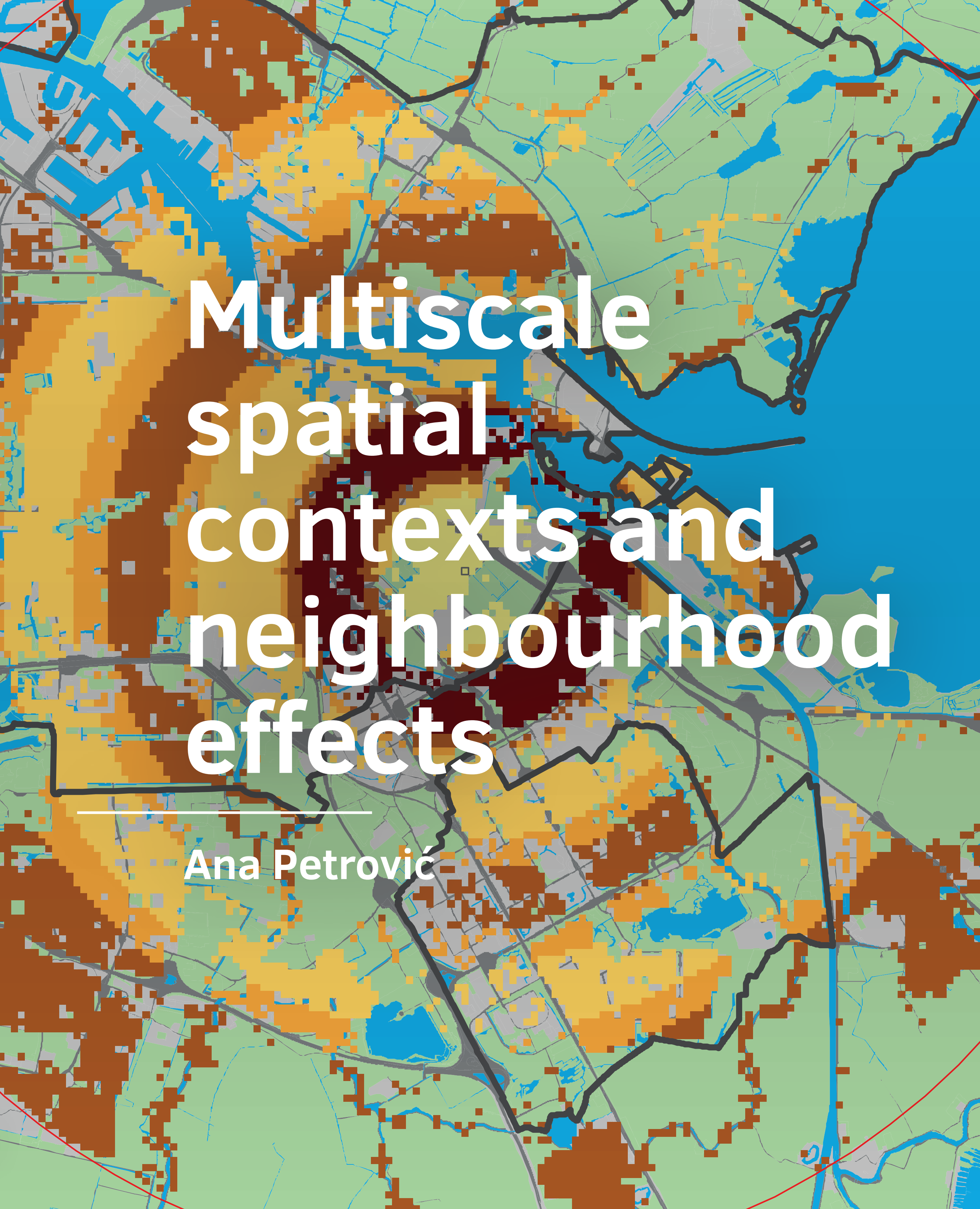

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Multiscale spatial contexts and neighbourhood effects

Dissertation

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by the authority of the Rector Magnificus, prof. dr. ir. T.H.J.J. van der Hagen,
chair of the Board for Doctorates
to be defended publicly on
Tuesday, 15 September 2020 at 10:00 o'clock

by

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TOC

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TOC

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Contents

List of Tables

List of Figures

Summary

This thesis has developed alternative methods of operationalising neighbourhoods at multiple spatial scales and used them to advance our understanding of spatial inequalities and neighbourhood effects. The underlying problem that motivated this thesis is that many empirical studies use predefined administrative units, and this does not often align with the underlying theory or geography. Despite the extensive literature on neighbourhood effects and, more generally, on sociospatial inequalities, spatial scale remains an under-analysed concept. As a response to this research gap, this thesis takes a multiscale approach to both theory and empirical analysis of neighbourhood effects, highlighting the multitude of spatial processes that may affect individual outcomes of people. To operationalise this, we created bespoke areas (centred around each location) at a range of one hundred scales representing people's residential contexts, primarily in the Netherlands but also in multiple European capitals. Using microgeographic data and a large number of scales combined with small distance increments revealed subtle changes in sociodemographic characteristics across space. In doing so, we provided new insights into ethnic segregation, potential exposures to poverty, and neighbourhood effects on income, all in light of the fundamental issue of spatial scale: The analyses of sociospatial inequalities are substantially affected by the scale used to operationalise spatial context, and this varies within and between cities and urban regions. The aim of this thesis was therefore not to find a single, 'true' scale of neighbourhood, but to acknowledge, operationalise, and better understand the multiplicity of spatial scales.

1 The problems of the 'neighbourhood' and its effects on people

Since the early 1990s, many scholars have debated a basic hypothesis of 'neighbourhood' or 'contextual' effects: namely, that the residential context has an independent effect on individuals over and above their personal and family characteristics. Although this claim is fundamentally supported by an already substantial literature (see, e.g., Dietz, 2002; Sampson et al., 2002; Chaix, 2009), the idea remains controversial due to inconclusive empirical evidence. Galster (2008) outlines six paramount obstacles to obtaining unbiased estimates of neighbourhood effects on individuals. First among them is defining the scale of a neighbourhood.

Regardless, most of the empirical research into spatial inequalities has used predefined administrative neighbourhoods, often at a single scale. However, social processes operate regardless of administrative boundaries (Manley et al., 2006; Jones et al., 2018). Hence, a critical point was the introduction of bespoke neighbourhoods (Johnston et al., 2000; Buck, 2001; MacAllister et al., 2001). Unlike administrative units with fixed boundaries, bespoke neighbourhoods are centred around each individual residential location (an exact address or a very small area). As the potentials of bespoke neighbourhoods have been recognised in the neighbourhood effects research, they have been increasingly used (Bolster et al., 2007; Andersson & Malmberg, 2014; Veldhuizen et al., 2015). However, they are still relatively uncommon within this large body of literature. Probably the most important reason behind this is the pragmatic approach of using administrative neighbourhoods for which data are normally collected and/or published, due to either limited access to alternative sources or focusing on other methodological challenges. Related to this, empirical literature on neighbourhood effects has thus far paid insufficient attention to the theoretical guidelines regarding the definition of neighbourhood, and many researchers and policy makers have assumed that the same type of administrative units (at the same spatial scale) equally well explains residential contexts in various places.

Despite the limited attention to the definition of neighbourhood in the empirical research on neighbourhood effects, social scientists have long been aware that the choice of spatial scale affects empirical analyses. Openshaw and Taylor (1979) formulated the modifiable areal unit problem (MAUP), which shows that statistical analysis can yield different results when the same spatial data form areas of different sizes or boundaries of spatial units are placed in different ways. Measuring the characteristics of residential context, such as deprivation and ethnic concentration, at various spatial scales is therefore crucial for understanding the causes and consequences of sociospatial inequalities. Ultimately, the lack of attention to the definition of a neighbourhood is one of the reasons why there is no consensus regarding the existence and the strength of neighbourhood effects.

2 Research aim and questions

The aim of this thesis is **to develop alternative methods of operationalising neighbourhoods at multiple spatial scales and use them to better understand spatial inequalities and neighbourhood effects**. To achieve this aim, this dissertation answered five research questions, in five chapters, each of which consists of a published paper or a paper manuscript. We first investigated what was lacking in the conceptualisation of neighbourhood, thus ensuring that the theoretical

TOC

approaches to people-space relations are implemented via appropriate spatial data (see Chapter 2). Secondly, the thesis asked how we could operationalise sociospatial contexts at multiple spatial scales to study potential exposure to contextual characteristics, such as ethnic compositions, in different geographical settings (see Chapter 3). As extension of the previous research question, we investigated how various dimensions of ethnic segregation varied over spatial scale in different European capitals (see Chapter 4). Applying the same core method when analysing another contextual characteristic relevant for individual outcomes, the following study asked how contextual poverty varied over spatial scale in different places – within and between municipalities in the Netherlands (see Chapter 5). Finally, the dissertation asked how contextual poverty at various spatial scales affected individual income in different urban regions in the Netherlands (see Chapter 6).

3 Data and methods

The fundamental data source for this thesis are the individual-level register data for the full population of the Netherlands, which we used in three studies (Chapters 3, 5 and 6). The registers contain sociodemographic characteristics of people, such as age, gender and education, and, crucially, the place of residence geocoded at 100m by 100m grid cells (Bakker, 2002). For Chapter 4, we used similar microgeographic data for seven European countries, which contained residents' ethnic origin, geocoded at the same spatial level as the Dutch register data – 100m by 100m grid cells. Unlike most of the literature, the research within this thesis therefore started from very small neighbourhoods, close to exact residential locations. We then aggregated the fine-grained spatial data and created bespoke areas, centred around each cell, at 100 different spatial scales, and thus increasingly overlapping. These scales form a *distance profile* with small increments in distance, which made it possible to look at space in a more continuous way, from micro to macro perspective.

Distance profiles containing the range of 101 scales appear in all empirical studies within this thesis, whereby each chapter adds its own methodological contribution. Chapter 3, where the method was first developed, also measures the scalar variability across the distance profiles using the entropy index (Shannon, 1948). Chapter 5 builds up by using a hierarchical measure of entropy, namely the Theil index (Theil, 1967), to measure both the scalar variability of distance profiles and the inequality between places at multiple spatial scales. In Chapter 6, we enriched the commonly used fixed effects models by combining them with our method of multiscale bespoke areas. The chapter also introduces the 'bespoke scale term' to take into account the increasingly overlapping areas in the neighbourhood effects models. Although using a different data source, Chapter 4 also applies the distance profiles – in calculating different dimensions of segregation, such as evenness and exposure, at the range of scales. With two defining features of our method – spatial scale and bespoke neighbourhoods, the thesis has a strong methodological focus, but it also contains the first empirical applications.

4 Summary of the research results

Delving into conceptual issues, Chapter 2, which was published in the journal *Progress in Human Geography*, postulated that the operationalisation of neighbourhoods should start from theory: Various effects of place on people occur because of a multitude of processes. To accommodate this variety of processes, spatial context needs to be operationalised at different scales, within and beyond predefined administrative neighbourhoods, depending on the mechanism under study, geographic setting and individual characteristics of people. To achieve this, two different strands of literature – firstly, the theoretical approaches to neighbourhood effects and, secondly, spatial data analysis – can and should be more tightly related. Increasingly available and detailed spatial data make it possible to operationalise various spatial contexts, revealing homogeneity and heterogeneity in space from the very local to regional scale.

One way of operationalising spatial context at a wide range of different scales was demonstrated in Chapter 3, published in the journal *Annals of the American Association of Geographers*, following the recommendation of Chapter 2 to conceptualise space more continuously. This means representing the residential location from the moment someone opens their 'front door' up to a large area of the city they may experience as they travel. These scales can be depicted in distance profiles, which was based on the idea of segregation profiles, introduced by Lee et al. (2008) and Reardon et al. (2008), but developed here in a more detailed scalar approach. This method was employed in all empirical studies within this dissertation. Chapter 3 developed the method using the example of the share of non-Western ethnic minorities, thus representing space as ethnic exposure surface and analysing ethnic fragmentation of three Dutch cities (Amsterdam, Utrecht, and Groningen). Using the range of spatial scales showed that people in these cities, particularly in Amsterdam, were potentially exposed to very different spatial contexts at multiple scales, notably – but not only – the smaller ones, depending on where they live within the city. A unique application of entropy – for measuring scalar variability of the distance profiles, demonstrated that some people have rather constant spatial contexts, while for others the context changes with the increasing distance from home.

The idea of comparing different places at multiple scales, introduced in Chapter 3, was further explored in the subsequent chapters. Specifically, Chapter 4 demonstrated that European capitals had very different levels of ethnic segregation for each of the studied dimensions (centralisation, evenness and exposure) and that for the latter two dimensions these levels varied with spatial scale, in different ways in different cities, and within these cities between their cores and hinterlands. While at one spatial scale one city appears to be more segregated than others, at another scale the relationships between cities may change. The highly segregated city may no longer be so, while the integrated city may become segregated, thus confirming that our assessment of segregation largely depends on the size of the areas we are considering. Unlike the majority of the segregation literature, we found that segregation does not necessarily decrease with spatial scale.

The following two chapters (5 and 6) applied the same method of multiscale measures of population, depicted as distance profiles, analysing – instead of ethnicity – contextual poverty (Chapter 5) and its effects on people (Chapter 6). Chapter 5 compared the levels of contextual poverty within and between Dutch municipalities, where *the context* involved multiple spatial units, so that the inequality became a multiscale as opposed to a mono-scale issue. Focussing on both bigger cities and smaller municipalities, the chapter revealed that the national inequality primarily came from the concentrations of poverty in areas of a few kilometres, located in cities. These cities have different spatial patters of contextual poverty, such as multicentre, core-periphery and east-west, while smaller municipalities have under-average levels of poverty in the national comparison. In addition to the inequality between municipalities, there are considerable within-municipality inequalities, particularly among micro-areas of a few hundred metres. In a bigger picture of the thesis, we can see that both Chapters 3 and 5 depicted distance profiles and measured their scalar variability using (hierarchical) entropy, but looking at two distinct contextual characteristics, namely the shares of non-Western (Chapter 3) and low-income people (Chapter 5). A comparison of these two chapters' results gives us insight and allows us to conclude that the share of low-income people in the Netherlands varies with spatial scale, but to a lesser extent than the share of non-Western people. Having distinct spatial patterns, these two characteristics should not automatically be considered to vary in the same way without further investigation.

Finally, the scales at which poverty concentrates, as found in Chapter 5, are not necessarily the scales at which the biggest neighbourhood effects occur. The very smallest spatial scale is not automatically the scale of the greatest effect, as has been often suggested by the majority of neighbourhood effects studies addressing the question of scale, but smaller spatial contexts *are* generally more strongly related to individual income than the larger ones. This was the main outcome identified in Chapter 6, which applied the multiscale measures of population in modelling the effects of contextual poverty on individual income. Considering all urban regions in the Netherlands combined, as well as four distinct regions of Amsterdam, Rotterdam, Utrecht, and Groningen, resulted in scale- and place-specific estimates of contextual effects. Analysing a wide range of scales, the study revealed methodological issues of representing neighbourhoods as inappropriate, particularly too large spatial units. The most important one is the deterministic relationship between the variance in urban structure and the estimated contextual effects across spatial scale, in the absence of theory.

5 Synthesis of the results, and lessons learned

So, what are the lessons learned from this thesis? Spatial scale is a defining parameter of inequalities within and between places and their effects on people: Cities are unequal not only as a whole, but also because they have smaller and bigger neighbourhoods that stand out. And within these cities and neighbourhoods, there are micro-spaces that have even more extreme characteristics – concentrations of different ethnic or socioeconomic groups. The spatial context of people encompasses everything from this micro-scale to the city or regional one, including the way these scales are connected – from uniformity to gradual or abrupt changes across space. Living in a specific place may affect individual socioeconomic status, but the magnitude of this relationship changes when we consider spatial contexts at different scales.

In line with the existing literature, we found fewer sociospatial inequalities and weaker (mostly negative) neighbourhood effects on income in our study areas – which mainly comprised the Netherlands but also included seven European capitals – than similar studies have found in the North-American context (see Friedrichs et al., 2005; Van Ham et al., 2012). However, we found substantial variation between and within places, particularly at smaller spatial scales, where the spatial inequalities and contextual effects are generally the greatest. Despite the immense importance of the micro-contexts, causality does not necessarily occur at the lowest scale and work backwards, but instead runs in different directions (Sheppard & McMaster, 2004). In this regard, our study showed a few unexpected findings, which challenge the existing literature. Specifically, we found that neighbourhood effects were not strongest at the very smallest spatial scale, which is rarely found in the studies comparing different scales (for an exception, see Buck, 2001). We also found that segregation did not necessarily decrease with spatial scale, which is in line with Johnston et al. (2016), but not with the majority of the segregation literature. We can therefore conclude that spatial processes work in all directions across scale.

Theoretical and conceptual contributions

From the above, three theoretical and conceptual strands, as well as three methodological ones can be derived as main contributions of this dissertation:

1 The neighbourhood effects literature needs an *integrative theoretical approach* that explicitly connects the variety of spatial processes relevant for individual outcomes with corresponding scales (see Chapter 2). The theoretical approach should also include the question how spatial processes develop across space and what are the relations between different scales. For example, the concept of distance decay can be used to operationalise diminishing potential exposure and interaction across space (see Chapter 6).

2 If we accept that there are a multitude of processes, then it becomes more appropriate to describe them using the term *'spatial contextual effects'* than *'neighbourhood effects'*. The majority of literature uses 'neighbourhood effects' inconsistently referring to very different spatial contexts, which may be relevant, but they need to be adequately termed: One person belongs to spatial contexts at multiple scales, which have different roles for their residents.

3 Because of the multiscale nature of neighbourhood, neighbourhood effects literature needs a *multiscale approach*, which takes into account different types of contexts that people are exposed to, within and beyond their officially defined neighbourhood, and which is also be place-dependent, taking into account different geographic settings.

Methodological contributions

1 The multiscale approach makes it possible to better understand the modifiable areal unit problem (MAUP). The 'modifiable areal units' were not treated as a problem for this study, but a resource, as put by Manley et al. (2006). In this study, different scales are integral parts of a distance profile, so that they all give an opportunity to explain *how* contextual characteristics transform across space.

2 By quantifying the scalar variability, we in fact describe different types of spatial contexts, which are relatively uniform for some people, while others are potentially exposed to very different contexts at various distances around their home, including abrupt changes – social cliffs (see Chapter 3). In this thesis, entropy measures the inequality within and between places at multiple scales, which is a hierarchical and multiscale use of entropy; it also measures the inequality *across* scales starting from one specific location, which is a cross-scale use of entropy.

3 Variability in urban structures is a major methodological issue with regression models related to spatial scale, which has a notable impact on the results in the absence of theory. In spatial data analysis, it is well known that aggregation implicitly means less variation (see, e.g. Haining, 2003; Manley, 2014). This is particularly dangerous when too large areas are used to represent neighbourhoods (Chetty & Hendren, 2018), as lower variability in urban structure may result in bigger spatial contextual effects. This dissertation should increase awareness of what kind of contexts (from neighbourhood to region) are actually operationalised with spatial units available in the data, which is important from the perspective of both scientific research and social policies.

6 Societal and scientific relevance of the thesis

Taking a multiscale approach in research is important, because different problems require different solutions at different spatial scales. It is thus at best misleading and at worst dangerous to use large areas as neighbourhoods, to which policy makers then attach conclusions, plans and designs aimed at small neighbourhoods. This pertains, for example, to the European Union policies on the integration of migrants, as well as to the national or regional policies on urban renewal or social mix. These policies do not necessarily require action in officially defined neighbourhoods, but sometimes in a wider spatial context. However, they may also need to start from micro-spaces, because people start to meet and interact with other people in the immediate surroundings of their homes, which may be very different from more distant parts of the city. In turn, this helps to determine how these people experience their neighbourhoods and cities; moreover, it can shape their attitudes towards others.

The research on neighbourhood effects is interdisciplinary, and researchers from different backgrounds should not focus exclusively on the field-specific concepts and methods. For example, we have suggested that methods from physical geography (see, e.g., Fisher et al., 2004) can also be used for studying the social attributes of space. Most importantly, spatial scale, and space in general, should be equally relevant for all researchers exploring neighbourhood effects, including those in economics, sociology and health studies. Our work should prompt researchers to use the existing findings more cautiously, to consider spatial scale more carefully, and to use more accurate terms when referring to different spatial contexts.

Based on the findings of this thesis, future research on segregation trends should start from the assumption that these trends may be different for different spatial scales. And the studies on contextual effects should assume that people are affected by various spatial contexts simultaneously. Accordingly, policy responses should be open for more flexible spatial definitions of neighbourhoods: Although important, neighbourhoods – as they are officially defined – are not always the most appropriate level of intervention. They are parts of larger urban systems, and, at the same time, they may contain many spatial inequalities within themselves, starting from the often overlooked micro-spaces. This dissertation does not suggest that all researchers need to consider this wide range of spatial scales. It does, however, suggest that the multiscale approach is a way to better understand sociospatial inequalities and neighbourhood effects, because different scales reveal different spatial processes. Place matters for individuals, but we need to carefully consider what we mean by place and in what way it might matter.

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Samenvatting

In dit proefschrift worden alternatieve methodes ontwikkeld voor de operationalisering van buurten op verschillende ruimtelijke schalen, die vervolgens worden gebruikt om ons inzicht te vergroten in ruimtelijke ongelijkheden en buurteffecten. Het onderliggende probleem dat de motivatie vormde voor dit proefschrift is dat veel empirische studies gebruik maken van vooraf gedefinieerde bestuurlijke eenheden, die vaak niet aansluiten op de onderliggende theorie of geografie. Ondanks de uitgebreide literatuur over buurteffecten, en sociaalruimtelijke ongelijkheden in meer algemene zin, blijft ruimtelijke schaal een onvoldoende geanalyseerd concept. Als reactie op deze lacune in het onderzoek wordt in dit proefschrift een meerschalige benadering gehanteerd van zowel de theorie als de empirische analyse van buurteffecten, met bijzondere aandacht voor de talrijke ruimtelijke processen die individuele uitkomsten voor mensen kunnen beïnvloeden. Om dat te operationaliseren hebben wij gebieden op maat gecreëerd (gecentreerd rond elke locatie) met een spectrum van honderd schalen die de wooncontexten van mensen vertegenwoordigen, met name in Nederland, maar ook in een aantal Europese hoofdsteden. Het gebruik van microgeografische gegevens en een groot aantal schalen in combinatie met kleine afstandsvergrotingen bracht subtiele veranderingen in sociaaldemografische kenmerken in de ruimte aan het licht. Op die manier hebben we nieuwe inzichten gekregen in etnische segregatie, potentiële blootstelling aan armoede en buurteffecten op het inkomen. Dit alles in het licht van de fundamentele kwestie met betrekking tot ruimtelijke schaal, namelijk het feit dat analyses van sociaalruimtelijke ongelijkheden substantieel worden beïnvloed door de schaal die wordt gehanteerd om de ruimtelijke context te operationaliseren, en dat deze zowel binnen als tussen steden en stedelijke gebieden verschillen. Het doel van dit proefschrift was dan ook niet om één ‘correcte’ schaal voor de buurt te vinden, maar om de veelheid aan ruimtelijke schalen te onderkennen, te operationaliseren en beter te begrijpen.

1 De problemen met de ‘buurt’ en de effecten daarvan op mensen

Sinds begin jaren negentig discussiëren talrijke academici over een basishypothese over ‘buurteffecten’ of ‘contextuele effecten’, namelijk dat de wooncontext een onafhankelijk effect zou hebben op individuele personen die verder gaat dan hun persoonlijke kenmerken en die van hun familie. Hoewel deze bewering fundamenteel

TOC

wordt ondersteund door een reeds omvangrijke literatuur (zie bijv., Dietz, 2002; Sampson et al., 2002; Chaix, 2009), blijft het een controversieel idee door een gebrek aan sluitend empirisch bewijs. In Galster (2008) worden zes belangrijke obstakels geïdentificeerd die het verkrijgen van onvertekende schattingen van buurteffecten op individuele personen in de weg staan. De eerste daarvan is de definitie van de schaal van een buurt.

Desondanks is bij het meeste empirische onderzoek naar ruimtelijke ongelijkheden gebruik gemaakt van vooraf gedefinieerde bestuurlijke buurten, vaak op één en dezelfde schaal. Sociale processen voltrekken zich echter onafhankelijk van bestuurlijke grenzen (Manley et al., 2006; Jones et al., 2018). Derhalve was de introductie van buurten op maat (Johnston et al., 2000; Buck, 2001; MacAllister et al., 2001) een kritiek punt. In tegenstelling tot bestuurlijke eenheden met vaste grenzen zijn buurten op maat gecentreerd rond individuele woonlocaties (d.w.z. een exact adres of zeer klein gebied). Aangezien de mogelijkheden van buurten op maat zijn onderkend binnen het onderzoek naar buurteffecten, worden deze steeds vaker gebruikt (Bolster et al., 2007; Andersson & Malmberg, 2014; Veldhuizen et al., 2015). Maar binnen dit brede aanbod aan literatuur zijn ze nog steeds relatief ongebruikelijk. De belangrijkste reden daarvoor is waarschijnlijk de pragmatische aanpak waarbij bestuurlijke buurten worden gebruikt waarvoor normaal gesproken gegevens worden verzameld en/of gepubliceerd, naar aanleiding van beperkte toegang tot alternatieve bronnen of een focus op andere methodologische uitdagingen. In dat verband is in de empirische literatuur over buurteffecten tot dusverre onvoldoende aandacht besteed aan de theoretische richtlijnen met betrekking tot het definiëren van buurten. Veel onderzoekers en beleidsmakers gaan ervan uit dat één en hetzelfde type bestuurlijke eenheid (op dezelfde ruimtelijke schaal) wooncontexten op verschillende locaties even goed verklaart.

Ondanks de beperkte aandacht die in het empirisch onderzoek naar buurteffecten aan de definitie van een buurt is besteed, zijn sociale wetenschappers zich er allang van bewust dat de gekozen ruimtelijke schaal invloed heeft op empirische analyses. Openshaw en Taylor (1979) hebben het ‘modifiable areal unit problem‘ (MAUP) geformuleerd, waaruit blijkt dat statistische analyse verschillende resultaten kan opleveren wanneer dezelfde ruimtelijke gegevens gebieden van verschillende omvang beschrijven of grenzen van ruimtelijke eenheden anders worden geplaatst. Het is daarom essentieel om de kenmerken van een wooncontext, zoals achterstand of etnische concentratie, op verschillende ruimtelijke schalen te meten als we inzicht willen krijgen in de oorzaken en gevolgen van sociaalruimtelijke ongelijkheden. Helaas is het gebrek aan aandacht voor de definitie van een buurt een van de redenen waarom er geen consensus bestaat over het bestaan en de zwaarte van buurteffecten.

2 Onderzoeksdoel en -vragen

Het doel van dit proefschrift is **om alternatieve methodes te ontwikkelen voor de operationalisering van buurten op verschillende ruimtelijke schalen en deze te gebruiken om beter inzicht te verkrijgen in ruimtelijke ongelijkheden en buurteffecten**. Om dat doel te bereiken worden in dit proefschrift vijf onderzoeksvragen beantwoord in vijf hoofdstukken, die elk bestaan uit een reeds gepubliceerde paper of manuscript voor een paper. Als eerste hebben we onderzocht wat er aan de conceptualisatie van buurten ontbrak, om te garanderen dat de theoretische benaderingen van de relatie tussen mens en ruimte op basis van passende ruimtelijke gegevens worden geïmplementeerd (zie hoofdstuk 2). Ten tweede wordt in dit proefschrift de vraag gesteld hoe we sociaalruimtelijke context op verschillende ruimtelijke schalen zouden kunnen operationaliseren om onderzoek te doen naar potentiële blootstelling aan contextuele kenmerken, zoals etnische samenstelling, in verschillende geografische settings (zie hoofdstuk 3). Als uitbreiding van de voorgaande onderzoeksvraag hebben we onderzocht hoe in een aantal Europese hoofdsteden verschillende dimensies van etnische segregatie per ruimtelijke schaal varieerden (zie hoofdstuk 4). Door dezelfde kernmethode toe te passen op de analyse van een ander contextueel kenmerk dat relevant is voor individuele uitkomsten wordt in het volgende onderzoek onderzocht hoe contextuele armoede op verschillende locaties varieerde per ruimtelijke schaal, zowel binnen als tussen Nederlandse gemeentes (zie hoofdstuk 5). Ten slotte wordt in dit proefschrift de vraag gesteld hoe contextuele armoede op verschillende ruimtelijke schalen het individuele inkomen beïnvloedt in verschillende stedelijke regio's in Nederland (zie hoofdstuk 6).

3 Gegevens en methodes

De fundamentele gegevensbron voor dit proefschrift bestaat uit de individuele gegevens in registers voor de gehele populatie van Nederland, waarvan we voor drie onderzoeken (hoofdstukken 3, 5 en 6) gebruik hebben gemaakt. De registers bevatten sociaaldemografische kenmerken van mensen, zoals leeftijd, geslacht en opleidingsniveau en – wat cruciaal is – het woonadres inclusief een geocodering op basis van een rooster met cellen van 100 x100 meter (Bakker, 2002). Voor hoofdstuk 4 hebben we vergelijkbare microgeografische gegevens voor zeven Europese landen gebruikt, waaronder de etnische achtergrond van inwoners, met een geocodering op hetzelfde ruimtelijke niveau als de Nederlandse registergegevens: een rooster met cellen van 100 x 100 meter. In tegenstelling tot de meeste literatuur werden voor het onderzoek in dit proefschrift zeer kleine buurten, vlakbij exacte adressen, als uitgangspunt genomen. Vervolgens hebben we de fijnmazige ruimtelijke gegevens geaggregeerd en gebieden op maat gemaakt, gecentreerd rond elke cel en op 100 verschillende ruimtelijke schalen, waardoor steeds meer overlap ontstond. Deze schalen vormen een *afstandsprofiel* waarvan de afstand in kleine stappen toeneemt, waardoor het mogelijk werd om de ruimte van micro- tot macroperspectief met meer continuïteit te beschouwen.

Afstandsprofielen met dit bereik van 101 schalen worden in al het empirische onderzoek in dit proefschrift gebruikt, waarbij elk hoofdstuk een eigen methodologische bijdrage levert. In hoofdstuk 3, waar de methode voor het eerst wordt ontwikkeld, wordt ook de scalaire variabiliteit tussen afstandsprofielen gemeten op basis van de entropie-index (Shannon, 1948). Hoofdstuk 5 bouwt daarop verder door het gebruik van een hiërarchische maat voor entropie, namelijk de Theil-index (Theil, 1967), om zowel de scalaire variabiliteit tussen afstandsprofielen te meten als de ongelijkheid tussen locaties op verschillende ruimtelijke schalen. In hoofdstuk 6 verrijken we veelgebruikte modellen voor vaste effecten door deze te combineren met onze methode op basis van meerschalige gebieden op maat. In dit hoofdstuk wordt tevens de ‘bespoke scale term’ geïntroduceerd om rekening te kunnen houden met de steeds sterker overlappende gebieden in de modellen voor buurteffecten. Hoewel in hoofdstuk 4 een andere gegevensbron wordt gebruikt, worden ook daar de afstandsprofielen toegepast voor het berekenen van verschillende dimensies van segregatie – zoals gelijkmatigheid en blootstelling – over het gehele bereik aan schalen. Gezien de twee essentiële kenmerken van onze methode – ruimtelijke schaal en buurten op maat – heeft dit proefschrift een sterke methodologische focus, maar het bevat tevens de eerste empirische toepassingen.

4 Samenvatting van de onderzoeksresultaten

In hoofdstuk 2, dat is gepubliceerd in het tijdschrift *Progress in Human Geography*, wordt dieper ingegaan op conceptuele aspecten en wordt gesteld dat de operationalisering van buurten gebaseerd moet zijn op theorie: plaatsen hebben verschillende effecten op mensen vanwege een veelheid aan processen. Om deze variëteit aan processen te accommoderen moet ruimtelijke context op verschillende schalen worden geoperationaliseerd, zowel binnen als buiten de grenzen van vooraf gedefinieerde bestuurlijke buurten, afhankelijk van het mechanisme dat wordt onderzocht, de geografische setting en individuele kenmerken van mensen. Om dat te bewerkstelligen kunnen en moeten twee verschillende stromingen binnen de literatuur – ten eerste, theoretische benaderingen van buurteffecten en ten tweede, de analyse van ruimtelijke gegevens – nauwer met elkaar in verband worden gebracht. Dankzij de steeds betere beschikbaarheid van steeds gedetailleerdere ruimtelijke gegevens is het mogelijk om verschillende ruimtelijke contexten te operationaliseren, waardoor homogeniteit en heterogeniteit in de ruimte van een zeer lokale tot op regionale schaal zichtbaar worden.

Eén manier om de ruimtelijke context op een breed spectrum aan verschillende schalen te operationaliseren wordt gepresenteerd in hoofdstuk 3, dat is gepubliceerd in het tijdschrift *Annals of the American Association of Geographers*, als opvolging van de aanbeveling uit hoofdstuk 2 om ruimte meer aaneengesloten te conceptualiseren. Dat betekent dat de woonlocatie wordt gerepresenteerd vanaf het punt waarop iemand 'de voordeur opendoet' tot en met een groot gebied van de stad waar diegene doorheen reist. Deze schalen kunnen worden weergegeven in afstandsprofielen, gebaseerd op het concept van segregatieprofielen dat door Lee et al. (2008) en Reardon et al. (2008) is geïntroduceerd, maar hier in meer detail volgens een scalaire benadering wordt uitgewerkt. Deze methode wordt gehanteerd in al het empirische onderzoek in dit proefschrift. In hoofdstuk 3 wordt de methode ontwikkeld op basis van het voorbeeld van het aandeel niet-westerse etnische minderheden, waarbij de ruimte wordt weergegeven als een oppervlak aan etnische blootstelling en de etnische fragmentatie van drie Nederlandse steden (Amsterdam, Utrecht en Groningen) wordt geanalyseerd. Op basis van het spectrum aan ruimtelijke schalen wordt zichtbaar gemaakt dat mensen in deze steden, met name Amsterdam, op verschillende schalen potentieel worden blootgesteld aan zeer uiteenlopende ruimtelijke contexten, met name – maar niet beperkt tot – de kleinere, afhankelijk van waar in de stad zij wonen. Een unieke toepassing van entropie – voor het meten van de scalaire variabiliteit van de afstandsprofielen – toont aan dat sommige mensen een vrij constante ruimtelijke context hebben, terwijl voor anderen de context verandert naarmate de afstand tot hun woning toeneemt.

Het idee om verschillende locaties op meerdere schalen te vergelijken, dat in hoofdstuk 3 wordt geïntroduceerd, wordt in de daaropvolgende hoofdstukken verder verkend. Zo wordt in hoofdstuk 4 aangetoond dat Europese hoofdsteden zeer uiteenlopende niveaus aan etnische segregatie vertonen voor elk van de onderzochte dimensies (centralisatie, gelijkmatigheid en blootstelling) en dat deze niveaus voor de twee laatstgenoemde dimensies varieerden met de ruimtelijke schaal, op verschillende manieren tussen verschillende steden én binnen deze steden tussen de kern en het achterland. Terwijl op één ruimtelijke schaal de ene stad sterker gesegregeerd lijkt dan andere, kunnen de verhoudingen tussen steden op een andere schaal veranderen. Een zwaar gesegregeerde stad is het dan mogelijk niet meer, terwijl een geïntegreerde stad juist gesegregeerd wordt, wat bevestigt dat onze beoordeling van segregatie grotendeels afhankelijk is van de omvang van de gebieden waarnaar we kijken. In tegenstelling tot het overgrote deel van de literatuur over segregatie kwamen wij tot de conclusie dat segregatie niet per se afneemt met de ruimtelijke schaal.

In de daaropvolgende hoofdstukken (5 en 6) wordt dezelfde methode van meerschalige populatiemetingen weergegeven als afstandsprofielen toegepast voor de analyse van contextuele armoede in plaats van etniciteit (hoofdstuk 5) en de gevolgen daarvan voor mensen (hoofdstuk 6). In hoofdstuk 5 worden de niveaus aan contextuele armoede binnen en tussen Nederlandse gemeentes vergeleken, waarbij *de context* wordt gevormd door meerdere ruimtelijke eenheden, zodat de ongelijkheid meerschalig wordt in plaats van enkelschalig. Door aandacht te besteden aan zowel grotere steden als kleinere gemeentes wordt in dit hoofdstuk zichtbaar gemaakt dat de landelijke ongelijkheid voornamelijk is toe te schrijven aan de concentratie van armoede in stedelijke gebieden van enkele kilometers. Deze steden vertonen uiteenlopende ruimtelijke patronen aan contextuele armoede – zoals multicentrisch, kern-periferie en oost-west – terwijl kleinere gemeentes ten opzichte van het land als geheel benedengemiddelde niveaus aan armoede kennen. Naast de ongelijkheid tussen gemeentes zijn er ook aanzienlijke ongelijkheden binnen gemeentes, met name tussen microgebieden van een paar honderd meter. Als we het proefschrift van een afstand beschouwen wordt duidelijk dat in zowel hoofdstuk 3 als hoofdstuk 5 afstandsprofielen en de scalaire variabiliteit werden gemeten op basis van (hiërarchische) entropie, maar met aandacht voor twee verschillende contextuele kenmerken, namelijk de percentages niet-westerse mensen (hoofdstuk 3) en laagbetaalde mensen (hoofdstuk 5). Een vergelijking van de bevindingen van deze twee hoofdstukken verschaft ons inzicht en stelt ons in staat om te concluderen dat het aandeel laagbetaalden in Nederland weliswaar per ruimtelijke schaal verschilt, maar minder dan het aandeel niet-westerse mensen. Deze twee kenmerken vertonen elk een eigen ruimtelijk patroon en moeten daarom niet automatisch en zonder verder onderzoek worden verondersteld op dezelfde manier te variëren.

Ten slotte zijn de schalen waarop armoede zich concentreert, zoals gevonden in hoofdstuk 5, niet noodzakelijkerwijs de schalen waarop de grootste buurteffecten zich voordoen. De allerkleinste ruimtelijke schaal is niet per se de schaal van het grootste effect, zoals in het merendeel van de onderzoeken naar buurteffecten die zich bezighouden met schaal veel wordt gesuggereerd, maar kleinere ruimtelijke contexten vertonen in het algemeen wel een sterker verband met individuele inkomens dan grotere. Dat is de voornaamste bevinding van hoofdstuk 6, waarin meerschalige populatiemetingen worden toegepast voor het modelleren van de effecten van contextuele armoede op individuele inkomens. Beschouwing van alle stedelijke regio's in Nederland, evenals de vier afzonderlijke regio's Amsterdam, Rotterdam, Utrecht en Groningen, resulteert in schaal- en plaatsgebonden schattingen van contextuele effecten. Bij de analyse over een breed spectrum aan schalen bracht het onderzoek methodologische problemen aan het licht die de representatie van buurten ongeschikt kunnen maken, met name in het geval van te grote ruimtelijke eenheden. De belangrijkste daarvan is het deterministische verband tussen de variantie in stedelijke structuur en de geschatte contextuele effecten over meerdere ruimtelijke schalen zonder theoretische basis.

5 Synthese van de resultaten en de geleerde lessen

Wat hebben we van dit proefschrift geleerd? Ruimtelijke schaal is een bepalende parameter voor ongelijkheden binnen en tussen locaties en het effect daarvan op mensen. Steden vertonen niet alleen als geheel ongelijkheid, maar ook doordat zij kleine en grote buurten hebben die eruit springen. Binnen deze steden en buurten zijn er microruimtes die nog extremere kenmerken vertonen: concentraties van verschillende etnische of sociaaleconomische groepen. De ruimtelijke context van mensen omvat het gehele bereik van deze microschaal tot en met stads- of regioschaal, inclusief de manier waarop deze schalen met elkaar zijn verbonden, van uniformiteit tot geleidelijke of abrupte veranderingen in de ruimte. Wonen op een specifieke locatie kan gevolgen hebben voor iemands individuele sociaaleconomische status, maar de sterkte van dit verband verandert wanneer we op verschillende schalen naar ruimtelijke contexten kijken.

