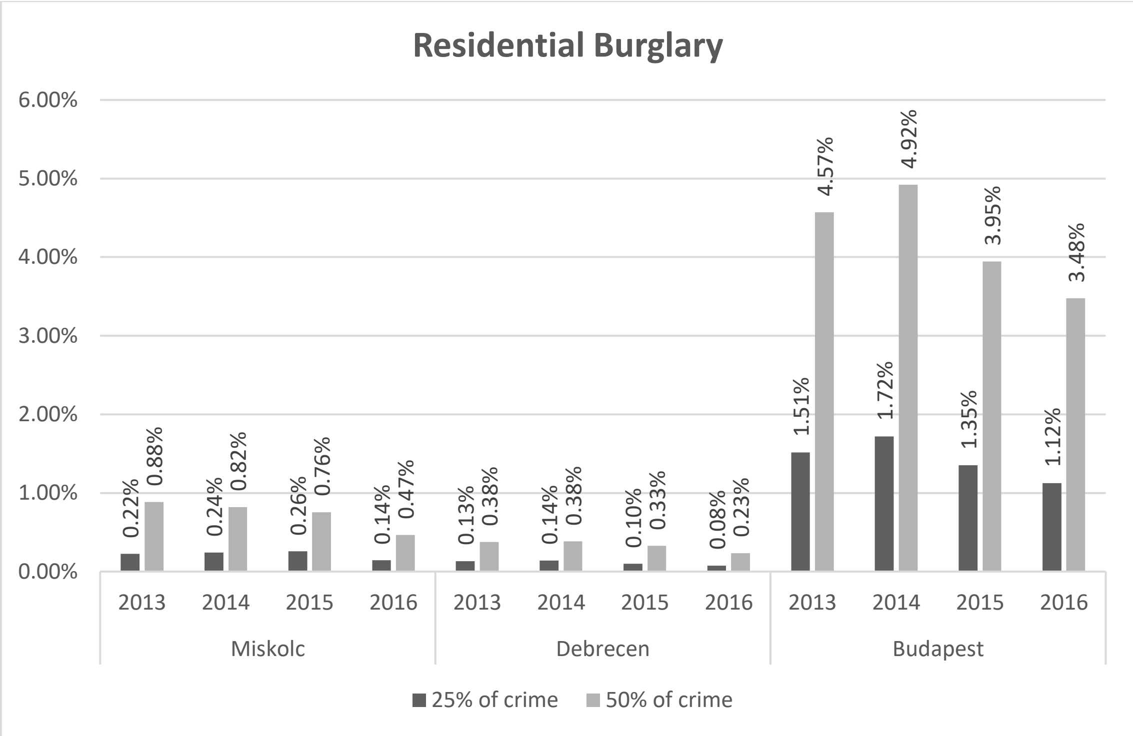

Figure 12: Percentage of grid cells responsible for 25% and 50% of residential burglary crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

Residential burglary is the crime type with the lowest concentration in each of the three cities analyzed in this thesis. Even so, the results show that residential burglary becomes more concentrated over time in all three cities.

Starting with Miskolc, a clear trend is visible, where fewer grid cells account for the same share of residential burglary over time, which means concentration increases. For 25% of residential burglary incidents, the share of grid cells decreases from 0.22% in 2013 to 0.14% in 2016. For 50% of incidents, the share decreases from 0.88% in 2013 to 0.47% in 2016.

Debrecen shows the same pattern, with an even clearer decline in values. For 25% of residential burglary incidents, the share of grid cells decreases from 0.13% in 2013 to 0.08% in 2016. For 50%, the share decreases from 0.38% in 2013 to 0.23% in 2016. This indicates that residential burglary becomes more concentrated in Debrecen over the study period.

In Budapest, the overall trend also points towards increasing concentration, but with a brief interruption in 2014. For 25% of residential burglary incidents, the share of grid cells decreases from 1.51% in 2013 to 1.12% in 2016. However, in 2014 it increases to

1.72%, which indicates a temporary decrease in concentration (i.e., burglary was spread across more grid cells in that year). For 50% of incidents, the share of grid cells decreases from 4.57% in 2013 to 3.48% in 2016, with the highest value again in 2014 (4.92%), showing the lowest concentration during the four-year period.

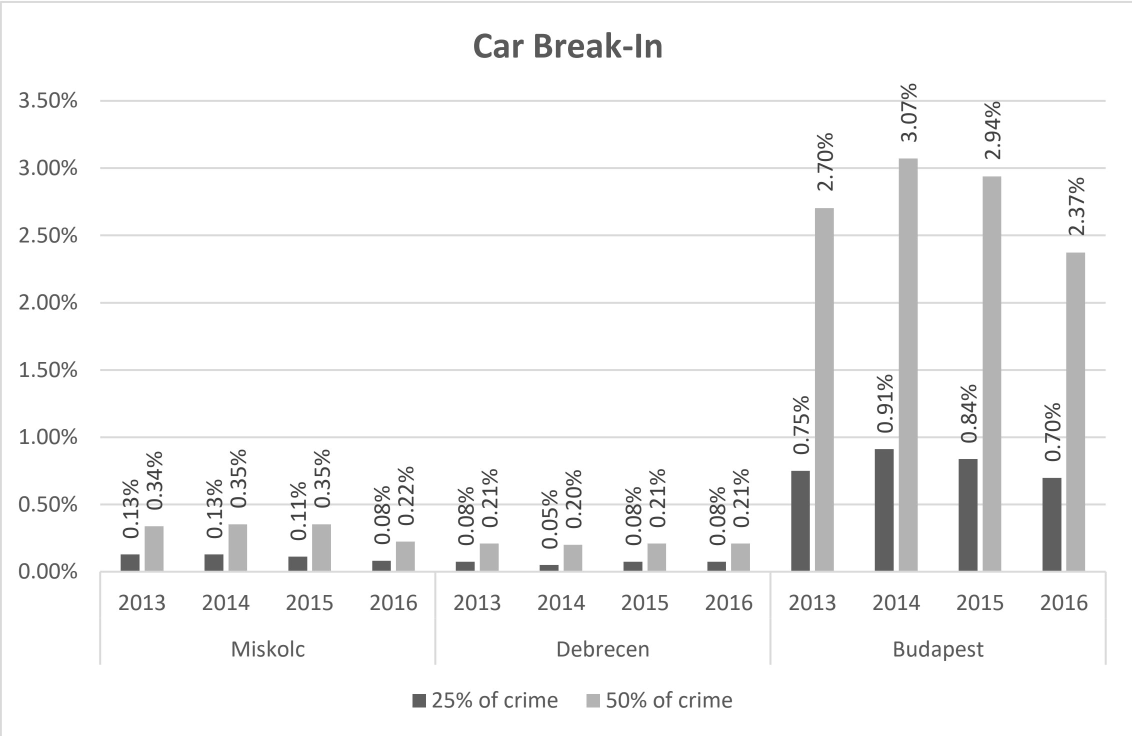

Figure 13: Percentage of grid cells responsible for 25% and 50% of car break-in crime incidents between 2013 and 2016 in Miskolc, Debrecen and Budapest

The last analyzed crime type is car break-in. In Miskolc, the pattern is similar to the other categories, where car break-in becomes more concentrated over the four-year period. For 25% of car break-in incidents, the share of grid cells decreases from 0.13% in 2013 to 0.08% in 2016. For 50%, the share decreases from 0.34% in 2013 to 0.22% in 2016.

Car break-in is also the first crime type where no clear change is visible in one of the cities. In Debrecen, concentration remains stable over time. For 25% of car break-in incidents, 0.08% of grid cells account for that share in 2013 and the value remains 0.08% in 2016. For 50%, the value is 0.21% in 2013 and remains the same in 2016.

