THE LINK BETWEEN ETHNIC SEGREGATION AND SOCIO-ECONOMIC STATUS: AN ACTIVITY SPACE APPROACH

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ABSTRACT
The extent to which ethnic segregation results from differences in socio-economic factors remains a seminal topic of debate. The growing literature demonstrating the multifaceted phenomenon of segregation urges more focus on individuals' spatial and social interactions. We applied an activity space approach and considered ethnic differences in individuals' activity spaces as an indicator of spatial segregation. We used mobile phone and survey datasets in Estonia. We show that place-based segregation indices derived from both datasets indicate similar levels of ethnic segregation. From an activity space perspective, the results show that the main socio-economic factor affecting the extensity of activity spaces is self-estimated social status rather than education and income. Results show that ethnic inequality in spatial behaviour is not straightforward, but rather that it is linked to how individuals position themselves in society. We argue that socio-economic factors need to be controlled to examine ethnic segregation from activity space perspective.

Key words: segregation; socio-spatial inequality; socio-economic status; activity space; human mobility; mobile phone data

INTRODUCTION

One central topic in the social sciences is the search for a better understanding of underlying factors explaining the phenomenon of ethnic segregation in urban spaces (Piekut *et al.* 2019; Woods 1979). The topic is seminal given the increasing diversity and rising socio-spatial inequalities manifested in urban societies (Malmberg *et al.* 2013; Tammaru *et al.* 2016). This has generated growing inter-ethnic prejudices and simmering tensions, which can hinder social sustainability and the well-being of cities – a challenge for research and policy.

One of the prevailing topics in segregation discourse has been whether the ethnic or the socio-economic dimension is more relevant to the generation of spatial segregation, and the degree to which ethnic spatial segregation is linked to differences in the socio-economic status (SES) between ethnic groups. However, the latter linkage remains unclear due to contradictory study results obtained in several socio-cultural contexts. These contradictory findings may stem from neglecting the importance of spatial and temporal dimensions and the way spatial segregation is being studied. By examining only the sedentary residential population division in fixed spatial units while neglecting the dynamic nature of segregation over time and the spatial mobility aspect in segregation research could cause biases in measuring the segregation phenomenon (Cass *et al.* 2005; Kwan 2013). Also, problems with the prefixed spatial units and the issue of a spatial scale affecting segregation levels are often overlooked (Manley *et al.* 2019).

Spatial segregation research is already moving beyond solely the residential domain (see Piekut *et al.* 2019), considering segregation in the occupational (Ellis *et al.* 2004), educational (Burgess *et al.* 2005) and leisure domains (Kukk *et al.* 2019). New methods are applied to revise spatial units for segregation research (Poorthuis 2018). Still, research focuses on a 'single' spatial dimension while neglecting the multifaceted lives of people – the different places they visit, the social interactions and practices they pursue and the growing spatial mobilities they undertake. We argue that spatial segregation research ought to put individuals and their daily lives at the core of the research to improve the understanding of the multidimensional phenomenon of segregation. With this in mind, our study follows the growing literature in segregation research that advances and operationalises an activity space approach (Schnell & Yoav 2001; Wang *et al.* 2012; Atkinson & Flint 2004; Järv *et al.* 2015; Shelton *et al.* 2015; Silm *et al.* 2018).

Our research objective is twofold. First, to test the classical socio-spatial segregation thesis (Blau 1977; Hechter 1978) and to explain ethnic spatial segregation as a function of SES (Mack 1951) – one of the most sociologically significant factors underlying social inequality. Second, to contribute in the person-based segregation literature by examining factors influencing individual activity space as an indicator of potential exposure to interaction with others. To do so, we used a survey and a novel mobile phone-based positioning dataset. We examined how and to what extent ethnic and SES differences occur in activity spaces.

We applied mobile phone data as a promising medium for understanding the spatial mobility of people – revealing when and where phones are used and considered as a proxy for individuals' spatial practices (Ahas *et al.* 2010; Wang *et al.* 2018b). Hence, we took these data as being the best-available information about the spatial mobility of individuals. The questionnaire data offer a large set of explanatory information about the social context and SES of individuals, despite the limited spatial information. To our knowledge, this is the first attempt to compare survey and mobile phone datasets using an activity space approach in spatial segregation research.

ACTIVITY SPACE AS AN INDICATOR OF EXPOSURE AND INTERACTION

Segregation is generally considered to be the unequal interaction between social groups (Hechter 1978), whereas from a geographical perspective, it is considered to be the unequal presence of social groups in a physical space as an indicator of potential exposure to interaction with others (Massey & Denton 1988). Segregation is not solely about (the potential for) social interaction with others 'in' the place where one lives or works, but it exist everywhere people go, perform activities and have the opportunity to interact with other people, and how it changes over time (Schnell & Yoav 2001; Sheller & Urry 2006; Wong & Shaw 2011). Rather than merely measuring the spatial divide between social groups and their potential exposure to other groups, the focus is shifting towards individuals – how segregated are individuals' daily lives and what is their overall segregation experience in society. This allows us to capture and understand different dimensions of the multifaceted phenomenon of segregation (Schnell & Yoav 2001; Wang *et al.* 2012).