In lijn met de bestaande literatuur hebben we minder sociaalruimtelijke ongelijkheden en zwakkere (voornamelijk negatieve) buurteffecten op het inkomen aangetroffen in de door ons bestudeerde gebieden – hoofdzakelijk Nederland maar ook zeven Europese hoofdsteden – dan bij vergelijkbaar onderzoek werd aangetroffen in Noord-Amerikaanse context (zie Friedrichs et al., 2005; Van Ham et al., 2012). We hebben echter aanzienlijke variatie waargenomen tussen en binnen locaties, met name op kleinere ruimtelijke schalen, waar de ruimtelijke ongelijkheden en contextuele effecten over het algemeen het sterkst zijn. Hoewel microcontexten enorm belangrijk zijn, is er op de laagste schaal niet noodzakelijkerwijze sprake van causaliteit en werkt deze niet per se terug, maar neemt verschillende richtingen aan (Sheppard & McMaster, 2004). Wat dat betreft zijn uit ons onderzoek een aantal onverwachte bevindingen naar voren gekomen, die met de bestaande literatuur conflicteren. Concreet hebben we vastgesteld dat buurteffecten niet het sterkst waren op de allerkleinste ruimtelijke schaal, iets wat zelden wordt bevonden in onderzoek waarbij verschillende schalen met elkaar worden vergeleken (voor een uitzondering, zie Buck, 2001). Daarnaast hebben we waargenomen dat segregatie niet per se afneemt met de ruimtelijke schaal, wat in overeenstemming is met Johnston et al. (2016), maar niet met het merendeel van de literatuur over segregatie. Daarom kunnen we concluderen dat ruimtelijke processen in alle richtingen over schalen plaatsvinden.

Theoretische en conceptuele bijdragen

Uit het bovenstaande kunnen drie theoretische en drie conceptuele gedachtegangen worden ontleend, evenals drie methodologische, die als de voornaamste bijdragen van dit proefschrift kunnen worden beschouwd:

1. In de literatuur over buurteffecten bestaat behoefte aan een *integratieve theoretische benadering* waarbij expliciet verbanden worden gelegd tussen de verschillende ruimtelijke processen die relevant zijn voor individuele uitkomsten en de daarbij behorende schalen (zie hoofdstuk 2). De theoretische benadering moet tevens rekening houden met de vraag hoe ruimtelijke processen zich in de ruimte ontwikkelen en wat de verbanden tussen verschillende schalen zijn. Zo kan bijvoorbeeld het afstandsverval worden gebruikt om afnemende potentiële blootstelling en interactie in de ruimte te operationaliseren (zie hoofdstuk 6).

2. Als we accepteren dat er sprake is van meerdere processen, verdient het de voorkeur om deze aan te duiden met de term *'ruimtelijke contextuele effecten'* in plaats van *'buurteffecten'*. In het merendeel van de literatuur wordt 'buurteffecten' inconsistent gebruikt om te verwijzen naar sterk uiteenlopende ruimtelijke contexten, die weliswaar mogelijk relevant zijn, maar adequaat moeten worden aangeduid: elk persoon behoort tot ruimtelijke contexten op meerdere schalen, die verschillende rollen toekennen aan bewoners.

3. Gezien de meerschalige aard van buurten bestaat in de literatuur over buurteffecten behoefte aan een *meerschalige benadering*, waarbij rekening wordt gehouden met verschillende soorten contexten waaraan mensen zowel binnen als buiten hun officieel gedefinieerde buurt worden blootgesteld, en die tevens plaatsafhankelijk is door rekening te houden met verschillende geografische settings.

Methodologische bijdragen

1. De meerschalige benadering maakt het mogelijk om meer inzicht te krijgen in het 'modifiable areal unit problem' (MAUP). De 'modifiable areal units' zijn voor dit onderzoek niet als probleem beschouwd, maar als hulpmiddel, zoals beschreven door Manley et al. (2006). In dit onderzoek maken verschillende schalen integraal deel uit van een afstandsprofiel, waardoor deze allemaal een mogelijkheid bieden om uit te leggen *hoe* contextuele kenmerken in de ruimte veranderen.

2 Door de scalaire variabiliteit te kwantificeren, beschrijven we in feite verschillende soorten ruimtelijke contexten, die voor sommige mensen relatief uniform zijn, terwijl anderen op verschillende afstanden van hun woning potentieel worden blootgesteld aan zeer uiteenlopende contexten, inclusief abrupte veranderingen, zogenaamde 'social cliffs' (zie hoofdstuk 3). In dit proefschrift is entropie een maat voor de ongelijkheid binnen en tussen locaties op verschillende schalen, wat neerkomt op een hiërarchische en meerschalige toepassing van entropie. Entropie wordt ook gebruikt als maat voor de ongelijkheid *tussen* schalen, met een specifieke locatie als startpunt, wat neerkomt op een schaaloverschrijdend gebruik van entropie.

3 Variabiliteit in stedelijke structuren is een groot methodologisch probleem bij regressiemodellen die gerelateerd zijn aan ruimtelijke schaal, wat gezien het ontbreken van theorie merkbare gevolgen heeft voor de resultaten. Het is bekend dat bij de analyse van ruimtelijke gegevens aggregatie impliciet minder variatie betekent (zie bijv. Haining, 2003; Manley, 2014). Dat is met name riskant als er te grote gebieden worden gebruikt om buurten te vertegenwoordigen (Chetty & Hendren, 2018), aangezien minder variabiliteit in stedelijke structuur kan leiden tot grotere ruimtelijke contextuele effecten. Dit proefschrift is erop gericht meer bewustzijn te creëren ten aanzien van welke soorten contexten (van buurt tot regio) daadwerkelijk worden geoperationaliseerd met ruimtelijke eenheden die beschikbaar zijn in de data, wat van belang is voor zowel wetenschappelijk onderzoek als sociaal beleid.

6 Maatschappelijke en wetenschappelijke relevantie van dit proefschrift

Het is belangrijk om bij onderzoek voor een meerschalige benadering te kiezen, omdat verschillende problemen op verschillende ruimtelijke schalen om verschillende oplossingen vragen. Daardoor is het in het gunstigste geval misleidend en in het slechtste geval zelfs gevaarlijk om grote gebieden als buurten te gebruiken, waaraan beleidsmakers vervolgens conclusies, plannen en ontwerpen verbinden die zijn bedoeld voor kleine buurten. Dit geldt bijvoorbeeld voor het beleid van de Europese Unie ten aanzien van de integratie van migranten, evenals nationaal en regionaal beleid met betrekking tot stedelijke vernieuwing of de sociale mix. Dergelijk beleid vraagt niet per se om ingrijpen in officieel gedefinieerde buurten, maar soms juist in een bredere ruimtelijke context. Het kan echter ook noodzakelijk zijn om microruimtes als uitgangspunt te nemen, omdat mensen elkaar ontmoeten en met elkaar omgaan in de directe omgeving van hun woning, waar het sterk kan verschillen van meer afgelegen delen van de stad. Dat vergemakkelijkt het op zijn beurt om te bepalen hoe deze mensen hun buurt en stad ervaren en kan bovendien hun houding tegenover anderen beïnvloeden.

Het onderzoek naar buurteffecten is interdisciplinair en onderzoekers met verschillende achtergronden moeten zich niet uitsluitend richten op de concepten en methodes die specifiek zijn voor hun vakgebied. Wij suggereren bijvoorbeeld dat methodes uit de fysische geografie (zie bijv., Fisher et al., 2004) ook kunnen worden gebruikt om de sociale kenmerken van ruimte te bestuderen. Het voornaamste is dat ruimtelijke schaal, en ruimte in het algemeen, even relevant moet zijn voor alle onderzoekers die buurteffecten bestuderen, waaronder economen, sociologen en gezondheidskundigen. Ons werk wil onderzoekers motiveren om de bestaande bevindingen terughoudender te gebruiken, meer aandacht te besteden aan ruimtelijke schaal en passender termen te gebruiken om naar verschillende ruimtelijke contexten te verwijzen.

Gezien de bevindingen in dit proefschrift zal onderzoek naar segregatietrends in de toekomst uit moeten gaan van de aanname dat deze trends op verschillende ruimtelijke schalen verschillend kunnen zijn. En bij onderzoek naar contextuele effecten moet worden aangenomen dat mensen worden beïnvloed door verschillende ruimtelijke contexten tegelijk. Bijgevolg moeten beleidsresponsen ruimte houden voor flexibelere ruimtelijke definities van buurten, want hoewel buurten zoals officieel gedefinieerd belangrijk zijn, vormen ze niet altijd het meest passende interventieniveau. Ze maken deel uit van grotere stedelijke systemen en bevatten tegelijk zelf mogelijk een groot aantal ruimtelijke ongelijkheden, vanaf het niveau van de vaak genegeerde microruimtes. In dit proefschrift wordt niet gesuggereerd dat alle onderzoekers rekening moeten houden met dit brede spectrum aan ruimtelijke schalen. Wel wordt echter gesuggereerd dat de meerschalige benadering een manier biedt om sociaalruimtelijke ongelijkheden en buurteffecten beter te begrijpen, doordat verschillende schalen verschillende ruimtelijke processen zichtbaar maken. Voor individuele personen zijn locaties belangrijk, maar we dienen zorgvuldig te overwegen wat wij onder een locatie verstaan en op welke manier die belangrijk kan zijn.

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TOC

1 Introduction

The places where we live affect our individual outcomes, such as health, education and income. This idea is embedded in a large body of literature on neighbourhood effects (Ellen & Turner, 1997; Dietz, 2002; Van Ham et al., 2012). Neighbourhood effects are strongly related to sociospatial inequalities, because unequal living conditions and opportunities for education, work, etc. in different neighbourhoods can have positive or negative effects on people. Consequently, this idea has motivated many social policies and interventions in deprived neighbourhoods (see e.g. Van Kempen & Priemus, 1999; Musterd & Ostendorf, 2008; Manley et al., 2013), because living in these places is associated with, for example, worse educational outcomes for children or labour market outcomes for adults.

Sociospatial inequalities are usually connected with the spatial segregation of different socioeconomic groups, such as low-, middle- and high-income, and particularly with concentrated deprivation; however, they are also associated with spatial segregation of ethnic groups. Growing economic inequalities, as well as international and internal migrations, have only intensified *spatial* inequalities (see Tammaru et al., 2016). While concentrated deprivation is often associated with negative outcomes, in part because people are thought to be exposed to bad role models in the neighbourhood, spatial concentrations of ethnic groups can have both negative and positive aspects. For example, ethnic segregation can hinder integration of ethnic minorities, on the other hand, and improve socioeconomic status of migrants through social networks in the neighbourhood, on the other hand (see, for instance, Merry, 2016). In addition, both deprivation and ethnic concentration may result in the stigmatisation of residential areas.

Geography is not neutral. Unequal opportunities in terms of availability of institutions and services, role models and social networks in the neighbourhood, and stigmatisation of certain parts of the city are only some examples of the residential processes that affect people. The literature classifies them in more detail, jointly terming them the 'mechanisms of neighbourhood effects' (Sampson et al., 2002; Galster, 2012), although they operate in a variety of smaller and larger spatial contexts. Critically, one common feature of all the 'neighbourhood effects' is that they are spatial effects – they explain how geographic patterns of social and environmental phenomena affect people. The term 'neighbourhood' is commonly used, both in everyday life and in scientific literature, to denote the spatial context in which people live and to which they are exposed. However, the reality of spatial contextual effects is much more complicated, and its parameters cannot be encapsulated by the single word ‘neighbourhood’. This thought is not new in literature, but it has not been fully conceptually developed, operationalised and empirically applied. Through the lens of multiscale measures of spatial context, this thesis demonstrates that *spatial contextual effects* are more pertinent to understanding how place affects individuals than *neighbourhood effects*. The thesis sheds light on the multiscale nature of the spatial context, differences between places and their effects on people.

1.1 The problems of the ‘neighbourhood’ and its effects on people

Since the early 1990s, many scholars have debated a basic hypothesis of ‘neighbourhood’ or ‘contextual’ effects: namely, that the residential context has an independent effect on individuals over and above their personal and family characteristics. Although this claim is fundamentally supported by an already substantial literature (see, e.g., Dietz, 2002; Sampson et al., 2002; Chaix, 2009), the idea remains controversial due to inconclusive empirical evidence. This is because quantifying neighbourhood effects is a daunting task (see Manski, 1993). Among other challenges, authors often emphasise residential sorting (non-random movement of people into neighbourhoods that makes it hard to prove the direction of causality) and uncertainty about the definition of neighbourhoods (Diez Roux, 2004; Gauvin et al., 2007). Galster (2008) outlines six paramount obstacles to obtaining unbiased estimates of neighbourhood effects on individuals. First among them is defining the scale of a neighbourhood.

Regardless, most of the empirical research into spatial inequalities has used predefined administrative neighbourhoods, often at a single scale, while comparing different spatial levels of administrative units is rare. For example, Overman (2000) pointed out that different process influenced school dropout at different spatial scales, while Prouse et al. (2014) showed that, in small cities, lower-scale administrative units explained income inequality better than the ones at the higher scale. Besides the issue of scale, administrative units are particularly problematic in representing the residential context of people who live close to the boundary of the spatial unit. Generally, social processes operate regardless of administrative boundaries (Manley et al., 2006; Jones et al., 2018).

Hence, a critical point was the introduction of bespoke neighbourhoods (Johnston et al., 2000; Buck, 2001; MacAllister et al., 2001). Unlike administrative units with fixed boundaries, bespoke neighbourhoods are centred around each individual residential location (an exact address or a very small area). Delineating them, therefore, requires small-scale spatial units to start with, which can then be aggregated at various spatial scales around individuals. The idea of centring neighbourhoods around each individual and expanding the scale in concentric circles, based on distance or a number of nearest neighbours, has been well known in spatial data analysis and presents the core of the methods relying on spatial association (see, e.g. Anselin, 1988). As the potentials of bespoke neighbourhoods have been recognised in the neighbourhood effects research, they have been increasingly used (Bolster et al., 2007; Andersson & Malmberg, 2014; Veldhuizen et al., 2015). However, they are still relatively uncommon within this large body of literature.

There are multiple reasons why multiscale bespoke neighbourhoods have not yet been extensively applied and researchers rarely strive for more discerning definitions of neighbourhood. Probably the most important reason is the pragmatic approach of using administrative neighbourhoods for which data are normally collected and/or published, due to either limited access to alternative sources or focusing on other methodological challenges. Related to this, empirical literature on neighbourhood effects has thus far paid insufficient attention to the theoretical guidelines regarding the definition of neighbourhood, which is the first point of discussion in this thesis. Another reason is the traditional focus on a single city, such as Chicago as an archetype area for studying neighbourhood effects (see Sampson, 2012), and the lack of interest in how the parameters of neighbourhoods could vary across space. Therefore, many researchers and policy makers have assumed that the same type of administrative units (at the same spatial scale) equally well explains residential contexts in various places. Comparing different places, specifically those with different urban forms is another example of the 'missing geography' in the neighbourhood effects research. Therefore, we need to understand the importance of spatial scale in different settings, both within municipalities and across municipalities, urban regions or even countries.

Social scientists have long been aware that the choice of spatial scale affects empirical analyses. On the basis of the increasing correlations between variables with the increasing spatial scale (Gehlke & Biehl, 1934), Robinson (1950) formulated ecological fallacy – the problem of inferring about individuals from aggregated data. Accordingly, statistical inference from data aggregated in different ways leads to similar errors. Openshaw and Taylor (1979) formulated this as the modifiable areal unit problem (MAUP), which shows that statistical analysis can yield different results when the same spatial data form areas of different sizes or boundaries of spatial units are placed in different ways. Most importantly, the MAUP is not solely a statistical issue, but a way to understand social process, suggesting that various processes operate at different spatial scales (Manley et al., 2006; Jones et al., 2018). Distance is at the core of the issue of the spatial scale and many social phenomena and processes depend on proximity and distance, even in a digital and globalised world. Measuring the characteristics of residential context, such as deprivation and ethnic concentration, at various spatial scales is therefore crucial for understanding the causes and consequences of sociospatial inequalities. Ultimately, the lack of attention to the definition of a neighbourhood is one of the reasons why there is no consensus regarding the existence and the strength of neighbourhood effects.

1.2 Research aim and questions

The aim of this thesis is **to develop alternative methods of operationalising neighbourhoods at multiple spatial scales and use them to better understand spatial inequalities and neighbourhood effects**. Given the limited knowledge of the spatial scale of neighbourhood, as well as the problems with using administrative units to study social phenomena, we created bespoke areas at a wide range of scales to represent the sociospatial context. To advance our understanding of spatial inequalities and neighbourhood effects, we applied these measures to study potential exposure to poverty, and neighbourhood effects on income in the Netherlands, as well as ethnic segregation wider in Europe. To achieve this aim, the thesis answers five key questions in five studies – one theoretical and four empirical. This is outlined in Figure 1.1.

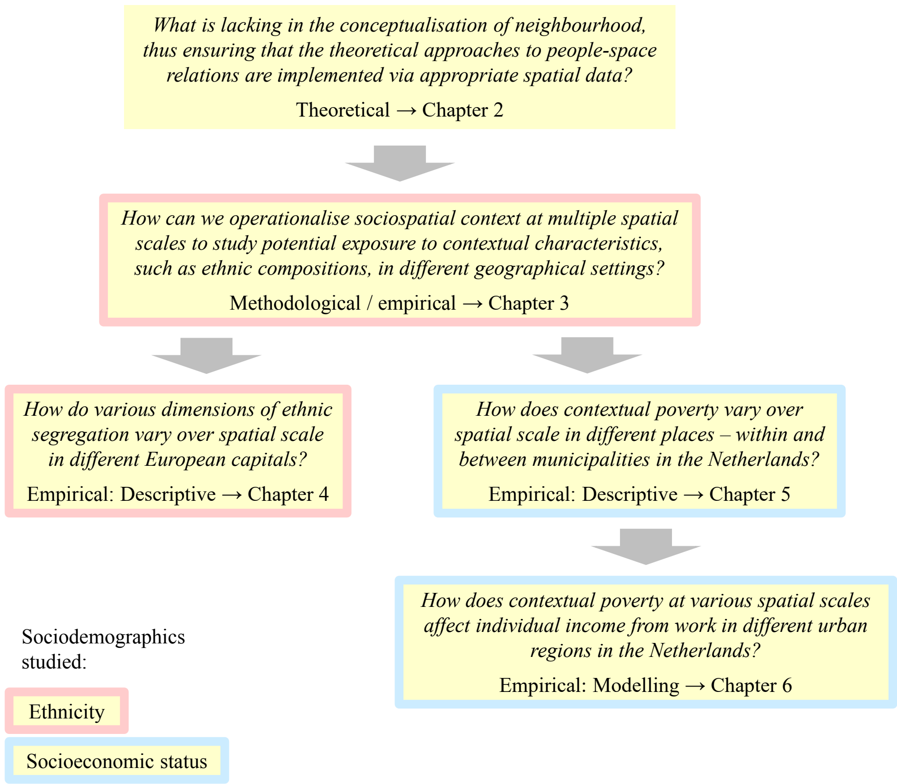

FIG. 1.1 Research questions

At the most fundamental, theoretical level, the thesis askes the following question: **What is lacking in the conceptualisation of neighbourhood, thus ensuring that the theoretical approaches to people-space relations are implemented via appropriate spatial data?** To answer this question, Chapter 2 combines two strands of literature that have been developing separately – theoretical approaches to neighbourhood effects and spatial data analysis. This hybridisation of two seemingly independent areas of research shows that studying spatial contextual effects should be grounded in theory. One must recognise not only that neighbourhood is essentially spatial, but also that people's sociospatial context is more complex than a single-scale administrative neighbourhood. Therefore, the chapter introduces a change in the paradigm – from neighbourhood to spatial context effects research, which will be used throughout the study.

Developing the alternative methods of representing the spatial context starts from the following question: **How can we operationalise sociospatial context at multiple spatial scales to study potential exposure to contextual characteristics, such as ethnic compositions, in different geographical settings?** This question directly addresses the gaps in the literature, where multiscale, bespoke concepts of neighbourhood and differences within and between places have thus far received limited attention. Therefore, Chapter 3 develops a method of operationalising residential context as bespoke areas at a range of spatial scales, from micro to macro, which can be used to study segregation and neighbourhood effects.

The three subsequent empirical studies (Chapters 4, 5 and 6) apply the method developed in Chapter 3 to better understand spatial inequalities in two characteristics of residential context, namely ethnic segregation, as well as contextual poverty and its effects on individuals. Given that the method in Chapter 3 was developed on the example of ethnicity in Dutch cities, the thesis expands this analysis to a European-wide question, namely: **How do various dimensions of ethnic segregation vary over spatial scale in different European capitals?** Along with ethnicity, the thesis examines another important contextual characteristics relevant for individual outcomes, but this time related to socioeconomic status of people, addressing the following question: **How does contextual poverty vary over spatial scale in different places – within and between municipalities in the Netherlands?** Finally, the issue of contextual poverty develops into the question of its effects on individuals: **How does contextual poverty at various spatial scales affect individual income from work in different urban regions in the Netherlands?**

1.3 Data and methods

The fundamental data source for this thesis are the individual-level register data for the full population of the Netherlands, which we used in three studies (Chapters 3, 5 and 6). The registers contain sociodemographic characteristics of people, such as age, gender and education, and, crucially, the place of residence geocoded at 100m by 100m grid cells (Bakker, 2002). This detailed spatial data has recently become available in only a few countries. For Chapter 4, we used similar microgeographic data for seven European countries, which contained residents' ethnic origin, geocoded at the same spatial level as the Dutch register data – 100m by 100m grid cells. Unlike most of the literature, the research within this thesis therefore started from very small neighbourhoods, close to exact residential locations.

We then aggregated the fine-grained spatial data at increasingly large scales using the method of bespoke neighbourhoods. Building on the existing research that considers different spatial scales, but limited to a few scales at most, we examined space from a more detailed perspective, using a much wider range of scales. We therefore created bespoke areas, centred around each cell, at 100 different spatial scales, and thus increasingly overlapping. These scales form a *distance profile* with small increments in distance, which made it possible to look at space in a more continuous way, from micro to macro perspective.

Distance profiles containing the range of 101 scales appear in all empirical studies within this thesis, whereby each chapter adds its own methodological contribution. Chapter 3, where the method was first developed, also measures the scalar variability across the distance profiles using the entropy index (Shannon, 1948). Chapter 5 builds up by using a hierarchical measure of entropy, namely the Theil index (Theil, 1967), to measure both the scalar variability of distance profiles and the inequality between places at multiple spatial scales. In Chapter 6, we enriched the commonly used fixed effects models by combining them with our method of multiscale bespoke areas. The chapter also introduces the 'bespoke scale term' to take into account the increasingly overlapping areas in the neighbourhood effects models. Although using a different data source, Chapter 4 also applies the distance profiles – in calculating different dimensions of segregation, such as evenness and exposure, at the range of scales. With two defining features of our method – spatial scale and bespoke neighbourhoods, the thesis has a strong methodological focus, but it also contains the first empirical applications.

1.4 Thesis outline

After this introduction, Chapter 2 establishes the broad intellectual background of the thesis, linking theoretical approaches to neighbourhood effects with spatial data analysis. The chapter emphasises the importance not only of theory, but also of the availability and appropriate analysis of spatial data. While Chapter 2 outlines the vast possibilities of using microgeographic data to operationalise sociospatial context, the next one proposes a multiscale method for this.

Chapter 3 is the methodological backbone of the thesis. Via the example of potential exposure to non-Western ethnic minorities, the chapter shows how sociospatial context varies over spatial scale, in different locations within and between three

Dutch cities (Amsterdam, Utrecht and Groningen). The multiscale bespoke areas created in this chapter can be used for studying segregation and neighbourhood effects, examples of which appear in the following research steps.

Methodological solutions from Chapter 3 were then applied in the following three studies to examine ethnic segregation in seven European capital cities (Chapter 4), and contextual poverty and its effects on individual income in the Netherlands (Chapters 5 and 6 respectively). Chapter 4 demonstrates how various dimensions of ethnic segregation vary over spatial scale in different capital cities in Europe, namely Amsterdam, Berlin, London, Paris, Madrid, Lisbon and Rome. This chapter does not have a separate theoretical framework, but builds on Chapter 3 by considering the sociospatial context from the perspective of spatial scale and ethnicity, specifically the segregation of non-Western ethnic minorities, but this time in multiple European countries.

The following two chapters also apply the method of using multiscale bespoke areas developed in Chapter 3, but this time for studying people's socioeconomic status instead of ethnicity. Chapter 5 shows how contextual poverty, conceptualised as potential exposure to low-income people in the residential context, varies over spatial scale in different places – within and between municipalities in the Netherlands. This elucidates contextual poverty in the Netherlands and sets up the analysis of contextual effects in the final empirical Chapter 6. This chapter reveals how potential exposure to low-income people at various spatial scales affects individual income from work in different urban regions in the Netherlands, focussing on Amsterdam, Rotterdam, Utrecht, and Groningen regions.

The discussion and conclusions in Chapter 7 summarise and synthesise the research findings, outline the benefits and limitations of the data and methods used and suggest how the current study can be further developed.

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2 Freedom from the tyranny of neighbourhood

Rethinking sociospatial context effects

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ABSTRACT

Theory behind neighbourhood effects suggests that people's spatial context potentially affects individual outcomes across multiple scales and geographies. We argue that neighbourhood effects research needs to break away from the 'tyranny' of neighbourhood and consider alternative ways to measure the wider sociospatial context of people, placing individuals at the centre of the approach. We review theoretical and empirical approaches to place and space from diverse disciplines, and explore the geographical scopes of neighbourhood effects mechanisms. Ultimately, we suggest how microgeographic data can be used to operationalise sociospatial context, where data pragmatism should be supplanted by a theory-driven data exploration.

KEYWORDS

neighbourhood effects, sociospatial context, microgeographic data, spatial scale, bespoke neighbourhoods

2.1 Introduction

Current research linking the residential context to individual outcomes is inconclusive with regard to the strength and importance of neighbourhood effects, and the mechanisms behind them (Van Ham et al., 2012). The literature often highlights several methodological challenges for quantitative neighbourhood effects research, including bias caused by the non-random selection of people into neighbourhoods, and the endogeneity of neighbourhood characteristics, in other words a correlation between variables used to explain the neighbourhood effect and the error term of the model. Both are major obstacles in determining 'real' causal relationships between spatial contexts and individual outcomes (see Manski, 1993). However, this paper focuses on the more fundamental issue of the definition of neighbourhood itself – an important challenge as yet given surprisingly little attention (Galster, 2001; Lupton, 2003; van Ham & Manley, 2012).

Early investigations into neighbourhood effects used ethnographic research methods, observing life in specific neighbourhoods (see, for instance, Wilson, 1987; Wacquant & Wilson, 1989). Although the neighbourhood was the starting point of enquiry, the focus was on the sociospatial structures within local communities rather than in the neighbourhood itself. Although secondary data and quantitative methods were also used by some early scholars investigating neighbourhood effects (Lewis, 1966), the quantitative study really took off during the late 1990s, spurred by the increasing availability of microdata and computing power. This allowed researchers to model the effects of living in deprived neighbourhoods on individual outcomes, for example by using data from the 1990s Moving to Opportunity program (Katz et al., 2001; Leventhal & Brooks-Gunn, 2003).

While ethnographic research generally focussed on a named and identifiable neighbourhood and local reputation, quantitative research needed geocoded individual level microdata linked to the characteristics of a diverse range of neighbourhoods, across a whole city, region or even country. As a result, most quantitative studies on neighbourhood effects use a data-driven definition of neighbourhood – the administrative neighbourhood boundaries which were readily available in the data. These administrative neighbourhoods, which may not appropriately reflect a 'residential neighbourhood' at all, are often the only aspect of the sociospatial context of people which is recorded in data. This is no surprise, as administrative neighbourhoods are used for the delivery of policy and the collection of (Census) data based upon the political and social needs of the state, rather than based on underlying social processes that administrative units are said to delineate (Manley et al., 2006; Jones et al., 2018).

The pragmatism to adopt administrative neighbourhoods means that much quantitative research on neighbourhood effects has been driven by data availability rather than driven by theoretical considerations (Jencks & Mayer, 1990; Sampson et al., 2002). It is unrealistic to presume that a single spatial entity can adequately capture all relevant characteristics of the sociospatial context which might influence individual outcomes (Raudenbush & Sampson, 1999; Galster, 2001; Nicotera, 2007). Of course, all across the social sciences, complex phenomena have been studied using simplified assumptions about human behaviour and the urban environment, often because of the lack of appropriate data and analytic tools (Kwan, 2000). Indeed, a reduction from the complexity of the real world is required in order to say something meaningful. However, if we start from a theoretical perspective, it becomes clear that many of the assumed causal mechanisms studied as ‘neighbourhood effects’ actually reflect effects from multiple contexts with differing temporal and spatial scopes. Crucially, the residential administrative neighbourhood is only one of these scopes (Sampson et al., 2002; Galster, 2012).

To move forward, we propose a thought experiment: Rather than being driven by data availability, what if we start from theory and specify the data required from that perspective? Moreover, since quantitative research on neighbourhood effects depends on data availability, once we have considered the data requirements, how can research benefit from the increasing availability of microgeographic secondary data? With the availability of richer spatial data, quantitative studies have started to consider a larger number of spatial scales, which shed new light on multiple spatial contexts which affect people (Andersson & Musterd, 2010). Recently, alternative approaches to zonation, particularly in the form of bespoke neighbourhoods (or egohoods), centred around each person, have emerged (Johnston et al., 2000; Petrović et al., 2018). So far, microgeographic data have enabled the move away from fixed single scale administrative neighbourhood boundaries to bespoke multiscale spatial contexts (see Andersson & Malmberg, 2014).

Within the context of our thought experiment, this paper discusses how microgeographic data can be used to operationalise sociospatial contexts within the theoretical framework of neighbourhood effects. We discuss three conceptual issues, starting with the most fundamental one, how place and space have traditionally been conceptualised in different disciplines studying neighbourhood effects. We then focus on theoretical neighbourhood effects mechanisms and their relevant geographies (Galster, 2012), which leads to hypotheses on idealised spatial units for testing specific contextual effects. To operationalise these spatial units, we need to know more about the nature of spatial data and how to use them to explore social processes, and this is the third conceptual issue discussed. Building on these three *conceptual issues* (concepts of place and space, geography of neighbourhood effects mechanisms, and the nature of spatial data), we consider the *operationalisation* of sociospatial contexts in quantitative empirical studies of neighbourhood effects. We review selected studies which use different approaches to the geography of neighbourhood effects, ranging from fixed bounded administrative neighbourhoods to a multiscale representation of the sociospatial context (Andersson & Malmberg, 2014; Petrović et al., 2018). Ultimately, we discuss how microgeographic data can further improve the neighbourhood effects research.

2.2 Modifiable geographies of neighbourhood effects

2.2.1 Concepts of space and place

Concepts of space and place have played a role in various disciplines dealing with neighbourhood effects, such as geography, sociology, criminology, economics and health studies. Here we briefly discuss concepts of space and place, starting from the perspective of health studies, which brings together epidemiology, geography and sociology (Curtis & Rees Jones, 1998; Tunstall et al., 2004; Cummins et al., 2007). The distinction between space and place in health geography suggests that space is *where* a location is, and place relates to *what* that location is (see Tunstall et al., 2004). The notion of place, therefore, reflects the social and physical attributes of particular spaces and moves us beyond a Euclidean notion of space, as a dimension in which phenomena are distributed, to a more nuanced structure. On the one hand, this view of place as an interpretation of space invokes a study which 'can be as rich as the study of time through social history' (Tunstall et al., 2004). On the other hand, such a distinction between place and space can relegate *space* to a mere geometric notion. The view of space as a residual dimension, a flat surface, has been criticised by human geographers, particularly Doreen Massey (see, e.g., Massey, 2005). Space is, according to Massey, a cut through time, connecting stories and biographies and things existing at the same time, and therefore a dimension of simultaneity and multiplicity. Space presents us with the existence of others and, therefore, with the question of 'the social' (Massey, 2005). Throughout geographical analysis, these notions of place and space (place/space distinction and dynamic, unbounded space) have been invoked within analytical frameworks – the former for focussing on specific places as local contexts, and the latter for dynamising and unbinding space as one integrated spatial context.

A discussion on space and place in understanding neighbourhood effects also includes a distinction between context, as a measure of social environment, and composition as an individual level factor (Pickett & Pearl, 2001). This distinction has advanced health geography, supporting the relevance of place for individual health in addition to individual level effects (Duncan et al., 1998; Diez Roux, 2002). However, the '*relational approach'* questions the strict distinction between context and composition, because the characteristics of people and the places they live in are interrelated (Macintyre et al., 2002; Cummins et al., 2007), and social space is in fact a product of our relations and connections with each other (Massey, 2005). Authors such as Curtis and Rees Jones (1998); Bernard et al. (2007), referring to Giddens' (1984) structuration theory, emphasise the mutual relationships between social structures and people's behaviour, which means that neighbourhood structures have a strong influence on individuals, but also individual behaviour shapes neighbourhood contexts. The relational approach precludes places from having fixed characteristics and defines them as 'dynamic and constantly evolving entities' with positive and negative consequences for their residents (Cummins et al., 2007), playing at multiple spatial scales.

Spatial scale is strongly related to discussions on space and place in the field of neighbourhood effects and beyond (Smith, 2000; Brenner, 2001). Debates on place in health geography draw attention to distinct characteristics of places and the relations between the spatial and the social, often at a micro scale. Neighbourhood scale is, however, still undertheorised, despite some studies operationalising places at different scales (Tunstall et al., 2004). Different disciplines have focussed on different spatial scales: While health geography has focussed on smaller scales, following the concept of place, other disciplines such as criminology have more gradually moved from the macro- to the micro-. During the 19th century, crime was frequently studied at the regional and city levels (see Weisburd et al., 2008), and mid-20th century Chicago sociologists shifted the focus to neighbourhoods and communities, particularly by developing the concept of social disorganisation (Thomas, 1966; Park, 1967). Theoretical perspectives continued to focus on even smaller spatial scales, such as specific locations within neighbourhoods (Eck & Weisburd, 2015), through the introduction of the 'routine activities' perspective (Cohen & Felson, 1979) as well as the 'crime pattern theory', where place is explicitly taken into account as a 'backcloth' of human behaviour (Brantingham & Brantingham, 1993).

TOC

Which scales of spatial context are relevant for understanding social phenomena is not immediately clear. Suttles (1972) has argued that urban households identify four scales of neighbourhoods, starting from the block, where children can play without supervision, up to an entire sector of the city. While this rather general overview needs to be adapted for specific settings, such as city size and urban form, the multiplicity of scales is an ever-present issue in defining neighbourhood, which is more complex than a bounded unit at a single spatial scale. However, the predominant view of the neighbourhood remains a 'geographically bound unit', even by authors emphasising social connections as a criterion for defining neighbourhoods (Chaskin, 1995). In contrast, Massey (1994) conceptualises neighbourhood as a set of overlapping social networks with various spatial extents. Because social connections are not strictly bounded in space, neighbourhoods are inherently fuzzy entities which are difficult to define and to operationalise. The fuzziness of boundaries is important not only for small-scale neighbourhoods but also because of the lack of true (or fixed) sets of regions at the macro scale (Isard, 1956; Altman, 1994).

Fuzzy neighbourhoods are *overlapping* spaces as opposed to mutually exclusive discrete units. Neighbourhoods imbricate not only because of social, but also organisational, political and economic processes (Logan & Molotch, 2007). The overlapping of community boundaries implies that residents do not see the city as divided into mutually exclusive local areas with hard borders, but they see a multitude of overlapping neighbourhoods simultaneously (Hunter, 1974). Although community and neighbourhood are distinct concepts (Hunter, 1974; Sampson, 2004), this is not crucial at this point, particularly given the emphasis on the social dimension of neighbourhood: If communities, as not necessarily spatial entities, overlap in space, this is also true for neighbourhoods, which are by definition spatial. Within the neighbourhood effects literature, the concept of overlapping fuzzy neighbourhoods has been made operational as 'bespoke neighbourhoods' or 'egocentric neighbourhoods' (Johnston et al., 2000). A bespoke neighbourhood is an area surrounding an individual, starting from a very small spatial unit, and as a consequence, bespoke neighbourhoods of multiple individuals overlap. The corresponding concept of 'egohoods' (Hipp & Boessen, 2013) introduced an important conceptual turn in the spatial analysis of crime, which has a very long tradition of using non-overlapping units with administratively defined boundaries (Weisburd et al., 2009).

Bespoke neighbourhoods at multiple scales are a key to understanding the relationships between (adjacent) neighbourhoods, particularly through the notion of *spatial spillovers*. Spillover effects between neighbourhoods have, so far, received less attention than the corresponding concept of spillovers in economics (Dietz, 2002). Exceptionally, Sampson et al. (1999) identified *spatial externalities* as a product of collective practices in one neighbourhood benefiting surrounding areas. Although the term ‘neighbourhood’ is usually associated with an autonomous bounded area, the interest in spillover characteristics of neighbourhoods suggests that the spatial context is much more complex that just an independent coexistence of adjacent neighbourhoods. Lupton (2003) identified the following three key issues in conceptualising the spatial context in the neighbourhood effects research: the complex relationships between places and people living there, the issue of neighbourhood boundaries, and the relationship of one neighbourhood to another. Overlapping spaces at multiple spatial scales can address all three issues more competently than a single bounded spatial unit.

Ultimately, the concepts discussed above are pervaded by the relationship between space and time. Both space and time are multiscalar, and both are crucial for measuring exposure to context, with two key temporal perspectives. The first is the heterogeneity of places which people are exposed to during their daily space-time paths (Hägerstrand, 1970), including the residential, but also school, work and other environments (van Ham & Tammaru, 2016). The second is ‘spatial times’ (Massey, 2005) which incorporate influences of different places on an individual during their lifecourse – a sequence of neighbourhoods forming an individual’s neighbourhood history (van Ham et al., 2014). Contextual effects arise from multiple spatial and temporal domains as well as linkages and interactions between them. Underlying mechanisms are very diverse, but if we know what mechanism we examine, we can hypothesise about its spatial and temporal scope.

2.2.2 Mechanisms of contextual effects and their spatial scope

The neighbourhood context is thought to influence a broad spectrum of individual life outcomes, including health, education or socioeconomic status, and people respond to (changes in) context in different ways (Sampson, 2012). There is no single *neighbourhood effects* theory, as the term covers a multitude of processes (Sampson et al., 2002). Galster (2012) categorised the assumed mechanisms behind neighbourhood effects into four categories: social-interactive, environmental, geographical, and institutional mechanisms. Dependent on the outcome under study, some spatial processes are more relevant than others, and, accordingly, some spatial contexts have greater importance than others.

Social-interactive mechanisms include, for example, peer effects on an individual’s behaviour and attitudes, local social norms, social networks, social cohesion and control (Galster, 2012). These mechanisms require (potential) contact and interaction between people, and as such are likely to play out a very local scale. We can generally assume that peer group effects operate at the small spatial scale, such as a block or several streets (van Ham & Manley, 2012), and that residents feel more socially integrated in their own ‘street’ than further away (Taylor & Brower, 1985).

Environmental mechanisms, such as exposure to air or water pollutants, are the most difficult to capture within discretely defined imposed neighbourhood boundaries. Besides ecological (toxic) conditions of environment, these mechanisms include exposure to violence, and physical conditions, such as the quality of public space and noise pollution (Galster, 2012). Particularly in large cities, the geography of health impacts shifts from the neighbourhood level to city level, or even to regional dimensions of air and water pollution, so that environmental burdens are increasingly displaced to greater scales (Sorensen & Okata, 2011). Conversely, the impact of contaminated land, often a factor in brown field building, may be highly localised and specific.

Geographic mechanisms refer to the neighbourhood’s location relative to larger-scale political and economic structures, and includes public services, as well as the spatial mismatch between neighbourhoods and job opportunities (Galster, 2012). Although the mismatch originates as a driver of unemployment of African-Americans in the United States (Kain, 1968), physical proximity to jobs is equally relevant in Europe (van Ham et al., 2001; Gobillon et al., 2011). However, the scale of the mismatch depends on the local setting, since the scale at which a mechanism operates may vary between places and over time (Manley et al., 2006; van Ham & Manley, 2012).

The fourth type of mechanisms identified by Galster (2012) were institutional mechanisms, including the interface between neighbourhood residents and vital markets related to physical conditions in the neighbourhood, local education, healthcare and other institutions to which residents have access, but also stigmatisation (Galster, 2012). Neighbourhood reputation and stigmatisation is associated with well-known, even officially defined neighbourhoods, or areas of specific types of housing or residents’ ethnic backgrounds. Mechanisms which relate to access or exposure to people, resources, or harms, can be better served by bespoke measures of neighbourhood characteristics rather than by administrative neighbourhood boundaries.

Neighbourhood effects research is often used to design policies to reduce negative outcomes. The spatial contexts at which these policies are implemented is often invoked as the analytical frame for empirical research. However, neighbourhood effects mechanisms are not about officially defined administrative neighbourhoods, but about a variety of spatial contexts across fuzzy space. The fuzziness of space is bi-directional. It arises from both the overlapping *individual* contexts of multiple people, and the fact that individuals may belong to *multiple contextual scales*, which Galster and Sharkey (2017) term the spatial opportunity structure. Moreover, different people can be influenced by the neighbourhood in different ways or degrees (Bernard et al., 2007; Small & Feldman, 2012), due to different activity spaces (Kwan, 1999) or different relations to the neighbourhood during their life course (Ellen & Turner, 1997; Forrest & Kearns, 2001). Therefore, the conceptualisations of neighbourhood in neighbourhood effects research should more closely match the underlying mechanisms. This implies that the term 'spatial context effects' more closely matches what we try to understand than the term 'neighbourhood effects'.