In Budapest, car break-in becomes more concentrated over time, but with a brief decrease in concentration in 2014, similar to the pattern observed for residential burglary. For 25% of car break-in incidents, the share of grid cells decreases from 0.75% in 2013 to 0.70%

in 2016, while 2014 shows the highest value 0.91%, meaning the lowest concentration during the period. For 50% of car break-in incidents, the share of grid cells decreases from 2.70% in 2013 to 2.37% in 2016, with the highest value of 3.07% in 2014.

Across the four crime types, the results show mostly consistent trends over the 2013–2016 period, with crime becoming more concentrated in many cases. There are a few exceptions. In Budapest, simple assault becomes slightly less concentrated over time. In Miskolc and Debrecen, aggravated assault also becomes slightly less concentrated over time. Finally, for car break-in in Debrecen, concentration remains essentially unchanged.

In the next step, these results are compared with earlier LoCC research, starting with Weisburd's (2015) first large multi-city study, which compared crime concentration patterns in both large and small cities. For this comparison, the four crime categories in this thesis are combined into one overall category to make the results more comparable.

However, it is important to note that the unit of analysis differs between the studies. Weisburd's (2015) study uses street segments, whose average length varies considerably across the eight cities, ranging from 183 feet in Tel Aviv–Yafo to 681 feet in Ventura, while the Hungarian results in this thesis are based on uniform 200 × 200 meters grid cells. Even with this limitation, the comparison is still useful because it provides a broader reference point for interpreting how strongly crime concentrates in cities of different sizes.

In Figure 14, the results for Budapest are compared with the larger cities from Weisburd's multi-city LoCC study (2015), where the cities Sacramento, Seattle, New York, Cincinnati, and Tel Aviv–Yafo were analyzed. In Figure 15, the two smaller Hungarian cities Miskolc and Debrecen are compared with the smaller cities in Weisburd's study, which are Brooklyn Park, Redlands, and Ventura.

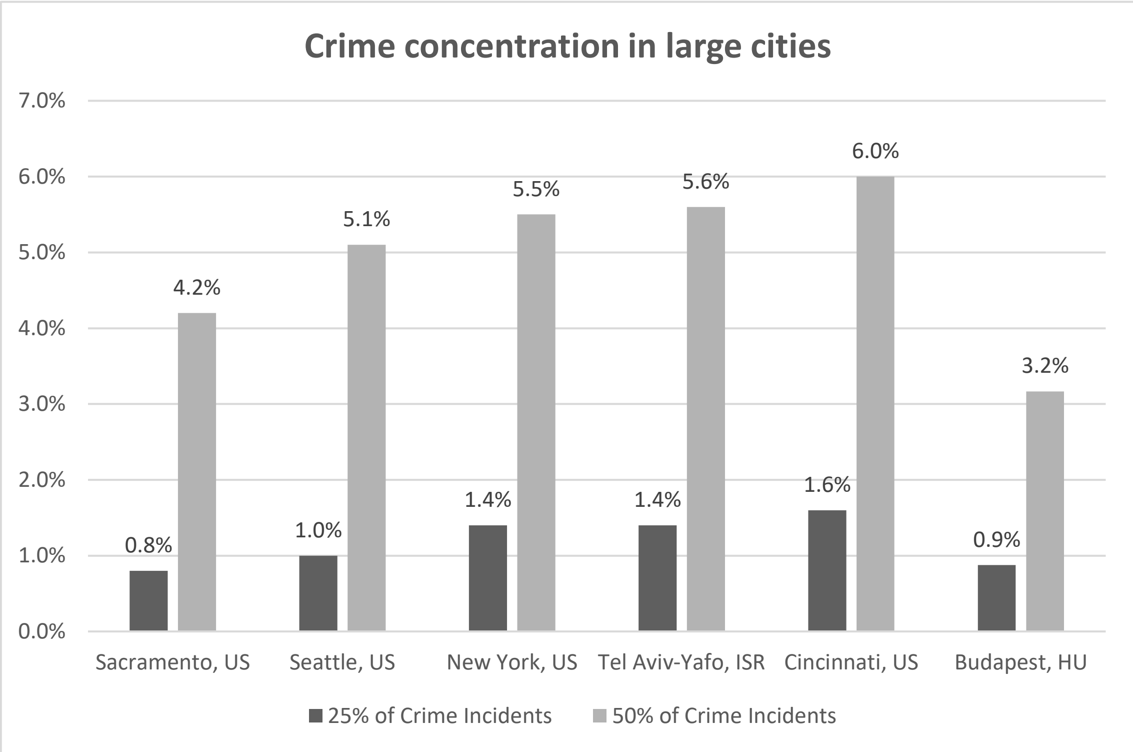

Figure 14: Comparison of percentage of grid cells responsible for 25% and 50% of all crime in large cities

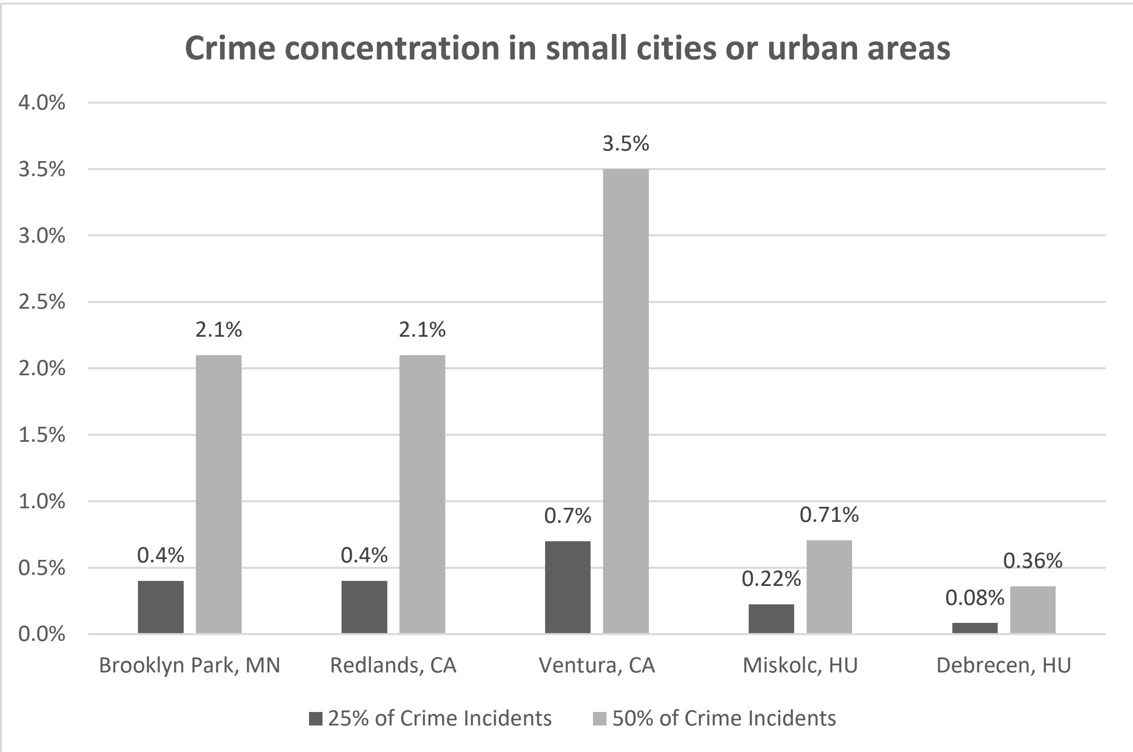

Figure 15: Comparison of percentage of grid cells responsible for 25% and 50% of all crime in small cities or urban areas

Overall, these comparisons are consistent with the pattern reported by Weisburd (2015): crime tends to be more concentrated in smaller cities than in larger cities. In the large US cities, the share of street segments accounting for 50% of crime ranges from 4.2% in Sacramento to 6% in Cincinnati (5.1% in Seattle and 5.5% in New York). In the smaller US cities, the values are noticeably lower with 2.1% in Brooklyn Park, 2.1% in Redlands, and 3.5% in Ventura. A similar pattern is visible in Hungary. In Budapest, 3.2% of 200 × 200 meters grid cells account for 50% of all crime incidents, while the values are much lower in the two smaller cities, with 0.71% in Miskolc and 0.36% in Debrecen.