The emerging research on understanding socio-spatial inequality and segregation from an individual's daily life perspective stems from the broad notion of individual activity space (Golledge & Stimson 1997). An activity space is generally defined as a geographic extent delineated by the locations in which an individual has direct contact due to social activities, and travel between and around those locations during a certain time period – daily, monthly, yearly (Järv *et al.* 2014). The concept captures spatial, temporal and social dimensions of individuals' daily lives. Thus, it is well-established and used to examine individuals' spatial behaviour, encountering and interaction with other people, and their exposure to surrounding physical and social environment (Perchoux *et al.* 2013; Wong & Shaw 2011).

The activity space approach is applicable in segregation research from several theoretical perspectives. Stemming from the time geography framework (Hägerstrand 1970), an individual's space-time path within their activity space reveals the probability of social interaction, or even indicates the trajectories of segregation (Atkinson & Flint 2004). Our need for physical face-to-face contacts to sustain social ties denotes that our activity space indicates the spatial extent of our social networks (Cass *et al.* 2005). Furthermore, activity space indicates exposure to other people and the potential for establishing new contacts. According to social network theory (Granovetter 1973), establishing the weak social ties is crucial for individual's opportunities, and being integrated to new communities (of the majority group) – a cornerstone of the acculturation of the immigrant population (Berry 1997). Hence, not only do more extensive activity spaces for people from a minority population indicate better chances to establish the relevant weak ties and to integrate, it also indicates an ability to achieve upward social mobility (Faist 2013).

The concept of activity space allows us to improve our understanding of the segregation phenomenon beyond direct social interaction between people, and consider how the exposure to the surrounding environment contributes to the segregation in individuals' daily lives. According to structuration theory (Giddens 1984), the duality of social structure and agency means that locations visited and space-time paths that constitute one's activity space are not just empty entities in an abstract space in which interactions between people take place, but they are also active milieux that influence individuals, and in turn are influenced by them. Put differently, people are also affected by non-social interaction with the surrounding environment, both physically real and socially imagined (Soja 1980). Moving in and through space is part of the socio-spatial dialectic that constitutes one's moral dispositions, 'norms' and ethical judgements (Valentine 2008). Hence, the cognitive embodied experience of and exposure to a surrounding socio-physical environment within one's daily life shapes both one's identity as well as social, emotional and psychological perceptions of places. In turn, this influences one's social interaction and use of physical space that eventually (re)shapes an individual's segregation experience and spatial segregation at large.

Given the above, we see the concept of activity space as an excellent medium for understanding individuals' constant exposure to and interaction with our surrounding environment and other people during our daily lives, and eventually providing a new perspective on the multifaceted phenomenon of segregation.

MEASURING ETHNIC SEGREGATION IN ACTIVITY SPACES

We have already witnessed the emerging activity space-based (also referred to as person-based or people-based) segregation research strand (Schnell & Yoav 2001; Wong & Shaw 2011). Here, the concept of individual activity space is conceptualised and operationalised to examine the dimensions of segregation regarding language (Farber *et al.* 2012), ethnicity (Järv *et al.* 2015), education (Shareck *et al.* 2014), religion (Greenberg Raanan & Shoval 2014), age (Silm *et al.* 2018) and housing type (Wang & Li 2016).

In this research strand, many studies have measured the characteristics of an individual activity space such as extensity, intensity, diversity, exclusivity and space-time trajectories

(Lee & Kwan 2011; Wang *et al.* 2012; Jones & Pebley 2014; Järv *et al.* 2015; Wang & Li 2016; Tan *et al.* 2017; Silm *et al.* 2018; Zhang *et al.* 2019). Differences in these characteristics between social groups are considered to be one facet of activity space segregation. Given that the characteristics are quantified in several ways, enumerating activity locations (or neighbourhoods) indicates the diversity of one's activity space (Wang *et al.* 2012; Silm *et al.* 2018). Intensity is based on the visitation frequency (Silm *et al.* 2018) or the time spent in these activity locations (Kukk *et al.* 2019). Differences in individuals' space-time trajectories within their activity spaces can be measured from a space-time nexus perspective by combining the physical space-time trajectories of individuals with social interaction in one's social network (Lee & Kwan 2011).

Extensity – the spatial extent of an activity space – is considered to be an indication of a spatial concentration of an individual's activities, like social practices, interaction and mobility (Wang *et al.* 2012; Järv *et al.* 2015). This further indicates the ability to reach social opportunities and resources in a physical space (Wang & Li 2016; Zhang *et al.* 2019). Extensity is based on the size of an activity space (Järv *et al.* 2015; Tan *et al.* 2017), the average travel distance between the locations visited and home (Wang *et al.* 2018a), and the standard distance between activity locations (Wang *et al.* 2012). According to Järv *et al.* (2015), the segregation dimension of concentration can be interpreted as an individual activity space perspective in which concentration refers to a relative amount of physical space used by an individual from one's entire physical environment. Thus, individuals belonging to a certain social group and using less of their physical environment in their daily lives compared to members of other social groups are considered to be concentrated in society.