2.2.3 The nature of spatial data and social processes

Social processes occur regardless of the administrative boundaries within which data are normally collected (Manley et al., 2006; Jones et al., 2018). While many spatial scales and zonation schemes are theoretically possible, study areas are not analogous to samples in statistics which are randomly drawn from the set of all possible study areas (Longley et al., 1999). On the contrary, spatial data is often autocorrelated, meaning that the value of an observation is similar to those of nearby observations. This 'special' feature of spatial data (Anselin, 1989) counteracts a basic statistical principle of observation independence. Spatial autocorrelation is, however, not a nuisance, but a means to understand social processes. As long ago as the 1930s, Stephan (1934) wrote that '[d]ata of geographic units are tied together, like bunches of grapes, not separate, like balls in an urn', and crucially that 'by virtue of their very social character, persons, groups and their characteristics are interrelated and not independent'. In spatiotemporal processes, such as neighbourhood effects, 'nearby' and 'distant' need to be identified both spatially and temporally (see above on space and time being multiscalar). What happens in a location at one point in given time is related to events in nearby locations and at nearby times, although the transition to nearby spaces and times need not be linear (Goodchild, 2004).

Spatial dependence has traditionally been used to identify clusters. Pioneering work included mapping hot spots of disease in epidemiology and health geography, where small-area data have long been available (Cuzick & Elliott, 1992), as well as crime mapping in empirical research and practice of criminology (Weisburd & McEwen, 2015). Mapping clusters reveals that spatial dependency does not occur everywhere equally. Spatial heterogeneity is, therefore, another 'special' feature of spatial data (Anselin, 1995), such that we need to consider local characteristics of places, not universal generalities (Getis, 1999). In this respect, geographically weighted regression (GWR) examines how regression parameters vary across space (Brunsdon et al., 1996; Fotheringham et al., 2003). Both spatial autocorrelation and spatial heterogeneity are scale-dependent, as while smaller spatial units have their micro-characteristics, they are also simultaneously part of larger structures with macro characteristics. Spatial scale is a lens through which we can analyse spatial homogeneity and heterogeneity.

The modifiable areal unit problem (MAUP) is an important consequence of spatial heterogeneity (MAUP; Openshaw & Taylor, 1979; Openshaw, 1984). MAUP refers to the phenomenon that the results of analyses depend on the *scale* of spatial units chosen, as well as on the precise *zonation* of the units at a single scale on the ground. Relatedly, we can conceptualise two aspects of scale. The first relates to the scale at which social structures exist and over which the processes operate and is known as the *phenomenon scale*. This contrasts with the second, the *analysis scale*, which relates to the size of the units at which these phenomena are empirically measured and analysed (Montello, 2001). Whilst it might seem trivial to suggest that analysis scale should correspond to the phenomenon scale from the research and policy perspective, often they do not. Compared to the natural sciences, research regarding scale in social sciences has been less explicit and precise (Gibson et al., 2000). Matching the phenomenon and analysis spatial representation of social processes is associated with a high degree of uncertainty in space and time, as defined within the uncertain geographic context problem (Kwan, 2012). As a consequence, available spatial data often do not match the mechanisms behind neighbourhood effects that we want to study and understand.

2.3 From neighbourhood effects to sociospatial context research

The literature has often treated neighbourhoods a-spatially, or implemented only discrete parts of the theoretical concerns we outline. Where a neighbourhood is given sufficient conceptual space, it remains a nuisance rather than as a fundamental focus of the research question. Besides critiquing this pragmatic approach, we point out some theoretically-informed examples operationalising sociospatial contexts, which can be applied more widely.

Opposing concepts of neighbourhood include ‘objective’ and perceived neighbourhoods, fixed and bespoke neighbourhoods, single-scale and multiscale neighbourhoods, homogenous and heterogeneous neighbourhoods (see reviews by Nicotera, 2007; Chaix et al., 2009). Small-sample qualitative studies and large-sample quantitative studies fundamentally differ in exploring sociospatial context. Qualitative studies reveal information that quantitative studies of large populations are unable to explore, particularly with regard to residents’ perceptions of neighbourhoods. Neighbourhood boundaries imposed by an outsider researcher, neglect residents’ experiences, which can be relevant for individual outcomes. In contrast, large-sample quantitative studies require simplified assumptions about neighbourhood size and boundaries, but yield more generalisable and comparable results. The generalisation of neighbourhood related findings can be problematic.

Qualitative surveys reveal that residents differ in their assessment of the neighbourhood, whereby assessments of some neighbourhood characteristics such as social disorder, are more easily aggregated from multiple responses than other characteristics such as social interactions (Coulton et al., 1996). Additionally to qualitative methods, including discussion groups or interviews (Davidson et al., 2008), geographic information systems (GIS) are increasingly used to assess residents’ perception of neighbourhood size and boundaries (Lohmann & McMurran, 2009). In a study of low-income communities in 10 cities in the USA, Coulton et al. (2013) found that neighbourhoods delineated from GIS maps drawn by respondents are smaller than typical census tracts, but larger than those gained from residents’ answers on an ordinal scale or qualitative questions. GIS-based studies result in different conclusions regarding whether and which sociodemographic characteristics of people determine how they perceive their neighbourhoods (see, e.g. Lee & Campbell, 1997; Orford & Leigh, 2014). This mirrors different settings in which the studies are conducted, in addition to different methods used.

Large-sample quantitative studies can also learn from this and pay more attention to various spatial settings and individual sociodemographics. Individual heterogeneity arising from ethnographic research has been identified as very useful for quantitative studies of neighbourhood effects (Small & Feldman, 2012), but these two types of research are still rarely combined. Furthermore, as Chaix et al. (2009) note, methods used to delineate *perceived* neighbourhoods can also be used for *objectively experienced* neighbourhoods, which may be more informative in understanding individual outcomes, given that contextual effects rely on exposure and interaction. Methods for detecting objectively experienced neighbourhoods use location-aware technologies such as GPS and mobile phone tracking to find activity spaces (Ahas et al., 2010; Chaix et al., 2013). While these methods have relaxed spatial and temporal constraints (Shaw, 2010), delicately measuring exposure in space and time, they have also intensified ethical issues in data collection.

When data on activity spaces are not available, empirical studies sometimes compare administrative units at different spatial scales. These studies demonstrate the relevance of spatial scale, particularly the constraints of the lack of small-area data for representing local contexts. For example, Prouse et al. (2014) in their study on income inequality in Halifax, Nova Scotia (Canada), criticised the coarse scale of the census tracts as a predominant proxy for neighbourhoods. Instead, the authors suggested that in smaller cities dissemination areas, as defined within census tracts, following distinctive features such as roads or waterways and encompassing 400 to 700 people, are more useful. This conclusion appreciates not only spatial scale, but also urban form, specifically distinguishing between bigger and smaller cities. However, we should not focus on micro-geographies to the detriment of larger spatial structures.

Moving beyond the administrative unit, neighbourhood effects studies increasingly compare different spatial scales by aggregating the smallest available units to higher scales using 'bespoke neighbourhoods' (Bolster et al., 2007; Stein, 2014; Veldhuizen et al., 2015). Bespoke neighbourhoods tackle the fact that people living on the edge of an administrative neighbourhood might associate themselves with, or be influenced by the adjacent neighbourhood. Exploring spatial scale of bespoke neighbourhoods has the potential to advance our understanding of the wider residential context. This was illustrated by Petrović et al. (2018) who constructed bespoke neighbourhoods at 101 spatial scales, ranging from the very micro (100 by 100 metre grids) to very large spatial units. They showed that multiscale understandings of spatial context differ between locations within one city, but also between cities with different urban forms. So far, most neighbourhood effects studies have investigated within-neighbourhood effects – the effect of the neighbourhood in which someone lives, whereas few studies have considered neighbourhood as being imbedded in a wider spatial context (Graif et al., 2016), the influence of 'neighbouring neighbourhoods' (Bolster et al., 2007), or adjacent neighbourhoods forming an extra-local context (Sampson, 2001). When analysing this wider context and spatial autocorrelation, crucially urban form also needs to be considered (Petrović et al., 2018).

As discussed earlier, it is not only space that is multiscalar, but also time, and we need to understand contextual effects in a multiscalar space-time framework. For example, van Ham et al. (2014) studied the intergenerational effects of neighbourhood in Sweden by reconstructing individual neighbourhood histories from the moment of leaving the parental home. They showed that growing up in a deprived neighbourhood increases the likelihood of living in a similar neighbourhood later in life. And Hedman et al. (2015) showed that the childhood neighbourhood affected individual income up to 17 years after leaving the parental home. Wodtke et al. (2011) showed that longer term exposure to deprived neighbourhoods has a strong effect on school outcomes, and that the effects of social exposures have long temporal lags.

The lack of appropriate data sometimes leads to the conclusion that the MAUP, or geography in general, are irrelevant for individual outcomes. For example, Brännström (2005) did not find effects of either census areas or parishes on individual income and receipt of social assistance in Sweden. As noted by Andersson and Musterd (2010), both of these spatial units are heterogeneous and may obscure processes occurring at smaller spatial scales. Looking into these smaller scales is increasingly possible by the availability of microgeographic data in form of small grid cells, and further differentiation of spatial scales were achieved by starting with grid cells and aggregating them to larger scales of bespoke neighbourhoods (Östh et al., 2014; Petrović et al., 2018). Thus, microgeographic data makes it possible for researchers to move away from predefined (administrative) neighbourhoods to spatial contexts which are both individualised and multiscalar (in space and time). This development signals a turn from the study of neighbourhood effects to the study of sociospatial contextual effects.

2.4 The role of microgeographic data in future contextual effects research

Microgeographic data include spatial data with a fine spatial resolution, such as point data or areal data for regularly (grids) or irregularly shaped polygons, e.g. census tracts. These data can come from various sources, including (government) registers or large-scale surveys. According to the fractal principle, ‘all geographic phenomena reveal more detail with finer spatial resolution, at predictable rates’ (Goodchild, 2004). As such, the ‘special’ features of spatial data – spatial autocorrelation and spatial heterogeneity (Anselin, 1995, see Section 2.3.) – should be recognised, not as problems, but as opportunities (Fotheringham et al., 2000). In this respect, microgeographic data offer numerous opportunities to advance research into contextual effects.

2.4.1 Spatial and relational thinking

Analytic tools and techniques in neighbourhood effects research often treat spatial units in the same way as any other variables. Three basic ways of dealing with spatial data include using regular statistical methods and ignoring spatial dependence; acknowledging that spatial dependence exists and trying to remove it to justify using aspatial methods; and taking spatial autocorrelation explicitly into account and explaining it from a theoretical perspective. The latter approach benefits the neighbourhood effects research, although even spatial statistics often treat this spatial dependence as a nuisance and something that should be corrected, rather than as an important source of information. The increasing availability of microgeographic data motivates social scientists to think about how they represent sociospatial context and how to integrate spatial analysis in their research.

In comparison with the natural sciences, the social sciences have been slower to exploit GIS although the spatial dimension is no less important for social than for natural processes. Maps can be found in early social science, but many disciplines moved away from these roots developing other methodologies (Steinberg & Steinberg, 2005). Current trends in data science make mapping particularly relevant, because visualisation helps elucidate complex spatiotemporal patterns. GIS has not been sufficiently reconciled with neighbourhood effects studies. An exception is the work of Knaap (2017), who mapped the spatial opportunity structure to link the geography of opportunity with the mechanisms of neighbourhood effects. GIS expresses geography as a series of layers, capturing unique but related features. The spatial opportunity structure (Galster & Sharkey, 2017) is similarly organised as a series of contextual characteristics, such as ethnic and income compositions. Methods such as geographically weighted regression (GWR) can be used to operationalise spatial context by the interaction of multiple contextual characteristics, as well as the characteristics themselves in nearby locations. This can be a useful exploratory tool, which gives specific results for different locations rather than a single universal result.

Relational theory suggests that space can be understood only through relations. This includes subjective relations between people as well as individual spatial perceptions of neighbourhood, but also ‘objective’ relations as functional distances to schools, healthcare or other services. Relational perspectives on place emphasise the position of places relative to each other (Cummins et al., 2007). There is no spatial knowledge without metric information about distance and relative locations of places (Montello, 1998). Furthermore, conditions in one neighbourhood are not independent of conditions in adjacent neighbourhoods, which makes spatial autocorrelation the fundamental tenet of the research question. Finally, the connections between physically distant places, including mobility trajectories of people or regional labour markets, may also be important for individual outcomes. Distances and spatial relations can be more accurately measured using microgeographic data.

Precise measures of locations come not only from recording people's residential locations using population registers or census data, but also from following people's mobility using new technologies such as mobile sensing. Whilst innovative, this development also increases privacy concerns (Campbell et al., 2008). For instance, de Montjoye et al. (2018) proposed four models for the privacy-conscientious use of mobile phone data for research, including limited release, pre-computed indicators and synthetic data, remote access and question-and-answer. Some of the models can be applied to other types or sensitive data, such as health data, although none of these models cuts through the complexity of the use of sensitive data for research (de Montjoye et al., 2018). Privacy issues particularly concern the increasing linking of different sources of (sensitive) data, such as administrative records, survey data or areal imagery.

2.4.2 Fuzzy and bounded space

Neighbourhoods are 'geographic objects with indeterminate boundaries' (Burrough & Frank, 1996). Imposed boundaries matter to different extents for various neighbourhood effects mechanisms or for the same mechanism in different settings. For example, administratively defined neighbourhoods with high shares of ethnic minorities may be stigmatised, as might areas abutting asylum centres, but the extent of these areas may not coincide with administrative units. Different types of bounded and fuzzy spaces drive individual residential histories so that while people may rely on officially defined neighbourhoods such as school districts when selecting potential neighbourhoods, they may also pay attention to (functional) distances to transportation sites or other services. When moving into the neighbourhood, exposure to others depends less on administrative boundaries and more on proximity, so that the relevant contexts becomes even more fuzzy. Microgeographic data makes it possible to better understand bounded spaces, for instance heterogeneity in ethnic compositions or housing types within administrative units, but also fuzzy spaces of potential or actual exposure to context.

Individual exposure to context can be better represented with exposure surfaces in a 'moving window' defined at multiple spatial scales rather than fixed spatial units. For example, if a small area where an individual lives is surrounded by a markedly different larger area, this is masked when the two areas are combined into a large single unit. With the moving window this does not happen (Jones et al., 2018). Exposure surfaces via a moving window can also move us beyond discrete-space modelling. For neighbourhood effects (which are by definition spatial processes), the commonly used fixed effects model completely removes space, leaving neighbourhood as an isolated unit (Bell et al., 2018). Moreover, the use of an individual as their own control unit in a fixed effects model denies group level effects and assumes independence of outcomes across areas, rendering the question of neighbourhood effects meaningless. Two basic ways to take spatial dependence into account are hierarchical structures of space in multilevel models, and spillovers captured in spatial econometric models. Both approaches can be related to how social processes work, recognising not only the coexistence, but also the interdependence, of multiple spatial scales. Additionally, very small areas, close to exact geographic coordinates, also offer possibilities for continuous-space modelling. The continuous treatment of space can reveal the spatial distribution of outcomes and the scale of spatial variations, in contrast to measuring characteristics of the neighbourhood in more traditional, bounded, sense which may obscure or underestimate the effect of context as a more complex spatiotemporal category (Cummins et al., 2007).

Many individual outcomes depend on duration of exposure to different places, such as the residential neighbourhood and school for education outcomes, or residence and workplace for labour market or health outcomes. Therefore, microgeographic data can also improve the connection between time and space: We can adapt spatial scale to the temporal scope we are interested in, for example by using micro-locations for exposures on daily space-time paths, or larger scales for long-term exposure to, say, poverty. While administrative units precisely define a neighbourhood boundary, the location of an individual within that area remains unknown, microgeographic data can reveal the location of an individual more precisely, while the boundaries of their *multiple* neighbourhoods are fuzzier. Thus, to measure multiple spatial scales, the question become where to set thresholds.

2.4.3 Thresholds in fuzzy space

Thresholds exist even in a fuzzy space. Without limits, there can be neither difference nor identity (Abrahamsson, 2018). Setting thresholds in bespoke neighbourhoods using microgeographic data is particularly challenging, both because of the individual character of the neighbourhood and because of the fuzzy space. Bespoke neighbourhoods are usually based on distance or population counts. Population based bespoke neighbourhoods can be constructed from geographical coordinates for each individual. Using micro-scale grid cells, small increments in distance can be more accurately applied than small increments in population, because grid cells themselves are created based on distance. Even irregularly shaped spatial units can be used, although they are more challenging for delineating both distance and population.

The choice between specific techniques for delineating bespoke neighbourhoods is not solely a technical issue, but a theoretical one as well. On the one hand, some institutions or services are located based on the population served, which justifies the population count thresholds. Elsewhere, the area over which these people are distributed is important, because distance determines accessibility and exposure. For example, direct residential environments and exposure to first neighbours are normally associated with short distances regardless of the number of neighbours, although the density of neighbourhood can also affect social processes. Furthermore, since the same number of people can be distributed over very different areas, population size alone is not sufficient to characterise large scale contexts. In addition to distance, local patterns of land use (e.g. housing, play area, transportation infrastructure, etc.) can assist in setting thresholds in fuzzy space.

Considering multiple spatial scales in a fuzzy space has been achieved by using spatial profiles, which consist of a range of bespoke neighbourhoods from micro to macro scales. Based on the egocentric framework (see Lee et al., 2008), Spielman and Logan (2013) created profiles of individual buildings, which show how the surrounding social compositions change with scale. Petrović et al. (2018) created distance profiles of exposure to sociospatial context at a range of 101 spatial scales and measured the variability of the distance profiles across scales. While in some locations the context changed gradually, abrupt changes in other distance profiles revealed ‘social cliffs’ (Dean et al., 2018; Petrović et al., 2018). Uncovering these marked sociospatial changes is relevant for neighbourhood effects research, because micro locations and local changes in exposure are often at the core of the theory, but in the empirical research they have often been studied through a proxy of too coarse bounded spatial units. Fuzziness of space as well as changes and limits in the fuzzy space have received more attention in studying natural than social phenomena (see Burrough & Frank, 1996; Fisher, 2000). However, in identifying the extent of a mountain from the perspective of different people, Fisher et al. (2004) dealt with similar issues, particularly spatial scale. The methods which they used to identify morphometric classes (peaks, slopes, channels and ridges) of a mountain could also identify ‘social cliffs’, ‘social cleavages’ and other classes of exposure surfaces in urban settings. These methods can be used to further develop the concept of distance profiles representing sociospatial context.

TOC

Regardless of the metrics (e.g. distance, population counts, travel time) used to delineate bespoke neighbourhoods, the smaller the scale, the more ‘bespoke’ neighbourhoods can be, and the bigger the scale, the more ‘shared’ and overlapping neighbourhoods are. The multiscale bespoke neighbourhood perspective, therefore, draws attention to both local peculiarities and extreme contextual conditions on the one hand, and large-scale shared contexts on the other hand. This is what the theoretical approaches to neighbourhood effects mechanisms ask for and how sociospatial context is likely to be operationalised in the future more often, given the increasing availability of microgeographic data.

2.5 Structuring the uncertainty of sociospatial context

The overview of theoretical concepts of space and place and mechanisms of spatial contextual effects, as well as the review of the empirical literature were permeated by issues of spatial scale and boundaries in fuzzy space. This, combined with the immense possibilities of microgeographic data, leads to uncertainty in the operationalisation of sociospatial context. Empirical studies which address the issue of spatial scale sometimes note that there are no theoretical guides as to the scale at which contextual effects operate (see, e.g. Plum & Knies, 2015). In this section, we bring some structure to the relationship between contextual mechanisms and spatial scales. Although uncertainty in the operationalisation of sociospatial context cannot be avoided, it can be structured in a way that shows which mechanism is most likely to operate at which scales, as well as on which factors this likeliness depends.

Figure 2.1 shows a matrix of contextual mechanisms and spatial scales. The density shows the likely relevance of a specific scale for a specific mechanism. For example, while peer group effects normally operate at a small spatial scale, school districts extend to larger scales. Some mechanisms may operate at multiple scales simultaneously, particularly processes like stigmatisation. While labour market factors generally operate at larger spatial scales, the exact extent of local labour markets varies across regions. With a single spatial scale, we run the risk of cutting through various mechanisms, capturing relevant scales for some and less relevant scales for other mechanisms, represented with horizontal lines in Figure 2.1.

Which scale is the most relevant also depends on the sociodemographic characteristics of people and the urban setting, which can be illustrated with an example: One child grows up in a street with poor neighbours, but in a middle-class district, and goes to a middle-class school. Another child goes to the same school and lives in the same urban district, but in a street with richer neighbours. Both children live in the same urban region so their spatial contexts are shared at some scales and distinct at others, and they include interactions between individual, family, neighbourhood, city and regional level factors.

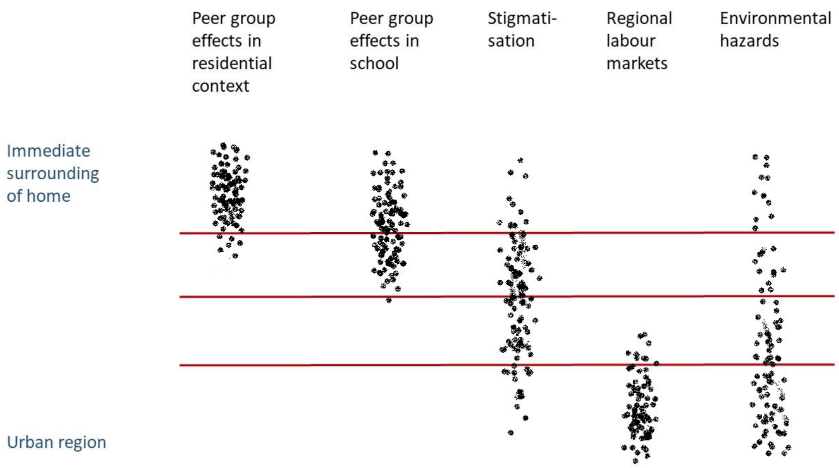

FIG. 2.1 Spatial scales of contextual mechanisms

Ultimately, neighbourhood effects research should be reconciled with more individual- and family-oriented perspectives on human development, by recognising the key lower-level context – the family, and its mediating position between an individual and the neighbourhood (Lee, 2001; Hedman et al., 2019), and well as the interaction of other factors, such as genes, with the environment (see e.g. Boardman et al., 2013). Although technology has become increasingly important in the social domain, many forms of social life remain spatially organised. Many types of behaviours are spatially concentrated, so that even individuals who use Internet the most concentrate in certain neighbourhoods (Sampson, 2012).

General hypotheses about specific mechanisms and their spatial scope are as important as the knowledge of the spatial and temporal setting. Theory can inspire qualitative studies in various settings, based on which hypotheses for quantitative

TOC

studies can be formulated. Ethnographic studies, therefore, have an intermediate role between theory and quantitative studies – to help generate clearer and more specific hypotheses, but also to provide qualitative data which can be linked with administrative records. The way to implement the theory of contextual mechanisms in quantitative studies would then be firstly, to formulate general hypothesis, for distinguishing between different mechanisms, e.g. peer group effects operate at smaller spatial scale than stigmatisation (see Figure 2.1); secondly, to analyse the spatial and temporal setting, e.g. stigmatisation takes larger spatial scope in a big city and increases over time as the concentration of poverty increases; thirdly, to formulate specific and nuanced hypotheses regarding affected people, e.g. people from the neighbourhood with different vocations or of different age are affected in different ways.

2.6 Conclusions

In this paper, we built on conceptual and empirical work related to neighbourhood effects, to raise spatial awareness and integrate knowledge from various disciplines, particularly because spatial data are increasingly detailed and more accessible to researchers. We identified increasing interest in spatial scale and bespoke neighbourhoods, but also discordances between the theoretical approaches to contextual effects and the empirical research. Therefore, we proposed ways in which microgeographic data can further advance contextual effects research. The first is that data should remind us that contextual effects research is about the space around us, and that we should adopt a spatial perspective from approaches which actively use it, such as GIS. Second, with microgeographic data we can implement the concepts of fuzzy space. Concomitantly, we should not forget landmarks or boundaries which are easily recognised, and we should use different concepts of space (fuzzy and bounded) when appropriate. Third, fuzzy space and particularly its thresholds need to be further explored using microgeographic data, for example in form of spatial profiles. Spatial profiles show that MAUP is not a mere *problem*, but also a *resource* of studying a range of spatial scales of context.

Quantitative research depends on the synchronised availability of good-quality data, well-formulated hypotheses which can be expressed in mathematical terms, analytic tools and techniques, and technology to facilitate the analysis (Haining, 2003). Formulating hypotheses is a crucial initial step, ideally the main determinant in the choice of appropriate spatial data. Theoretical approaches to the mechanisms of neighbourhood effects should guide these hypotheses, where, for example, social mechanisms generally differ from institutional mechanisms in both spatial scale and zonation schemes. The hypotheses can be refined by exploring spatial patterns of area characteristics, e.g. housing types or poverty concentrations in different (parts of) cities and with the results of qualitative research of the study area. Crucially, microgeographic data put a wider variety of scaling and zonation schemes into practice, and, therefore, make it feasible to follow theoretical approaches to neighbourhood effects and bring back spatial thinking into neighbourhood effects research.

A parallel between theorising place and space and the availability of spatial data can be drawn from the health geography or criminology, where the concept of place was given more attention compared to other (sub)disciplines within the neighbourhood effects research (see also a similar observation by Haining, 2003). Further parallels can be drawn between theoretical approaches such as peer group effects, spatial spillovers or the relational approach, on the one hand, and the nature of spatial data, notably spatial autocorrelation, on the other hand, which are often considered separately, either studying social theory or technical properties of spatial data. By linking theoretical and spatial analysis approaches, the grounding for neighbourhood effects research increases as does our knowledge about *phenomenon scale*. Together, this can then inform *analysis scale*. The role of microgeographic data is then to better link the phenomenon and the analysis scale, as well as to give attention to both micro-locations and large-scale urban, institutional and economic structures.

A parallel also exists between geographic objects with fuzzy boundaries in physical and human geography. Geography, the most spatial of disciplines (Massey, 1995), should enrich the neighbourhood effects research by facilitating zonation systems that are less arbitrary and can capture various mechanisms of contextual effects more accurately than predefined administrative areas. Also methods used in physical geography to operationalise geographic phenomena which are fuzzy for scale reasons (Fisher et al., 2004) can be used to dynamise space and make it relevant for the broad social science. Using microgeographic data, neighbourhood effects research can give more attention to location, distance and exposure, spatial dependence and heterogeneity, taking into account multiple neighbourhood membership. Microgeographic data move us from the autonomous bounded spatial units to continuous space, in which neighbourhoods are much fuzzier than is generally assumed, and where spatial contextual effects should be investigated rather than 'neighbourhood' effects.

Using standard administrative units has for a long time been a defining feature of neighbourhood effects research. This is understandable as many datasets require specific geographies to be used. However, the increasingly availability of microgeographic data is helping social scientists to better understand sociospatial context and arrive at clearer conclusions about contextual effects. The variety of spatial contexts that are possible to study using microgeographic data should not only remain alternative ways of operationalisation of neighbourhoods. Instead, they should become a paradigm of the spatial contextual research. Where the neighbourhood effects literature argues for more attention to the definition of neighbourhood, we even go one step further, and argue that in order for neighbourhood effects research to move on, we need to break away from the tyranny of neighbourhood, and consider the effects of the broader sociospatial context of people.

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3 Multiscale measures of population

Within- and between-city variation in exposure to the sociospatial context

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ABSTRACT Appreciating spatial scale is crucial for our understanding of the sociospatial context. Multiscale measures of population have been developed in the segregation and neighbourhood effects literatures, which have acknowledged the role of a variety of spatial contexts for individual outcomes and inter-group contacts. Although existing studies dealing with sociospatial inequalities increasingly explore the effects of spatial scale, there has been little systematic evidence on how exposure to sociospatial contexts changes across urban space, both within and between cities. This paper presents a multiscale approach to measuring potential exposure to others. Using individual level register data for the full population of the Netherlands, and an exceptionally detailed multiscalar framework of bespoke neighbourhoods at 101 spatial scales, we measured the share of non-Western ethnic minorities for three Dutch cities with different urban forms. We created individual and cumulative distance profiles of ethnic exposure, mapped ethnic exposure surfaces, and applied entropy as a measure of scalar variation to compare potential exposure to others in different locations both within and between cities. The multiscale approach can be implemented for examining a variety of social processes, notably segregation and neighbourhood effects.

KEYWORDS spatial scale, distance profile, entropy, urban form, ethnic exposure

3.1 Introduction

Spatial scale is a critical dimension of social and physical attributes of an environment (Smith, 2000; Reardon et al., 2008). The relevance of scale has been well established for the segregation literature (see, for instance, White, 1983; Wong, 2004; Clark et al., 2015; Jones et al., 2015), the neighbourhood effects literature (Galster, 2001; Andersson & Musterd, 2010; van Ham & Manley, 2012; Vallée et al., 2014), and more broadly research of sociospatial inequalities (Suttles, 1972; Manley et al., 2006; Prouse et al., 2014), where scale is often addressed as one aspect of the modifiable areal unit problem (MAUP; see Openshaw & Taylor, 1979; Manley, 2014). Sociospatial inequalities can be more fully understood by exploring variation in geographic contexts across multiple scales – within the so-called spatial opportunity structure – rather than by confining to a single geographic context (Galster & Sharkey, 2017). Crucial for understanding spatial foundations of social inequality is the measurement of population characteristics, whose multiscalar representations have evolved with the increasing availability of detailed spatial data.

One common way to explore scale is to compare measures of population at two or more spatial scales of neighbourhood (see, e.g., the studies by Overman, 2000; Johnston et al., 2004; Bolster et al., 2007; Vallée & Chauvin, 2012; Duncan et al., 2014). Most studies use standard administrative units, but acknowledge that these spatial units are often too large and do not represent the structure of the population that they are interested. The neighbourhood effects literature, therefore, increasingly uses bespoke neighbourhoods, areas centred on an individual, to measure exposure to the sociospatial context (introduced by Johnston et al., 2000; Buck, 2001; MacAllister et al., 2001). Using finer grained geocoded data has intensified the shift in the neighbourhood effects literature from the *neighbourhood* to a sociospatial context comprised of scalable bespoke *neighbourhoods* (Andersson & Malmberg, 2014). Although the bespoke neighbourhood approach is not indisputable (Vallée & Shareck, 2014), it does provide a lens through which attention can be given to the effects of location when measuring population. Hipp and Boessen (2013), who used 'egohoods' (their term for bespoke neighbourhoods) of different radii to explore variation in crime, argue that this 'individual social environment perspective' captures heterogeneity across the city and represents the social landscape more accurately than fixed, non-overlapping spatial units.

The individual social landscape can be conceptualised as a multiscale measure of population and represented as the spatial profile of a (residential) location. The idea builds on the segregation profiles introduced by Reardon and colleagues (Reardon et al., 2008; Reardon et al., 2009), which have developed into spatial profiles (see Spielman & Logan, 2013; Clark et al., 2015; Fowler, 2015; Hennerdal & Nielsen, 2017). These spatial profiles depict for a focal location the potential exposure to others as scale changes, and characterise places as complex sociospatial contexts. Although Fowler (2015) suggested how to describe segregation profiles using a range of indicators, expressing scalar variations in population measures, particularly for a larger number of scales, remains a big challenge.

The spatial profiles of potential exposure to others spread over the urban mosaic of neighbourhoods. Contemporary cities are often ethnically and socioeconomically fragmented (Jenks et al., 2008; Marcińczak et al., 2015; Tammaru et al., 2016), and some of them have evolved into polycentric urban regions (Danielzyk et al., 2016). However, very little attention has been given to the issue of how exposure to others changes across scale throughout urban space, when moving through a single city or between multiple urban regions. Some studies used multiscale methods to compare specific scales in different metropolitan areas, without considering different urban forms (Lee et al., 2008; Reardon et al., 2008; Östh, Clark, et al., 2014). Others demonstrated the need to define context for particular population groups located in specific parts of a single city rather than for the city as a whole (Manley et al., 2015; Johnston et al., 2016).

The aim of this paper is to better understand the effects of scale and location on the measurement of potential exposure to others. The paper presents a multiscale approach to measuring potential exposure to the sociospatial context, by addressing the following objectives: (1) to explore how scale matters for measuring exposure to sociospatial context; (2) to propose a novel method of measuring scalar complexity of exposure to sociospatial context in different locations; (3) to show how scale impacts exposure to sociospatial context in different ways in three different cities in the Netherlands; (4) to show how locational differences in exposure to sociospatial context fragment the city at multiple scales for different population groups.

This study used register data including the full population of the Netherlands, whose place of residence was geocoded at the level of 100m by 100m grid cells. We studied three cities with different urban forms, namely Amsterdam, Utrecht, and Groningen. Around each cell in these cities, we delineated bespoke areas at 101 spatial scales, capturing very diverse contexts from the immediate surroundings of a dwelling, to much larger areas. In these areas, we measured the share of non-Western ethnic minority people (contextual characteristic often used; see, e.g., Clark & Drinkwater, 2002; Friedrichs et al., 2003; Moore & Diez Roux, 2006) and mapped the ethnic exposure surface of the cities. We then focussed on individual locations and created their distance profiles – spatial profiles consisting of measures of population in

101 bespoke areas defined using Euclidean distance. Using Shannon's (1948) entropy index, a complexity measure originally derived in information theory, we quantified the variation in multiscale measures of non-Western population and compared different locations within and across cities. For the three cities, we created cumulative distance profiles, and on the example of Amsterdam, we compared the individual distance profiles for two population groups (Western and non-Western).

3.2 Ethnic exposure in urban space: The role of spatial scale

Distance and its meanings are at the core of research into sociospatial inequality. Distance relates to access to employment and public facilities, exposure to crime, violence, and site-specific pollution, as well as potential access and exposure to other people. Proximity to other people features social networks, contact and interaction with others (Logan, 2012). In socially and ethnically diverse cities, *social* distances and ethnic identities are often reflected in *spatial* distances (Häußermann & Siebel, 2001; Berding, 2008). Different ethnic or income groups are often segregated within and between cities (see, for instance, Friedrichs & Triemer, 2009; Marcińczak et al., 2015; Tammaru et al., 2016). The fact that people tend to locate close to their co-ethnics (Schelling, 1971) has many underlying causes, but is also thought to have effects on the socioeconomic outcomes of individuals (Friedrichs et al., 2003). The segregation literature generally assumes that sociospatial isolation of groups intensifies intergroup prejudice (Tredoux & Dixon, 2009). In line with this, the 'contact hypothesis' relies on the idea that interaction among members of different groups reduces intergroup prejudice (Allport, 1979; Pettigrew & Tropp, 2006). Along with the positive aspects of proximity to other groups, the neighbourhood effects literature generally hypothesises that living in a spatial concentration of disadvantaged people negatively affects individual health, employment or educational outcomes of people (see Van Ham et al., 2012; Manley et al., 2013; Van Ham et al., 2013).

Although exposure to other people is studied for various reasons, all studies related to sociospatial inequalities rely on some measure of population characteristics. The representation of these characteristics depends on scale as a spatial or temporal dimension used to measure and study phenomena (Gibson et al., 2000; Montello, 2001). Many social processes have quite complex spatial and temporal dimensions, with a high degree of uncertainty, as defined within the uncertain geographic context problem (UGCoP; Kwan, 2012). Specifically, spatial scale is one aspect of the modifiable areal unit problem, concerned with the size of spatial units (MAUP; Openshaw & Taylor, 1979; Manley, 2014). However, population data available for social research have long been too limited to explore the scalar complexity.

Standard administrative areas are frequently deployed to represent individual sociospatial contexts. Despite being practical, conventional spatial units have a number of limitations. Administrative units are designed for specific purposes, such as jurisdiction or post-delivery, rather than for social research, and are unlikely to reflect the spatial processes contained within the data (see Jones et al., forthcoming). Further, administrative units do not always conform to temporal consistency through multiple redesigns and boundary changes over time. Biases arise as a consequence of the boundary effect, whereby people living close to the edge of an administrative unit may experience greater connection with people in an adjacent unit than to those in unit they live. The limitations of administrative units might culminate in a mismatch between the analysis scale and the actual phenomenon scale (Montello, 2001). For example, even when available at more than one scale, administrative units are never small enough to represent people's immediate environment. Lee et al. (2008) empirically demonstrated the limitations of administrative units (census tracts) in measuring residential segregation, supporting the use of multiple spatial scales.

With the increasing availability of geocoded micro-data, researchers can more adequately represent people's sociospatial contexts at the scales relevant for the social processes under study, such as segregation and neighbourhood effects. On the one hand, microgeographic data present substantial methodological challenges, offering a potentially infinite number of possible scales and zonation schemes. On the other hand, such detailed data is also a resource of new information about the area under investigation (Manley et al., 2006). The finer the spatial data, the greater the possibilities for analysing various scales, starting with exploratory analysis. Mapping sociospatial inequality using microgeographic data makes it possible to reveal and investigate small-scale spatial patterns (vom Berge et al., 2014), while larger scales remain important for mapping spatial opportunity structure (Knaap, 2017). More accurate geographic data provides information on both the micro-locations where exposure to other people starts (around one's home) and how the population to which individuals are potentially exposed changes in continuous space.

3.2.1 Scale from the individual (bespoke) perspective

Bespoke neighbourhoods are increasingly used as an alternative to administrative units to represent people's sociospatial contexts. A bespoke neighbourhood is a neighbourhood which has the residential location of an individual in the centre and represents an exposure surface to sociospatial phenomena. As a consequence, the bespoke neighbourhoods of two neighbouring individuals overlap, but are not the same. An ideal estimation of the environment people are exposed to on a daily basis would require substantial information about their daily space-time paths (Hägerstrand, 1970). The inquiry of individual daily activities, social networks and perception of spaces (Mennis & Mason, 2011; Kwan, 2012) has provided important insights into people's actual activity spaces and 'personal cities' (Weber & Kwan, 2003). Since such information is often not available, especially not for large populations, bespoke neighbourhoods can be created around people's residential locations, but also around workplaces and other key locations on space-time paths.

An increasing number of studies have used bespoke neighbourhoods around people's places of residence to asses neighbourhood effects on personal health and health-related issues (Duncan et al., 2014), political attitudes and voting behaviour (MacAllister et al., 2001; Johnston et al., 2004), or socioeconomic status (Bolster et al., 2007; Andersson & Musterd, 2010; Hedman et al., 2015). These studies usually compare two or more spatial scales of bespoke neighbourhoods in an attempt to relate different spatial scales to different contextual influences on individual outcomes. As Vallée and Shareck (2014) noted, bespoke neighbourhoods are not considered as 'better' than administrative units. Certainly, people do not necessarily reach and experience their environment equally in all directions, just like their activities are not determined by arbitrary administrative boundaries. However, the idea of placing an individual in the centre and measuring the socioeconomic composition of the surrounding area is largely supported by studies on residents' perceptions, where people are asked to delineate their neighbourhood themselves. The main finding from these studies is that neighbourhoods as defined by residents are different, notably smaller, than conventional spatial units such as census tracts (Omer & Benenson, 2002; Lohmann & McMurran, 2009; Coulton et al., 2013). As noted by Hipp and Boessen (2013), respondents generally place themselves in the centre of the neighbourhood, although this is rarely highlighted in the findings of such studies (but see Coulton et al., 2001; Grannis, 2009).

An individual is not located in the centre of a single bespoke neighbourhood, but in the centre of a range of nested and interconnected areas. This is important because the share of ethnic minorities, for instance, in a larger area surrounding an individual dwelling can be an indicator of the neighbourhood population trajectory, which may influence people's decisions to move in or out (Crowder & South, 2008). Thus, while too coarse aggregations mask relevant spatial patterns, an exclusive focus on smaller areas removes neighbourhoods from their broader context. Within the social sciences, the continuous approach to spatial scale has been most prominent in segregation research. Although scale was long ago recognised as crucial for developing more advanced segregation measures (see e.g. White, 1983; Wong, 2004), the continuous perspective on scale arose with the 'segregation profiles', presented by Reardon and colleagues (Reardon et al., 2008; Reardon et al., 2009).

The idea of segregation profiles motivated several researchers to explore how local conditions of segregation blend with broader spatial contexts (Spielman & Logan, 2013; Clark et al., 2015; Fowler, 2015; Hennerdal & Nielsen, 2017). These studies focused on understanding spatial patterns of segregation by grouping locations in order to form homogenous clusters, while defining context and measuring individual exposures in particular locations have received less attention. Spielman and Logan (2013) created individual profiles (which they termed 'egocentric signatures'), although they aggregated the profiles into clusters. Therefore, their method mainly aims at improving our understanding of the social structure of cities and not at assessing individual exposures. Fowler (2015) went perhaps the furthest in exploring the multiscale segregation profiles by describing the functional form of a profile. In line with other U.S. studies employing segregation profiles, the author uses block-level population counts converted to a population density surface and interpolated to raster cells (see Reardon & O'Sullivan, 2004) to create micro-geographies.