At the same time, this comparison should be interpreted carefully because the unit of analysis differs. Weisburd (2015) uses street segments, whereas this thesis uses 200 × 200 meters grid cells. The results are therefore not directly equivalent, but the comparison is still useful as a broad reference point for how concentration differs between larger and smaller urban contexts.

Finally, a more directly comparable comparison is made with Brussels, where LoCC was tested using 200 × 200 meters grid cells in a European setting (Khalfa et al., 2023).

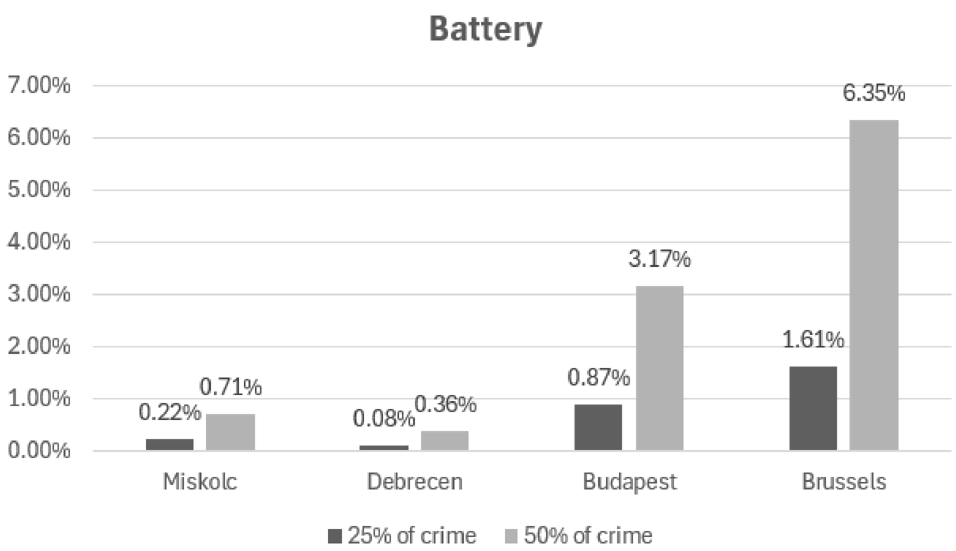

Figure 16: Percentage of grid cells responsible for 25% and 50% of battery in Brussels and Hungary

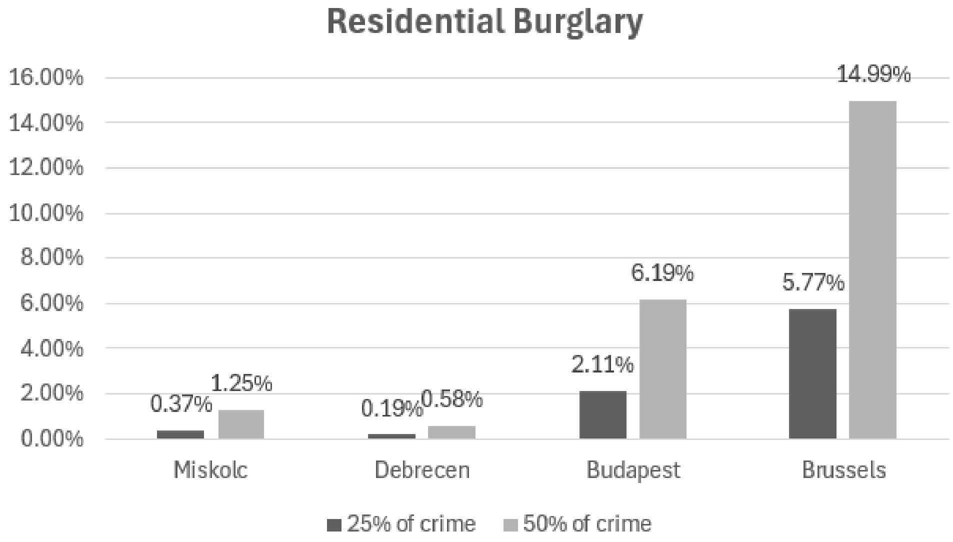

Figure 17: Percentage of grid cells responsible for 25% and 50% of residential burglary in Brussels and Hungary

Figures 16 and 17 compare the cumulative percentage hypotheses for 25% and 50% of crime incidents in Brussels, Budapest, Debrecen, and Miskolc, using 200 × 200 meters grid cells. The Budapest data covers the period 2013–2016, while the Brussels data covers 2007–2016.

Looking at battery and residential burglary, the figures show that both crime types are highly concentrated in all four cities, but the degree of concentration differs. Based on the cumulative percentage values, crime is more concentrated in Budapest than in Brussels for both categories, because Brussels reaches 25% and 50% of crime with a smaller share of grid cells. The two smaller Hungarian cities show the strongest concentration overall, especially Debrecen.

For battery, 0.22% of grid cells account for 25% of incidents in Miskolc, and 0.08% in Debrecen. In Budapest, the value is 0.87%, while in Brussels it is 1.61%. For 50% of battery incidents, the values are 0.71% in Miskolc, 0.36% in Debrecen, 3.17% in Budapest, and 6.35% in Brussels. Overall, this shows very strong concentration in the two smaller Hungarian cities, and lower concentration in the two capitals.

For residential burglary, the same broad pattern appears. For 25% of incidents, 0.37% of grid cells account for that share in Miskolc and 0.19% in Debrecen, compared to 2.11%

in Budapest and 5.77% in Brussels. For 50%, the values are 1.25% in Miskolc, 0.58% in Debrecen, 6.19% in Budapest, and 14.99% in Brussels.

Across all four cities, battery is more concentrated than residential burglary, meaning that a smaller share of grid cells accounts for the same share of crime. Overall, the results suggest that the two smaller Hungarian cities show the highest concentration, while both capitals show lower concentration levels. At the same time, Brussels shows higher values than Budapest for both crime types in this comparison. This may partly reflect differences in the time period covered and in how crime is recorded and classified.

5.2. Lorenz Curve

This chapter presents the Lorenz curves for each category across the three cities, to visualize how crime is distributed across the micro places. The curves plot the cumulative percentage of places on the horizontal axis against the cumulative percentage of crime on the vertical axis, after ordering places by the number of incidents. The diagonal 45 degrees line represents a situation of perfect equality, meaning that crime would be evenly spread across all places. The more a curve deviates from this diagonal and rises steeply at the beginning, the more crime is concentrated in a small share of places (Khalfa et al., 2023).

It is also important to note that all numeric values reported from the Lorenz curves are taken from the underlying cumulative distribution table (cumulative % of places and cumulative % of crime) used to plot each curve, rather than being estimated visually from the figures themselves.