Neighbourhood effects research is by definition interested in individual exposures to sociospatial context and benefits from multiscalar population measures. Scalable bespoke neighbourhoods motivated by segregation profiles, but using population counts (the *k* nearest neighbours) have been implemented in modelling neighbourhood effects in Sweden (Andersson & Malmberg, 2014), as well as for measuring segregation (Östh, Clark, et al., 2014; Östh, Malmberg, et al., 2014). Thus, both segregation and neighbourhood effects research have been shifting from measuring characteristics of a fixed neighbourhood to the analysis of individual exposures in a multiscalar geographical context, with the aim to better understand residential context.

Although different methods can be used for creating bespoke neighbourhoods, they are all scale-dependent, and need not solely rely on Euclidean distance or population counts. For example, road network (van Ham et al., 2001; Frank et al., 2005; Oliver et al., 2007) and travel time buffers (McGuirk & Porell, 1984; Wang, 2000; Reardon et al., 2008) more accurately measure access to jobs, services or resources, but can only be feasibly performed in small-sample studies, because of the data requirements and computational complexities. Critically, regardless of the method chosen to derive bespoke neighbourhoods (different types of distance or population thresholds), researchers still need to make decisions regarding the scales at which area characteristics are measured, and to be aware of the way in which altering scale changes the results. This study contributes to the literature by proposing a method of measuring scalar complexity of exposure to sociospatial context in different locations.

3.2.2 Distance profiles of sociospatial context and urban form

Ideally, the scale of bespoke neighbourhoods should be theoretically specified, for example, by associating different mechanisms of neighbourhood effects with different spatial scales (Galster, 2012). However, for many social processes related to segregation and neighbourhood effects a clear theory of scale is lacking, or they may be operating at multiple scales simultaneously. Arguably the main reason is that the scale of many social phenomena largely depends on the particular geographic setting, so that processes might operate differently in different locations within one city and between cities. In this paper, we conceptualise sociospatial contexts as distance profiles of potential exposure to others. We argue that the complexity of these distance profiles strongly depends on the urban mosaic of neighbourhoods, and, therefore, on urban form.

Urban form is essentially multiscalar, as it is used to describe both intra- and inter-urban patterns and connections at multiple spatial scales (Kloosterman & Musterd, 2001a; Davoudi, 2003). A simple way to categorise urban forms is by distinguishing monocentric and polycentric cities. This distinction appeared as cities with multiple centres (polycentric cities) emerged, as opposed to the monocentric cities with one central business district (Anas et al., 1998; van Houtum & Lagendijk, 2001). However, contemporary cities are rarely monocentric, but rather polycentric to different extents. Polycentricity within cities is characterised by multiple clusters of population and economic activities, which merge into one larger interdependent system (Anas et al., 1998).

At the same time, urban regions with cities as centres have developed. These urban systems involve two or more formerly independent and distinct cities which are located relatively close to each other and have started to integrate more, such as the Dutch Randstad, the Flemish Diamond, and the German Ruhr region (Dieleman & Faludi, 1998; Kloosterman & Musterd, 2001b; Meijers, 2007; Danielzyk et al., 2016). So, two scales of polycentricity are the most obvious (the city and the regional scale), although at a more elaborate level, both intra- and interurban polycentricity can have various scales.

Although the concept of polycentricity predominantly relates to economic and institutional structures, the spatial distribution of different population groups is also one aspect of polycentricity, which goes hand-in-hand with urban fragmentation in a wider social, cultural and economic context (Jenks et al., 2008). The urban mosaics of larger cities show a variety of neighbourhoods with different types of housing and with concentrations of ethnic and socioeconomic groups (Tammaru et al., 2016). The concentration of disadvantaged groups often leads to territorial stigmatization of certain parts of the city, which may extend to much larger scales than what is usually characterised as the 'neighbourhood'. As a result, parts of some metropolitan cities, such as New York's Bronx, Berlin's Neukölln and Amsterdam's Bijlmer, have a 'blemish of place' at the national or even the international level (Wacquant, 2007). With increasing social polarisation and the growing size and diversity of racial/ethnic 'minorities', economic status and ethnicity have become some of the most important factors of spatial fragmentation in urban space (Champion, 2001; Jenks et al., 2008).

Fragmentation in the urban discourse is usually interpreted as a generating process or a way of operating the city, or as a spatial phenomenon or state, but also as an urban experience or a way of perceiving the city (Kozak, 2008). We apply multiscale measures of population as a means to assess sociospatial fragmentation in urban space as potential exposure to 'others' in urban space. The distance profiles we use to measure the potential exposure to others will be affected by intra- and inter-urban polycentricity. Population measures at different spatial scales will be affected by urban form, and as a result altering scale will reveal different profiles of potential exposure depending on the location within a city, but also between cities. As different ethnic groups occupy different spaces in cities, multiscale measures of population reveal important ethnic differences in the exposure to others at various scales (Manley et al., 2015; Johnston et al., 2016). Besides the within-city variations, cross metropolitan comparisons of segregation have shown different impacts of spatial scale in different metropolitan regions, without addressing the issue of urban form (Lee et al., 2008; Reardon et al., 2008; Östh, Clark, et al., 2014). The aim of this paper is to better understand the effects of scale and location on the measurement of potential exposure to others, by profiling the scalar complexity in different places both within one city and across cities with different urban forms.

3.3 Data and methods

We used individual level register data covering the full population of the Netherlands, geocoded on 100m×100m grid cells, for the year 2013 (Sociaal Statistisch Bestand – SSB, see Bakker, 2002; Houbiers, 2004). For our analysis, we chose three distinct cities with different population sizes and inter- and intra-urban forms. The first two are Amsterdam, the most populated city in the country (810,000 people living on 165km^2), and Utrecht, ranking the fourth (330,000 people, 95km^2). Both Amsterdam and Utrecht are part of the Randstad, the largest conurbation in the Netherlands. The third city, Groningen, has the seventh largest population in the country (200,000) in the area of 80km^2, and is spatially isolated in comparison with the other two cities. In terms of intra-urban polycentricity, Amsterdam and Utrecht have more diverse urban structures than Groningen.

For these cities, we studied the proportion of people belonging to non-Western ethnic minority groups within a highly detailed multiscalar framework. We simplified ethnicity into two categories, the first including native Dutch and other people with a Western background, and the second representing people with a non-Western background.[1] Whilst we chose to focus on ethnicity for the purposes of the discussion below, the approach we exemplify is suitable for studying other population characteristics at multiple scales.

The core of our method consists of creating bespoke areas of 101 different spatial scales. The base scale is represented by the 100m×100m cell itself, and the starting point for the measures is the share of non-Western people for each 100m×100m cell in the three cities (each city map in the Results section displays approximately 68,000 cells). From the base cell as a centre, other bespoke areas spread in hundred concentric circles, radii of which range from 100m up to 10km, with 100m increments. Each of these bespoke areas is comprised of all cells whose centroid is located within the specific bandwidth[2].

To represent the ethnic exposure surface of the cities approached from different spatial scales, we created a series of uniform maps[3]. In each map, the measured values at a specific scale are assigned to the base cell, although the values are based on measures for a single cell (0.01km^2) up to its wider surroundings (314km^2 for the largest circle). Increasing the scale might exceed the boundaries of a city and include parts of the surrounding area, even parts of other, adjacent cities.

We then focussed on specific locations and created individual distances profiles of ethnic exposure for each 100m×100m cell, containing percentages of non-Western people measured at all 101 scales. For each individual distance profile (so for each cell), we expressed the scalar complexity using the entropy index. The concept of entropy has been utilised in many different scientific disciplines with different purposes and different formulas. Unlike the common use of entropy in the research of sociospatial inequalities – for assessing segregation between different population groups (see, for instance, Reardon & O'Sullivan, 2004), we use entropy to capture in one index the complexity of exposure to one population group at a range of spatial scales.

Our index is based on Shannon's entropy index (1948), which was originally derived for measuring uncertainty of a message content in the information theory. We measured to what extent individual distance profiles vary within a range of values (0 to 100 percent of people with a non-Western background) in bespoke areas at 101 scales. So, the distance profile line can have one of 101 values[4] at each of the 101 scales. If the percentage is the same at all scales, the distance profile has low entropy. If the distance profile is spread over more categories (different percentages of non-Western people at different scales), the profile has high entropy. This is calculated as follows:

$$H(X) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i) ,$$

where x_i is a value (percentage of non-Western people), and $p(x_i)$ is the proportion of scales with the same value. The minimum entropy would reach 0 for a completely flat distance profile, whereas the maximum possible entropy for this number of categories and scales is less than 7. The theoretical maximum for an entropy profile would contain 101 values (0-100 percent of non-Western people) across the 101 spatial scales, i.e. each spatial scale would have a different percentage of non-Western people. Low-entropy profiles are in general very flat, although at certain scales there might be sudden shifts.

Besides comparing the individual locations within and between cities using the entropy index, we compared the cities as a whole based on their cumulative distance profiles. Cumulative profiles of potential ethnic exposure compile the results for individual profiles along all the scales, and consist of 101 parallel boxplots, with a single boxplot for each scale. This provides two useful insights, namely into the variability within each scale – how population characteristics vary when measured at different locations within one city using the same scale (the within-scale variability), as well as into the variability between scales – how the measures vary when using different scales (the between-scale variability).

In addition to creating the aggregate population measures for specific cities, we also assessed intra-urban fragmentation for different population groups. Therefore, we compared the exposures to non-Western ethnic minorities at different scales for Western and non-Western ethnic groups in the same city (Amsterdam). For this, we multiplied each individual distance profile with its occurrence (the numbers of Western and non-Western people who live in that cell). We then plotted the exposures of these two groups to non-Western people at multiple scales jointly in one graph to explore to which extent the exposures overlap or diverge.

3.4 Results

The series of city maps for Amsterdam in Figure 3.1 demonstrates the instability of multiscale measures of non-Western population in a continuous way. Figure 3.1A to 3D show the share of people with a non-Western background, measured at four different spatial scales, ranging from 100m×100m cells (3A) to areas with a radius of 10km (3D). (The supplementary online video containing maps for all 101 scales in Amsterdam, Utrecht and Groningen, gives an overview of all three study areas and demonstrates the scalar changes in more detail.) The colour of each cell in Figure 3.1A denotes the percentage of minorities in that actual cell, which represents people’s immediate residential environment. This is an urban mosaic of ethnicity in Amsterdam, in which people have very different potential exposures to others as they open the front door of their house, in the immediate surroundings of their dwelling. There are clear concentrations of minorities in the Western and South-Eastern parts of Amsterdam (Westelijke Tuinsteden and Bijlmer) as well as the East and the North.

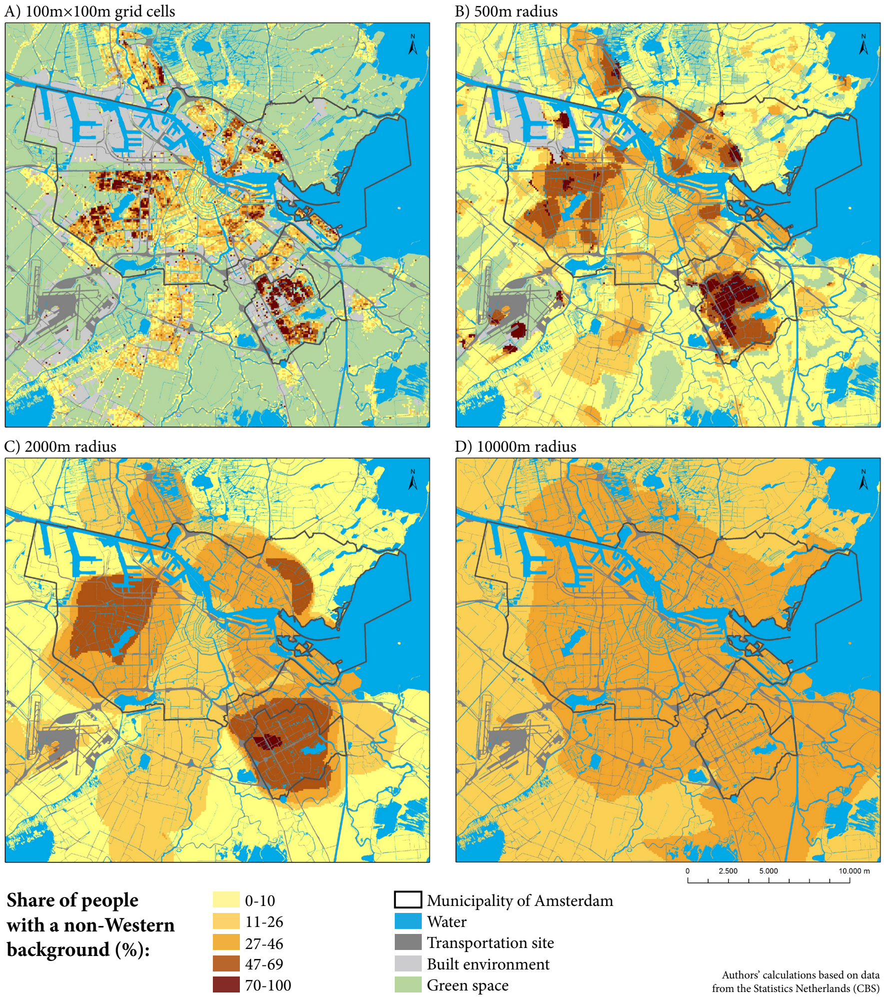

FIG. 3.1 Maps of Amsterdam in 2013 for four sample scales: Share of people with a non-Western background in bespoke areas with various radii

Figure 3.1B shows the percentage of non-Western ethnic minorities in a way that each 100m×100m cell is coloured based on the percentage minorities in an area with a 500m radius from that cell; Figure 3.1C shows the same for a radius of 2km. These maps show potential ethnic exposure of people living in a particular cell for larger areas around their residence. Consider a cell in Figure 3.1A with a relatively low percentage of minorities, but surrounded by other cells with the highest percentage of minorities. Then at the scale of the dwelling or street the potential exposure to ethnic minorities is low, but as soon as the residents travel to the next street, their potential exposure to ‘others’ increases.

The higher spatial scale of 10km represents the ethnic makeup of the whole urban area (Figure 3.1D), which is very different from our starting point, namely the lowest spatial scale of 100m by 100m, representing experiences of residents just around their home. Different scales, therefore, reveal different lived contexts, as certain clusters of high concentrations of minorities are recognizable at specific scales, but not distinctive at others. With this detailed geocoded data and the large number of scales, we can observe how measures of population gradually change with scale, as opposed to the cross-sectional view of specific scales.

Of particular interest in this study is the distance profile of potential exposure for all 101 scales, which depicts the path that specific location follows from the scale of context mapped in Figure 3.1A to the one in Figure 3.1D. Each cell has its own distance profile showing how the share of non-Western people varies as we alter the scale in specific locations (with increasing distance from the starting cell representing a residential location). This profile represents the potential exposure to others as people move away from their location of residence. In this study, we propose to capture this variation in potential exposure in one entropy index, expressing the scalar complexity of exposure to ethnic minorities in each 100m by 100m cell in our study area. Figure 3.2 compares the distance profiles with the highest and the lowest entropies across the three cities (Amsterdam, Utrecht, and Groningen).

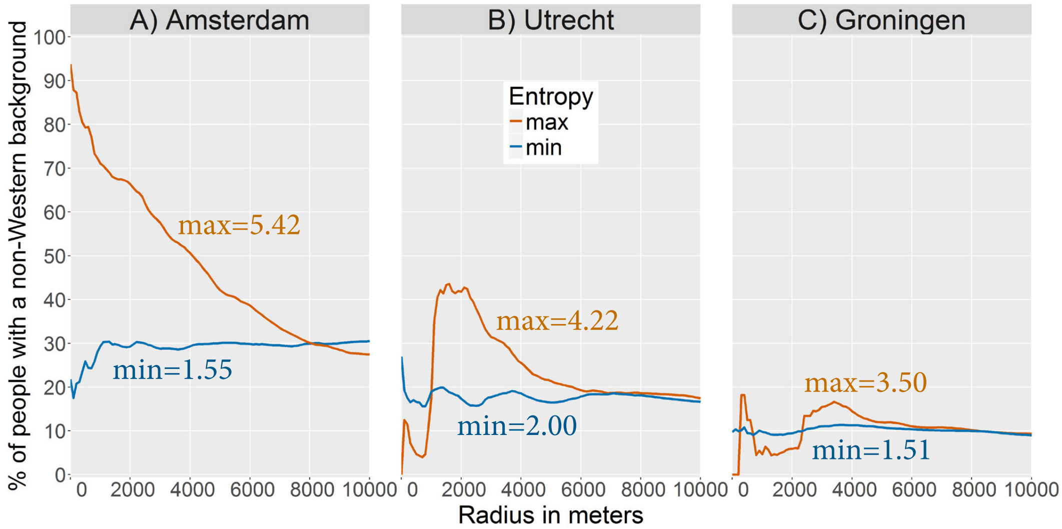

FIG. 3.2 Individual distance profiles with minimum and maximum entropies in Amsterdam, Utrecht, and Groningen, in 2013

Distance profiles with low entropy are fairly flat, i.e. the percentage of non-Western minorities is constant at most of the scales. The minimum-entropy distance profiles from the three cities differ in the overall level of the share of non-Western minorities (around 30 percent in Amsterdam, 20 percent in Utrecht, and 10 percent in Groningen). The most constant multiscale measures of exposure to non-Western people are found in Groningen (Figure 3.2C). Amsterdam reaches almost the same minimum entropy in Groningen (Figure 3.2A), with more variant micro-scales. Unlike Amsterdam and Groningen, even the least variant distance profile in Utrecht slightly varies also at meso scales, with an entropy of no less than 2 (Figure 3.2B).

Compared to minimum entropy profiles, the maximum entropies differ even more across the three cities. The closest profile to the theoretical maximum lies in Amsterdam (5.4). By contrast, the profiles associated with Utrecht do not reach this level, while the maximum in Groningen (3.5) corresponds to a medium entropy in Amsterdam. Therefore, maximum entropy demonstrates how relative is the concept of scalar variability in different settings, i.e. what is considered big variability in one setting may be very different from what is considered big in another. On the other hand, minimum entropy underlines the difference in the broader, large scale contexts of the cities, showing that scale-invariant measures of population may be constant across scale at very different levels in different settings.

As follows from the Figure 3.2, Amsterdam has the biggest range of entropy, so the biggest variety of distance profiles. We have, therefore, mapped the distance profile entropy for all the cells in Amsterdam to gain more insight into the within-city variability. Entropy was mapped together with the percentage of non-Western minorities at the lowest spatial scale, namely the base cell or the starting point of the distance profile (see Figure 3.3). The ethnic composition at this lowest scale represents the potential exposure in the immediate surroundings of a dwelling, and what happens along the entire distance profile is represented by the entropy index. The combination of the values in the starting cell, and the distance profile is important, as two distance profiles might have a similar entropy value, but very different starting points.

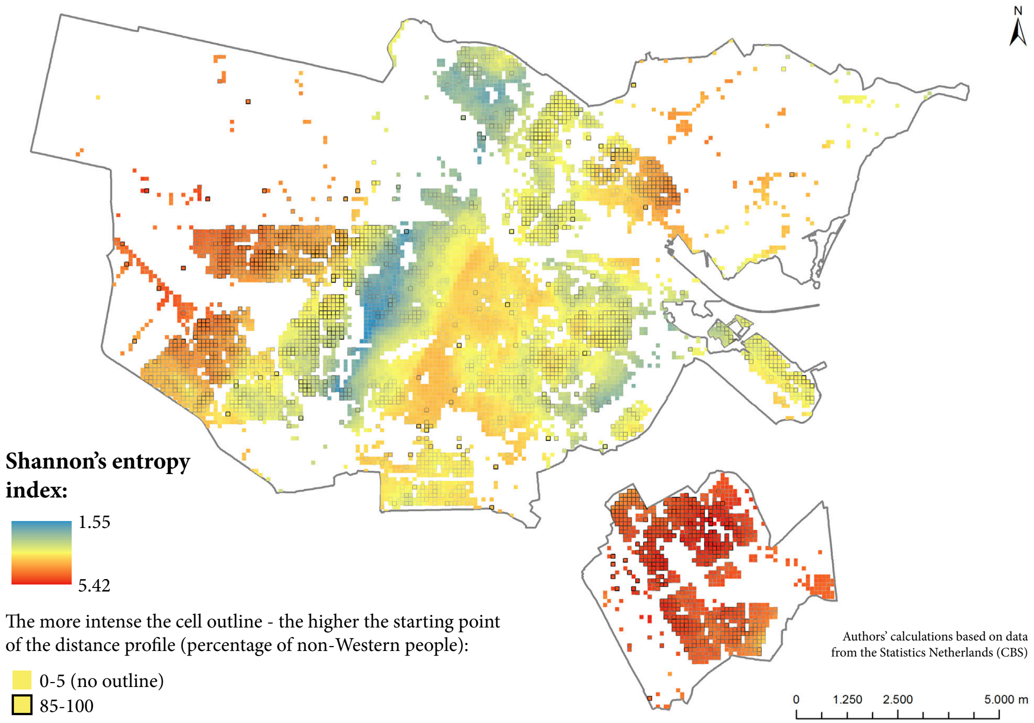

FIG. 3.3 Entropy and starting point of distance profiles in Amsterdam in 2013

Cells with the lowest entropy are predominantly located in a distinctive strip in the middle part of the city in direction southwest-northeast (blue area, gradually changing to yellow). So, if we measure ethnic exposure in this part of the city, even big changes in scale of bespoke areas will not dramatically change the results, except for the smallest scales, where sudden shifts are possible. As can be seen by the cell outline, the base cells in the low entropy strip generally have a low percentage of non-Western ethnic minorities, which is around the city average or lower. Consequently, the inhabitants of these cells are not exposed to high percentages of minorities in their immediate locale, nor are they exposed to minorities as distance increases from their residence. There are also individual base cells, or small clusters of base cells, scoring low entropy with a very high percentage of ethnic minorities (dark outline), where the starting point of the distance profile is very different from the rest of the profile. These small-scale concentrations of ethnic minorities are surrounded by larger areas with predominantly Western residents. In this case, small concentrations of ethnic minorities can be easily overlooked when bigger scales are used, although such small environments are relevant for studying social contacts in the neighbourhood.

Cells with comparably high percentages of non-Western minorities in the southwestern part of Amsterdam in the Bijlmer, have high entropy, often quite close to the theoretical maximum. This implies that the associated distance profiles have high starting values of ethnic exposure at a low scale, and that the exposure drops considerably with increasing distance, for example from one hundred to 30 percent. Overall, the larger the scale the lower the measured percentage of non-Western minorities as larger scales approximate city averages. Comparable patterns can be observed for profiles with high entropy, but with a low starting point. Although starting low (so a very different potential exposure around the dwelling), these profiles reach high percentages of non-Western people at one of the lower spatial scales and then follow the gradual decline as described for the profiles with high entropy and a high starting point.

While low entropy (flat profiles around the city average at multiple scales) and high entropy (gradual decrease of the share of minorities towards the city average) are fairly straightforward, medium entropy can be associated with different patterns of distance profiles. Medium-entropy profiles are sometimes ‘wavy’, with different segments below or above the city average. In any case, the smaller the entropy, the closer the distance profile line is to the flat line of the city average. The most dramatic changes in potential exposure with increasing distance occur if the entropy is low and the percentage of ethnic minorities in the base cell is either very high or very low. Low entropy with a percentage of ethnic minorities considerably higher or lower than the city average means that the population measures at meso- and macro-scales are consistent, whereas micro-scales are very distinct from their surroundings. The most gradual changes in potential exposure occur in profiles with high entropy, including very different percentages of non-Western people at various scales. These profiles can also start with both high and low percentages, but, in any case, their high entropy indicates a downward slope of potential exposure towards larger scales.

After focussing on individual distance profiles and comparing them both between cities and within the city of Amsterdam, we created cumulative distance profiles for Amsterdam (Figure 3.4A), Utrecht (Figure 3.4B), and Groningen (Figure 3.4C), to illustrate the effects of different urban forms on measuring potential exposure to non-Western minorities. In each figure, an array of 101 boxplots jointly shows both the within-scale variability (information within each of the boxplots for each of the 101 scales), and the variability between scales (the changes in boxplots along the *x*-axis). In Amsterdam, the percentage of non-Western ethnic minorities at the smallest spatial scale (100m×100m; the first boxplot at the left side of the Figure) has the maximum variability (0-100 percent), with the interquartile range (covering the middle 50 percent of the data) between 8 and 46 percent and the median of 22 percent.

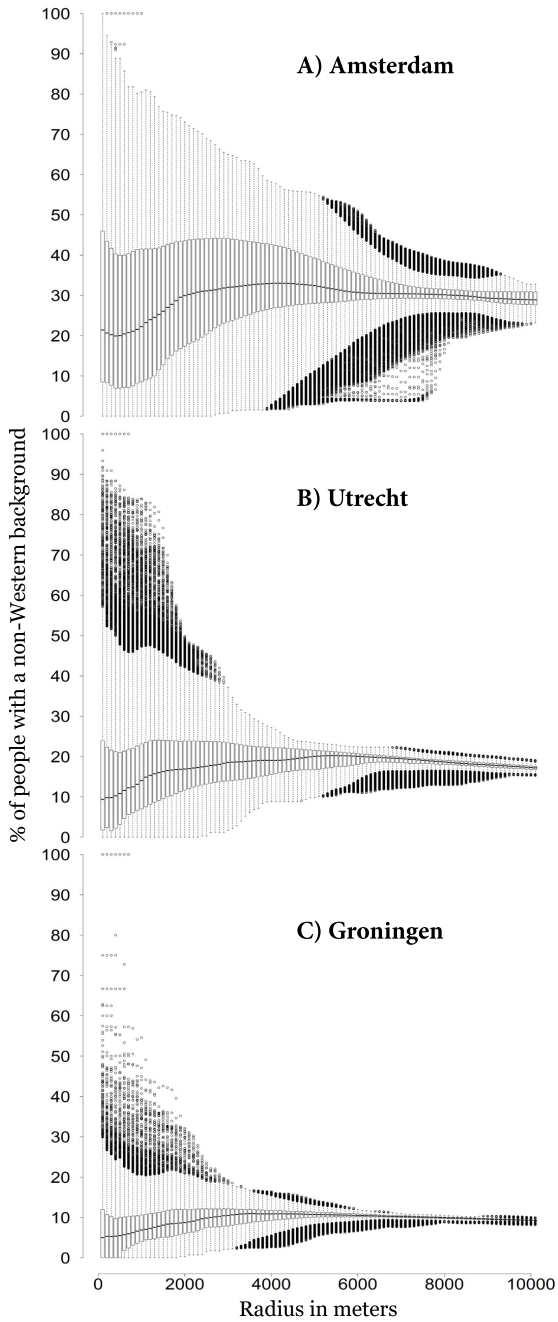

FIG. 3.4 Cumulative distance profile of Amsterdam, Utrecht, and Groningen, in 2013: Boxplots for bespoke areas at 101 scales

On the contrary, at the 10km scale (the last boxplot at the right), the median is 28 percent, with a much smaller range of values, because at higher spatial scales the percentage of minorities is averaged out over very large areas, approximating the city average.

The interest in comparing the three city figures lies in the multiscale comparisons of potential ethnic exposures, which depend on different levels of polycentricity in population distributions. Where in Amsterdam the full range of values is covered (from 0 to 100 percent minorities in an area), this is less the case in Utrecht, and much less the case in Groningen. Different population distributions are more clearly visible in the interquartile ranges. The quicker the interquartile range narrows the more equally spread the population is within the urban area of the city. In other words, if the interquartile range is narrow at already a relatively local scale, as is the case in Groningen with its mono-centric urban form, the percentage of ethnic minorities in local areas must be fairly representative of the city as a whole, whereas if the interquartile range is relatively wide even at higher scales, such as in the case of Amsterdam, it follows that there must be distinct clusters of ethnic minorities in specific parts of the urban environment.

The fluctuations of multiscale population measures are related to levels of polycentricity in both intra- and inter-urban forms of the cities. In Amsterdam, which is the largest of the three cities, the area encompassed by the city is much greater and more diverse than for Groningen (the smallest). While Amsterdam is highly polycentric, Groningen has less conspicuous centres, even less than Utrecht, which covers only slightly bigger area than Groningen. So, the Groningen profile demonstrates that the whole city can be represented by a much smaller scale (around the 4000m) than for Amsterdam, where there is a far greater level of variation at much higher scales. In addition to intra-urban form, the regional urban structure also affects multiscale measures of population through exposure to the population of adjacent municipalities at higher scales, and particularly at the edge of cities. In Amsterdam and Utrecht, the bespoke neighbourhoods at larger scales (and those centred close to the city border also at smaller scales) include cells from the adjacent municipalities, whereas in Groningen, which is spatially relatively isolated from other cities, spreading across the city border has minor effects on population measures, which is one of the reasons for only slight changes in the distance profile of Groningen at larger scales. Because of both intra- and inter-urban forms, the same scale captures different spatial contexts in different cities.

A crucial question at this point is why this all matters and what we can learn from comparing distance profiles for different residential locations and for different cities with different urban forms. Where the literature is increasingly moving from using administrative areas to using bespoke individual neighbourhoods, the question on what is the ‘right scale’ is ever more pressing. Our approach is not to represent potential exposure to non-Western people at one particular scale of bespoke neighbourhood, but to use a (continuous) multiscale measure of population, represented as the spatial profile of a (residential) location. This profile includes a whole range of exposures, and, crucially, we show that these profiles are very different for different locations in different cities. So, where two locations within the same city, or in two different cities, can have the same exposure value at one particular scale, it is likely that they will have very different profiles at a large range of scales. This is relevant when investigating neighbourhood effects, because sociospatial interactions are likely to be multiscalar as well.

This is illustrated in a final step of analyses. We have learned from the cumulative distance profiles that the potential exposure to non-Western ethnic minorities varies within and between scales in Amsterdam more than in Utrecht and Groningen. For research on segregation and neighbourhood effects, it is important to investigate whether different population groups (in our case Western and Non-Western ethnic groups) experience the ethnic exposure surface of their city in different ways. Figure 3.5 contains the share of non-Western ethnic minorities across the spatial scales for all individuals in Amsterdam, and compares the two population groups. The range and interquartile range presented in Figure 3.4A are now split in two fragments, for each of the two groups, using colour-coded areas (yellow for Western, blue for non-Western people).

The ranges of distance profiles of the two population groups are quite similar, with two exceptions (light blue and light yellow areas). Median and interquartile ranges, however, reveal considerable between-group differences. The bottom part of Figure 3.5 is constructed to show the overlapping distance profiles of the two smaller plots in the top half of Figure 3.5. The comparison of the profiles demonstrates that ethnic exposures of half of the non-Western minority people do not overlap with the ethnic exposure of half of the Western people at all spatial scales up to almost 7km. So, these groups have completely different ethnic exposures. Moreover, the overlap of the area above the 1st quartile of the non-Western profiles (covering 75 percent of profiles of non-Western people), and the area below the 3rd quartile of the Western profiles (covering equal proportion of profiles of Western people) is as small as the dark green area in the middle of the graph. In terms of the exposures gained by residents of Amsterdam, the figure shows that the ethnic group to which an individual belongs clearly impacts their sociospatial context in the same city at multiple spatial scales.

TOC

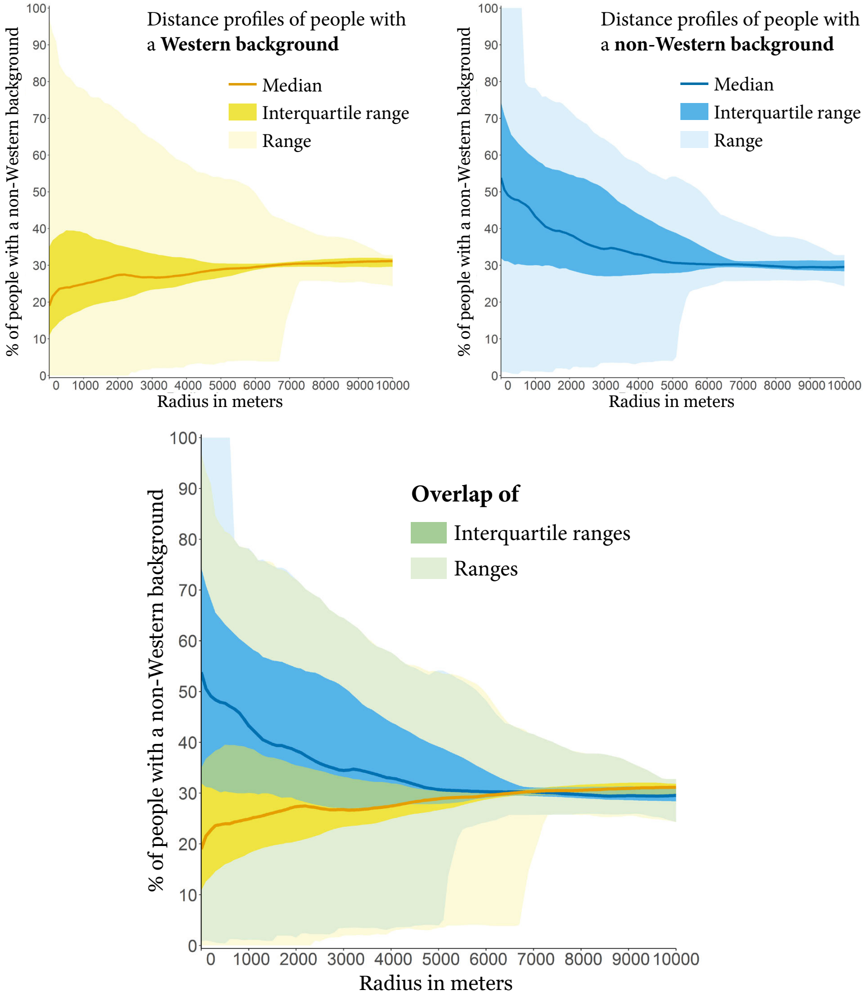

FIG. 3.5 Fragmentation as potential exposure to others: Distance profiles of Western and non-Western people in Amsterdam in 2013

3.5 Discussion and conclusions

This paper started by acknowledging the importance of scale as a critical dimension of sociospatial context. Literatures on segregation and neighbourhood effects have paid ample attention to the role of scale in understanding sociospatial inequalities and their effects on people. Increasingly, the literature uses bespoke neighbourhoods besides conventional administrative units. Where most studies only consider one or two scales of neighbourhoods, we have represented the sociospatial context as continuous, multiscalar and complex, thus preventing the presentation of neighbourhood (as a place of exposure) as a static single scale entity (Manley et al., 2006). This idea is related to the segregation profiles as introduced by Reardon and colleagues (Reardon et al., 2008; Reardon et al., 2009). Our contribution to the field is that we have conceptualised sociospatial contexts using complex distance profile measuring potential exposure, in this case to ethnicity. And we have captured this complexity by utilising entropy. Empirically, our distance profiles consist of bespoke areas over 101 scales. This exceptionally detailed approach confirms (and also intensifies) the relevance of spatial scale, as long established in the segregation and neighbourhood effects literature. Most importantly, the paper offers ways to use scale to better understand exposure to the sociospatial context – by mapping various scales of context, quantifying the scalar variation, and comparing different places and different population groups across multiscalar urban space.

Underpinning the multiscalar framework is the idea that the spatial units representing people's immediate neighbourhoods are the keystones which drive spatial patterns at both smaller and larger scales. This was illustrated in the maps of ethnic exposure surface of Amsterdam, starting from the micro context of 100m by 100m grids to the ethnic makeup of a large urban area. The maps brought into focus the potential exposure to others when opening the front door of your house (the micro-scale), but also their wider surroundings, what might be termed meso and macro scales and which have also been shown to be important in studies of urban phenomena such as segregation (see Manley et al. 2015). Together, the series of maps uncovered the social landscape of the city as multiscalar and continuous, consisting of various individual, overlapping sociospatial contexts.

A key contribution of this study is that we used Shannon's (1948) entropy to measure the variability of exposure to others across spatial scales for specific locations. The entropy index gives us insight into the scale aspect of the MAUP, by quantifying to what extent altering scale affects the measurement of contextual characteristics in different places. Entropy also expresses the uncertainty of a measurement at a given scale as representation for a wider range of scales. Further studies should test whether contextual effects on individual outcomes change in combination with scalar changes in contextual characteristics. This study has benefited from microgeographic grid data in the Netherlands, but the approach is still applicable in countries where such data is not available. For instance, the small census blocks in the U.S., mesh blocks in New Zealand and Australia, and Output Areas in the UK all offer candidates for further exploration.

Besides quantifying the scalar variation as uncertainty of measuring contextual characteristics, the entropy index comprehensively describes a wide range of scales as a social environment beyond the immediate neighbourhoods. The entropy index of a residential location combined with the actual exposure in this micro area showed that similar local contexts may have very different 'context of context', including both abrupt and gradual changes towards the average share of ethnic minorities in the city. The meaning of this becomes more clear by using an example. When studying potential exposure to non-Western people, a distinction can be made between locations with a very high micro concentrations of ethnic minorities immediately surrounded by a larger area with an average share of minorities, and high micro concentrations that only gradually change towards the city average. The people living in these two hypothetical locations will have very different potential exposures to others when they move away from their dwelling, which is highly relevant for segregation and neighbourhood effects studies.

The effect of scale becomes particularly apparent when comparing cities with different urban forms. This paper systematically explored the variation in exposure to sociospatial context for a large number of scales in three different cities. Although urban form is rarely considered in research on sociospatial inequalities, we have argued and shown that urban form is related to how populations are arranged across space, and how this affects multiscale measures of sociospatial context. At a given spatial scale, the context of context may be very different in different cities, notably with different size and urban form. Both inter-urban and intra-urban polycentricity are reflected in ethnic concentrations at various scales. This is clearly seen when comparing the Amsterdam or Utrecht (different in size, but both parts of the Randstad conurbation) distance profiles of ethnic exposure with that of Groningen (almost the same area as Utrecht, but spatially more isolated).

We illustrated the relevance of our multiscalar measures of population by comparing potential ethnic exposures for Western and non-Western people in Amsterdam. The two population groups are potentially exposed to very different shares of non-Western ethnic minorities even at larger scales, especially in a context of a polycentric urban form and strong urban fragmentation. Their ethnic exposure profiles, therefore, appear as different sociospatial fragments of the same city, persistent at a wide range of scales. Further studies should test in which ways and to which extents this multiscale fragmentation affects socioeconomic outcomes of individuals from the two population groups.

Finally, the multiscale measures of population revealed 'social cliffs' (borrowing from the notion of social tectonics by Robson & Butler, 2001) both in individual environments across urban space as well as between different population groups within one city. Exemplified with the share of non-Western minorities, our approach is applicable to other population characteristics, such as income, education or age. The presented variation over scale urges caution in choosing singular spatial scales and suggests that attention must be given to multiple spatial contexts when exploring sociospatial inequalities. We find more variation and greater complexity in spatial patterns with more detailed spatial data and a wider range of scales, but this is a way to better understand exposure to others across urban space based on the location where ones lives. Scalar variation is likely to be the result of systematic and predictable processes and, as such, warrants further intensive study in the research of sociospatial inequalities.

Notes

1 Statistics Netherlands defines a person to have a foreign background if they are first generation immigrants (i.e. if they are born abroad), or if one of their parents belongs to the first generation. A distinction is made between Western and non-Western backgrounds, so that individuals from Europe (excluding Turkey), North America and Oceania as well as individuals from Indonesia and Japan are defined as Western. The justification for the latter two ethnic groups being Western lies in their social and economic position in Dutch society. Conversely, people originating from Africa, South America, or Asia are categorised as people with a non-Western background, which is, according to most policy makers, comparable to 'ethnic minorities' (Alders, 2001).

2 We do not apply any distance decay function, as we want to robustly compare different scales, but our approach can be modified to investigate spatial scale in different ways.

3 Maps for four sample scales in Amsterdam are included in the Results section. An accompanying video available online presents the three cities and contains all 101 scales.

4 We have rounded percentages to the closest integer. Coarser rounding has the effect of smoothing the profile lines and leads to more similar entropies between different profiles.

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4 Multiscale and multidimensional segregation of non-Western migrants in seven European capitals

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ABSTRACT

Despite the fact that ethnic segregation is an important issue for European cities, there are few comparative cross-European studies on the topic. Those studies that have investigated segregation have done so for single cities or countries and often overlooked the specific geographies of scale of segregation. This paper investigates ethnic segregation in seven European capitals, namely Amsterdam, Berlin, Lisbon, London, Madrid, Paris, and Rome, at a range of spatial scales, starting from 100m by 100m grid cells. We used three dimensions of segregation (centralisation, evenness, and exposure) to help us understand the potential for people to meet, a crucial aspect for the integration of migrants. We found that European capitals had very different levels of ethnic segregation for each of the studied dimensions and that these levels varied with spatial scale, in different ways in different cities, and within these cities between their cores and hinterlands. Unlike the majority of the segregation literature, we found that segregation does not necessarily decrease with spatial scale.

4.1 Introduction

Europe has long been a continent of internal and external migration. The distribution of migrants from outside Europe, and especially asylum seekers, is a major challenge for European unity. But also the distribution of migrants within each country presents many challenges, especially for larger urban areas. According to Arbaci (2007), levels of ethnic segregation in European cities are high, but there are stark differences between countries and cities. A recent comparative study on European capital cities (Tammaru, van Ham, Marcińczak, & Musterd, 2016) reported important links between high socio-economic segregation and increased immigration to Europe.

Despite the fact that ethnic segregation is an important issue for European cities, there are few comparative cross-European studies on the topic. Those studies that have investigated segregation have done so for single cities or countries and often overlooked the specific geographies of scale of segregation. The scale at which segregation is measured is important to understand the potential for different groups to meet in the urban environment. These issues are important because the meaning of segregation varies between cities: individuals in a city where small concentrations of immigrants are scattered across the city will have a different potential exposure to each other than in a city where immigrant concentrations are clustered in specific neighbourhoods within the city. The potential for exposure to 'others' matters, because where exposure is low, the chances for population groups to mix, meet and interact is also reduced. Also, when exposure is low, it becomes harder for immigrants to learn the language or to access the local labour market (Bauer, Epstein, & Gang, 2005; Beckhusen, Florax, de Graaff, Poot, & Waldorf, 2013; Danzer, Feuerbaum, Piopiunik, & Woessmann, 2018).

Much of the previous work on segregation has used administrative units as neighbourhoods, areas designed for the delivery of policy and the collection of statistical data. Such administrative neighbourhoods are rigid and do not reflect the spatial context of individuals well. Consider an individual who lives on the edge of a neighbourhood. This person will have very different social and exposure experiences than individuals living in the centre of the same neighbourhood. The smaller the neighbourhood, the closer it resembles the actual residential location of a person, but at the same time the larger picture of the residential context is lost. Therefore, it is important to adopt a bespoke multiscale approach to measuring segregation. Bespoke multi-scale measures of population are defined for each residential location and are sensitive to urban form (Petrović, van Ham, & Manley, 2018), and therefore it is important to take a comparative perspective to investigate at which spatial scales segregation manifests itself in different urban contexts.

This paper investigates ethnic segregation in seven European capitals, namely Amsterdam, Berlin, Lisbon, London, Madrid, Paris, and Rome. These cities present a mix of immigration and welfare contexts in Europe. The paper addresses the following questions: Firstly, what are the levels of ethnic segregation in each city and how do these levels vary between the cities? Secondly, how does segregation manifests itself at different geographical scales, and how does this vary between the cities? Thirdly, how do levels of segregation vary between metropolitan cores and hinterlands? In this paper, we use the following well-established dimensions of segregation: centralisation, evenness and exposure (Massey & Denton, 1988). To investigate the effects of scale, we use a recently developed method using 101 increasingly large bespoke areas (Petrović et al., 2018). These bespoke areas at multiple spatial scales, delineated by drawing circles of various radii around each person's home, more closely represent an individual's residential context than administrative units. While most segregation studies focus on core cities, we consider entire urban regions of the seven capitals, using a definition of Functional Urban Areas (FUA) by the OECD (2012).

4.2 Data and methods

This study uses innovative data provided by the European Commission in the context of the D4I challenge, which is sourced from national statistical institutes of seven EU countries (Netherlands, Germany, Portugal, UK, Spain, France, and Italy; see Alessandrini, Natale, Sermi, & Vespe, 2017). The dataset contains harmonised, high resolution spatial data (cells of 100m by 100m) on ethnic origin of migrants. Categorising immigrants is challenging, since each country has its own immigration history, mix of ethnic groups and definitions to group ethnicities. In defining ethnic groups, some countries rely on citizenship, while others rely on the country of origin. For comparative analysis, preferably a single definition must be used. For the seven case cities in this study we have aggregated people into two groups. The native population together with Western immigrants are compared to non-Western immigrants, where non-Western immigrants are the ones of African, Asian or Latin-American origin[1]. This distinction relies on the Statistics Netherlands conceptualisation of the population with a Western and non-Western background, which roughly categorises ethnic minorities based on their social and economic position in the receiving society (see Alders, 2001).

To define urban areas we have used a definition of the Functional Urban Areas (FUA) developed by the OECD and the EU. Using this definition increases the international comparability of the economic, social and environmental performance of metropolitan areas (OECD, 2012). The FUA consists of the densely populated core and hinterlands (periphery), with a labour market which is highly integrated. We have applied the core and hinterlands boundaries on the grid cells provided within the context of the D4I challenge. Using these FUA's allows us to compare the urban spaces in the seven countries consistently.

We examine three dimensions of segregation. The first is centralisation, which directly uses the FUA definitions to measure the relative concentration of the two groups in the urban core. It ranges from 0 to 1, and represents the proportion of members of one group (Western or non-Western) living in the urban core. The second measure, the dissimilarity index, measures the evenness of the distribution of the population across the urban space. Migrants can be unevenly distributed across the neighbourhoods of the FUAs so that they are overrepresented in some neighbourhoods and underrepresented in others. The index ranges from 0, when the share of migrants in the neighbourhood is the same as in the entire urban area and there is no segregation, up to a value of 1, when there is complete segregation. The third dimension, exposure, complements the second measure. This measures the possibility of interaction between the two groups in residential spaces at various spatial scales, on the one hand, or the isolation of the non-Western group of the other hand. Unlike evenness, exposure depends on the absolute sizes of Western and non-Western populations. Together, these dimensions make it possible to compare different aspects of segregation across all the cities.

Both evenness and exposure depend on the size of neighbourhoods used in the urban space. Standard administrative units, although practical, do not represent social processes such as segregation; they are different sizes in different countries, inconsistent over time, and individuals are not always centrally located within them. Individuals who live close to the edge of unit may be more connected with those people in a neighbouring area than individuals in their own unit. Moreover, small spatial scales may be insufficient to represent an individual's local environment and so it is important to use neighbourhoods of multiple sizes to better characterise the potential experiences individuals may have (Petrović et al., 2018). To examine how evenness and exposure continuously change, we measured them over 101 different spatial scales of bespoke areas. We started from small spatial building blocks of 100m by 100m grid cells (the lowest available spatial unit available for comparative cross-European research), and increased the radius in 100m increments up to a 10km radius. The smaller areas capture the immediate differences in the surroundings for individuals. The bigger the areas, the more they overlap, as they are delineated around each person's home. Using these areas we compute distance profiles for each of the dimensions of segregation of non-Western migrants in all seven capitals. The distance profiles of segregation show how segregation changes as an individuals' neighbourhood border moves further away from their home: it starts from the very small residential context and expands towards larger, more general, areas (see Petrović et al., 2018).

4.3 Results

The most striking concentration of non-Western migrants occurs in London, where many small neighbourhoods with a majority of non-Western people cluster in large areas of the urban core (Figure 4.1). Non-Western migrants concentrate in urban cores in most of the other cities, too, especially in Amsterdam and Berlin, perhaps because urban cores of these cities offer more economic and housing opportunities for migrants. In the South European capitals, non-Western migrants are more equally scattered in the core and hinterlands. Latin American migrants, who compose the majority of non-Western migrants in Madrid, settle not only in the core, but also in the hinterlands of Madrid. This is especially the case for the relatively small group of African migrants, probably because of more accessible and affordable housing in the hinterlands. However, in Madrid and Lisbon language and job opportunities may also determine the distribution of non-Western migrants. With a similar language as the native population, Latin American migrants in Madrid and Lisbon can find jobs in the private, and public sectors inside and outside the urban core and so the Latin Americans are scattered in the FUA of Lisbon as in Madrid. Lisbon also has the largest share of African population among all the seven cities, and they tend to concentrate in the core area. This leads to a different spatial pattern compared to Madrid. The insights from the maps regarding migrants' locations in urban cores as opposed to hinterlands bring us to the first dimension of segregation which we examined, namely centralisation.

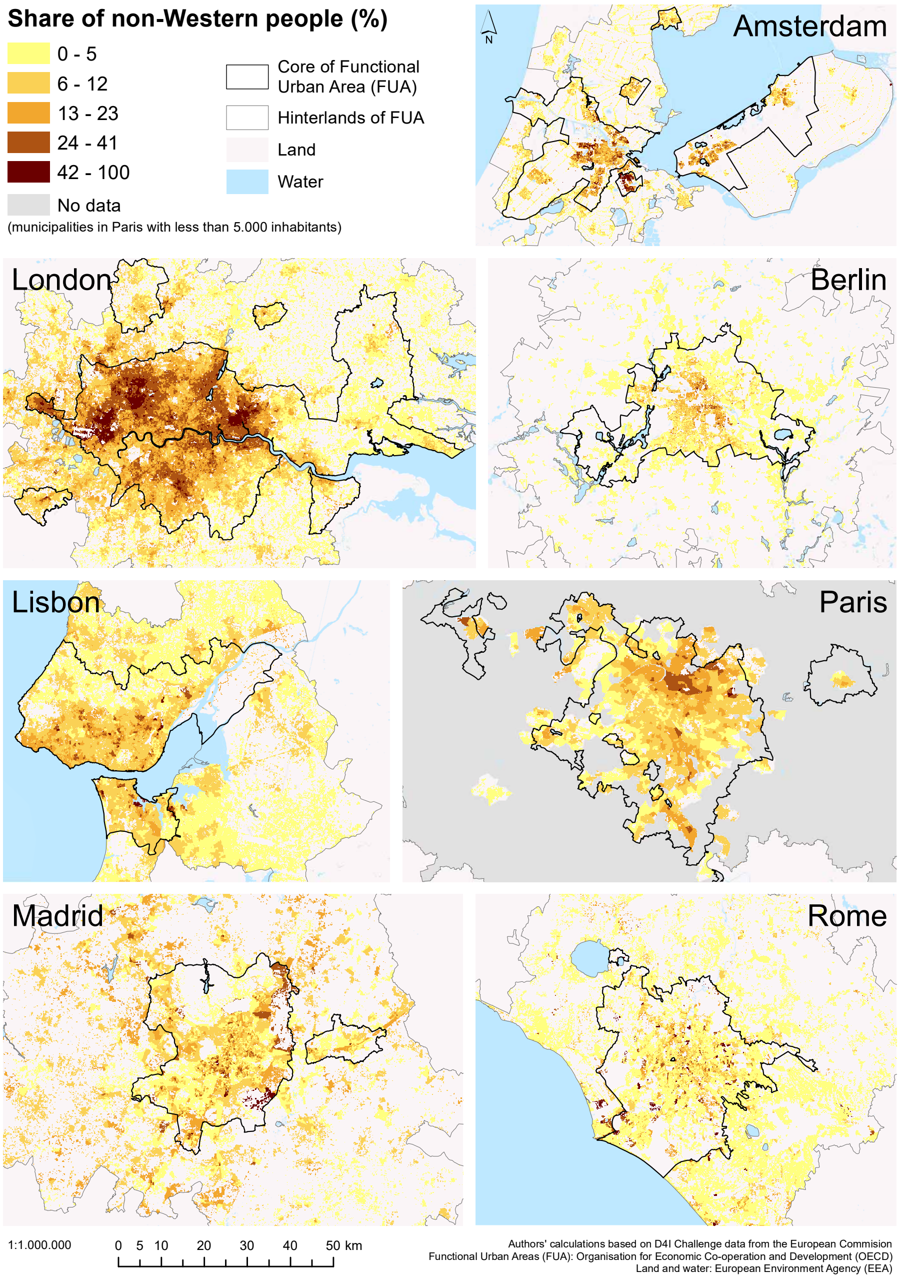

FIG. 4.1 Share of non-Western people in 100m by 100m grid cells in metropolitan areas (cores and hinterlands) of seven European capitals

4.3.1 Centralisation

Table 4.1 reports the proportion of non-Western people living in the densely populated and economically stronger urban core of the FUA. Using the centrality index, we can see that in Berlin the non-Western migrants almost exclusively settle in the urban core (see also the Berlin map in Figure 4.1). The centrality index also confirms the insights from the maps that non-Western people are the least centralised in Madrid, with confirmation of the scattered spatial pattern in the Madrid map. The biggest difference between the indices for the two groups occurs in Amsterdam. Here, non-Western people tend to locate in the urban core more than Western individuals, a pattern also repeated in Rome. Madrid and Rome are, therefore, the metropolitan areas whose hinterlands have received considerable shares of non-Western people in that setting. However, the share of the population in these group is very different in these cities (Table 4.2). Overall share of non-Western people in Rome is low in comparison with Madrid which has a considerable share of non-Western people. By comparison, London is the city with the highest share of non-Western people, who are very centralised in the urban core.

TABLE 4.1 Index of centrality of Western and non-Western people

City	Index of centrality	
	Western	Non-Western
Amsterdam	0.67	0.89
Berlin	0.79	0.98
Lisbon	0.84	0.91
London	0.77	0.93
Madrid	0.76	0.81
Paris	0.91	0.94
Rome	0.64	0.83

TABLE 4.2 Share non-Western people in different parts of FUA

City	Share of non-Western people (%)		
	Urban core	Hinterlands	FUA
Amsterdam	17.03	4.80	13.30
Berlin	7.06	0.76	5.77
Lisbon	12.21	6.85	11.38
London	20.52	6.27	17.66
Madrid	10.41	8.20	9.89
Paris	10.05	6.74	9.77
Rome	4.89	1.88	3.84

4.3.2 Evenness

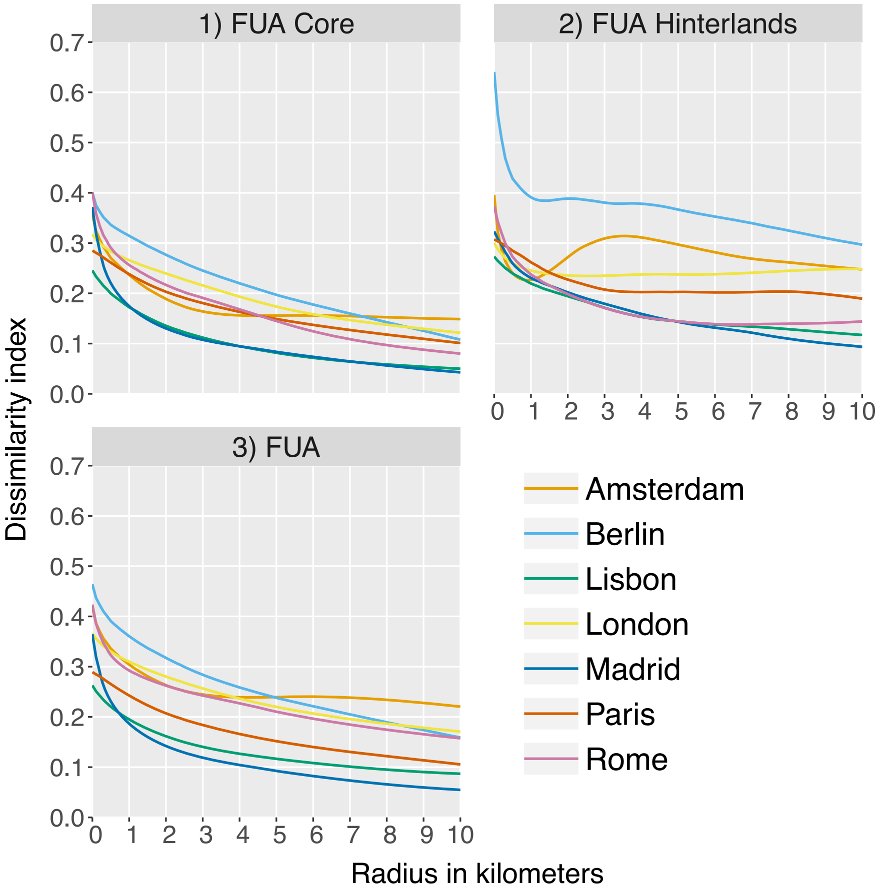

FIG. 4.2 Distance profiles of the dissimilarity index

So far, we have compared the urban cores and hinterlands, in terms of the concentration of migrants. However, migrants can be unevenly distributed within these areas and so it is important to examine the evenness of segregation. This is quantified using the dissimilarity index, reported as the percentage of the members of one group who would need to move to achieve an even distribution across the city. For example, a value of 0.4 means that 40% of a group would need to move to have even shares of both groups in all residential areas. We can use residential areas of various sizes to measure evenness, which is why the size of neighbourhood matters: An individual can have no non-Western migrants in the immediate surrounding of their home, but as the spatial reach of the person's neighbourhoods extends, they have many more non-Western neighbours a bit further from home. But they can still meet at the neighbourhood café or the children could meet in the neighbourhood school. In this case, non-Western migrants are underrepresented in the immediate neighbourhood, and become overrepresented in the bigger areas. We measured the evenness at the range of spatial scales by computing distance profiles (Figure 4.2), which depict the distance from people's home on the horizontal axis, and the unevenness of the distribution on the vertical axis (higher values show greater unevenness). By plotting all the capital cities together we can compare how segregation changes with scale and across national contexts.

In most of the cities, non-Western migrants are more unevenly distributed in the hinterlands than in the urban core: Hinterlands generally have less non-Western people than the urban cores, but these people locate in specific parts of the hinterlands, most likely in places where they can access and afford housing or settle close to family. This occurs at different spatial scales in different cities. In Berlin hinterlands, which have very low percentage of non-Western migrants, these minorities are particularly overrepresented in neighbourhoods with less than 1km radius. In Amsterdam, whose hinterlands have larger share of non-Western people (5%) than Berlin, the overrepresentation occurs in scales up to 5km radius. The distance profile of the Amsterdam hinterlands highlights areas with high shares on non-Western people are located close to areas with lower shares, forming a mosaic structure within 1km radius. However, within 3–5km, the share of non-Western migrants grows, reducing the variation in exposures. Using the distance profiles of segregation, we can identify the spatial scales with high segregation in each city. While unevenness often decreases with the increasing scale, the 3.5km scale in Amsterdam hinterlands shows that this is not always the case.

The results for the range of scales suggest that measuring evenness at single administrative scales may obscure smaller-scale neighbourhood level ethnic compositions. For example, although at larger scales almost evenly distributed, non-Western migrants in Madrid are segregated in small neighbourhoods, particularly in the urban core. Although Lisbon and Madrid have similar low levels of segregation at many of the larger scales, the fine-grained spatial scale reveal that they are very different, where Madrid is more segregated than Lisbon at smaller scales (in areas with less than 1km radius). By contrast, Madrid is the *least* segregated city at the largest scale but, along with Rome and Berlin, one the *most* segregated city at the smallest spatial scales.

4.3.3 Exposure

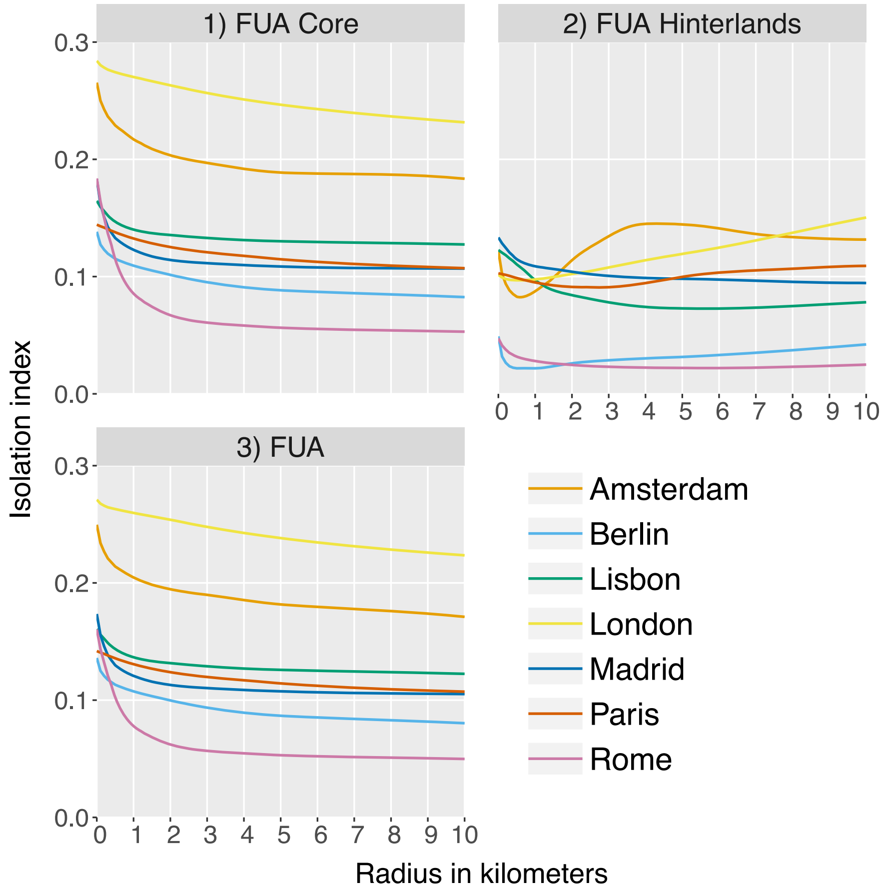

FIG. 4.3 Distance profiles of the isolation index

While evenness compares neighbourhoods' ethnic composition with that of the average of the FUA, exposure explicitly takes into account the relative size of the non-Western population: if the share of non-Western population is high in the city, then they are less likely to be exposed to the other ethnic groups in their neighbourhood of residence. The indices of exposure thus measure the 'meeting potential' between Western and non-Western people in the same neighbourhood, which is conditional of the overall size of the group in the given city. We use the isolation index to quantify this experience. The results are reported in Figure 4.3. Where a low value is reported, spatial isolation is low and high potential for inter-ethnic interaction exists, and vice versa.

Rome, with the lowest share of non-Western people, has the lowest isolation and highest potential of meeting and interaction between our two ethnic groups. However, although the low value of the isolation index at most of the spatial scales, at the smallest spatial scale, which could represent the experience gained when a resident opens their front door, the isolation of the non-Western group in Rome is larger than in Berlin, Madrid, Paris and Lisbon. Crucially, this shows the value of the multi-scalar approach in understanding the urban form and is a feature that would be overlooked using single scale administrative units. The isolation index reveals a different picture in London when compared with previous results. Although overall segregation is not the highest, the relatively high value of the isolation index of the non-Western group, particularly in the urban core, is distinctly higher than in other cities. The urban core of London, and the entire FUA (but not the hinterlands) have the highest proportions of non-Western migrants of all the urban cores and FUAs (see Table 4.2). This large population potentially experiences little exposure to Western people, a finding that is persistent across spatial scales.

Although persistent segregation at multiple spatial scales is a common phenomenon on Europe, some cities, such as Madrid or Amsterdam, have more variation in segregation. Furthermore, the indices of Rome or Berlin, which have different levels of segregation (comparing to other cities) in different dimensions (low isolation, but high dissimilarity), show that spatial patterning of segregation is very different and thus needs to be measured both along multiple scales and multiple dimensions.

4.4 EU and policy relevance

In this study, we examined segregation from a bespoke and multiscale perspective. We used three dimensions of segregation to help us understand the potential for people to meet, a crucial aspect for the integration of migrants. Overall, we identified differencing levels of segregation and potential exposure, and that neighbourhood size and local context in terms of the share of non-Western migrants mattered in how ethnic groups potentially experience segregation. Innovatively, this gave insight into segregation at a range of spatial scales.

The harmonised definitions of FUAs used on the study facilitate international comparability of the economic, social and environmental experiences of the metropolitan areas (OECD, 2012). One of the ‘social performances’ of a city is how to deal with segregation and integration of migrants. Using the FUAs, we compared segregation in densely populates urban cores and in the related hinterlands, and the different dimensions we examined tell us about different aspects of segregation: Evenness showed that people in small neighbourhoods in Berlin, Rome or Madrid urban cores, potentially experience their residential ethnic context in a very different way than their city in general. By contrast, exposure demonstrated that spatial isolation of large non-Western populations was highest in London and Amsterdam, and therefore the potential for interaction with the Western population in residential neighbourhoods is low.

Detailed spatial data including the distribution of ethnic groups is key to understand segregation at various spatial scales, which allows us to design policy interventions at most efficient spatial scales. Comparative analysis of multiple countries provides a basis for the EU-level policies. However, different concepts of ethnic origin, such as place of birth and citizenship, in different countries need to be considered. Residential segregation is related to segregation in other life domains such as education, work and free time (van Ham & Tammaru, 2016). Spatial scale and the dimension of residential segregation, including centralisation, evenness and exposure, affect segregation in other domains. For example, the scale of residential segregation suggests whether schools in specific parts of the metropolitan areas are also segregated or how big are potentials for inter-group interaction in public spaces. In light of the recent immigration to Europe, the analyses should be further developed by focussing on subgroups of the non-Western migrants, such as African, Asian and Latin-American. These groups have different residential preferences as well as economic and cultural requirements, which are likely to result in spatial patterns of segregation along multiple scales and multiple dimensions.

Notes

1 The data from Portugal does not distinguish people by the country of origin. Therefore, non-Western migrants in Lisbon also include people from Anglo-America, because they cannot be separated from Latin-American migrants.

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4.5 Appendix

TABLE 4.3 Three dimensions of segregation, adapted from Massey and Denton (1988)

Dimension	Index	Formula
Centralisation	Centrality	$PUC_x = X_{UC} / X$ $PUC_y = Y_{UC} / Y$
Evenness	Dissimilarity	$D_d = \frac{1}{2}\sum_{i=1}^{n}\left\lvert\frac{x_{di}}{X_d} - \frac{y_{di}}{Y_d}\right\rvert$
Exposure	Isolation	${}_xP_{xd} = \sum_{i=1}^{n}\left(\frac{x_{di}}{X_d}\right) * \left(\frac{x_{di}}{t_{di}}\right)$

d – scale of bespoke area; *d = 0, 1, 2, … , 10km*

n – number of grid cells the urban area (core, hinterlands, FUA)

X_{UC} – number of non-Western people in the urban core

X – number of non-Western people in the FUA

x_{di} – number of non-Western people measured at scale *d* for grid cell *i*

X_d – number of non-Western people measured at scale *d* for the whole urban area (core, hinterlands, FUA)

Y_{UC} – number of Western people in the urban core

Y – number of Western people in the FUA

y_{di} – number of Western people measured at scale *d* for grid cell *i*

Y_d – number of Western people measured at scale *d* for the whole urban area (core, hinterlands, FUA)

t_{di} – total population measured at scale *d* for grid cell *i*

PUC_x – proportion of non-Western people living in the urban core

PUC_y – proportion of Western people living in the urban core

D_d – dissimilarity index at scale *d*

${}_xP_{xd}$ – isolation index at scale *d*

5 Multiscale contextual poverty in the Netherlands

Within- and between-municipality inequality

Ana Petrović, David Manley & Maarten van Ham

Submitted to an international peer-reviewed journal

ABSTRACT

Contextual poverty refers to high shares of people with a low income in a certain (residential) space, and it can affect individual socioeconomic outcomes as well as decisions to move in or out of the neighbourhood. Contextual poverty is a multiscale phenomenon: High levels of poverty at the regional scale can reflect regional economic structures. Meso-scale concentrations of poverty within cities are related to city-specific social, economic and housing characteristics. Exposure to poverty at lower spatial scales, such as housing blocks and streets, influences individuals through social mechanisms such as role models or social networks. These sub-micro spatial scales of exposure to poverty are often neglected, largely due to a lack of data. This paper is based on the premise that sociospatial context is necessarily multiscalar, and therefore contextual poverty is a multiscale problem that can be better understood through the inequality within and between places at different spatial scales. The question is how to compare different spatial contexts if we know that they do not consist of range of spatial scales. Our measure of contextual poverty embraces 101 spatial scales and compares different locations within and between municipalities in the Netherlands. We found that the national inequality primarily came from the concentrations of poverty in areas of a few kilometres, located in

cities, which have different spatial patters of contextual poverty, such as multicentre, core-periphery and east-west. In addition to the inequality between municipalities, there are considerable within-municipality inequalities, particularly among micro-areas of a few hundred metres.

KEYWORDS contextual poverty, spatial scale, spatial inequality, distance profile, exposure, Theil index

5.1 Introduction

Over the last two or three decades, socioeconomic inequalities in European cities have been growing, and this has led to increasing spatial concentrations of people with low income in certain (residential) areas (Tammaru et al., 2016). Living in poverty concentration neighbourhoods can affect socioeconomic outcomes of people, such as their education and labour market performances (Van Ham et al., 2012); moreover, it can influence individual decisions to move in or out of the neighbourhood (Sampson et al., 2002; Bolt & Van Kempen, 2003; Van Ham & Clark, 2009). Contextual poverty can emerge at the scale of streets, or housing blocks, inner-city neighbourhoods or suburbs, or even regions. This makes contextual poverty a *multiscale* problem which is related to both the causes and consequences of poverty. Multiple factors, such as economic and housing structures, can lead to concentration of poverty at different spatial scales from region to neighbourhood, while poverty at various spatial scales can affect individual outcomes of people through a variety of contextual effects mechanisms (see Sampson et al., 2002; Galster, 2012), including social mechanisms at a smaller scales and stigmatisation at larger ones (Petrović et al., 2019). So, with increasing scale, there are new contexts introduced at which poverty expresses itself spatially, and at which individual outcomes are affected.

Even within countries with relatively low levels of poverty, there are regional differences, where some parts of the country are poor compared with other parts (Williamson, 1965), and to go below the scale of the region, some neighbourhoods in cities or towns are poorer than others. In fact, there are inequalities at different levels of the urban system, both between and within cities, and at different spatial scales. Inequalities at different spatial scales contribute to national level inequalities, as well as to people's individual exposure to inequalities in their spatial context. Interestingly, the literatures on global inequality, segregation and neighbourhood effects, which are all concerned with contextual poverty, rarely start from the premise that sociospatial context is necessarily multiscalar. Instead, analyses are often carried out using a single scale, often drawing on readily available administrative spatial units. Using a single scale can neglect important spatial context effects at other scales and we argue that spatial inequality and its effects cannot be fully understood by simply taking one arbitrary scale available in the data.

The overall aim of this paper is to better understand inequality in contextual poverty throughout space at different scales and to compare different residential locations as parts of an integrated urban system, and not as isolated spatial units. We use a multiscale approach to understand spatial inequality in contextual poverty in the Netherlands, by answering the following questions: Firstly, how big is spatial inequality in contextual poverty in the Netherlands and where does it come from – from which spatial scales in which levels of the urban system (within and between municipalities)? Secondly, in which ways, and to what extent, do different municipalities contribute to national level inequality – and at which spatial scales? Finally, how can we compare different spatial contexts if we know that they consist not only of a single spatial unit but of a range of spatial scales?

Methodologically, spatial scale is one aspect of the modifiable areal unit problem (MAUP; Openshaw, 1984; Manley et al., 2006; Manley, 2014), which suggests that measuring areal characteristics is affected by the size and exact boundaries of the spatial units. We argue, however, that the variability of scales is not a problem, but a reflection of multiple sociospatial processes and contexts in which people live (Manley et al., 2006; Petrović et al., 2019). We operationalised multiscale contextual poverty as distance profiles, which include a range of 101 bespoke areas (centred on individual locations), which represent people's spatial contexts starting from very small neighbourhoods up to the city or regional level (see Petrović et al., 2018). These distance profiles then show for each location how potential exposure to poverty changes across spatial scale. For this, we used register data for the full population of the Netherlands, geocoded to 100m by 100m grid cells. To capture the complexity of spatial inequality, we used the Theil multilevel index of inequality (hierarchical entropy). Although entropy can be used to measure spatial inequality between units at a certain spatial scale, this paper goes further. It applies entropy at *multiple* spatial scales and uses it to measure inequality *across* different spatial scales in a single location. Using data for the whole of the Netherlands (100m by 100m grid cells), the study reveals what spatial scales of residential context are particularly relevant to better understand potential exposure to poverty in different municipalities in the Netherlands.

TOC

5.2 Spatial inequality in contextual poverty: The issue of spatial scale

5.2.1 The measurement of poverty

Although the literature generally distinguishes between absolute and relative poverty (George, 1980; Hagenaars, 2017), poverty is an inherently *relative*, socially constructed concept (MacPherson & Silburn, 2002). Contextual poverty is relative in many ways: We need to define what poverty is within a certain frame of reference, and also to compare different areas. Poverty can be conceptualised and measured in many ways, but the most common and straightforward concept is monetary poverty, whose indicator is an 'at-risk-of-poverty rate', i.e. the percentage of households or individuals with an equivalent net disposable income below a threshold (Goedemé & Rottiers, 2011). Indeed, relative income poverty measures should rather be regarded as indicators of poverty *risks* than of poverty *per se* (Bäckman, 2009). Most research in Europe set the threshold of the risk of poverty at a percentage of the national median income. Based on the work of ILO and OECD, low income is usually defined as being below two thirds of the median income (Fritzell & Ritakallio, 2010; Goedemé & Rottiers, 2011; ILO, 2013; vom Berge et al., 2014), but lower cut-off points, such as those of 50% or 40% of the median, are also used (see Dixon & Macarov, 2002; Marlier, 2007; Bäckman, 2009).

Besides the threshold of poverty risk, a fundamental issue is choosing the unit over which poverty is measured. Most empirical studies use the household as the lowest level at which data is disaggregated (MacPherson & Silburn, 2002). Another possibility is to use individuals as the unit of analysis, which may give different results, depending on household compositions. Due to the difference in size between richer and poorer households, the numbers of households and individuals below the poverty threshold may give different evidence of poverty incidence (Anand, 1983). So, the definition of poverty will depend on the threshold of low income as well as on the basic unit of measure (individual or household) we used. After we chose a certain definition, spatial measures of poverty will depend on the spatial scale.

TOC

5.2.2 Exposure to poverty from macro to micro scale

Large-scale concentrations of poverty reflect regional economic structures and labour market conditions. Income inequality at very large scales, between countries and regions, has received a lot of attention in the economic and geographic literatures (Wilkinson & Pickett, 2006), because they help to understand economic performance, the cost of labour and housing, but also internal and even international migration. Therefore, most of the data are aggregated to large spatial units and many institutions which deal with causes or consequences of poverty work at the national or regional level. Although large-scale inequalities are in themselves important, what is missing is that they are rarely considered in relation to smaller spatial scales. Metropolitan inequalities are necessary to fully understand neighbourhood-level mechanisms, as they represent an extralocal context of neighbourhood-level processes (Sampson, 2001). Large spatial scales, therefore, represent the ‘context of context’ for the small-scale neighbourhoods (Petrović et al., 2018). External contextual mechanisms result from a neighbourhood’s location relative to economic and political structures, for instance in terms of accessibility to jobs or public services (van Ham et al., 2001; Horner, 2004).

Concentrations of poverty within cities at the so-called meso-scales are related to city-specific social, economic and housing characteristics. For example, many Dutch and Swedish cities contain large urban districts composed predominantly of social housing (Bolt et al., 2010). These urban districts attract more low-income residents than areas with other types of housing, while the better-off residents are prone to leave them (Bolt et al., 2009). Part of a city may develop a reputation based on its demographics or housing types and, as a consequence, the residents may be stigmatised by people from outside the neighbourhood, including potential employers (Wacquant, 1993; Taylor, 1998; White, 1998). Both the ‘objective’ quality of specific residential areas and their perceived reputation may affect people’s decision to move in to or out of the neighbourhood (Permentier et al., 2009; Sampson, 2012). These are all examples of processes operating at various meso-scales.

Exposure to poverty at small spatial scales influences people through social-interactive mechanisms, such as role models or social networks (Sampson et al., 2002; Galster, 2012). These mechanisms can, for example, impact on an individual’s job search behaviour, which often motivates studies on the effects of neighbourhood poverty on individual socio-economic status (see, for example, Van der Klaauw & Van Ours, 2003). Although these studies normally refer to social-interactive mechanisms, they often use spatial units that are too large to capture these mechanisms. Furthermore, poverty in the micro spatial context is important at any level of social organisation of the population within the local community. Even in the absence of the local social organisation, neighbourhood as an immediate surrounding of home still remains an area of exposure (Sampson, 2001). Therefore, small spatial scales are necessary to operationalise proximity as a potential for exposure and contact in the residential context. At the same time, we should not forget that these micro spatial contexts are embedded within larger urban contexts.

Measuring spatial attributes at various spatial scales from micro to macro generally gives different results, which is formulated as the modifiable areal unit problem (Openshaw & Taylor, 1979). However, altering spatial scale is more than a technical *problem* – it is a way to better understand the spatial context of people, from the immediate surrounding of their home up to a wider context of the city. This range of spatial scales can be represented as a *distance profile*, which includes a range of areas around an individual's residential location at increasingly large spatial scales (Petrović et al., 2018). Therefore, distance profiles show how the residential context of an individual changes at different spatial scales. At the same time, depending on where they live, different people have different spatial contexts (at multiple scales), and even an individual has different spatial contexts at different spatial scales.

5.2.3 Inequality within and between places

In all areas from very small neighbourhoods to urban regions, poverty can be better understood through the comparison with other areas: One neighbourhood is poorer than other neighbourhoods; during their life, people can move from a poorer to a richer part of the city; one region in the country is known for being better-off than other regions, e.g. for providing more opportunities for education and work. Poverty can, therefore, be analysed through the lens of spatial inequality. While a large body of literature studies inequality between countries (see, e.g. Bäckman, 2009), national policy makers are primarily concerned with inequalities between different places within a country. However, empirical evidence of the spatial inequalities often exits only for specific scales, because research often focusses either on regional inequalities or inequalities between administratively defined neighbourhoods within specific cities (see, e.g. Najib, 2019). Considering both regional inequalities – between cities, and neighbourhood inequality – within cities, or even within what is officially considered as 'neighbourhood', helps us understand what spatial scales matter more in specific cases. For instance, when there is great differentiation within neighbourhoods, micro location might matter more than marco areas which are largely homogenous. Likewise, when the differences between cities or regions increase, macro context more clearly determines the spatial footprint of inequality and consequently people's individual life courses.

Regional inequalities in the Netherlands exist between the largest cities and the rest of the country as well as between core cities and suburbs. In the Netherlands cities are, on average, poorer than rural areas – in fact, the more inhabitants a municipality has, the larger is the share of low-income people, ranging from 7% in municipalities with less than 10,000 people, to 9% in municipalities with 50,000-100,000 people, up to 16% in municipalities with more than 250,000 people (four largest cities), in year 2012 (Vrooman et al., 2014). Almost a quarter of all low-income households lives in the four largest cities (Amsterdam, Rotterdam, The Hague and Utrecht; see Vrooman et al., 2014). Focusing on specific urban regions, inequalities exist between core cities and their hinterlands. Van Kempen and Priemus (1999) warned that Dutch cities were moving towards a doughnut structure typical of American cities, where poverty concentrates in central cities, surrounded by relatively better-off suburbs.

In addition to higher shares of low-income people in big cities, low income residents are often spatially concentrated in specific neighbourhoods. Poor neighbourhoods are, therefore, found disproportionately in the larger urban areas, with almost 30% of the poor neighbourhoods being located in the cities of Amsterdam, Rotterdam, The Hague and Utrecht (Bolt & Van Kempen, 2003). The poorest neighbourhoods in the country, which are targeted by urban policies, are located within the largest cities (Musterd & Ostendorf, 2008; Aalbers, 2012). Even within these neighbourhoods there are certainly further inequalities. However, many studies do not operationalise neighbourhoods at small spatial scales, largely due to the lack of data. Furthermore, notwithstanding the dominance of big cities, spatial inequalities may be no less important in smaller ones.

This paper aims to understand contextual poverty through multiple spatial scales, including the full urban system, where small neighbourhoods are parts of larger urban areas. Inequity occurs between residential contexts of different people, living in different parts of their municipality, and different urban regions of the country, which we measure using the multilevel Theil index. Crucially, the measurement starts from the premise that the spatial context of people changes as they move further and further from their home and this is how they experience inequality continuously in space.

5.3 Data and methods

To investigate different spatial scales of residential context, we created bespoke areas (centred around individual locations) at 101 scales. For this, we used individual level register data for the full population of the Netherlands, geocoded on 100m×100m grid cells (Sociaal Statistisch Bestand – SSB, see Bakker, 2002; Houbiers, 2004), for the year 2013. Starting from each grid cell, bespoke areas spread in one hundred concentric circles, with radii ranging from 100m up to 10km with 100m increments, to form a distance profile (for a more detailed description of this method, see Petrović et al., 2018). The lowest scale – the 100m×100m grid cell – represents an area of 0.01km^2, while the largest 'circle' spreads over 314km^2. At all these spatial scales, we measured contextual poverty as the share of people who had a low income (from work or social benefits) in 2013. To define low income, we used a low threshold of below 40% of the national median income, given the high income level in the Netherlands compared to other countries.