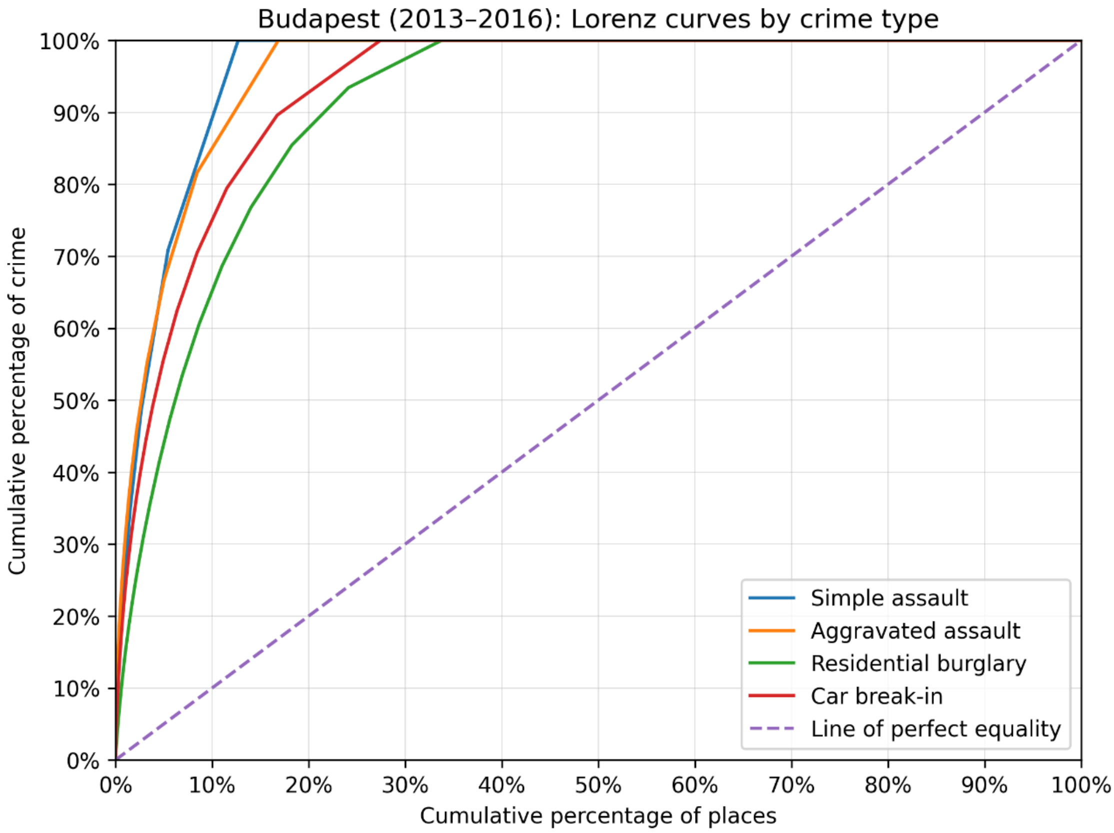

Figure 18: Lorenz curves for all four crime types in Budapest for the period 2013-2016

Figure 18 presents the Lorenz curves for Budapest for the period of 2013–2016 for simple assault, aggravated assault, residential burglary and car break-in. The curves show that all four crime types are concentrated, but they differ in how strongly they concentrate between different crime types. Overall, simple assault and aggravated assault show the highest concentration, as their curves rise steeply at the beginning. Residential burglary is the least concentrated category, as its curve remains closer to the line of perfect equality for a longer part of the x-axis, meaning that more places are needed to account for the same cumulative proportion of crime.

To illustrate this numerically, in Budapest around 0.91% of places account for 25% of simple assaults, and around 2.84% account for 50% of simple assaults. For aggravated assault, around 0.68% of places account for 25%, and around 2.67% account for 50%. For car break-in, around 1.11% of places account for 25%, and around 4.00% account for 50%. Finally, residential burglary reaches 25% within around 2.11% of places and 50% within around 6.19% of all places. These values confirm what is visible in Figure 18, mainly that both assault types show the highest concentration, while residential burglary is the category with the least concentrated.

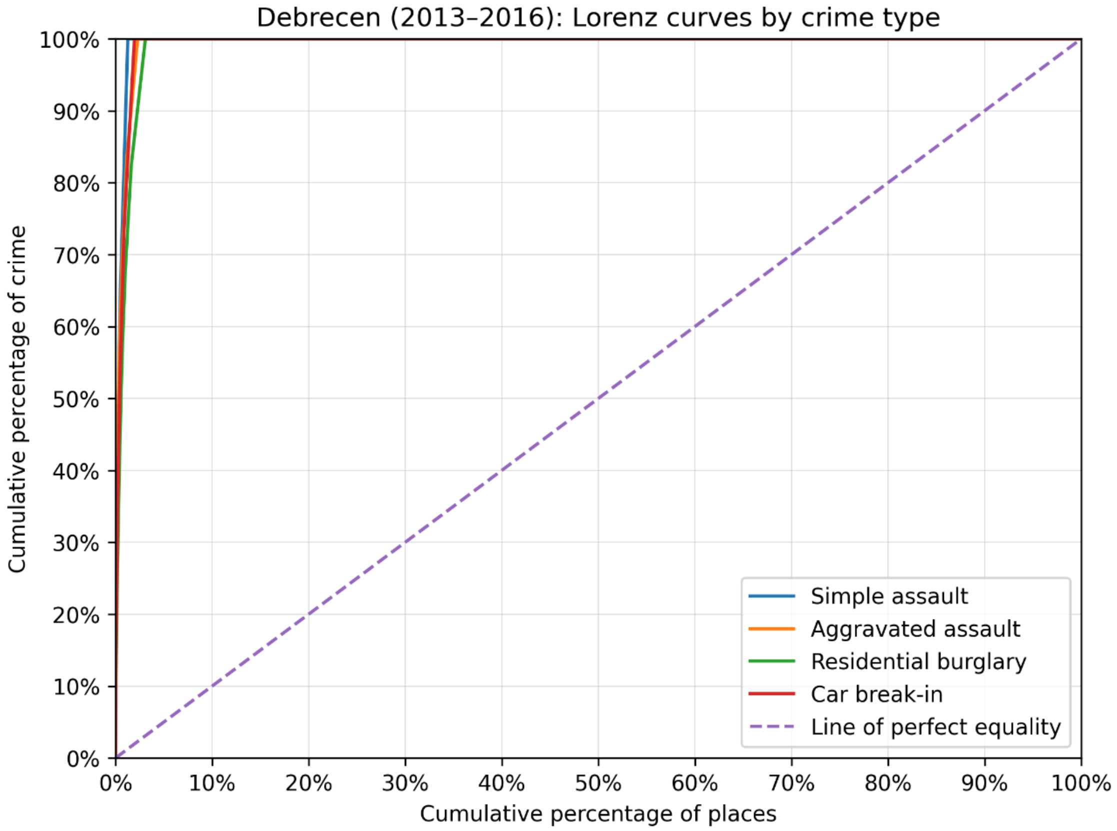

Figure 19: Lorenz curves for all four crime types in Debrecen for the period 2013-2016

Figure 19 presents the Lorenz curves for Debrecen for the period of 2013–2016 for all four categories. In Debrecen, all curves are extremely close to the left edge of the figure, which means that crime is highly concentrated and that most differences between crime types happen in the very first part of the x-axis. In other words, a very small proportion of grid cells already accounts for a very large proportion of crime. This creates a visibility problem when the full 100% range of the x-axis is shown, because almost the entire curve is concentrated into the first few percent of places.

For this reason, Figure 20 shows a second version for Debrecen with a zoomed x-axis, where only 0–10% cumulative percentage of places is visualized. This zoom makes the curves readable and allows comparison between crime types in the part of the distribution where the concentration occurs.

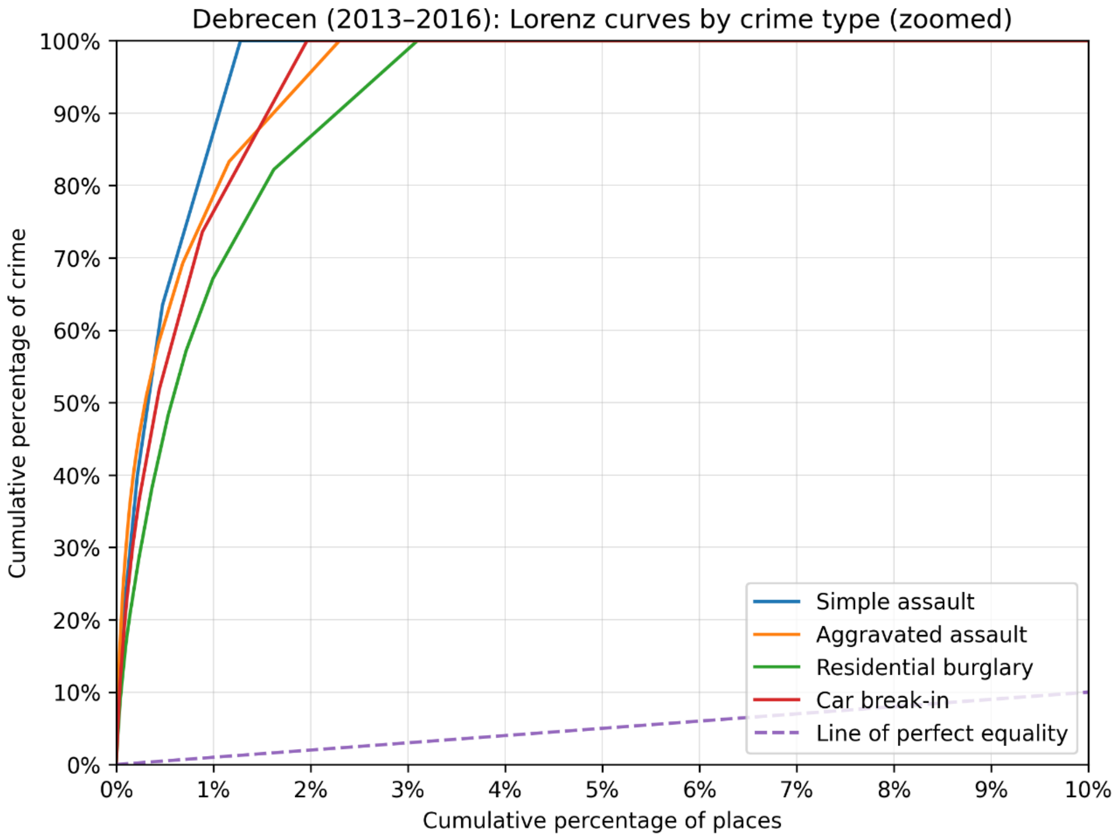

Figure 20: Lorenz curves for all four crime types in Debrecen with 0-10% zoom on the x-axis (2013-2016)

To describe this high concentration numerically, in Debrecen around 0.11% of places account for 25% of simple assaults, and around 0.33% account for 50% of simple assaults. For aggravated assault, around 0.07% of places account for 25%, and around 0.30% account for 50%. For car break-in, around 0.13% of places account for 25%, and around 0.42% account for 50%. Finally, residential burglary reaches 25% within around 0.19% of places and 50% within around 0.57% of all places. This very high concentration of crime explains why the curves rise steeply and reach high cumulative percentages of crime within only a very small percentage of places. Similar to Budapest, simple assault shows the highest concentration while residential burglary shows the lowest concentration of all four crime types in Debrecen.

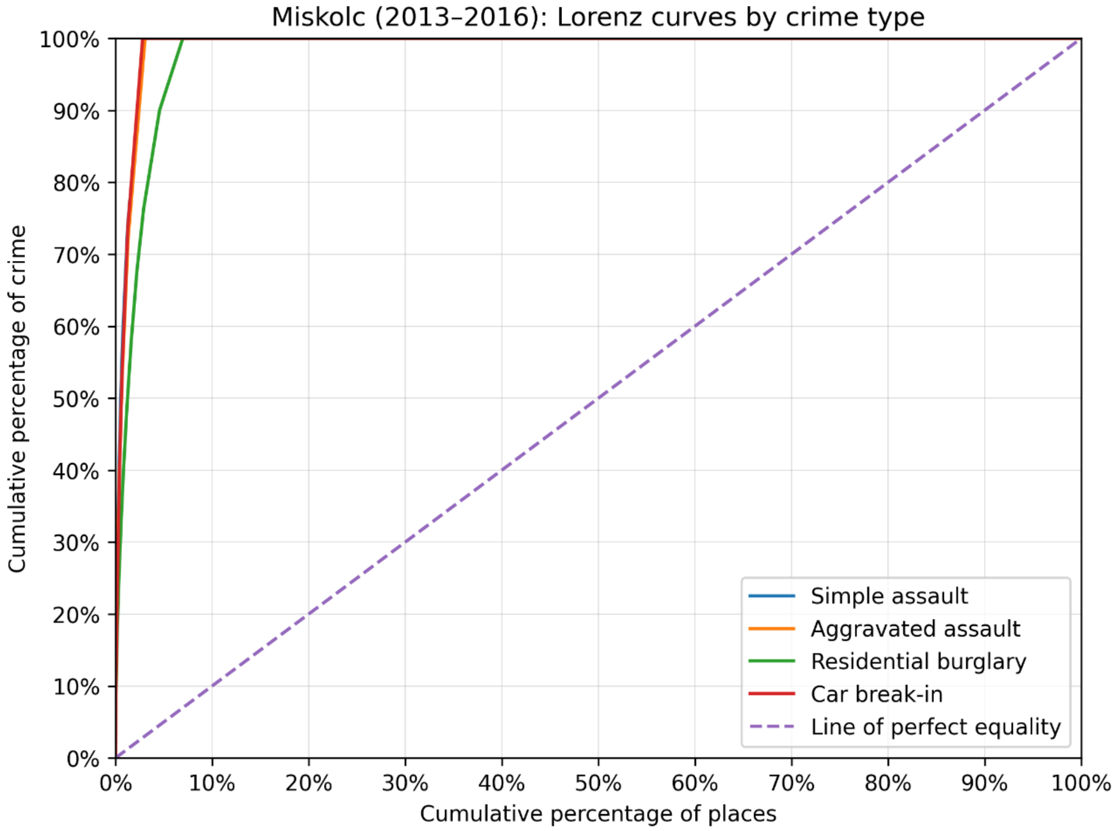

Figure 21: Lorenz curves for all four crime types in Miskolc for the period 2013-2016

The Lorenz curves for Miskolc present a similar issue to those for Debrecen. Figure 21 becomes difficult to read on its standard scale, because the curves rise very steeply at the beginning and several curves overlap. This overlap indicates that some crime categories have very similar concentration patterns and therefore follow almost the same cumulative distribution.

Therefore, like for Debrecen, a second figure for Miskolc with a zoomed x-axis, where only 0–10% cumulative percentage of places is visualized in Figure 22. This figure makes it possible to visually compare the Lorenz curves for Miskolc and discuss differences between the categories in the relevant part of the distribution.