To compare poverty in different places and at different spatial scales, we used the Theil index (Theil, 1967). The Theil index is a hierarchical measure of entropy, so we can simultaneously compare areas at different levels of spatial organisation. The Theil index of *total* inequality, prior to its decomposition, would measure for each spatial scale how unequal is the share of low-income people in the bespoke areas of the specific size across the whole country. Since we investigate 101 spatial scales, our approach resulted in 101 Theil indices:

$$T = \sum_{i=1}^{n} s_i \log(ns_i)$$

$$s_i = y_i / \sum_{i=1}^{n} y_i$$

n = number of grid cells

y_i = share of low-income people for cell i, measured at specific scale

Since we are interested where this total inequality comes from and how different places contribute to national inequality, we compared the share of low-income people in the bespoke areas of the specific size *within* and *between* municipalities. Therefore, we decomposed the Theil index of inequality at each spatial scale into its within and between components to see to which extent the inequality comes from differences between areas within the same municipality and to which extent the municipalities differ among themselves. The two inequality components are calculated as follows:

$$T = \underbrace{\sum_{g=1}^{\omega} s_g \sum_{i \in g} s_{i,g} \ln\left(n_g s_{i,g}\right)}_{T_W} + \underbrace{\sum_{g=1}^{\omega} s_g \ln\left(n / n_g s_g\right)}_{T_B}$$

$$s_g = \sum_{i \in g} y_{i,g} / \sum_{i}^{n} y_i$$

$$s_{i,g} = y_{i,g} / \sum_{i=1}^{n_g} y_{i,g}$$

n_g = number of grid cells in municipality g

y_i = share of low-income people for cell i, measured at specific scale

T_W = Within-municipality component of inequality

T_B = Between-municipality component of inequality

Figure 5.1 illustrates this application of the Theil index using a few distance profiles. At each scale, the first level of the hierarchical entropy from the previous equation measures inequality in the share of low-income people in different locations within municipalities. From this, we can observe how unequal the areas within municipalities are in terms of contextual poverty, where the minimum index value of 0 would mean that they all have the same share of low-income people. From the second level of the index (that is, the between-municipality inequality), we can see if and by how much the areas within specific municipalities are above or below the national average in their potential exposure to contextual poverty. The between component of the index can, therefore, have both positive (indicating above national average) and negative values (indicating below national average). These values provide a range of within- and between-municipality indices (one index for each scale), to demonstrate the effect of scale on measuring spatial inequality in contextual poverty.

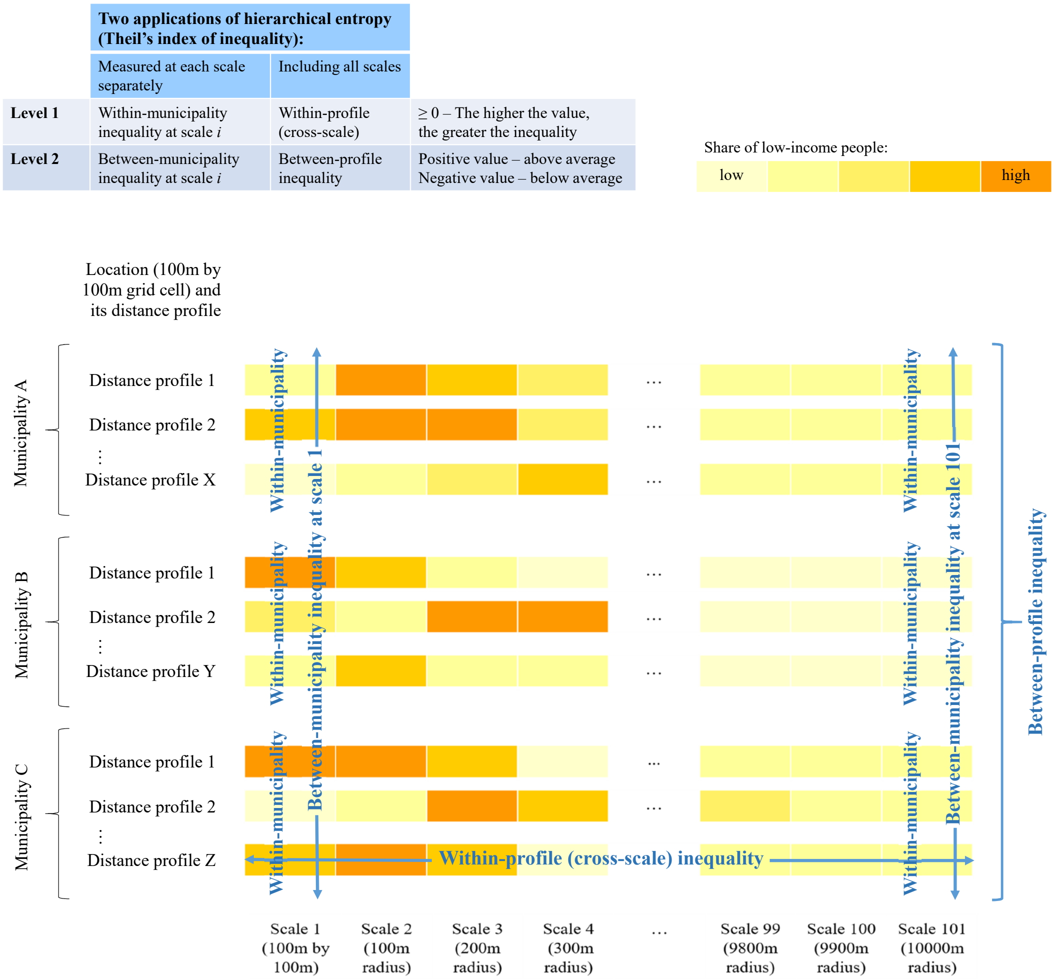

FIG. 5.1 Two applications of the Theil index of inequality

However, entropy can give us more than this: it can also be used to measure scalar variability in the contextual poverty across spatial scales (see Figure 5.1). This is a less common use of entropy, which was demonstrated by Petrović et al. (2018), who used Shannon's entropy to measure scalar variability in potential exposure to non-Western ethnic minorities. Here, we use Theil index to measure scalar variability in distance profiles encompassing the share of low-income people across 101 scales. This is the within-component of the index, measuring the inequality across scales within each distance profile, i.e. how the spatial context changes when we start from one location and include increasingly large areas (within-profile inequality).

TOC

At the next level, we measure the inequality between the multiscale distance profiles, that is whether and to which extent they are above or below the national average in exposure to contextual poverty (between-profile inequality). This way, we compare locations not as single-scale units, but as multiscale spatial contexts. The meaning of the elements in the Theil index equation is then the following:

n_g = 101 (number of scales in distance profile g)

y_i = share of low-income people at scale i

T_W = Within-profile (cross-scale) component of inequality

T_B = Between-profile component of inequality

5.4 Results

Before delving into the issues of multiscale spatial contexts, we start from the smallest available scale, showing the spatial distribution of low-income people in 100m by 100m grid cells. We then introduce other scales to get insight into how these various spatial contexts differ in terms of poverty levels, and to demonstrate the effect of spatial scale on measuring inequality. Finally, we encompass all the scales in one measure, showing the cross-scale patterns of the sociospatial inequality in the Netherlands.

5.4.1 Spatial distribution of low-income people at the micro scale

Figure 5.2 shows the share of low-income people measured at the smallest available scale in nine sample municipalities. This spatial scale reveals very small neighbourhoods, categorised at the national level, where low-income is below 40% of the national median. These municipalities present a mixture of places including some of the largest cities in the Netherlands (Amsterdam, The Hague, and Utrecht), as well as smaller nearby municipalities (Haarlem, Wassenaar, Zoetermeer, and Hilversum). However, it is notable that all of them are part of the Randstad, one of the largest urban conurbations in Europe. Additionally, we consider two middle-sized cities: Leiden, which is also a part of Randstad, and Groningen, a relatively isolated city in the north of the Netherlands. The maps in Figure 5.2 show that, in Amsterdam, low-income residents are scattered across the city, most likely as a result of the spread of social housing across many parts of the city. In the other cities, low-income people are more concentrated in the city centre. This is particularly the case in Groningen, where a lot of small low-income neighbourhoods form the most striking concentration of contextual poverty among the presented municipalities. On the contrary, smaller, peripheral municipalities of Haarlem, Wassenaar, Zoetermeer, and Hilversum have fewer low-income neighbourhoods, without obvious concentrations.

These maps give insight into the potential exposure to poverty in micro-neighbourhoods, which is a largely under-analysed scale of spatial context. However, for people it is also important to consider how their context changes throughout space. In many of these locations, the map would look differently if we delineated neighbourhoods at another spatial scale. Therefore, we need to complement the micro scale with the measures of contextual poverty at other scales in order to answer our first two questions: How big is the spatial inequality in contextual poverty in the Netherlands and where does it come from – from which spatial scales in which levels of urban system (within and between municipalities)? In which ways and to which extent different municipalities contribute to the national inequality – and at which spatial scales?

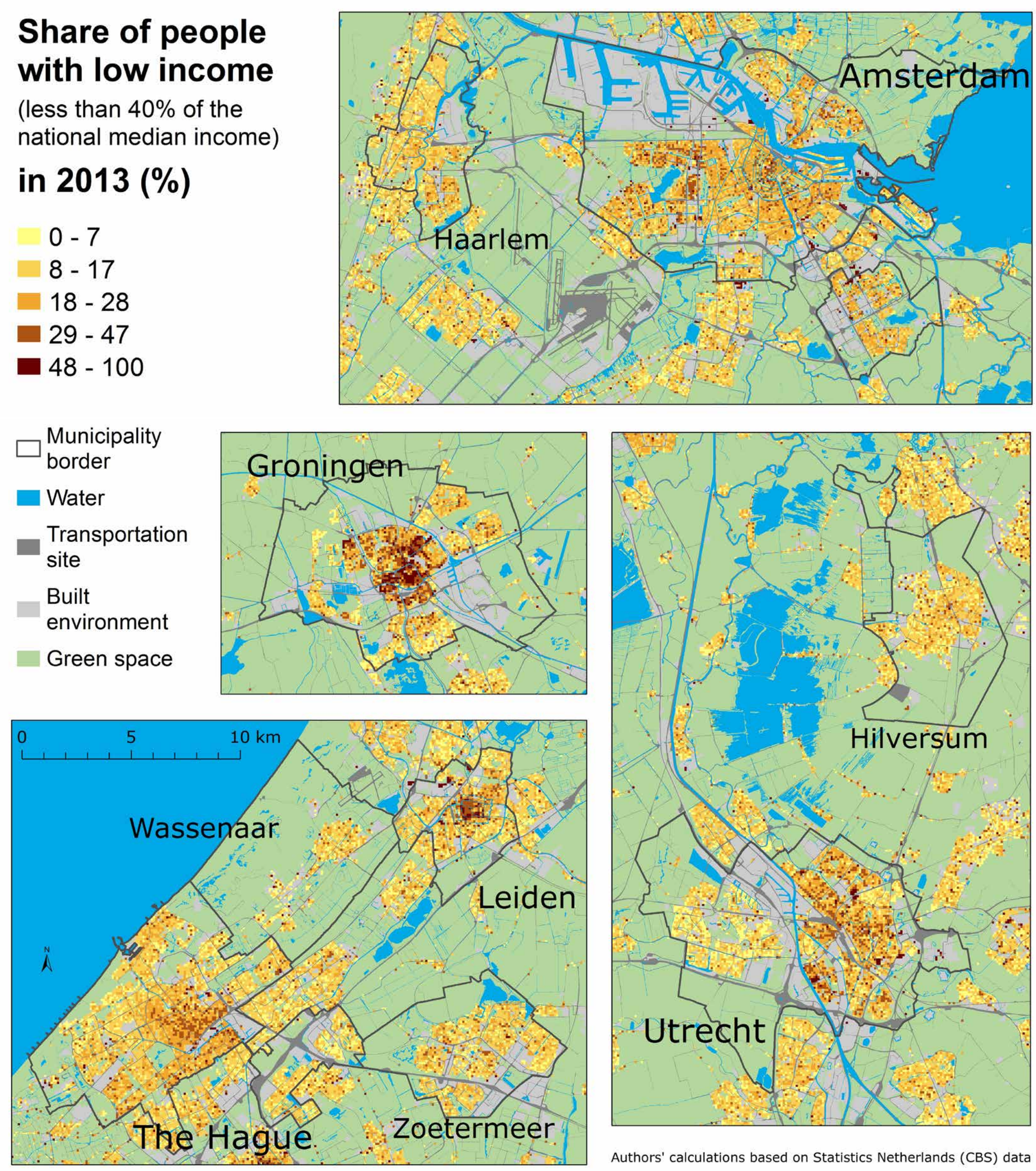

FIG. 5.2 Share of low-income people in 100m by 100m grid cells in nine sample municipalities

5.4.2 Multiscale spatial inequality within and between municipalities

To answer the first question regarding the national inequality, Figure 5.3 shows the Theil index of inequality in contextual poverty within and between all municipalities in the Netherlands, calculated separately for each of the 101 spatial scales. The left panel of the figure shows the inequity within municipalities, that is how different areas at the specific scale are in their poverty levels (spatial scale is shown on x-axis). The greater the value of the index, the greater is the within-municipality inequality. At the smallest scales (those under 1km), there are big within-municipality differences. We would expect this to be the case because a single municipality has a great variety of small neighbourhoods, ranging from those with a lot of poverty to the ones with very little or none. Moreover, at a fine spatial scale with relatively small populations, sharp differences can occur within a single municipality. By contrast, very low inequality within municipalities occurs at the largest spatial scales, where all people in one municipality share similar contexts. However, the most critical aspect from the graph is that even for areas with a 2-3km radius there are equal shares of low-income people, which indicates that Dutch municipalities generally do not have large areas with distinct poverty levels.

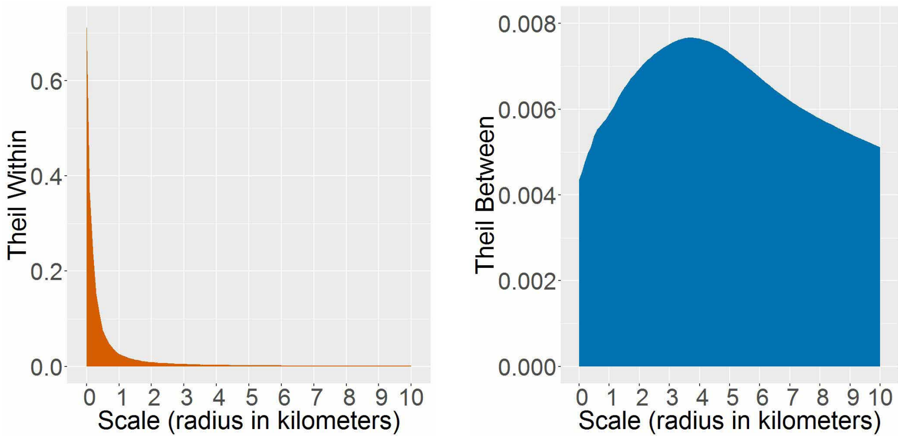

FIG. 5.3 The Theil index of inequality in contextual poverty within and between municipalities at 101 spatial scales

TOC

Beyond this general pattern for the whole country, there are, however, differences between municipalities, and these are shown in the right panel of Figure 5.3. Firstly, municipalities differ in potential exposure to poverty at the whole range of spatial scales, but to different extents. Secondly, the between-municipality index, which can be both positive and negative, is constantly positive. This is because the national level of poverty is low, so that poverty levels cannot go much lower, but the municipalities with above-average levels of poverty stand out and push the index towards the higher positive values. Thirdly, there is a peak at the scale of 4km. This means that, areas with a radius of 3-5km are the most appropriate for finding concentrations of poverty in the Netherlands, in general.

The Theil indices in Figure 5.3 include the data form all municipalities. However, each municipality may contribute in a different way to the overall inequality, which leads us to our second question: In which ways and to which extent different municipalities contribute to the national inequality – and at which spatial scales? Some municipalities have more diverse neighbourhoods than others (greater within-municipality inequality) and some have neighbourhoods with higher or lower poverty levels than neighbourhoods in other municipalities (greater – positive or negative – between-municipality inequality). The former is then measured by the within component of the Theil index; the latter – by the between component. Figures 5.4 and 5.5 show how the nine sample municipalities contribute to the overall inequality shown in Figure 5.3.

Figure 5.4 shows the within-municipality component of the Theil index – in other words, how unequal the areas are at various spatial scales within each of the nine municipalities. Increasing the scale at which we measure inequality helps us to identify how large areas with distinct shares of low-income people are. For example, in Utrecht, Groningen and The Hague, we can most clearly distinguish between parts of the city with unequal poverty levels, because the within-municipality persists up the scale of a few kilometres (in Utrecht even around 5km). In Groningen, spatial inequality extends for areas up to around 3km, but with a higher intensity than in other cities, which means that some areas (the city centre, see Figure 5.2) have extremely high shares of low-income people. On the contrary, Amsterdam has much less inequality at the meso scales, but has instead the greatest inequality of micro-neighbourhoods. Except Leiden, all larger and middle-sized cities have a great variety of neighbourhoods at the smallest spatial scales. The smaller municipalities of Haarlem, Wassenaar, Zoetermeer, and Hilversum have less inequality at all spatial scales, but their distinction from the bigger cities is particularly visible at the smallest scales, where the small municipalities have much less diversity in neighbourhood poverty.

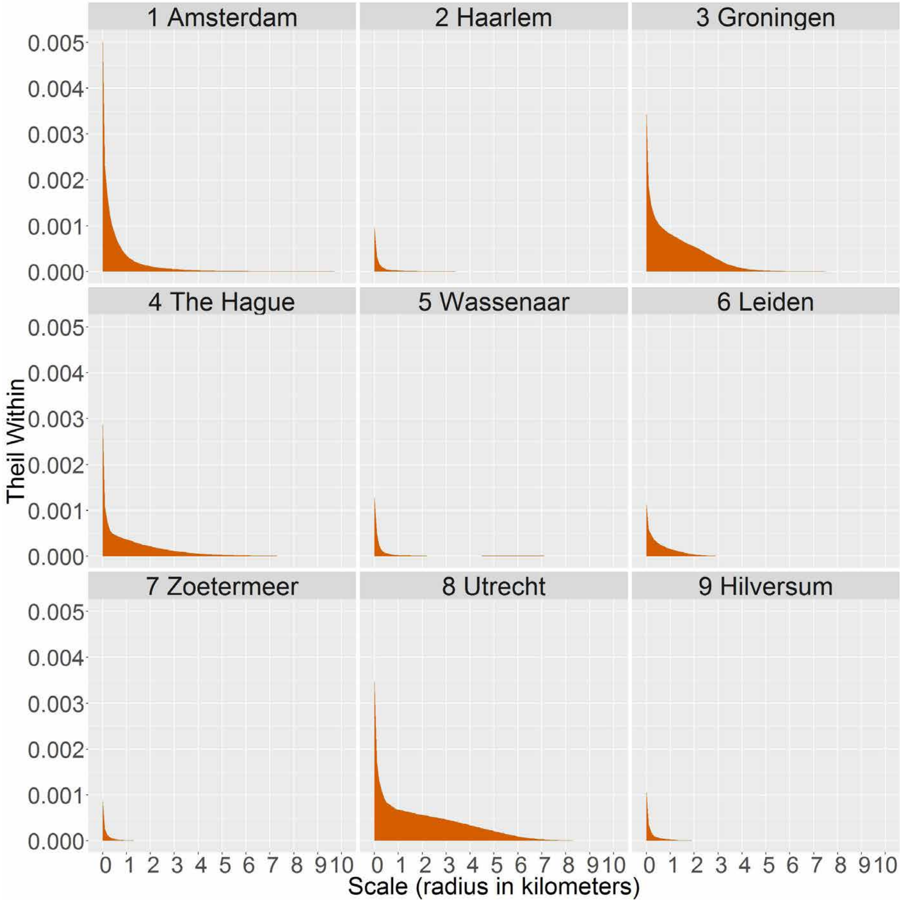

FIG. 5.4 Contribution of nine sample municipalities to the Theil index of inequality in contextual poverty within municipalities at 101 spatial scales

From the previous figure, we saw that the municipalities differed in their internal inequality. The decomposition also allows to explicitly compare the municipalities and explore if their poverty levels at various spatial scales is above or below the national level. Figure 5.5, therefore, shows in which ways specific municipalities contribute to the national inequality between municipalities shown in the right panel of Figure 5.3. The between component of the Theil index has a positive value if the municipality has more, and a negative value if the municipality has less poverty than the national average, at the specific spatial scale. Firstly, larger cities generally have more poverty than smaller, more peripheral municipalities.

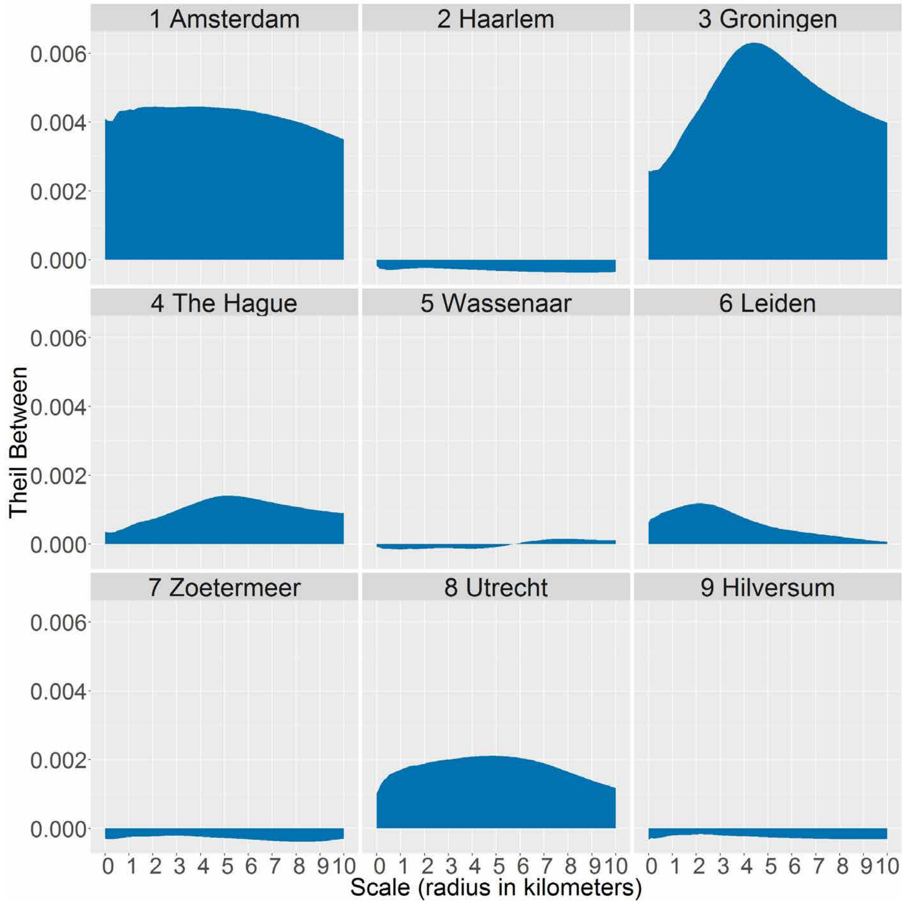

FIG. 5.5 Contribution of nine sample municipalities to the Theil index of inequality in contextual poverty between municipalities at 101 spatial scales

Secondly, the figure shows at which spatial scales and to which extent poverty level in a specific municipality is different to the national average. Amsterdam, the largest city, has notably more poverty than the Netherlands on average, measured at almost all scales, while Groningen stands out for its spatial concentrations of poverty within 4-5km radii. The Hague has yet another pattern of scalar variability in contextual poverty: Small neighbourhoods fairly represent the national average in poverty levels, but the poorer ones tend to concentrate spatially, resulting in increasingly high index values.

Unlike bigger cities, the smaller, peripheral municipalities contribute to the national inequality mostly with negative values. This is particularly the case for Haarlem, Zoetermeer, and Hilversum, at the finest spatial scales, because the majority of small neighbourhoods has less poverty than the national average. It is also the case for the scales larger than 5km, which often expand beyond the municipality border, including parts of other municipalities. In this manner, Wassenaar is an interesting case of a small municipality which does not have much poverty itself (therefore negative values for the scales up to 6km), but it is located between two cities with more poverty (The Hague and Leiden), and therefore has positive values at larger scales.

The case of Wassenaar shows that we cannot look at neighbourhoods as isolated spatial units; instead, they are parts of an integrated urban system. This finding also applies to the other municipalities. We can represent the increasingly large scales as a distance profile ranging from the small neighbourhood of 100m by 100m up to the area with a 10km radius. Considering all the scales simultaneously, however, introduces additional complexity in comparing different residential locations. Our final question is, therefore, how we can compare different spatial contexts in terms of poverty, knowing that they do not consist only of a single spatial unit but of a range of spatial scales. So, the unit of analysis becomes the distance profile, consisting of 101 scales, and we use them for studying spatial patterns of poverty at multiple spatial scales simultaneously.

5.4.3 Cross-scale patterns of spatial inequality

To answer the final question, the Theil index is again decomposed – this time into the within-profile (cross-scale) inequality (Figure 5.6), which is the scalar variability of distance profiles, and the between-profile inequality index (Figure 5.7), which compares the distance profiles in terms of poverty levels at the range of scales. Figure 5.6 shows relatively low variability in most of the distance profiles. This is because not only is the share of low-income people in the Netherlands low, but also because low-income people are relatively scattered. The scalar variability of this socioeconomic group appears to be lower than for non-Western ethnic minorities, which have more clustered spatial patterns (see a comparable analysis by Petrović et al., 2018).

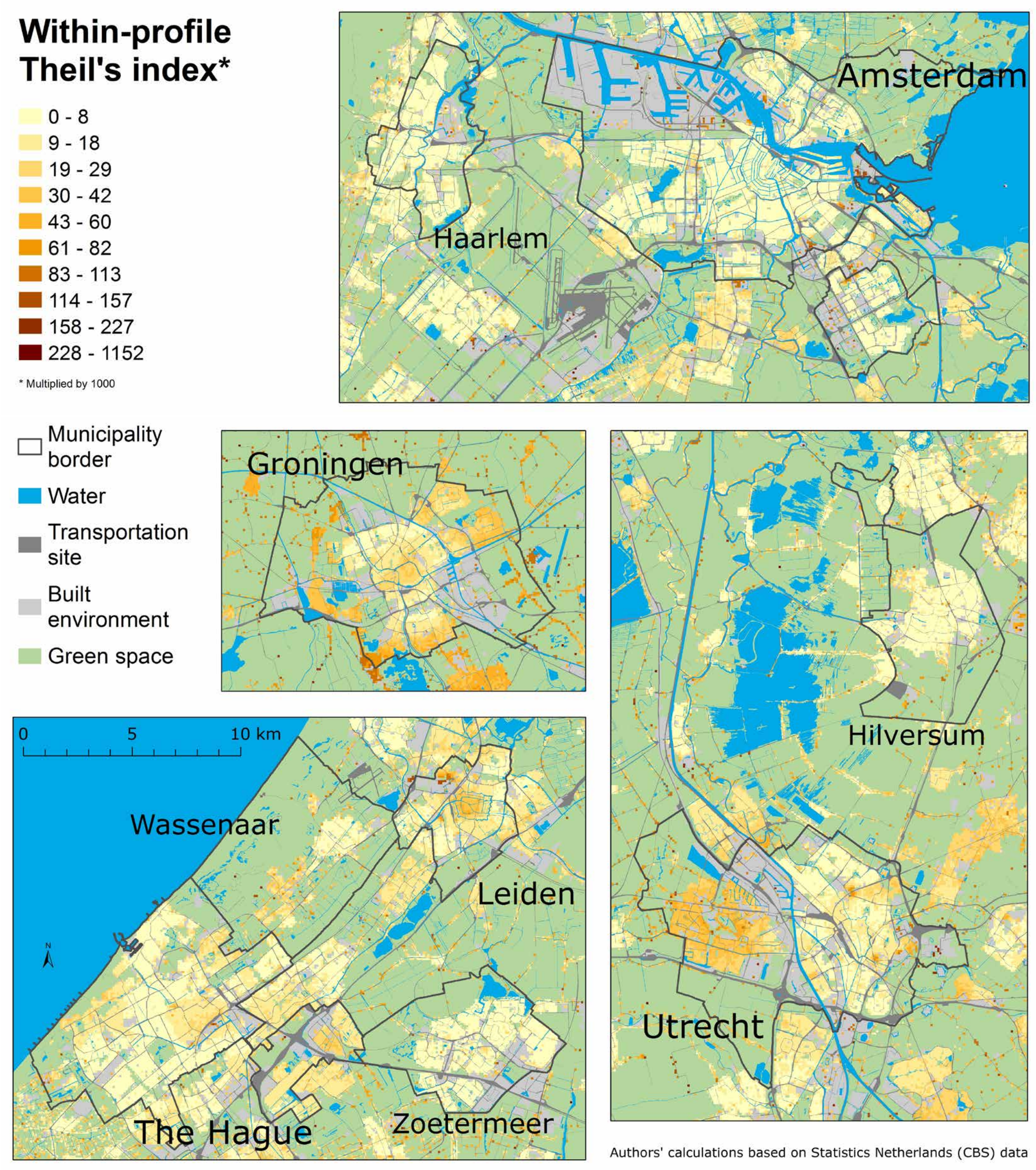

FIG. 5.6 The Theil index of inequality across spatial scales within distance profiles in nine sample municipalities

The exceptions of a greater cross-scale variability denote places with considerable spatial changes in contextual poverty. They are located in the city centre, and particularly in the periphery of Groningen, because people are exposed to very different spatial contexts as they move between these parts of the city. Another example is the western part of Utrecht, which is much more affluent than the larger, eastern part. These are both examples of greater variations at meso and macro scales, which result in greater cross-scale variability of the distance profiles than in other municipalities. In many residential locations in Leiden and The Hague, people are also potentially exposed to different levels of poverty as they move farther away from their home. In the rest of our study area – with the low within-profile variability – people's spatial context does not vary considerably and persistently at a wider range of scales: it may vary at smaller scales and then stabilises. This is why the majority of residential locations with the very low within-profile index can be seen in Amsterdam – the city that we already identified as having the spatial inequality primarily at the lowest scales.

In addition to having different patterns of scalar variability, distance profiles differ among each other in terms their overall levels of poverty. Figure 5.7 shows how each distance profile, consisting of 101 scales, contributes to the national inequality, among all the profiles. Two separate colour ramps differentiate the direction (red for positive and purple for negative) as well as the intensity of the index. The shading, therefore, reflects the levels of poverty to which people are potentially exposed in their place of residence, across a wide range of scales: Red areas score above the national poverty level, while purple areas score below. The difference between the positive and negative indices can be best explained using two extreme examples: If a poorer neighbourhood is surrounded by other poor neighbourhoods at a wider range of spatial scales, so that the contextual poverty is persistent across spatial scales, the distance profile will have a high, positive between-profile index (Figure 5.7). Cells with such profiles are usually clustered, most remarkably in Groningen, since they share similar larger-scale surroundings, forming distinct pockets of multiscale contextual poverty. On the contrary, if low poverty persists across a number of spatial scales, the profile has a low, negative index, and this means that people are exposed to little poverty in wider areas around their home. This can be seen in the smaller municipalities of Haarlem, Wassenaar, Zoetermeer, and Hilversum, with the exception of the northern neighbourhoods in Wassenaar, close to Leiden.

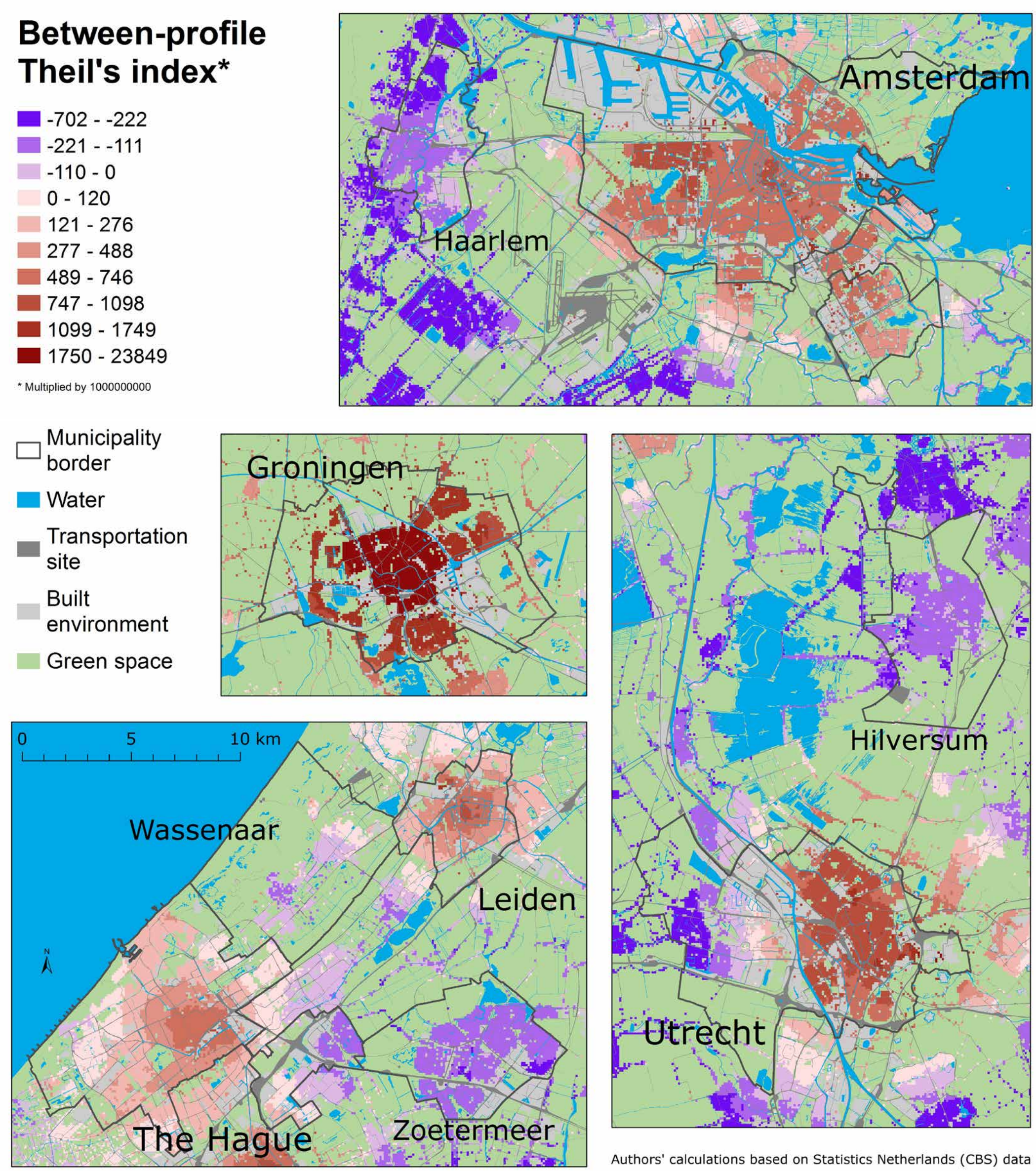

FIG. 5.7 The Theil index of inequality between multiscale distance profiles in nine sample municipalities

Figure 5.7 reports the spatial patterns at the regional level: smaller municipalities have much less poverty than the nearby big cities, but slightly more than the surrounding rural areas. We can see this from the direction and the intensity of the index across our entire study area: Haarlem, Hilversum, Zoetermeer, and a large part of Wassenaar score below the national poverty level (and also much lower than the big cities), but other, even smaller and more rural municipalities have even less poverty. Big cities are clearly characterised by multiscale contextual poverty. Among them, there are, however, different spatial patterns. Contextual poverty in Amsterdam can be described as multicentre, although in the national comparison these centres are not so conspicuous. Utrecht is clearly divided in the poorer eastern part (larger part around the city centre) and the newer and more affluent western part of the city. Therefore, being more affluent than Amsterdam and Groningen does not apply to the entire city of Utrecht, but to one spatially distinct part of the city. The Hague, Leiden, and Groningen have another spatial pattern of poverty – the core-periphery distinction, where the city centre is poorer, persistently at multiple scales, than the more peripheral parts of the city.

5.5 Discussion and conclusions

In this study, we analysed spatial inequality in contextual poverty within and between places, focussing on a few big cities and smaller municipalities in the Netherlands. For each 100m by 100m grid cell, we measured the share of low-income people at the range of 101 spatial scales, and we used the Theil index as a hierarchical measure of entropy to measure inequality. The results showed that scale considerably influenced the measurement of contextual poverty and consequently the comparisons of different places. Within- and between-municipality comparisons are crucial to understand contextual poverty, because we can only understand poverty in one area in reference to other areas within the same municipality and in other parts of the country.

Spatial scale is crucial to understand spatial inequality and this implies that policy measures should also be multiscale, and that different problems require different actions and interventions at different spatial scales. Given the great inequalities among very small neighbourhoods within municipalities, policies targeting contextual poverty should not simply rely on official neighbourhood definitions, overlooking the inner neighbourhood inequalities. National level polices should take into account that along with the within-municipality inequalities, there are considerable inequalities between municipalities: it might be the case that the scale of intervention that works in one city does not in another, even when they are both within the country and relatively closely located. Comparing all municipalities in the country, we identified the greatest poverty concentrations at the scales of 3-5km. These are, therefore, the scales at which poverty studies and measures at the national level should seek to intervene.

The first application of the Theil index – where we measured inequality within and between municipalities at a range of scales – revealed different spatial structures of neighbourhoods within the urban system. For example, while the micro neighbourhoods in The Hague did not considerably contribute to the national inequality (their poverty levels were about the national average), combined at meso scales they formed areas with above-average poverty levels in the national comparison. Changing inequality across spatial scale does not merely demonstrate the modifiable areal unit problem (MAUP); it adds to the literature such as Manley et al. (2006) and Jones et al. (2018), highlighting the process nature of the MAUP – the fact that different spatial scales capture different spatial processes. That these processes differ over space (as shown here) further highlights the need to identify the flexible geographies at multiple scales. We should also note that the processes vary over time as well. For example, smaller geographies reveal micro-concentrations of poverty, which have often been associated with social-interactive mechanisms of neighbourhood effects. Similarly, theory suggests that stigmatisation occurs at a larger spatial scale and our study has provided evidence on the spatial extent and location of areas which may be potentially stigmatised. At the largest scales, labour market factors, such as regional wage levels and migration of labour, become the most relevant. Here, our findings provide a basis for further investigations into spatial mismatch in labour markets.

Finally, various scales are parts of an integrated urban system. Therefore, the second application of the Theil index considered all scales of contexts in one location simultaneously. For an individual, inequality can be seen as a distance profile: some people potentially experience greater inequality because poverty levels change as they move further away from home. Furthermore, comparing different distance profiles showed that neighbourhoods differed not only in their own characteristics, but also that seemingly the same neighbourhoods may have different meso and macro contexts. Single spatial scale cannot give enough input for policy actions. Instead, various scales jointly define distinct areas of potential exposure to poverty and possible interventions.

The regional trend is that contextual poverty decreases as we go from big cities towards smaller municipalities, and further towards the surrounding rural areas. Although poverty is a prior concern of big cities, poverty in peripheral municipalities and middle-sizes cities in rural areas should not be lost out of sight. This study should generate more interest in the analysis of poverty in various urban (and rural) contexts. Using small increments in radius from the very micro to macro contexts allowed us to explore at a fine resolution the differences between locations, which revealed more detailed spatial patterns than when using fixed administrative boundaries. We particularly pointed out three different multiscale spatial patterns of contextual poverty – multicentre in Amsterdam, east-west in Utrecht, and core-periphery in The Hague, Leiden, and Groningen.

Measuring and understanding contextual poverty and its inequality over space largely depends on the spatial scale, because different spatial scales represent very different residential contexts. This is relevant for individuals who may be affected by the contextual poverty as well as for institutions at the local and national levels. Spatial scale may determine actions related to contextual poverty, because the same issue manifested at different spatial scale may require different solutions. Spatial scale also needs to be put in a certain context within the framework of spatial inequality, because differences occur both within and between places.

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6 Where do neighbourhood effects end?

The complexity of multiscale residential contexts

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ABSTRACT

There is no theoretical reason to assume that neighbourhood effects operate at a constant single spatial scale across multiple urban settings or over time. Despite this, many studies use large, single-scale, predefined, spatial units as proxies for neighbourhoods. Recently, bespoke neighbourhoods have challenged the predominant understanding of neighbourhood as a single static unit. This paper systematically examines how the estimates of neighbourhood effects vary when residential context is treated as a multiscale concept, how this translates across urban space, and what the consequences are when using an inappropriate scale, in the absence of theory. Using individual-level geocoded data from the Netherlands, we created 101 bespoke areas around each individual. We ran 101 models of personal income to examine the effect of living in a low-income spatial context, focusing on four distinct regions. We found that contextual effects vary over both scales and urban settings, with the biggest effects not necessarily present at the smallest scale. Ultimately, the magnitude of contextual effects is determined by various spatial processes, along with the variability in urban structure. Therefore, using an inappropriate spatial scale can considerably bias (upward or downward) spatial context effects.