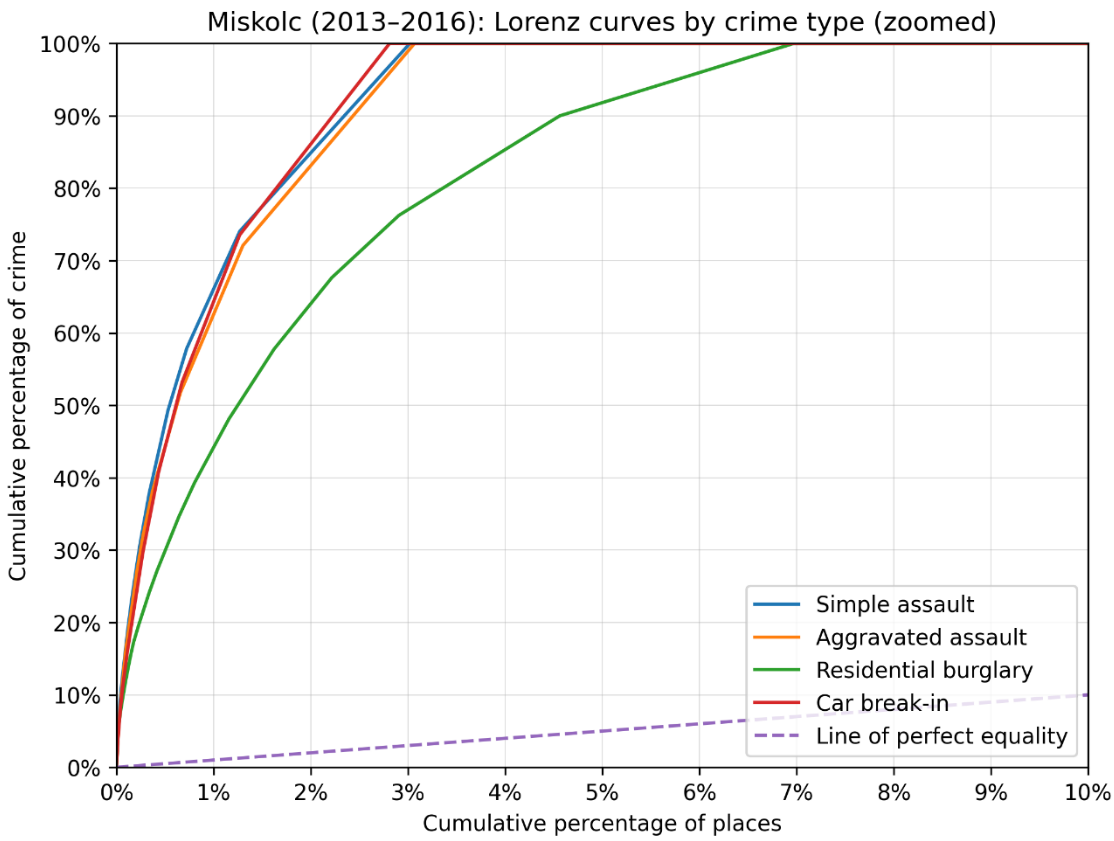

Figure 22: Lorenz curves for all four crime types in Miskolc with 0-10% zoom on the x-axis (2013-2016)

To describe this high concentration numerically, in Miskolc around 0.18% of places account for 25% of simple assaults, and around 0.55% account for 50% of simple assaults. For aggravated assault, around 0.19% of places account for 25%, and around 0.63% account for 50%. For car break-in, around 0.22% of places account for 25%, and around 0.63% account for 50%. Finally, residential burglary reaches 25% within around 0.37% of places and 50% within around 1.25% of all places. This very high concentration of crime explains why the curves rise steeply and reach high cumulative percentages of crime within only a very small percentage of places. This very high concentration of crime explains again why the curves rise steeply and reach high cumulative percentages of crime within only a very small percentage of places. Overall, these values are very close to Debrecen. In Miskolc, residential burglary is clearly the least concentrated category, while simple assault, aggravated assault and car break-in show very similar and highly concentrated patterns.

Overall, the Lorenz curves show that crime is highly concentrated across micro places in all three cities and across all four crime types. A consistent pattern across the cities is that residential burglary is the least concentrated category, meaning that a larger percentage of places are needed to account for the same cumulative proportion of crime. In contrast, the two assault categories show high concentration in all cities and reach high cumulative percentages of crime within a very small percentage of places. Comparing the cities, the two smaller cities, Debrecen and Miskolc, show an overall higher concentration than Budapest, as the curves rise more steeply and reach 25% and 50% of crime within an even smaller percentage of places.

5.3. Gini Coefficient

While the Lorenz curves provide a visual description of concentration, the Gini coefficient summarizes the same information in one value. In this thesis, G is reported as the standard Gini coefficient derived from the Lorenz curve. Higher values indicate higher concentration, meaning that fewer places account for more crime, while lower values indicate a wider distribution across places.

In addition to G, this thesis also reports the generalized Gini coefficient G′. This is important because for some crime types the number of places (200 × 200 meters grid cells) is larger than the number of incidents. In this situation, perfect equality is not achievable because many places must have zero incidents. The generalized Gini adjusts for this “more places than crimes” situation and therefore provides a more conservative concentration measure for comparisons (Bernasco and Steenbeek, 2017; Khalfa et al., 2023). For transparency and comparability with earlier LoCC studies, both G and G′ are presented, but G′ is used as the main measure for comparisons, because it is less sensitive to the “more places than crimes” situation.

In this section, G and G′ are reported for all three cities an each of the four categories for the study period of 2013–2016. Changes over time and spatial stability are examined separately in the SPPT analysis.

Table 9: Gini coefficients by city and crime type for the period of 2013–2016

City	Crime type	Incidents (c)	Places (n)	G	G′
Budapest	Simple assault	3,392	13,610	0.919	0.675
Budapest	Aggravated assault	6,232	13,610	0.912	0.807
Budapest	Car break-in	13,987	13,610	0.869	0.869
Budapest	Residential burglary	19,969	13,610	0.824	0.824
Debrecen	Simple assault	263	11,971	0.991	0.603
Debrecen	Aggravated assault	814	11,971	0.989	0.836
Debrecen	Car break-in	488	11,971	0.988	0.703
Debrecen	Residential burglary	994	11,971	0.983	0.793
Miskolc	Simple assault	420	6,224	0.983	0.742
Miskolc	Aggravated assault	394	6,224	0.981	0.705
Miskolc	Car break-in	363	6,224	0.982	0.698
Miskolc	Residential burglary	1,499	6,224	0.963	0.848

For Budapest, the generalized Gini coefficient G′ indicates high concentration across all four crime types, with values ranging from 0.675 to 0.869. Simple assault has the lowest G′ with a value of 0.675, while car break-in shows the highest G′ with a value of 0.869. Aggravated assault also shows a high level of concentration with a value of 0.807, and residential burglary is somewhat less concentrated compared to the other categories where G′ has a value of 0.824. In general, higher G′ values indicate a higher concentration, meaning that fewer places account for more crime, while lower values indicate a wider distribution across all places. These values confirm that all four categories are concentrated, but they also show that the comparison between cities becomes more nuanced once the generalized Gini coefficient is used.

In Debrecen, the generalized Gini coefficients remain high across all four crime types, ranging from 0.603 to 0.836, which confirms the very steep Lorenz curves. Simple assault has the lowest G′ with a value of 0.603, while aggravated assault shows the highest concentration, where G′ has a value of 0.836. Residential burglary is also highly concentrated with a G′ value of 0.793, and car break-in shows similarly high concentration with G′ being 0.703. Overall, the Debrecen results indicate that a very small number of grid cells accounts for a large number of crimes, which is consistent with the need to use a zoomed Lorenz curve to make differences visible.

Miskolc shows a similar pattern to Debrecen, with generalized Gini values between 0.698 and 0.848, again indicating high concentration across all categories. Car break-in has the lowest G′ with a value of 0.698, while residential burglary shows the highest concentration with G′ being 0.848. Simple assault and aggravated assault fall in between and are close to each other with G′ being 0.742 for simple assault and 0.705 for aggravated assault. Overall, the G′ values show that crime is highly concentrated in a small number of places, which matches the Lorenz curve results and explains why the Lorenz curve became difficult to read on its standard scale, without a proper zoom on the x-axis.

Overall, Table 9 shows that the interpretation of cross-city differences changes once the generalized Gini coefficient G′ is used as the main comparative measure. The standard G values suggest a stronger concentration in Debrecen and Miskolc across nearly all categories, but this pattern is influenced by the "more places than crimes" situation, especially in categories with only a few hundred incidents distributed across thousands of grid cells. Because G′ adjusts to this problem, it provides a clearer and more comparable picture. On this basis, Budapest can no longer be described as generally less concentrated than the two smaller cities. Instead, the pattern is more mixed across crime types: Budapest shows the highest concentration for car break-in, Miskolc shows the highest concentration for residential burglary, and Debrecen shows the highest concentration for aggravated assault, while simple assault does not show a consistent pattern of Budapest being the least concentrated city. This highlights an important limitation of the previous analyses. The cumulative percentage results and the visual impression from the Lorenz curves remain useful for describing concentration, but they can overstate differences across cities when many grid cells record zero incidents. Therefore, for the comparison between Budapest, Debrecen and Miskolc, the generalized Gini coefficient provides the clearest measure for interpretation.

5.4. Spatial Point Pattern Test

This chapter presents the results from calculating the Spatial Point Pattern Test, to examine the spatial stability of crime concentrations in all three cities between 2013 as base year and 2016 as test year. The SPPT evaluates whether the spatial pattern of crime across grid cells remains similar over time. To summarize the results, this chapter reports the global S-index and the robust global S-index. Because grid-based crime data contains many cells with zero incidents in both years, the robust global S-index is used here as the more informative measure for interpretation, as it places more emphasis on the crime-relevant parts of the spatial distribution.

Table 10: Spatial Point Pattern Test summary for Budapest, Debrecen and Miskolc (2013 vs 2016)

City	Crime type	Global S-index	Robust global S-index	Non-zero cells	Total cells	Non-zero %
Budapest	Simple assault	0.97	0.59	1089.00	13610.00	8.00
Budapest	Aggravated assault	0.95	0.55	1536.00	13610.00	11.29
Budapest	Car break-in	0.90	0.48	2662.00	13610.00	19.56
Budapest	Residential burglary	0.87	0.50	3503.00	13610.00	25.74
Debrecen	Simple assault	1.00	0.52	96.00	11971.00	0.80
Debrecen	Aggravated assault	0.99	0.56	197.00	11971.00	1.65
Debrecen	Car break-in	0.99	0.51	152.00	11971.00	1.27
Debrecen	Residential burglary	0.99	0.42	228.00	11971.00	1.90
Miskolc	Simple assault	0.99	0.45	119.00	6224.00	1.91
Miskolc	Aggravated assault	0.99	0.51	137.00	6224.00	2.20
Miskolc	Car break-in	0.99	0.41	102.00	6224.00	1.64
Miskolc	Residential burglary	0.97	0.44	301.00	6224.00	4.84

Table 10 presents the SPPT summary values for all cities and crime types: the global S-index, the robust global S-index, and the number of non-zero cells in relation to the total number of grid cells. The global S-index summarizes overall similarity between 2013 and 2016 across all grid cells. In grid-based crime data, many cells often have zero incidents in both years, which can push global similarity upward, especially in smaller cities or for rarer crime types. The robust global S-index places more emphasis on the informative parts of the distribution, namely the cells where crime is actually present, which makes it more useful when comparing crime types and cities with many zero cells.

Budapest shows high overall similarity between 2013 and 2016 across all four crime types, but the degree of stability differs depending on the offence category. Global S-index values are high across all four categories, indicating that the overall spatial structure is relatively stable over time. At the same time, the robust S-index values are noticeably lower, which suggests that the most relevant crime locations show moderate stability rather than perfect stability. Across the four Budapest categories, simple assault has the highest robust stability, followed by aggravated assault. In contrast, car break-in and residential burglary show lower robust stability, suggesting that the distribution of these crimes across the crime-relevant grid cells shifted more strongly between 2013 and 2016. Looking at the spatial distribution, the observed local changes are not evenly distributed across the city but occur in specific parts of Budapest rather than across the city as a whole. Overall, Budapest remains spatially stable between 2013 and 2016, but property crimes show more spatial change than assault categories.

Debrecen shows very high global S-index values across all four crime types. This indicates that the overall spatial pattern between 2013 and 2016 is highly similar when considering the full grid. However, the robust S-index values are clearly lower than the global values, which indicates that even though the general structure looks stable, there is still meaningful change in the cells where crime actually occurs. Compared to Budapest, Debrecen's results also reflect the fact that crime is distributed across far fewer active grid cells. Looking across crime types, aggravated assault shows the highest robust stability in Debrecen, while residential burglary shows the lowest robust stability. This means that residential burglary looks stable in general but shifts more across the active grid cells. From a spatial perspective, the local changes are limited and mainly concentrated in the city-center area rather than across the whole grid. Overall, Debrecen shows a pattern of very high aggregate stability, combined with moderate shifts in a small number of locations.

Miskolc also shows very high global S-index values for all four crime types, indicating strong overall similarity in the spatial pattern between 2013 and 2016. As in Debrecen, the robust S-index values are lower, highlighting that stability is not uniform when focusing only on the crime-relevant cells. There are also clear differences between crime types. Aggravated assault has the highest robust stability, while car break-in shows the lowest robust stability. Residential burglary also shows relatively low robust stability compared to the assault categories, consistent with the idea that property crimes are more likely to shift spatially across time. In spatial terms, the statistically meaningful local changes are concentrated in limited parts of the city rather than spread evenly across the urban area. Overall, the spatial pattern in Miskolc remains largely stable, but some parts of the crime distribution changed between 2013 and 2016, depending on the crime type.

When comparing the results across all cities and crime types, a clear pattern emerges from Table 10. Global S-indices are high in all three cities, indicating that the overall spatial structure of crime across grid cells is broadly stable from 2013 to 2016. Robust S-indices are consistently lower than global S-indices, showing that stability is weaker once attention is restricted to crime-relevant cells. This is particularly important for interpretation in cities with many zero cells. Budapest shows the strongest indication of local change within the crime-relevant grid cells, which is consistent with the fact that Budapest has a much larger number of active grid cells and greater spatial complexity overall. In both smaller cities, Debrecen and Miskolc, the overall pattern also remains stable, but the robust S-index still shows that meaningful changes occur within the subset of cells where crime is present. Across cities, assault categories tend to be more stable than property crimes, while residential burglary and car break-in generally show lower robust stability, indicating that property crimes are more likely to shift spatially across time.

In general, these SPPT results support the interpretation that crime in the three Hungarian cities is not only concentrated in micro-places, but that these concentrations also show substantial stability over time, especially at the city-wide level. At the same time, the robust global S-index shows that some parts of the pattern do shift, and that these shifts vary by crime type and by city.