KEYWORDS

neighbourhood effects, spatial scale, bespoke neighbourhoods, distance decay, socioeconomic status

6.1 Introduction

Sociospatial inequalities have been increasing in many European cities (Tammaru et al., 2016) which, in turn, results in the spatial concentration of low-income households. Governments have a long history of developing area-based policies to target deprived neighbourhoods, and such policies are partially based on the belief that living in a deprived area has a negative impact on individual outcomes – the so-called neighbourhood effect (see Ellen & Turner, 1997; Dietz, 2002; Galster, 2002; Durlauf, 2004 for reviews). Fundamentally, neighbourhood effects research asks if there is a (causal) association between the spatial context in which someone lives, and their life outcomes. Answering this question is hampered by issues including selection bias caused by the non-random sorting of people into neighbourhoods, and by the fundamental issue that lies *prior* to any of the other problems – uncertainty about what is a neighbourhood (see, e.g., Diez Roux, 2004). An essential aspect in the definition of any neighbourhood is its spatial extent.

Galster (2008) detailed some major challenges for neighbourhood effects research, the first of which is the spatial scale at which neighbourhoods are operationalised. Neighbourhood effects studies use one of three main approaches when considering scale. Firstly, most studies use a single spatial scale, usually administrative units, without exploring the consequences of this choice. This is somewhat surprising, as the importance of spatial scale is well-known in the methodological literature on the modifiable areal unit problem (MAUP; see Openshaw & Taylor, 1979; Manley, 2014). The second approach is to compare neighbourhood effects measured at different spatial scales. However only a handful of studies do this at most. Such studies found statistically significant relationships between residential context at various spatial scales and personal health (Lebel et al., 2007; Duncan et al., 2014), political attitudes and voting behaviour (MacAllister et al., 2001; Johnston et al., 2005), educational achievement (Andersson & Malmberg, 2014), as well as labour market outcomes (Andersson & Musterd, 2010; Hedman et al., 2015). Since the early 2000s, neighbourhood effects research has been enhanced by the use of bespoke neighbourhoods (Johnston et al., 2000), which are constructed around the residential location of an individual (ideally using geographic coordinates, but often aggregations of small areas) to represent the area surrounding them, at various spatial scales (see also Hipp & Boessen, 2013; Veldhuizen et al., 2013; Clark et al., 2015).

One common result in studies that compare the effects of different spatial scales has been the identification of stronger effects at smaller spatial scales (see, e.g., Bolster et al., 2007): in other words, localised neighbourhoods appear to matter for individual outcomes, although this is not universally the case (Buck, 2001). Crucially, it is difficult to compare different studies because they use a variety of scales to depict ‘neighbourhood’ – from the micro (Andersson & Musterd, 2010) to large administrative units such as U.S. counties (Chetty & Hendren, 2018). These very large spatial units are often much bigger than what would normally be considered by individuals as ‘their neighbourhood’, and also much bigger than the scales at which one would expect causal neighbourhood effects to occur (e.g. processes such as socialization and peer group effects).

Finally, the third way of dealing with the issue of spatial scale is to systematically examine its effect, varying only scale whilst everything else remains constant. Spielman et al. (2013) did so using simulated data and demonstrated that the misrepresentation of spatial scale of the neighbourhood systematically biased estimates of neighbourhood effects. To simulate the common research practice, they assumed there was a ‘true’ neighbourhood and an associated effect present at a specific spatial scale. However, in reality there is no single ‘true’ neighbourhood and no single ‘true’ neighbourhood effect, rather a multitude of spatial processes that take place, simultaneously, at various scales. Furthermore, this scale is unlikely to be constant over space or time: the same process may occur at several scales even in one location, and may vary over time, perhaps depending on the moment in an economic cycle. The scale(s) at which neighbourhood effects operate may be driven (in part) by the mechanism that is being investigated. Smaller neighbourhoods may be important to understand social interactive mechanisms, while processes such as area stigmatization may operate at a much larger spatial scale (Manley et al., 2006; van Ham & Manley, 2012). Between places, deprivation and affluence concentrate at different spatial scales, so that stigmatised areas may be relatively large in big cities, while smaller cities or towns may experience the same processes confined to smaller locales (Wacquant, 2007).

Given that causal processes operate at different spatial scales, it is more appropriate to use the term *spatial contextual effects* instead of *neighbourhood effects* (Petrović et al., 2018). As we expect causal processes to operate at various spatial scales, we need a multiscale approach to represent them (Petrović et al., 2018). This study systematically investigates how spatial context affects individual income, using microgeographic register data from the Netherlands. Our aim is to better understand how estimates of spatial contextual effects vary as that context is measured at different spatial scales across all urban regions in the Netherlands, highlighting the four regions of Amsterdam, Rotterdam, Utrecht, and Groningen. We used individual level register data for the whole population of the Netherlands (1999-2014), which includes low-level geocoding (100m by 100m grid cells) for each individual’s place of residence annually. We created bespoke areas (cantered around each person’s location) at 101 spatial scales (see Petrović et al., 2018), and measured the share of low-income people in these areas. For every scale, we ran a fixed effects model estimating individual income based on their residential context characteristics, including a distance decay function, thus generating parameter estimates of spatial context effects at the entire range of spatial scales. In doing so, we examined the appropriateness of operationalizing neighbourhood as a static single-scale entity (Manley et al., 2006) and explored the fallacies and potential risks of isolating specific spatial scales from a wider spatial context.

6.2 Multiscale spatial contexts and socioeconomic status of people

Many studies have examined neighbourhood effects on personal income as a proxy for socioeconomic status (see, for instance, Brännström, 2005; Bolster et al., 2007; Hedman et al., 2015). Although crucial for understanding neighbourhood effects, the spatial context in which someone lives is often operationalised pragmatically – perhaps using a single, predefined scale. Frequently, this means using spatial units constructed for administrative purposes to represent for neighbourhoods. However, the spatial context at multiple spatial scales can impact on their individual socioeconomic status through different mechanisms. For example, role models or personal social networks can influence job search behaviour and efficacy (Bala & Goyal, 1998; Topa, 2001; Dietz, 2002). These mechanisms belong to a wider group of social-interactive mechanisms (Sampson et al., 2002; Galster, 2012), and depend on the individual characteristics of people and their activity spaces. However, they generally operate within the local neighbourhood, often smaller than administrative units, and require exposure, if not contact, to other people.

The effect of the micro spatial context cannot be understood in isolation from the macro framework, which represents the 'context of context' for the small-scale neighbourhoods (Petrović et al., 2018). Using an example from Auckland, Manley et al. (2015) demonstrated that the microscale residential mosaic is framed by a relatively permanent macroscale structure of the city, where changes occur at a slower rate than in the micro-context. External (large-scale) contextual mechanisms result from a neighbourhood's location relative to economic and political structures, so that jobs or public services remain less accessible for some people than for others

(Kain, 1968; Ihlanfeldt & Sjoquist, 1998). Between the micro and macro spatial contexts, exist various meso-contexts, representing particular segments within the city (Manley et al., 2015; Petrović et al., 2018), which may earn reputations based on demographics, housing types, or other (historical or current) characteristics. This reputation may influence people's decision to move in or out of the neighbourhood (Sampson, 2012), but also cause stigmatization of their residents by, for example, potential employers (Wacquant, 1993; Taylor, 1998; White, 1998). Given the variety of possible spatial contextual effects, using a single scale could capture some of the processes, but it is very likely to miss many others (Petrović et al., 2019), despite representing the predominant approach in the estimation of neighbourhood effects, particularly those related to socioeconomic outcomes.

6.2.1 Spatial scale and bespoke neighbourhoods

For almost a century researchers have observed the effects of spatial scale on the results of statistical analyses (see, e.g., Gehlke & Biehl, 1934), and many authors have discussed the nature of neighbourhood together with the modifiable unit problem (MAUP; see, e.g., Flowerdew et al., 2008; Kwan, 2009). Alternative definitions of neighbourhood, beyond administrative units, are especially important for studying potential exposure to and interaction with other people. For example, Grannis (1998) used street networks, while Coulton et al. (2001) mapped residents' perceptions of neighbourhood boundaries. Although the residents had various, non-coterminous, perceptions, they commonly placed themselves in the middle of the neighbourhood. This matches earlier ideas that individuals place themselves in the centre rather than on the edge of a neighbourhood (Hunter, 1974; Galster, 1986). According to this view, neighbourhood boundaries are not fixed, but 'sliding', depending on residents' characteristics, their perceptions, and geographical setting. Sliding boundaries do not only come from the uncertainty of how to delineate neighbourhoods and the differences between people, but also reflect the multiscale nature of neighbourhood, where one person can belong to spatial contexts at multiple scales (Suttles, 1972).

The introduction of bespoke neighbourhoods into neighbourhood effects research (Johnston et al., 2000), allows the use of neighbourhoods of varying spatial scale (Chaix et al., 2005; Bolster et al., 2007; Veldhuizen et al., 2013). Studies using bespoke neighbourhoods have greater possibilities to explore spatial scale of context. They also tackle edge issues, which occur when a person lives close to the boundary of an administrative area, meaning their context may be better represented by adjacent administrative areas rather than the more distant parts of their ‘own’ neighbourhood. Small-scale spatial contexts are then more individual-specific (different for people in different locations), and as scale increases bespoke contexts become increasingly shared. Thus, spatial contexts of (increasingly distant) individuals overlap, which represents social landscape of the city more closely than non-overlapping areas (Hipp & Boessen, 2013). Bespoke neighbourhoods, therefore, reflect an individual’s location and distances within the context of one person, as well as the *overlapping contexts* of multiple people. They can be generated by starting from very small spatial units to very large areas, thus allowing a multiscale investigation of contextual effects. However, because different studies use different datasets, from different countries and cities, studying contextual effects on different outcomes, and at different spatial scales, consensus on the importance and impact of scale for neighbourhood effects is difficult to find.

6.2.2 Distance (decay) and spatial interactions

Distance has been used as an indicator of spatial interactions in the segregation literature, which has long emphasised that the measurement of segregation is sensitive to scale (Wong, 2003; Reardon et al., 2008; Manley et al., 2015). This holds for both the commonly used *aspatial* measures, which do not take into account spatial arrangement of units, as well as for spatial measures (Wong, 2004). Spatial measures of segregation incorporate information from neighbouring zones, and therefore give different results for different spatial structures and use overlapping egocentric environments rather than discrete spatially bounded areas (Reardon et al., 2008). This corresponds to the bespoke neighbourhoods used in the neighbourhood effects research, which at increasingly large scales also incorporate neighbouring zones and, therefore, give contextual measures which depend on the spatial structure and scale of the data.

The spatial measures of segregation at multiple scales normally incorporate distance-decay functions, whereby nearby zones have a greater influence on the resulting measure than those further away (Morgan, 1983; Reardon & O’Sullivan, 2004; Fowler, 2018), the so-called ‘distance-decay’ effect (Reardon et al., 2008). Olsson (1965) claimed that a correct transformation of the data is crucial for spatial interaction models – an idea which Taylor (1971) reviewed by investigating distance transformations and distance decay functions, some of which have also been applied in the segregation literature (see White, 1983). For example, segregation profiles, introduced by Reardon and colleagues (2008), depicting how segregation changes across spatial scales rely on a distance-decay function, ‘because it more plausibly corresponds to patterns of social interaction’ (Reardon et al., 2008, pp. 511). Spatial profiles were further explored studying multiple patterns of segregation (Lee et al., 2008; Östh et al., 2014), specifically clustering locations based on segregation levels (Spielman & Logan, 2013; Fowler, 2015; Hennerdal & Nielsen, 2017), but less often for studying individual exposure to context (Clark et al., 2015; Petrović et al., 2018).

Neighbourhood effects – partially as a consequence of segregation – are also affected by scale-dependency and distance decay (see also Petrović et al., 2018) especially those in the social-interactive domain. One challenge of addressing the issue of distance in the neighbourhood effects research is to demonstrate how the coefficient estimates vary with spatial scale; another challenge is how to include different scales in the models, so that they represent the impact of specific scales of the residential context, from the micro to macro. Although neighbourhood effects studies have, to date, generally found bigger effects with smaller spatial scales, the segregation literature has pointed out that the urban landscape is highly variable across small distances (Fowler, 2015; Johnston et al., 2015; Catney, 2016). This was explored by Chaix et al. (2005), who assessed the spatial scale of variability in the prevalence of mental disorders using the parameter that quantifies the rate of correlation decay with increasing distance between neighbourhoods. Here, larger areas then resulted in smaller neighbourhood effects. Furthermore, the correlation decay supports the idea that an individual's neighbourhood is a continuous field, whose influence decays with distance (Spielman et al., 2013), as opposed to a single, fixed geographic area, but also that the estimation of neighbourhood effects highly depends on the urban structure.

6.2.3 Urban structure and multiscale spatial contexts

Through a series of simulations, Spielman and Yoo (2009) illustrated how difficult it was to understand the relationship between individuals and their spatial context without considering the definition of neighbourhood and the urban structure of specific setting of the contextual effects. Petrović and colleagues (2018) used multiscale measures of population in bespoke neighbourhoods to show the effects of scale on measuring spatial context within and between cities. The effect of scale became particularly apparent when comparing cities with different urban forms, demonstrating that both inter- and intra-urban polycentricity are reflected in spatial context measures at various scales. This also highlights that one of the reasons of the limited understanding of spatial scale of contextual effects is the focus in the neighbourhood effects literature on single cities.

Spielman et al. (2013) examined how three spatial dimensions – the geographic definition of a person's neighbourhood, urban structure, and residential sorting – affected the assessment of neighbourhood effects within a simulated environment. They found that mis-specifying the spatial extent of the neighbourhood systematically biases the effect estimates. Simulating neighbourhood effects research by assuming there is one 'true' neighbourhood, the authors demonstrated that when overstating the extent of neighbourhood, the effect is underestimated, while when using neighbourhood below the scale of the effect, an overestimation resulted. However, there is no *single* neighbourhood, but a variety of spatial contexts to which a person belongs and which can affect them (see Petrović et al., 2019). Therefore, the models with the real data must include multiple neighbourhoods with multiple potential effects on people. For the other two spatial dimensions (urban structure and residential sorting), Spielman et al. (2013) found no systematic bias of the contextual effects estimates across spatial scale. Other studies showed that if sorting is taken into account, neighbourhood effects are smaller, but still exist (Van Ham et al., 2018). Plum and Knies (2015), however, argued that testing different spatial scales of neighbourhoods not only corresponds to a multitude of neighbourhood effect mechanisms, but also provides 'indirect assurance as to whether results are driven by selection into specific neighbourhoods'. To capture the uncertainty around contextual effects, studies should stop searching for one 'true' effect from the model with the best fit (Spielman & Yoo, 2009). Crucially, we should go further and abandon the idea of one 'true' neighbourhood conceptually, in order to understand different urban structures and contextual effects at different spatial scales.

The current paper systematically investigates in which way the estimates of contextual effects on individual income vary when using detailed multiscale measures of spatial context. We do so by characterizing contextual space using bespoke, overlapping areas at increasingly large spatial scales, in all twenty-two urban regions of the Netherlands. To examine the effect of various urban forms, the study then compares four distinct urban regions, each of them including the main city with a few surrounding municipalities. Those regions are Amsterdam, Rotterdam and Utrecht, as parts of Randstad, the largest conurbation in the Netherlands, as well as Groningen, a relatively isolated northern city in a rural environment[1]. The paper uses the multiscale measures of population at 101 spatial scales as independent spatial context variables in models of personal income. This generated an array of 101 parameter estimates for all urban regions combined, as well as for each of the four selected urban regions, allowing us to assess the variability in the contextual effects at a range of spatial scales.

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6.3 Data and methods

We used register data containing the entire population of the Netherlands recorded in the Social Statistical Database – SSD (*Sociaal Statistisch Bestand* – SSB; see Bakker, 2002; Houbiers, 2004). The longitudinal nature of the data allows us to follow individual residential histories for 15 years (from 1999 to 2014). Crucially, each person's place of residence is georeferenced to a 100m by 100m grid cell each year, allowing the construction of multiple bespoke neighbourhoods. Controlling for personal and household characteristics, we modelled contextual effects on personal income from work, corrected for inflation, for all men who were of working age (20-65) throughout the whole period (that is 20-51 in 1999 and then 34-65 in 2014). We include men only to avoid gender interactions (although important, the gender effect is not of primary interest in this investigation and we want to be able to isolate the impact of scale). For example, women in the Netherlands work part-time more often than men, and the register data does not include information about hours worked. We also excluded men for whom education data were not available, since the previous literature has shown that education is a major predictor of wages.

Besides education (defined as low, medium, or high), we identified the following individual characteristics at time t: age (regular and quadratic terms), ethnicity as belonging to either Western or non-Western backgrounds, type of household (couples, and single and other household types), and whether the individual has dependent children. To define ethnicity, we adopted the Statistics Netherlands (CBS) ethnic classification, as their definition of the non-Western group[2] reflects the use of 'ethnic minorities' within social policy in The Netherlands (Alders, 2001). The non-Western minorities in the Netherlands originate from Africa, South America or Asia, including Turkey and exclude Indonesia and Japan[3]. The other, major group in our ethnic classification is comprised of Dutch and other Western ethnicities together.

Our contextual variable is the proportion of individuals in the neighbourhood who have a low income. Here, income includes not only income from work but also from social welfare payments received by the working age population. To measure low income, we use the International Labour Organization (ILO) definition adjusted for the Dutch context. Thus, an individual has a low income if they are in receipt of less than 40 percent of the median income in the Netherlands[4]. We measured the share of people with a low income in the area at time $t-1$ to allow for the time lag of exposure to context. Of course, the length of exposure required to result in a change to the individual is also an issue of scale and temporality, but to concentrate on the spatial scale effect, we assume, in line with much of the literature, that a one year lag is sufficient. The smallest neighbourhood scale is represented by the 100m by 100m cell in which an individual lives, and we constructed 100 further bespoke neighbourhoods by increasing the radii by 100m increments to create a range of spatial contexts from 100m up to 10km (see Petrović et al., 2018). The purpose of varying the bandwidth so extensively is to examine the (in)stability of the models and to observe changes in the contextual effect over distance.

We modelled the contextual effects for men from all twenty-two urban regions in the Netherlands, controlling for whether they lived in one of the four largest cities (Amsterdam, Rotterdam, The Hague, and Utrecht), which are distinct from the rest of the country in terms of economic and urban development. To investigate the potentially differential effect of scale in multiple urban regions in the Netherlands, we then focused on four selected urban regions of Amsterdam, Rotterdam, Utrecht, and Groningen, restricting the sample to men who never moved from their region between 1999-2014 (although they could move *within* the region), to isolate the effect of each region. This allows us to keep as much of the design the same over time, and whilst there may be biases as a result, the impact of scale, will not be differentially confounded as a result of changing exposure to different contexts in other cities. To assess the impact of scale over time we ran 101 fixed effects models (one for each scale) for each of the four urban regions, keeping everything else constant, except the spatial scale of the residential context. The fixed effects model estimates the within (time) effect, controlling for the time invariant variables (observed and unobserved). Although the ethnic background is time-invariant, the models also include the interaction between this individual and the time-variant contextual characteristic (the share of low-income neighbours).

While individual characteristics are the same in the models at all spatial scales, the contextual characteristic was measured separately for each scale $s \in \{0, \ldots, 101\}$, which gave 101 estimates of each coefficient. To account for the conceptual meaning of residential contexts at various spatial scales, specifically the diminishing possibility for meaningful spatial interactions as scale increases, we have transformed the spatial context variable: The share of low-income people is multiplied by the 'bespoke scale term' (the squared distance in kilometres $d \in \{0, 0.1, \ldots, 10\}$) , which formulates the diminishing potential exposure with increasing distance, based on Tobler's first law of geography (Tobler, 1970). Squared distance belongs to a family of distance decay functions, widely studied in geography to find an appropriate measure of interaction intensity over distance (see Taylor, 1971), and it was a default applied in the original measures of multiscale spatial segregation by Reardon and O'Sullivan (2004). Besides the distance decay of potential exposure, our 'bespoke scale term' takes into account the spatial structure (see Fotheringham, 1981). At the smallest scale (100m by 100m cells, which do not overlap) the model uses the raw measure of the share of low-income people, since $d^2 = 0$. With increasing spatial scale, the bespoke residential contexts both increase in size and increasingly overlap with each other. This is formulated with the quadratic growth of d^2, which is proportional to the size of the area ($A = \pi r^2$). The so constructed models are represented in the following equation:

$$y_{it} = \alpha_{i,s} + \beta_s X_{it} + \beta_s X_{it-1,s}\,(1+d^2) + u_{it,s} \quad ,$$

where y_{it} is log income in 1000 euros of individual i at time t;

$\alpha_{i,s}$ is unobserved time invariant individual-specific effect in the model for spatial scale s;

β_s is matrix of parameters for spatial scale s;

X is regressor matrix of individual characteristics;

$X_{it-1,s}$ is share of low-income people in the residential context of individual i, measured at time $t-1$ at spatial scale s;

and $u_{it,s}$ is error term in the model for spatial scale s.

6.4 Results

We begin by describing individual characteristics of people from our study area (twenty-two urban regions in the Netherlands), focusing on the four distinct regions of Amsterdam, Rotterdam, Utrecht, and Groningen. After that, the analysis of contextual effects is presented in three steps: Firstly, we explore how the share of low-income people in the residential context varies with spatial scale, between people and over time. We then present the linear relationship between contextual poverty and the income of individuals at four sample scales. Finally, we analyse the estimates of spatial contextual effects from 101 fixed effects models for all urban regions, as well as for each of the four selected regions – spatial profiles of the effects of the share of low-income people at 101 scales on personal income. Our main interest is how these effects vary with increasing scale, how the variability in urban structure affects the results, and whether there are differences between the four urban regions.

TABLE 6.1 Descriptive statistics for all twenty-two urban regions: Individual characteristics and contextual characteristics at the spatial scale of 100m by 100m grid cells

All twenty-two urban regions N = 289,711; obs. = 4,345,665				
Variable	**Mean**	**Std. dev.**	**Min**	**Max**
Year at time *t*	2007	4.32	2000	2014
Log income in 1000 euros	3.59	0.72	-	-
Medium education (ref. = low)	0.34	0.47	0	1
High education (ref. = low)	0.63	0.48	0	1
Age	38.99	8.58	21	65
Age squared	1593.93	703.76	441	4225
Non-Western background	0.06	0.24	0	1
Children	0.54	0.50	0	1
Single or other household type (ref. = couple)	0.27	0.45	0	1
Living in one of the four largest cities	0.25	0.43	0	1
Share of low-income people	14.52	9.92	0	100
Non-Western background × share of low-income people	0.96	4.52	0	100
Living in one of the four largest cities × share of low-income people	3.85	8.14	0	100

Table 6.1 shows a descriptive overview of the individual characteristics from the models for all twenty-two urban regions (the white cells); these are constant for all 101 models. The table also contains the records of spatial context (the light blue cells) measured at 100m by 100m grid cells, which are used in the lowest scale models. Table 6.2 shows an analogous overview for each of the four selected urban regions. Among them, Rotterdam is distinct with the lowest education levels, Amsterdam has a greater proportion of single households without children, and both of these regions have more non-Western people than Utrecht and Groningen. The mean and standard deviation[5] values of income show that Utrecht and Rotterdam have similar average income levels, but Utrecht exhibits greater inequality in income. Groningen has the lowest average income and Amsterdam the biggest inequality (measured as standard deviation).

The spatial context characteristics at the lowest spatial scale (see Tables 6.1 and 6.2) show that in the immediate neighbourhood the potential exposure to low income ranges from 0 to 100 percent. However, in Groningen, 100m by 100m neighbourhoods have the highest average share of low-income people (18 percent) as well as the highest inequality (standard deviation of 15). The other three regions are more similar (14 percent low-income in Amsterdam and Rotterdam, 15 percent in Utrecht), which is also around the average level for all twenty-two urban regions. The inequality in exposure, however, varies more: Utrecht has a of standard deviation of 11, compared to 8 in both Amsterdam and Rotterdam.

TABLE 6.2 Descriptive statistics for the four urban regions (Amsterdam, Rotterdam, Utrecht, and Groningen): Individual characteristics and contextual characteristics at the spatial scale of 100m by 100m grid cells

Amsterdam **N = 36,594; obs. = 548,910**					**Rotterdam** **N = 23,443; obs. = 351,645**			
Mean	**Std. dev.**	**Min**	**Max**	**Variable**	**Mean**	**Std. dev.**	**Min**	**Max**
2007	4.32	2000	2014	Year at time *t*	2007	4.32	2000	2014
3.58	0.75	-	-	Log income in 1000 euros	3.62	0.68	-	-
0.36	0.48	0	1	Medium education (ref. = low)	0.39	0.49	0	1
0.61	0.49	0	1	High education (ref. = low)	0.56	0.50	0	1
39.41	8.35	21	65	Age	39.52	8.77	21	65
1622.60	687.71	441	4225	Age squared	1638.42	725.65	441	4225
0.12	0.33	0	1	Non-Western background	0.11	0.32	0	1
0.48	0.50	0	1	Children	0.56	0.50	0	1
0.34	0.47	0	1	Single or other household type (ref. = couple)	0.27	0.45	0	1
14.06	7.57	0	100	Share of low-income people	13.92	8.10	0	100
1.85	5.72	0	87.89	Non-Western background × share of low-income people	1.88	5.99	0	81.40
Utrecht **N = 18,409; obs. = 276,135**					**Groningen** **N = 10,094; obs. = 151,410**			
Mean	**Std. dev.**	**Min**	**Max**	**Variable**	**Mean**	**Std. dev.**	**Min**	**Max**
2007	4.32	2000	2014	Year at time *t*	2007	4.32	2000	2014
3.62	0.72	-	-	Log income in 1000 euros	3.47	0.70	-	-
0.31	0.46	0	1	Medium education (ref. = low)	0.33	0.47	0	1
0.66	0.47	0	1	High education (ref. = low)	0.64	0.48	0	1
39.48	8.42	21	65	Age	40.13	8.80	21	65
1629.36	695.91	441	4225	Age squared	1687.65	735.97	441	4225
0.06	0.23	0	1	Non-Western background	0.02	0.15	0	1
0.54	0.50	0	1	Children	0.53	0.50	0	1
0.26	0.44	0	1	Single or other household type (ref. = couple)	0.26	0.44	0	1
14.97	10.73	0	100	Share of low-income people	18.06	14.72	0	100
0.95	4.61	0	89.62	Non-Western background × share of low-income people	0.49	3.95	0	89.47

6.4.1 Multiscale residential context: The variability in urban structure

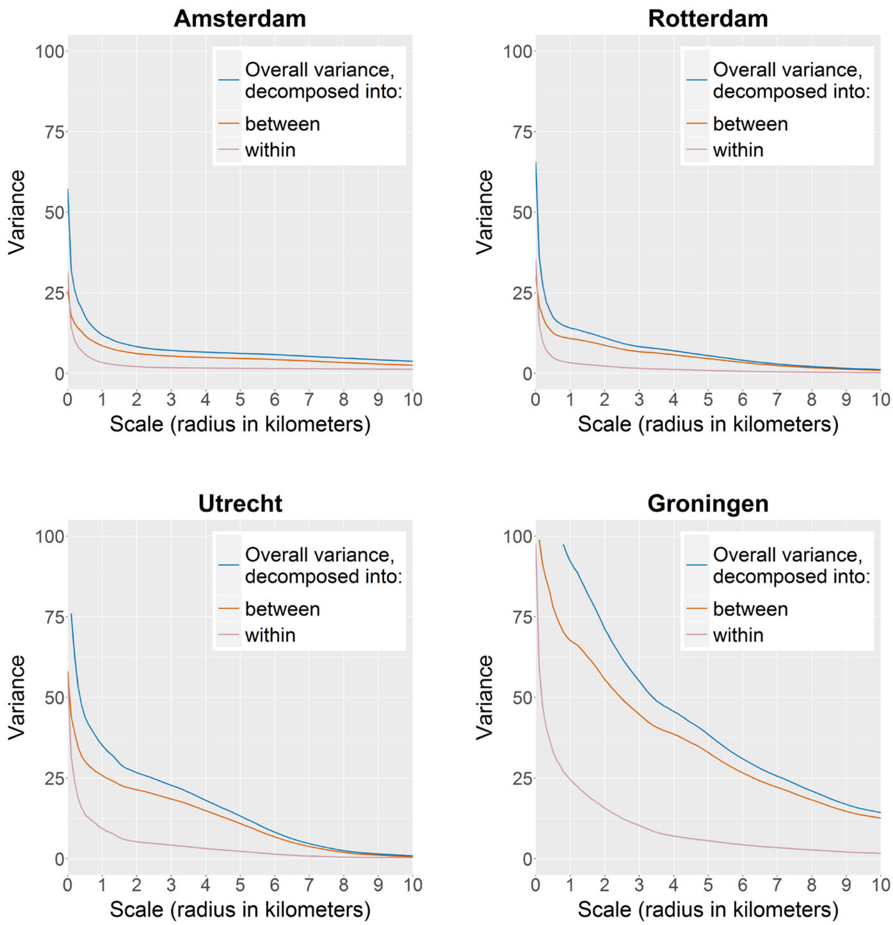

FIG. 6.1 Variance of the share of low-income people in spatial contexts measured at 101 spatial scales for the four selected urban regions

Tables 6.1 and 6.2 only include the spatial context parameters (share of low-income people) at the lowest spatial scale. Figure 6.1 shows the same variable for all 101 spatial scales, depicted using variance, and for each of the four selected urban regions (see Appendix for the figure for all urban regions). From the variance we can derive more information by decomposing it into two components that reveal different origins of inequality in exposure to contextual poverty. Firstly, there is the variance *between* people (which denotes differences between contexts of different people for the entire examined period) and secondly, the *within*-person variance (over time, averaged for all the people in the urban region).

The between people variance shows that different people were (potentially) exposed to different spatial contexts at multiple scales over the entire time period (1999-2013). These differences are the greatest in Groningen, but also substantial in Utrecht, where distinct types of context in terms of income levels have a radius of a few kilometres (the scale after which the between variance drops). The within (people) variance shows how much the context of people changes over time, either because they moved or because the neighbourhood around them changed (perhaps due to mobility of others or the changing characteristics of the residents within those neighbourhoods). These temporal changes are the greatest in the immediate area surrounding an individual's home (the smallest spatial scale). In Amsterdam and Rotterdam, they are greater than the variance between people, reflecting the fact that in these cities the residents are generally exposed to a wide variety of immediate neighbourhoods during their life. As scale increases, however, there are more permanent differences between contexts, rather than the temporal changes (the between variance is much bigger than the within variance). This is the evidence of temporal segregation: Different people remain living in different spatial contexts over the entire study, never or rarely mixing with other types of places (although they may have moved). In this study, we focus on the effects of changes in potential exposure to contextual poverty over time (here described by the within variance) and this is captured by the fixed effects model.

6.4.2 Relationship between multiscale context and individual income: The consequences of the choice of scale

Figure 6.1 reported the diminishing variance in contextual poverty across spatial scale, with particularly small variance at the scales of a few kilometres. Since our primary interest is the effect of the residential context on individual income, we next explore how the decreasing variance in urban structure affects the linear relationship between the contextual poverty and the individual income. Figure 6.2 demonstrates this for four sample scales (100m by 100m, 1km radius, 5km radius, and 10km radius) in the Amsterdam urban region. The graph contains all the data points, for all people and all years; although the individual observations have been blurred to maintain privacy, the main properties of the relationship remain intact. When comparing the four panels, it is clear that, as scale increases, so the range of the share of low-income people (shown on x-axis) decreases (confirming the observation from the variance graphs). Thus, at the smallest scale, people in the Amsterdam region are potentially exposed to the full range of the share of low-income neighbours (0-100 percent). By contrast, at the highest spatial scale (10km radius), this range of potential exposure has decreased to between 10 and 20 percent. This is a consequence of the larger areas containing a greater proportion of the population of the region, so that the differences exhibited at the finer spatial scales are 'smoothed out' at the higher scales. For the lower two spatial scales (100m x 100m and 1km radius), the more low-income people are in the residential context, the lower an individual's income becomes (Figure 6.2A and 6.2B). This negative relationship becomes weaker as scale increases (with 1km radius being weaker than the 100m by 100m).

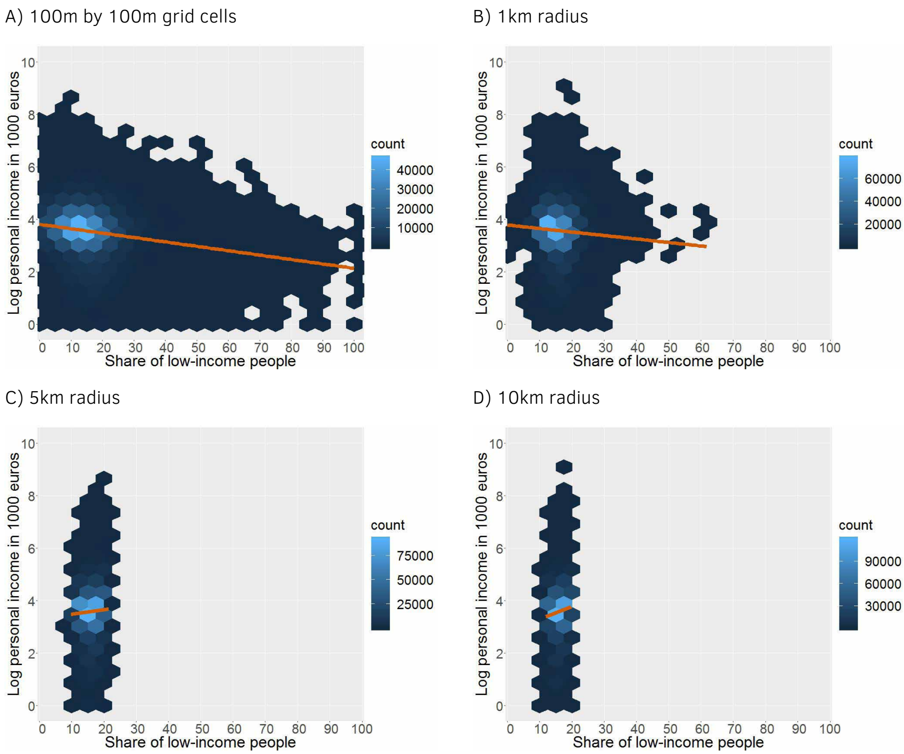

FIG. 6.2 Relationship between personal income and the share of low-income people, for four sample scale in Amsterdam – A) in 100m by 100m grid cells, B) in areas with 1km radius, C) in areas with 5km radius, D) in areas with 10km radius

TOC

By contrast, the figures for the two largest spatial scales report a positive relationship between individual incomes and contextual poverty (Figure 6.2C and 6.2D). Since the same analysis for single years[6] shows negative relationships, it is the addition of time (using the full period 1999-2014) that results in the positive relationship at the larger scales. This indicates that, as income increases over time (as individuals progress through their career), the share of low-income people in larger areas also increases, but at a faster rate, suggesting that sociospatial inequalities are growing in the Amsterdam region (see Tammaru et al., 2016). While the larger spatial context in which someone lives is important, its characteristics are very stable over time – much more so than at the lower scales. This is a consequence of the size of the area, where any individual altering their location or income cannot have a substantial impact over area characteristics. By comparison, in the smaller neighbourhoods individuals, being part of a smaller population, can exert much more influence on the local average, whose characteristics are then much noisier. Ultimately, this poses a question about where neighbourhood effects end: the smaller spatial scale is a local neighbourhood, but it is not clear at which scale (if any) this definition ends and whether that is the same for all places. In other words, what we are interested in now is where the localised neighbourhood context stops, and the shared context of the city begins.

6.4.3 Limits of neighbourhood: Where do neighbourhood effects end?

Our overarching question is how the effect of contextual poverty on individual income varies across a large range of spatial scales. We estimated 101 within-people (fixed) effects models of individual income (one for each spatial scale) for all twenty-two urban regions in the Netherlands (Figure 6.3), as well as for each of the four selected urban regions (Figure 6.4). It is not possible to present all the parameters of these models here, so we present the main results of interest: the parameter estimates of the effect of low-income people in the spatial context at all the scales. (See Appendix Tables 6.3 and 6.4 to get an idea of the full models, including all the variables, with the spatial context at the lowest spatial scale.) In both figures, the black lines follow the changes of the coefficient estimates over scale, while the shaded areas surrounding the lines show the confidence intervals.

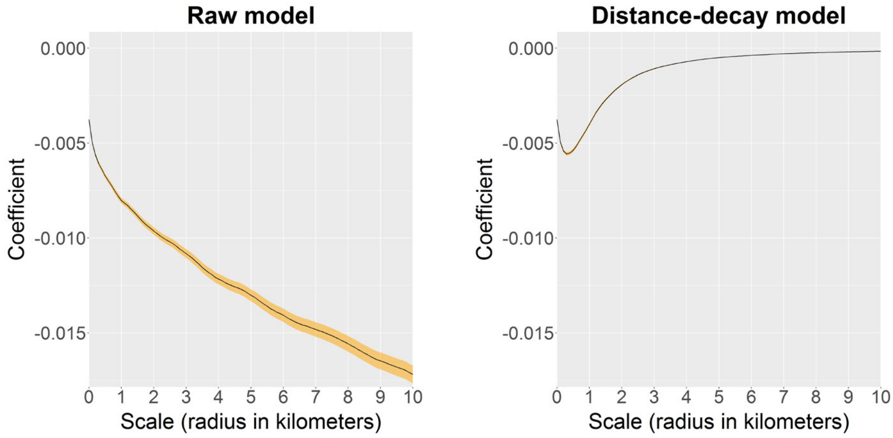

FIG. 6.3 Fixed effects coefficient estimates of the share of low-income people, measured at 101 spatial scales, on personal income from work for people in all urban regions in the Netherlands

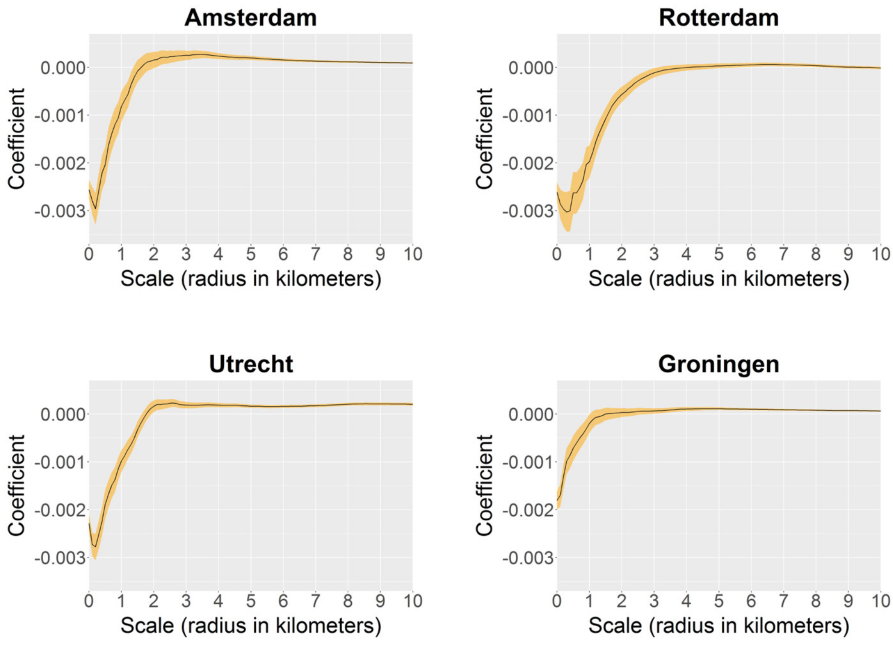

FIG. 6.4 Fixed effects coefficient estimates of the share of low-income people, for 101 spatial scales, on personal income from work for people in the four selected urban regions

Exploring the relationship between individual income and the spatial contexts across scale (in the previous section) suggested that, if we model contextual effects without a theoretical approach, the results will be determined by the variance in urban structure. The left panel of Figure 6.3 shows the results of the raw models (without distance decay incorporated) for all urban regions, across 101 scales. This results in an increasing effect across scales. Notably at the largest scales, the changes in the spatial context over time are so small that they appear to have a very large effect on individual income (that changes at the same rate in all models). For reference, the largest area in our study is almost ten times smaller than an average U.S. county, used as 'neighbourhood' in other influential studies (Chetty & Hendren, 2018). We suggest that these large effects at higher scales might be an artefact of the low variance at these scales, which we investigate further by using the distance-decay model, shown in the right panel of Figure 6.3. In this theoretically instructed model, the distance decay function represents a diminishing potential for exposure and interaction with spatial scale. The model takes into account the effect of deceasing variance at higher scales, and as a result avoids the issue that very small changes in the spatial context appear to have large effects on income. The comparison between the two models demonstrates how misleading results of neighbourhood effects studies can be when using a single spatial scale, particularly a large one.

Since we log-transformed income from work (in thousand euros), a relatively small coefficient of -0,001 results in each 1 percent increase in the share of low-income people is associated with 0.1 percent decrease in an individual's annual income from work. In line with previous European evidence, we did not find very strong contextual effects, but they are significantly different to zero. Crucially, the effects vary across spatial scales and, generally, decrease with increasing scale. It is also important to note that in order to focus on temporal changes we used fixed effects models, which gave average effects for all the people, although the between variance suggested that there were considerable differences between people, so that for some of them the contextual effect may well be stronger than for others.

In this study, we investigate differences between people from the four urban regions. Given the above findings, we continue to use the distance decay function. Figure 6.4 presents the within-people effect of contextual poverty at 101 scales on personal income from work; the four sections of the figure represent to the four urban regions (Amsterdam, Rotterdam, Utrecht, and Groningen). In each of the four regions, the negative effect of living in a spatial context with a high proportion of low-income people is stronger at smaller spatial scales, falling as scale increases to a point where the effect is (almost) zero. This is in line with previous studies, which predict that negative neighbourhood effects are stronger at smaller spatial scales, where the area represents localised contexts and within which people interact with their neighbours. The rate at which the negative spatial context effect diminishes and the point at which the effect becomes zero are, however, different in each of the four regions.

In contrast to the majority of existing studies dealing with spatial scale, the negative contextual effects are not the strongest at the very lowest scale, with the exception of Groningen. Most of other studies, however, do not use this smallest spatial scale or this detailed range of scales. The smallest scales represent the more immediate neighbourhood contexts that individuals experience when they leave the front door of their house. For our study, Amsterdam, Rotterdam, and Utrecht exhibit weaker spatial context effects at the smallest scale than at slightly larger scales (around 200-300ms), suggesting that it takes a few hundred metres to form a small-scale area which exerts the strongest effect on individual income. This reflects different and distinct urban structures of neighbourhoods in the three regions within the Randstad conurbation, compared to Groningen, a monocentric city surrounded by more rural municipalities, relatively isolated from large urban centres.

The scale at which the localised context becomes a shared context (the point at which the contextual effect becomes zero) is different for each urban region. This switch from local to shared occurs at the largest scale (3km) in Rotterdam, a city with the largest concentrations of poverty, compared to the other three regions, which potentially exerts a more scale-persistent negative effect on its residents' income from work. By contrast, Utrecht and Amsterdam show a switch at around 2km, while Groningen, the smallest of our urban regions, also has the earliest switch at 1.5km. Before reaching this point, some contextual effects profiles also contain small positive effects. The small positive effect at meso- and macro-scales indicates growing sociospatial inequalities not only in Amsterdam (see Tammaru et al., 2016), but also in Utrecht. Although people's income is increasing, they are simultaneously increasingly surrounded by low-income people. Critically, the results show that only slight changes in spatial scale can lead to different modelling outcomes and suggest that at each scale we model different spatial processes. An arbitrarily chosen spatial scale somewhere along the distance profile would, therefore, capture only some of the processes. Returning to the issue of using administrative areas for contextual effects studies, the scale of the administrative would give us a result somewhere between -0.003 and 0, depending on the scale chosen and would omit the other potential results.

6.5 Discussion and conclusions

Spatial scale is critical for understanding both the causes and consequences of sociospatial inequality. This paper has systematically investigated the effect of spatial scale on modelling individual income. We have operationalised the residential context of individuals using 101 bespoke areas, from the immediate surrounding of the home, (100m by 100m) up to areas extending over a 10km radius – a context that is similar for all the people within one city. For all twenty-two urban regions in the Netherlands, as well as four selected regions (Amsterdam, Rotterdam, Utrecht, and Groningen), we ran 101 fixed effects models – for 101 different spatial scales. Our results showed how the choice of spatial scale (in a specific geographic setting) influences the modelled outcomes. The study applied a distance decay function, which follows the theory of diminishing potential exposure of people to spatial context across distance, while taking into account the relationship between spatial scale and variance in urban structure.

Three lines of discussion follow from our results. Firstly, different spatial scales result in different estimates of contextual effects, because people belong to multiscale neighbourhoods, which are related to various spatial processes, operating from micro to macro scales. Spielman et al. (2013) demonstrated in a series of simulation experiments that using the ‘wrong’ scale can bias the estimated effect upwards or downwards, while the effect is correctly estimated when the ‘right’ scale is used. The success of this approach must be related to the investigation of a very specific and known process. In this study, we used real data, which contain a wide variety of potential processes and effects. These effects vary, because different spatial scales capture different processes, reflecting the complexity of the residential context and the fact that there is no such thing as one right scale, or a single true neighbourhood effect.

From this follows our second line of discussion – that a theoretical approach to spatial context effects is necessary. This study suggested the approach of distance decay in potential exposure and interactions in urban space. Using small increments in radius from the hypermicro- to macro-contexts revealed the differences between locations and changes over spatial scale at a finer resolution than is possible when using fixed administrative boundaries. The strongest evidence of a spatial context effect occurred at 200m in both Amsterdam and Utrecht, 400m in Rotterdam, while Groningen was the only urban region with the strongest effect at the lowest scale (100m by 100m). Modelling the effect using a single scale administrative area gives policy makers only limited, incomplete, or even misguided evidence. For example, inappropriately large administrative units obscure stronger effects from smaller spatial scales. Concomitantly, it should not automatically be assumed that the biggest effect occurs at the smallest spatial scale, but examine scale within a certain theoretical approach. Although this study did not directly examine social contagion or socio-interactive processes, it did examine small scales at which these mechanisms may occur, highlighting their incompatibility with larger spatial units. Increasingly large contexts can be used to show where the neighbourhood effects 'end' and other processes, such as growing regional inequalities, take over. Just like a distance decay function operationalises the diminishing effect of potential exposure to others as scale increases, processes such as stigma would require meso scale, while labour-market spatial mismatch requires regional geographies – in a different theoretical approach. Talking about neighbourhoods when using large (administrative) areas is theoretically confusing and technically problematic.

The latter argument is related to our third line of discussion – the variability in urban structure by spatial scale. The magnitude of contextual effects is theoretically determined by contextual effects mechanisms and their spatial scale. However, there is also a deterministic relationship between variance and regression coefficients, which explains why studies using very large spatial units as a proxy for neighbourhoods find big 'neighbourhood effects'. To demonstrate this, we first decomposed the variance of the share of low-income people into the between-people variance, which presents the more permanent spatial structure of the urban regions, and the within-people (temporal) variance, which is a combination of individual mobility and neighbourhood change. The amounts of variance in these two components at multiple spatial scales suggests that different processes, such as residential sorting of people, long-term concentration of poverty and neighbourhood change (or stability), are likely to play different roles at different scales. Crucially, both of the variance components decrease with spatial scale. The decreasing variance is not only a consequence of using bespoke neighbourhoods, as it occurs for all increasingly large spatial units. We demonstrated that 'neighbourhood effects' are found for large spatial units when using the 'raw' models, but when theory driven distance-decay models are used these effects disappear. This is because at larger scales there is little variance, especially when using a fixed effects model which is based on changes in area characteristics over time, and the temporal (within-people) variance was even smaller than the between-people variance. Not taking into account this relationship leads to misleading results revealing a big 'neighbourhood' effect for large-scale areas, which might have been the case in studies using very large U.S. counties as neighbourhood units (Chetty & Hendren, 2018). Due to the small variance at larger scales, these larger spatial contexts appear to have large effects when they are used as the neighbourhoods. Our distance-decay models, which are based on theory of diminishing potential exposure and interaction, include the relationship between distance and variance in spatial structure. When using the 'raw' models, this leads to misleadingly large estimates of 'neighbourhood effects', while in reality these are the result of low variance in context represented as large spatial units.

Neighbourhood effects are likely to be bigger if we consider variability by person and place (Spielman & Yoo, 2009). This paper has addressed the latter (variability by urban region), along with the prior issue of spatial scale, showing that the impact of scale is place-specific. Thus, there is no single correct scale of measuring residential context even within closely related places in the same country, such as the three regions within the Randstad conurbation (Amsterdam, Rotterdam, and Utrecht). Places in different countries may differ even more. The relationship between scale and geographic setting is a fundamental issue for national-level investigations into neighbourhood effects, or investigations taking in multiple urban areas, as measures of context at one scale possibly do not capture the same processes in different spaces, and the results of such projects can hardly be generalised. Variability in contextual exposure by person, which we only considered by looking at the between-people variance, is one of the most promising applications of bespoke neighbourhoods. Multiscale bespoke areas can embrace a variety of spatial contexts starting from a location that is more specific to an individual's residential location than administrative units. In doing so, we recognise the multiplicity of spatial contexts, rather than search for one generic fixed area as a global proxy for neighbourhood.

While early research on sociospatial inequalities was largely driven by the availability of data for administrative units, individual-level microgeographic data are increasingly accessible. Distances between individuals are playing a more important role in measuring segregation (Wong, 2016) and, according to this study, in assessing contextual effects. Within the study of neighbourhood effects, there are multiple and substantial methodological challenges (see van Ham & Manley, 2012), and the literature often highlights the issues of temporality or residential sorting, along with the endogeneity of neighbourhood characteristics. As such, the scale at which the neighbourhood is measured has often been relegated to the sidelines in the empirical literature. Our bespoke multiscale approach demonstrates the geographical uncertainty in modelling contextual effects and provides alternatives to pre-defined administrative units, usually adopted as a proxy for neighbourhood. The aim is not to give a definitive answer for the definition of neighbourhood, but to recognise that the multiple scales and the geographic setting of scale are fundamental for understanding spatial context effects. In short: It is time to put geography centrally into the neighbourhood.

Notes

1 The regions and their municipalities are mapped in Figure 6.5 in the Appendix, also showing the population and area sizes.
2 The CBS defines foreign background if someone is a first-generation migrant (they are born abroad, except for those born abroad to Dutch parents), or when someone's parents belong to the first generation. People with a foreign background are further divided into Western and non-Western backgrounds.
3 People from Indonesia and Japan are categorised as Western based on their social and economic position in Dutch society: Indonesians because of the historical linkages between the Netherlands and the former Dutch East Indies, and Japanese because they or their family member work for a Japanese company in the Netherlands (Alders, 2001).
4 The ILO definition is set at two thirds.
5 Minimum and maximum income values are not shown for privacy reasons as we work with full population data.
6 Not shown, but available upon request.

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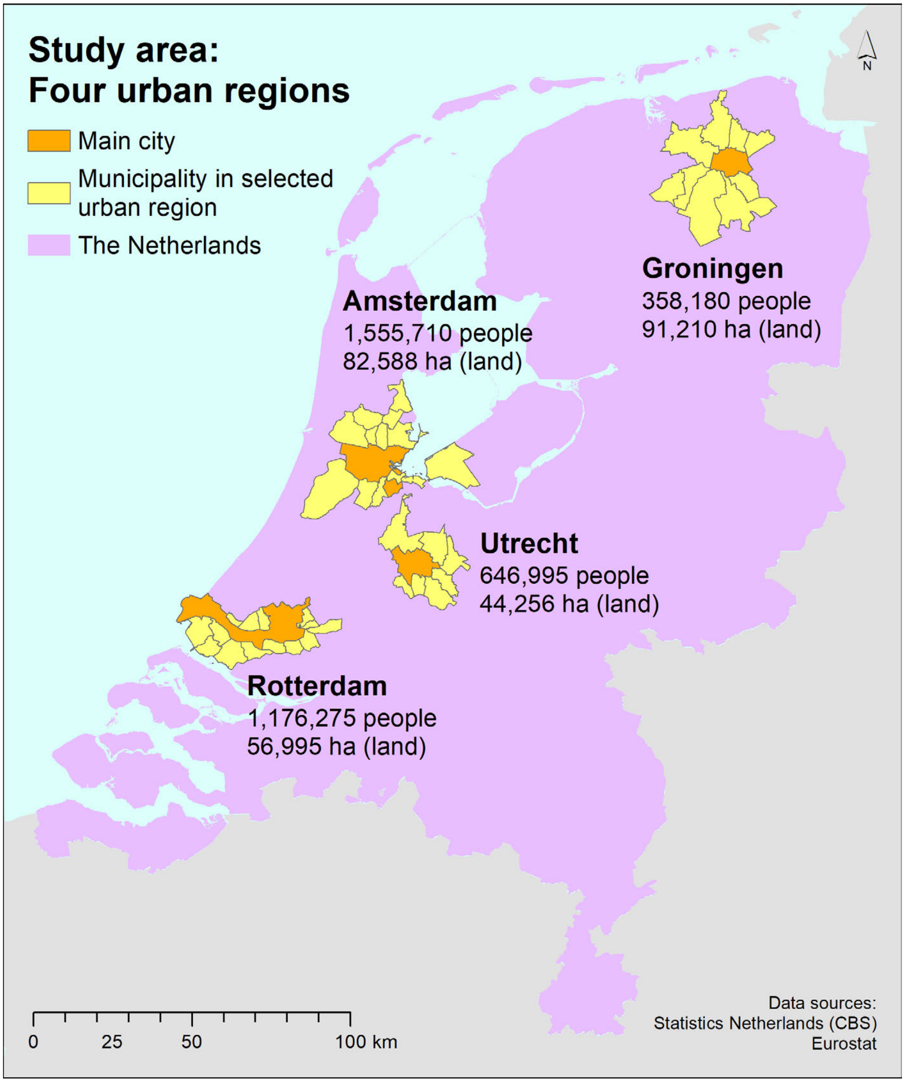

FIG. 6.5 Map of the four selected urban regions (Amsterdam, Rotterdam, Utrecht, and Groningen), with population and area sizes

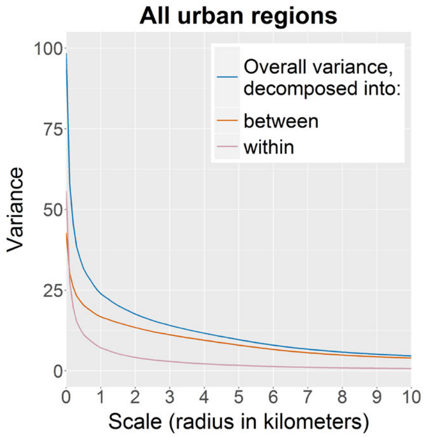

FIG. 6.6 Variance of the share of low-income people in spatial contexts measured at 101 spatial scales for all urban regions in the Netherlands

TABLE 6.3 Fixed effects model of the contextual effects of the share of low-income people, measured at the smallest spatial scale (100m by 100m grid cells), on personal income from work, for all urban regions in the Netherlands

Variable	Coefficient	Std. error	p
Medium education (ref. = low)	-0.0787888	0.0038986	0.000
High education (ref. = low)	0.525983	0.0040262	0.000
Age	0.2228118	0.0002335	0.000
Age squared	-0.0019331	0.00000284	0.000
Non-Western background	0	(omitted)	
Children	-0.0541454	0.0005376	0.000
Single or other household type (ref. = couple)	-0.0608013	0.0006394	0.000
Living in one of the four largest cities	0.0482651	0.0013277	0.000
Share of low-income people	-0.0037505	0.0000265	0.000
Non-Western background × share of low-income people	-0.000159	0.0001014	0.117
Living in one of the four largest cities × share of low-income people	0.0004442	0.0000569	0.000
Intercept	-2.234973	0.0059191	0.000

TABLE 6.4 Fixed effects models of the contextual effects of the share of low-income people, measured at the smallest spatial scale (100m by 100m grid cells), on personal income from work, for the four selected urban regions

Amsterdam				Rotterdam		
Coefficient	Std. error	p	Variable	Coefficient	Std. error	p
0.0688013	0.0120734	0.000	Medium education (ref. = low)	-0.0503765	0.0110403	0.000
0.465917	0.0124698	0.000	High education (ref. = low)	0.4196488	0.0114977	0.000
0.2171401	0.0007049	0.000	Age	0.2116035	0.0007436	0.000
-0.0018626	0.00000856	0.000	Age squared	-0.0017873	0.00000898	0.000
0	(omitted)		Non-Western background	0	(omitted)	
-0.0449021	0.001704	0.000	Children	-0.0612793	0.0017837	0.000
-0.0487584	0.0018461	0.000	Single or other household type (ref. = couple)	-0.061382	0.0022013	0.000
-0.0025581	0.0000989	0.000	Share of low-income people	-0.0026096	0.0001025	0.000
0.0001918	0.0002749	0.485	Non-Western background × share of low-income people	-0.0008061	0.0002956	0.006
-2.216017	0.0181207	0.000	Intercept	-1.937667	0.0181289	0.000
Utrecht				**Groningen**		
Coefficient	Std. error	p	Variable	Coefficient	Std. error	p
-0.0814482	0.0170857	0.000	Medium education (ref. = low)	-0.0022948	0.0216889	0.916
0.4778684	0.0175476	0.000	High education (ref. = low)	0.5783847	0.0223782	0.000
0.2250712	0.00096	0.000	Age	0.2082554	0.0012274	0.000
-0.0019524	0.0000115	0.000	Age squared	-0.0017526	0.0000145	0.000
0	(omitted)		Non-Western background	0	(omitted)	
-0.0591156	0.002212	0.000	Children	-0.0666252	0.003073	0.000
-0.0690865	0.002635	0.000	Single or other household type (ref. = couple)	-0.0512861	0.0035138	0.000
-0.0022824	0.0000946	0.000	Share of low-income people	-0.0018092	0.0000952	0.000
-0.0005106	0.0003972	0.199	Non-Western background × share of low-income people	-0.0018694	0.0005846	0.001
-2.289958	0.0251437	0.000	Intercept	-2.216017	0.0322089	0.000

7 Discussion and conclusions

This thesis has developed alternative methods of operationalising neighbourhoods at multiple spatial scales and used them to advance our understanding of spatial inequalities and neighbourhood effects. The underlying problem that motivated this thesis is that many empirical studies use predefined administrative units, and this does not often align with the underlying theory or geography. Despite the extensive literature on neighbourhood effects and, more generally, on sociospatial inequalities, spatial scale remains an under-analysed concept. As a response to this research gap, this thesis took a multiscale approach to both theory and empirical analysis of neighbourhood effects, highlighting the multitude of spatial processes that may affect individual outcomes of people. To operationalise this, we created bespoke areas at a range of one hundred scales representing people's residential contexts, primarily in the Netherlands but also in multiple European capitals. Using microgeographic data and a large number of scales combined with small distance increments revealed subtle changes in sociodemographic characteristics across space. In doing so, we provided new insights into ethnic segregation, potential exposures to poverty, and neighbourhood effects on income, all in light of the fundamental issue of spatial scale: The analyses of sociospatial inequalities are substantially affected by the scale used to operationalise spatial context, and this varies within and between cities and urban regions. The aim of this thesis was therefore not to find a single, 'true' scale of neighbourhood, but to acknowledge, operationalise, and better understand the multiplicity of spatial scales.

To achieve this aim, this dissertation answered five research questions, in five chapters, each of which consists of a published paper or a paper manuscript. We first investigated what was lacking in the conceptualisation of neighbourhood, thus ensuring that the theoretical approaches to people-space relations are implemented via appropriate spatial data. Secondly, the thesis asked how we could operationalise sociospatial contexts at multiple spatial scales to study potential exposure to contextual characteristics, such as ethnic compositions, in different geographical settings. As extension of the previous research question, we investigated how various dimensions of ethnic segregation varied over spatial scale in different European capitals. Applying the same core method when analysing another contextual characteristic relevant for individual outcomes, the following study asked how contextual poverty varied over spatial scale in different places – within and between municipalities in the Netherlands. Finally, the dissertation asked how contextual poverty at various spatial scales affected individual income in different urban regions in the Netherlands.

7.1 Summary of the research results

Delving into conceptual issues, Chapter 2, which was published in the journal *Progress in Human Geography*, postulated that the operationalisation of neighbourhoods should start from theory: Various effects of place on people occur because of a multitude of processes. To accommodate this variety of processes, spatial context needs to be operationalised at different scales, within and beyond predefined administrative neighbourhoods, depending on the mechanism under study, geographic setting and individual characteristics of people. To achieve this, two different strands of literature – firstly, the theoretical approaches to neighbourhood effects and, secondly, spatial data analysis – can and should be more tightly related. Increasingly available and detailed spatial data make it possible to operationalise various spatial contexts, revealing homogeneity and heterogeneity in space from the very local to regional scale.

One way of operationalising spatial context at a wide range of different scales was demonstrated in Chapter 3, published in the journal *Annals of the American Association of Geographers*, following the recommendation of Chapter 2 to conceptualise space more continuously. This means representing the residential location from the moment someone opens their 'front door' up to a large area of the city they may experience as they travel. These scales can be depicted in distance profiles, which was based on the idea of segregation profiles, introduced by Lee et al. (2008) and Reardon et al. (2008), but developed here in a more detailed scalar approach. This method was employed in all empirical studies within this dissertation. Chapter 3 developed the method using the example of the share of non-Western ethnic minorities, thus representing space as ethnic exposure surface and analysing ethnic fragmentation of three Dutch cities (Amsterdam, Utrecht, and Groningen). Using the range of spatial scales showed that people in these cities, particularly in Amsterdam, were potentially exposed to very different spatial contexts at multiple scales, notably – but not only – the smaller ones, depending on where they live within the city. A unique application of entropy – for measuring scalar variability of the distance profiles, demonstrated that some people have rather constant spatial contexts, while for others the context changes with the increasing distance from home.

The idea of comparing different places at multiple scales, introduced in Chapter 3, was further explored in the subsequent chapters. Specifically, Chapter 4 demonstrated that European capitals had very different levels of ethnic segregation for each of the studied dimensions (centralisation, evenness and exposure) and that for the latter two dimensions these levels varied with spatial scale, in different ways in different cities, and within these cities between their cores and hinterlands. While at one spatial scale one city appears to be more segregated than others, at another scale the relationships between cities may change. The highly segregated city may no longer be so, while the integrated city may become segregated, thus confirming that our assessment of segregation largely depends on the size of the areas we are considering. Unlike the majority of the segregation literature, we found that segregation does not necessarily decrease with spatial scale.

The following two chapters (5 and 6) applied the same method of multiscale measures of population, depicted as distance profiles, analysing – instead of ethnicity – contextual poverty (Chapter 5) and its effects on people (Chapter 6). Chapter 5 compared the levels of contextual poverty within and between Dutch municipalities, where *the context* involved multiple spatial units, so that the inequality became a multiscale as opposed to a mono-scale issue. Focussing on both bigger cities and smaller municipalities, the chapter revealed that the national inequality primarily came from the concentrations of poverty in areas of a few kilometres, located in cities. These cities have different spatial patters of contextual poverty, such as multicentre, core-periphery and east-west, while smaller municipalities have under-average levels of poverty in the national comparison. In addition to the inequality between municipalities, there are considerable within-municipality inequalities, particularly among micro-areas of a few hundred metres. In a bigger picture of the thesis, we can see that both Chapters 3 and 5 depicted distance profiles and measured their scalar variability using (hierarchical) entropy, but looking at two distinct contextual characteristics, namely the shares of non-Western (Chapter 3) and low-income people (Chapter 5). A comparison of these two chapters' results gives us insight and allows us to conclude that the share of low-income people in the Netherlands varies with spatial scale, but to a lesser extent than the share of non-Western people. Having distinct spatial patterns, these two characteristics should not automatically be considered to vary in the same way without further investigation.

Finally, the scales at which poverty concentrates, as found in Chapter 5, are not necessarily the scales at which the biggest neighbourhood effects occur. The very smallest spatial scale is not automatically the scale of the greatest effect, as has been often suggested by the majority of neighbourhood effects studies addressing the question of scale, but smaller spatial contexts *are* generally more strongly related to individual income than the larger ones. This was the main outcome identified in Chapter 6, which applied the multiscale measures of population in modelling the effects of contextual poverty on individual income. Considering all urban regions in the Netherlands combined, as well as four distinct regions of Amsterdam, Rotterdam, Utrecht, and Groningen, resulted in scale- and place-specific estimates of contextual effects. Analysing a wide range of scales, the study revealed methodological issues of representing neighbourhoods as inappropriate, particularly too large spatial units. The most important one is the deterministic relationship between the variance in urban structure and the estimated contextual effects across spatial scale, in the absence of theory.

7.2 Synthesis of the results, and lessons learned

So, what are the lessons learned from this thesis? Going back to our overarching aim – to better understand sociospatial inequalities and neighbourhood effects, we can conclude that spatial scale is a defining parameter of inequalities within and between places and their effects on people: Cities are unequal not only as a whole, but also because they have smaller and bigger neighbourhoods that stand out. And within these cities and neighbourhoods, there are micro-spaces that have even more extreme characteristics – concentrations of different ethnic or socioeconomic groups. The spatial context of people encompasses everything from this micro-scale to the city or regional one, including the way these scales are connected – from uniformity to gradual or abrupt changes across space. Living in a specific place may affect individual socioeconomic status, but the magnitude of this relationship changes when we consider spatial contexts at different scales.

In line with the existing literature, we found fewer sociospatial inequalities and weaker (mostly negative) neighbourhood effects on income in our study areas – which mainly comprised the Netherlands but also included seven European capitals – than similar studies have found in the North-American context (see Friedrichs et al., 2005; Van Ham et al., 2012). However, we found substantial variation between and within places, particularly at smaller spatial scales, where the spatial inequalities and contextual effects are generally the greatest. Despite the immense importance of the micro-contexts, causality does not necessarily occur at the lowest scale and work backwards, but instead runs in different directions (Sheppard & McMaster, 2004). In this regard, our study showed a few unexpected findings, which challenge the existing literature. Specifically, we found that neighbourhood effects were not strongest at the very smallest spatial scale, which is rarely found in the studies comparing different scales (for an exception, see Buck, 2001). We also found that segregation did not necessarily decrease with spatial scale, which is in line with Johnston et al. (2016), but not with the majority of the segregation literature. We can therefore conclude that spatial processes work in all directions across scale. From this, three theoretical and conceptual strands, as well as three methodological ones can be derived as contributions of this dissertation.

7.2.1 Theoretical and conceptual contributions

Firstly, the neighbourhood effects literature needs an *integrative theoretical approach* that explicitly connects the variety of spatial processes relevant for individual outcomes with corresponding scales. The basis for this was provided in the overview of how likely some contextual mechanisms are to operate at certain scales from the immediate surrounding of home up to larger parts of the city or urban region (see Chapter 2). This would serve to enrich the neighbourhood effects literature, which has, to date, reviewed a vast array of mechanisms (Sampson et al., 2002; Galster, 2012), implying but not explicitly focussing on their spatial scale. The theoretical approach should also include the question how spatial processes develop across space and what are the relations between different scales. A solution offered within this thesis was a distance-decay approach to operationalise diminishing potential exposure and interaction (see Chapter 6).

Secondly, if we accept that there are a multitude of processes, then it becomes more appropriate to describe them using the term *'spatial contextual effects'* than *'neighbourhood effects'*. 'Neighbourhood', 'area', and 'contextual' effects have already been in use (Diez Roux, 2001), but the majority of literature uses 'neighbourhood effects' inconsistently referring to very different spatial contexts, and invoking a term (neighbourhood) that often has little to do with the most commonly accepted definitions. These various *contexts* may be relevant, but they need to be adequately termed: One person belongs to spatial contexts at multiple scales, which have different roles for their residents.

Thirdly, because of the multiscale nature of neighbourhood, neighbourhood effects literature needs a *multiscale approach*, which takes into account different types of contexts that people are exposed to, within and beyond their officially defined neighbourhood. Using a range of scales in a continuous space, we want to emphasise that the spatial context which affects people is not an administratively constructed area, but a real geographic space. Therefore, this multiscale approach should also be place-dependent, taking into account the historically grown urban asset base (Robson et al., 2000; Kesteloot et al., 2006) in different geographic settings. Along with its conceptual relevance, the multiscale approach brings many methodological challenges. In this regard, this dissertation also offers three strands of methodological contributions.

7.2.2 Methodological contributions

Firstly, the multiscale approach makes it possible to better understand the modifiable areal unit problem (MAUP). Crucially, the 'modifiable areal units' were not treated as a problem for this study, but a resource, as put by Manley et al. (2006). The fact that measurements change across spatial scale is not a nuisance that should be corrected, nor is it even a problem that should be solved, but a result that should be interpreted. That the relationship changes with scale tells us something interesting about the linkage between the process and the scale at which we are measuring it. Specifically, in this study different scales are integral parts of a distance profile, so that they all give an opportunity to explain *how* contextual characteristics transform across space.

By quantifying the scalar variability, we in fact describe different types of spatial contexts, which are relatively uniform for some people, while others are potentially exposed to very different contexts at various distances around their home, including abrupt changes – social cliffs (see Chapter 3). Our second methodological contribution is that we used entropy to quantify this scalar variability. Although entropy is widely used for studying a wide range of phenomena, including sociospatial inequalities (see, e.g., White, 1986), it usually quantifies the inequality between spatial units at a specific scale. In this thesis, entropy measures the inequality within and between places at multiple scales, which is a hierarchical and multiscale use of entropy; it also measures the inequality *across* scales starting from one specific location, which is a cross-scale use of entropy.

Thirdly, variability in urban structures is a major methodological issue with regression models related to spatial scale, which has a notable impact on the results in the absence of theory. Decreasing variance with increasing scale is strongly related to the concept of spatial autocorrelation (see Chapter 2). At a larger scale, individuals become less similar (lower autocorrelation), and in turn aggregated spatial units vary less among themselves. In spatial data analysis, it is well known that aggregation implicitly means less variation (see, e.g. Haining, 2003; Manley, 2014). In the neighbourhood effects literature, this issue is largely neglected. This is particularly dangerous when too large areas are used to represent neighbourhoods (Chetty & Hendren, 2018), as lower variability in urban structure may result in bigger spatial contextual effects. Demonstrating the trends of spatial variance and contextual effects across scale, this dissertation should increase awareness of what kind of contexts (from neighbourhood to region) are actually operationalised with spatial units available in the data, which is important from the perspective of both scientific research and social policies.

7.2.3 Societal and scientific relevance of the thesis

For researchers and policy makers alike, it is crucial that spatial scale forms part of their understanding of sociospatial inequalities. It is in society's interest to know more about the magnitudes of segregation and neighbourhood effects and to address this in social policies and urban planning. Taking a multiscale approach in research is important, because different problems require different solutions at different spatial scales. It is thus at best misleading and at worst dangerous to use large areas as neighbourhoods, to which policy makers then attach conclusions, plans and designs aimed at small neighbourhoods. This pertains to the European Union policies, such as the ones on the integration of migrants, which motivated the release of the D4I Data Challenge data set, used in Chapter 4. It equally pertains to the national or regional policies on urban renewal or social mix. These policies do not necessarily require action in officially defined neighbourhoods, but sometimes in a wider spatial context. However, they may also need to start from micro-spaces, because people start to meet and interact with other people in the immediate surroundings of their homes, which may be very different from more distant parts of the city. In turn, this helps to determine how these people experience their neighbourhoods and cities; moreover, it can shape their attitudes towards others.

Measuring segregation and assessing neighbourhood effects depend not only on the spatial scale, but also on how various scales are treated in the models, due to methodological issues such as decreasing variance in urban structures. The research on neighbourhood effects is interdisciplinary, and researchers from different backgrounds should not focus exclusively on the field-specific concepts and methods. For example, we have suggested that methods from physical geography (see, e.g., Fisher et al., 2004) can also be used for studying the social attributes of space. Most importantly, spatial scale, and space in general, should be equally relevant for all researchers exploring neighbourhood effects, including those in economics, sociology and health studies. Our work should prompt researchers to use the existing findings more cautiously, to consider spatial scale more carefully, and to use more accurate terms when referring to different spatial contexts.

7.3 Methodological benefits and limitations of the study

Looking back at the theoretical approaches to neighbourhood effects and at the nature of spatial data, we can summarise the advantages of microgeographic data in three related points. Firstly, using microgeographic data, we can more precisely measure spatial dependency (homogeneity) – the main characteristic of spatial data (Anselin & Getis, 1992). This is in fact also the main premise of neighbourhood effects – that spatial proximity leads to similarity, i.e. that the characteristics of spatial context translate to individual outcomes. Secondly, microgeographic data simultaneously reveal changes in space, which is in the spatial data analysis termed spatial heterogeneity. These changes usually do not occur at the borders of administrative units. While spatial dependency remains pivotal for the neighbourhood effects research, spatial heterogeneity pinpoints abrupt changes in the residential context, which may affect people's behaviour or decision to move in or out of the neighbourhood. Thirdly, we can understand spatial dependency and spatial heterogeneity only through the lens of spatial scale. Spatial scale determines whether we capture spatial dependency or heterogeneity. This leads us to the ultimate advantage of microgeographic data: Although the term *microgeographic* emphasises the micro scale, the ultimate advantage of microgeographic data is that we can use them to better understand a range of spatial scales.

Despite all the benefits of microgeographic data, our methods have a few limitations, mainly related to the way we delineated the bespoke areas. They take the form of concentric circles, thus ignoring boundaries of the natural and built environment, such as canals and main roads, as potential dividers of social space (Lund, 2018). The concentric circles are also not adjusted to street networks (see Grannis, 1998), and Euclidean distance is, although a major, not the only parameter of accessibility (Kwan, 1998; Kim & Kwan, 2003). Additionally, people's activity spaces may not spread equally in all directions around their home (Kwan, 1999). For example, residents north of the city centre may be more oriented to the south and, therefore, more exposed to this part of their surroundings. While our methods reveal subtle changes across scale, they do not permit asymmetries in spatial effects (Dean et al., 2018). However, refining our multiscale bespoke areas in any of these aspects would have been even more time-consuming and computationally demanding than the actual method used.

Other methodological limitations relate to how the contextual characteristics are measured. For example, for the non-Western ethnic minorities we used the definitions of Western and non-Western backgrounds given by the Statistics Netherlands, although dividing all people into only two categories is an overly simplified view of ethnicity (Boschman & Van Ham, 2015). Similarly, we operationalised contextual poverty as the share of low-income people, though it is a much more complex phenomenon (see, e.g., Ostendorf et al., 2001). The main reason for using only the simple contextual characteristics was the computational power required to calculate them for all the 101 spatial scales for the whole country.

To accelerate this computationally intensive task, we participated in a pilot project in which we used the Dutch national supercomputer 'Cartesius'. The uniqueness of this project was that social scientists were able to work with the sensitive data of the Statistics Netherlands in a secure high performance environment, organised by ODISSEI (Open Data Infrastructure for Social Science and Economic Innovations). The pilot showed that a cluster computer can calculate extensive contextual characteristics in a considerably shorter time than would be possible with normal single-machine computing. In the long term, the results can be used to better understand the spatial structure of the social environment, the trends of spatial segregation at multiple scales and the consequences of these processes for individuals. Therefore, the limitations of this study can be taken into account in future research, provided a more advanced computational infrastructure.

7.4 Looking forward to future research

One of the most promising directions for continuing this research is to further develop and investigate the distance profiles. We showed that people are potentially exposed to very different multiscale spatial contexts, including relatively uniform spaces, but also to vastly different characteristics at different scales, such as small areas with almost no poverty surrounded by much poorer ones, or vice versa. In Chapters 3 and 5, we measured the variability of the distance profiles using the (hierarchical) entropy index, but much more can be done to classify distance profiles and explain their scalar variability, ranging from flat to spatially diverse.

Following the suggestion of Chapter 3 that different people are exposed to different contexts at multiple scales, various sensitivity analyses can develop from this study, for example by looking at spatial scale from the perspective of individuals with different sociodemographics. Likewise, different geographical settings can be further compared based on this dissertation's findings. Although Chapter 5 showed spatial patterns of contextual poverty within and between municipalities, not all of this could be considered in studying the effects of contextual poverty on individuals in Chapter 6. Future studies should therefore elaborate on how segregation and spatial contextual effects vary within and between urban regions, cities and smaller municipalities. While this thesis focussed on geography, the temporal dimension was only taken into account in the neighbourhood effects study in Chapter 6. The other, descriptive studies, however, can also extend into spatiotemporal analyses of segregation in the Netherlands and other countries. Thereby, future studies of sociospatial inequalities should address not only specific sociodemographics, such as ethnicity and socioeconomic status, but also their intersection.

Based on the findings of this thesis, future research on segregation trends should start from the assumption that these trends may be different for different spatial scales. And the studies on contextual effects should assume that people are affected by various spatial contexts simultaneously. Accordingly, policy responses should be open for more flexible spatial definitions of neighbourhoods: Although important, neighbourhoods – as they are officially defined – are not always the most appropriate level of intervention. They are parts of larger urban systems, and, at the same time, they may contain many spatial inequalities within themselves, starting from the often overlooked micro-spaces. This dissertation does not suggest that all researchers need to consider this wide range of spatial scales. It does, however, suggest that the multiscale approach is a way to better understand sociospatial inequalities and neighbourhood effects, because different scales reveal different spatial processes. Place matters for individuals, but we need to carefully consider what we mean by place and in what way it might matter.

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Curriculum Vitae

Ana Petrović

Ana Petrović was born in 1984 in Jagodina, and finished high school in Kragujevac, Serbia. She received a graduate diploma (master's degree equivalent) in Geography and Tourism Studies from the University of Niš, master's degree in Demography from the University of Belgrade, Serbia, and master's degree in Human Geography – Urban and Regional Research from the University of Bayreuth, Germany (with a scholarship from the German Academic Exchange Service – DAAD). Towards the end of her master's studies in Bayreuth, she worked as intern, and later as research assistant, at the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB) in Nuremberg, where she started working with the geocoded longitudinal individual-level data. In December 2014, she joined the DEPRIVEDHOODS project at TU Delft, where she continued working with the same type of geocoded data for the Netherlands. Her role within the project was to explore and analyse alternative definitions of spatial contexts for studying neighbourhood effects, which resulted in this thesis.

In addition to the DEPRIVEDHOODS project, Ana participated in two pilot projects, namely the Data for Integration (D4I) – Data Challenge of the European Commission, and the ODISSEI Secure Supercomputer (OSSC) pilot, organised by ODISSEI (Open Data Infrastructure for Social Science and Economic Innovations), Statistics Netherlands (CBS) and SURFsara. She presented her research at multiple international conferences and gave a few invited talks – at the University of St. Andrews (UK), University of Bielefeld (Germany), Joint Research Centre (JRC) of the European Commission in Brussels (Belgium), European University Institute in Florence (Italy), as well as a few presentations of the OSSC pilot in the Netherlands. During her PhD research, she spent one month at the Spatial Econometrics Advanced Institute (SEAI) in Rome (Italy), two weeks at the University of Bristol (UK), two weeks at the Max Planck Institute for Demographic Research (MPIDR) in Rostock (Germany), attending the Spatial Demography course, one month in the Essex Summer School in Social Science Data Analysis in Colchester (UK), and followed a few other courses in the Netherlands and Germany. So far, she has published two journal articles in the *Annals of the American Association of Geographers* and *Progress in Human Geography* and continued to work with her PhD supervisors as a postdoc researcher in the Urbanism department at TU Delft.

Publications

Peer-Reviewed Journal Articles

Petrović, A., Manley, D., van Ham, M. (2019). Freedom from the Tyranny of Neighbourhood: Rethinking Socio-Spatial Context Effects. *Progress in Human Geography*, Published online 28 August 2019 (open access).

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Submitted Papers and Work in Progress

Petrović, A., van Ham, M., Manley, D. (submitted to a peer-reviewed journal). Where Do Neighborhood Effects End? The Complexity of Multiscale Residential Contexts.

Petrović, A., Manley, D., van Ham, M. (submitted to a peer-reviewed journal). Multiscale Contextual Poverty in the Netherlands: Within and between-Municipality Inequality.

Petrović, A., van Ham, M., Manley, D. (abstract accepted for the IV ISA Forum of Sociology). Spatiotemporal Analysis of Intersectional Segregation in the Netherlands.

20#15

Multiscale spatial contexts and neighbourhood effects

Ana Petrović

This thesis has developed alternative methods of operationalising neighbourhoods at multiple spatial scales and used them to advance our understanding of spatial inequalities and neighbourhood effects. The underlying problem that motivated this thesis is that many empirical studies use predefined administrative units, and often this does not align with the underlying theory or geography. Despite the extensive literature on neighbourhood effects and, more generally, on sociospatial inequalities, spatial scale remains an under-analysed concept. As a response to this research gap, this thesis takes a multiscale approach to both theory and the empirical analysis of neighbourhood effects, highlighting the multitude of spatial processes that may affect individual outcomes of people. To operationalise this, we created bespoke areas (centred around each residential location) at a range of one hundred scales representing people's residential contexts, primarily in the Netherlands but also in multiple European capitals. Using microgeographic data and a large number of scales combined with small distance increments revealed subtle changes in sociodemographic characteristics across space. In doing so, we provided new insights into ethnic segregation, potential exposures to poverty, and neighbourhood effects on income, all in light of the fundamental issue of spatial scale: The analyses of sociospatial inequalities are substantially affected by the scale used to operationalise spatial context, and this varies within and between cities and urban regions. The aim of this thesis was therefore not to find a single, 'true' scale of neighbourhood, but to acknowledge, operationalise, and better understand the multiplicity of spatial scales.

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