6. Discussion

This thesis examines whether the law of crime concentration at place can also be observed in a Central European setting using 200 × 200 meters grid cells as the unit of analysis. Overall, the results support this assumption. Across Budapest, Debrecen, and Miskolc, crime is clearly concentrated in a small share of grid cells, which is consistent with the general idea of the law of crime concentration at place. At the same time, the results also show that concentration and stability are not identical across all cities and all crime types.

The first research question asked to what extent crime is concentrated in a small number of grid cells in each city. The results show that crime is strongly concentrated in a small number of grid cells in all three cities. The cumulative percentage results, Lorenz curves, and Gini measures all show a similar pattern: a small percentage of grid cells accounts for a large percentage of crime. This means that the micro-place perspective is also useful in the Hungarian case studies and that crime is not distributed evenly across urban space.

The second research question asked how concentration patterns differ between Budapest and the two smaller cities. The results show that differences do exist, but they should be interpreted carefully. Budapest has a broader crime footprint, with criminal offenses being recorded in a larger number of grid cells. Debrecen and Miskolc, in contrast, show fewer active grid cells. However, once the generalized Gini coefficient is taken as the main comparative measure, Budapest cannot simply be described as less concentrated than the two smaller cities. The generalized Gini results show a more nuanced picture in which concentration differs by crime type rather than following one simple pattern by city size. Therefore, the smaller cities should not simply be described as showing stronger concentration. Instead, the smaller cities have fewer active grid cells, while the degree of concentration still differs depending on the crime type and the measure used. In that sense, comparing three cities within the same country using the same grid is useful, because it shows that differences can still appear even when the data source and measurement approach are the same.

The third research question focused on differences between crime categories. Here, the results show that concentration varies clearly by crime type, but not always in the same way across all measures. In the cumulative percentage and Lorenz-curve results, the assault categories tend to appear more concentrated, while residential burglary appears less concentrated. However, the generalized Gini results show a more differentiated picture. In Budapest, car break-in has the highest G′ value, while in Miskolc residential burglary has the highest G′ value. This shows that the interpretation depends on the measure used and that conclusions about relative concentration should be based primarily on G′, because it adjusts for the "more places than crimes" situation. Overall, the findings confirm that crime types do not concentrate in the same way and that concentration patterns are not fully consistent across all four categories and all three cities.

The fourth research question addressed spatial stability over time. The SPPT results show high similarity between 2013 and 2016 across all three cities, especially when looking at the global S-index. At the same time, the robust S-index shows that stability is weaker once the analysis is limited to grid cells where crime is actually present. This is important because grid-based analyses include many cells with zero incidents in both years, which can make stability look higher. Budapest shows more change within the crime-relevant grid cells, which is consistent with the fact that it has more active places overall. In Debrecen and Miskolc, high global stability is partly influenced by large crime-free areas, while the robust index gives a clearer estimate of stability among crime-relevant places. Across crime types, assault categories appear more stable than property crimes. Local change should therefore only be interpreted in general terms and not at the level of individual grid cells.

The fifth research question asked how the Hungarian findings compare to the wider LoCC literature, especially grid-based European studies such as Brussels. The results are in line with earlier work showing strong micro-place concentration and substantial spatial stability. At the same time, the thesis also supports the value of a grid-based approach in European urban settings, where street segments are often less comparable because of differences in street structure and street-segment length. The Hungarian case studies therefore add further European evidence to the LoCC literature and show that the main pattern of concentration can also be identified outside the US context using a comparable grid-based approach.

Overall, the discussion shows that the law of crime concentration at place is supported in the three Hungarian cities, but also that the exact degree of concentration and stability depends on the crime type, the city context, and the measure used for interpretation. This is especially important for comparisons across cities, where the generalized Gini coefficient and the robust SPPT results provide the most informative basis for interpretation.

7. Conclusion

This thesis examined whether Weisburd's "law of crime concentration at place" can be observed in a Central European setting. Police-registered, geocoded crime incidents were analyzed for three Hungarian cities (Budapest, Debrecen, and Miskolc) using a uniform 200 × 200 meters grid as the micro-unit of analysis. The study period covered 2013–2016 and focused on four crime categories: simple assault, aggravated assault, residential burglary, and car break-in. Crime concentration was measured using cumulative percentage hypotheses, Lorenz curves, and Gini-based indicators, including the generalized Gini coefficient. Spatial stability over time was examined using the Spatial Point Pattern Test (SPPT) by comparing 2013 with 2016.

Overall, the results show that crime is highly concentrated at micro-places in all three cities. Across the different measures, a small percentage of grid cells account for a large percentage of crime incidents. This supports the main idea of the law of crime concentration at place in the Hungarian case studies and shows that a grid-based approach can capture micro-place concentration in European cities without relying on street segments.

The results also show that concentration is not identical across cities and crime types. Budapest has a broader spatial footprint of crime, with more grid cells recording incidents, while Debrecen and Miskolc have fewer active grid cells. At the same time, the generalized Gini results show that Budapest cannot simply be described as less concentrated than the two smaller cities. Instead, the comparison becomes more nuanced once the "more places than crimes" situation is considered, and the degree of concentration differs depending on the crime type and the measure used.

Differences between crime categories are also clear, but they are not identical across all measures. The cumulative percentage results and Lorenz curves suggest that the assault categories are more concentrated, while residential burglary appears less concentrated. However, the generalized Gini coefficient shows a more nuanced picture, in which the highest concentration differs by crime type and city. This means that different crimes do not concentrate in the same way and that conclusions about relative concentration should be based primarily on the generalized Gini coefficient.

The SPPT results add the time dimension to the analysis. They show that the spatial patterns of crime are largely stable between 2013 and 2016 in all three cities. At the same time, the robust S-index shows that this stability is weaker when the analysis is limited to grid cells where crime actually occurs. This is important, especially in grid-based data with many zero cells, because such cells increase measured stability. Budapest shows more change within the crime-relevant grid cells, while Debrecen and Miskolc remain highly stable overall. Across crime types, assault categories tend to be more stable than property crimes.

The Hungarian case studies are in line with earlier work in showing strong micro-place concentration and substantial spatial stability. At the same time, this thesis adds further European evidence by applying a comparable grid-based approach in three cities with different urban characteristics. Overall, the findings support the applicability of the law of crime concentration at place in a Hungarian setting and show that grid cells provide a suitable micro-geographic unit for studying crime concentration in European cities.

Despite limitations related to the study period, the selected crime categories, and the reliance on police-registered incidents, this thesis contributes to the growing European evidence that crime is highly concentrated at micro-places and that the LoCC framework is applicable beyond the US context.

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List of Resources

In accordance with the guidelines on independence and transparency in academic work, the following overview lists all artificial intelligence–based tools and resources used during the research process. The table indicates the specific purposes for which these tools were employed and explains how their outputs were incorporated into this thesis.

Tool	Intended Purpose	Affected Sections	Examples of Use
DeepL (DeepL SE)	Linguistic refinement and improvement of written expression	Phrasing, sentence structure, and clarity	Suggestions were carefully reviewed and selectively adopted
ChatGPT (OpenAI)	Assistance with phrasing and text structuring	Spelling and grammar checks, reformulation of sentences, and improvement of readability	Suggestions were reviewed, revised, and critically evaluated

All substantive findings, analyses, and evaluations are based on the author's own work and were developed independently. Artificial intelligence was not used to generate academic content or to complete tasks autonomously. Rather, it served solely as a supporting tool for linguistic refinement throughout the research process.

Eidesstattliche Erklärung

Ich versichere:

- dass ich die Masterarbeit selbstständig verfasst, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt und mich auch sonst keiner unerlaubten Hilfe bedient habe.
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