Some studies further consider the social context of the locations visited and delineated activity spaces in addition to differences in individual activity spaces. By considering the socio-economic context in the locations visited enables the segregation level of each activity space to be measured such as measuring segregation based on the time spent in locations while considering the ethnic compositions of given locations (Greenberg Raanan & Shoval 2014). More holistically, activity space segregation can be examined against multiple spatial scales and combined with social dimensions regarding one's social network, cultural and emotional aspects (Schnell & Yoav 2001; Shdema *et al.* 2018). However, in this study we focused on extensity as one facet of activity space segregation.

One reason for the emergence of activity space-based segregation research is the proliferation of big data sources (Kitchin 2014). New technologies collecting individual level data are actively applied in activity space segregation research, including GPS tracking (Shdema *et al.* 2018) and geo-located social media posts (Wang *et al.* 2018a). However, mobile phone positioning technology is used the most as a proxy for capturing human spatial mobility up to a country scale (Wang *et al.* 2018b). In ethnic segregation research, mobile phone data are used both to assess ethnic differences in individuals' activity spaces (Järv *et al.* 2015; Silm *et al.* 2018) and measure traditional place-based segregation (Silm & Ahas 2014; Mooses *et al.* 2016).

ETHNIC SEGREGATION AND SOCIO-ECONOMIC FACTORS

Despite extensive research on whether and to which degree ethnic segregation is related to differences in SES among ethnic groups, existing findings are contradictory. Findings show that socio-economic inequality is experienced when having a certain disadvantaged position in the hierarchy of resources, say economic or educational (Massey 1981). Ethnic segregation is explained foremost by the SES factor (Hwang *et al.* 1985) or is determined by an interaction between ethnicity and SES (Massey *et al.* 2009). The conclusion in a comparative study in 71 countries by Ezcurra and Rodríguez-Pose (2017) was that countries with higher ethnic segregation have higher levels of socio-economic inequality. However, the link between ethnic segregation and SES is not linear. People from higher social classes tend to self-segregate from other groups within the population, similarly to people from lower social classes (Marcińczak *et al.* 2017), and socio-spatial isolation is experienced both by highly disadvantaged and advantaged SES groups (Krivo *et al.* 2013). Hence, ethnic segregation may persist regardless of increasing income within an ethnic minority (Massey & Fischer 1999), and individual preferences and structural factors may influence residential mobility differently between certain SES groups (Tammaru *et al.* 2018).

Studies have also revealed the two-fold effect of ethnic segregation on economic inequality. First, members of minority group face a structural disadvantage in their labour opportunities, and second, minority group earnings are more dependent on the characteristics of the local job market (Lewin-Epstein & Semyonov 1992). At the same time, inequalities stemming from our daily physical environment regarding accessibility to resources, services and housing contribute to socio-spatial inequalities of people (Cass *et al.* 2005). Thus, the characteristics of one's daily habitual environment and individual SES are closely related. Ethnic segregation can be further explained by combining cultural and economic measures of societal inequality (Baldwin & Huber 2010). Ethnic prejudice as a cultural measure increases economic inequality between ethnic groups whereas ethnic diversity in a society decreases prejudices (Kunovich & Hodson 2002). However, ethnic segregation tend to stem less from prejudice and discrimination than from institutional factors such as political decisions about land use (Massey *et al.* 2009).

The subjective measures of social class are also applied to assess SES (Steiner 1953) – the self-estimated social affiliation to community can be seen as a part of one's self-definition which reflects on social inequality as a psychosocial phenomenon. Certainly, findings in socio-spatial inequalities depend on how social class/status is being conceptualised and linked to social inequality (Savage *et al.* 2015), but also to the way people perceive the structure of social inequality and how they position themselves within it (Irwin 2018). Recently, studies focusing on post-Soviet transition countries (e.g. Estonia) have applied a social stratification approach to assess SES and its link to social inequalities (Saar & Trumm 2018). We used Bourdieu's constructivist approach to understanding social status and inequality as a framework to express social stratification through the access, use and mutual convertibility of an individual's (economic, cultural, political, social) capital (Lauristin 2017).

CASE STUDY: ESTONIA

We examine Estonia, which has one of the highest ethnic minority populations in the EU – the majority of the population is Estonian-speaking, but one-third is Russian-speaking. The significant minority population is a result of the state policy-led immigration legacy during the Soviet occupation from 1944 to 1991 (Kulu 2004). Also, country's poverty and income inequality are among the highest in the OECD (OECD 2017). Thus, Estonia serves as a suitable country for testing the link between ethnic segregation and socio-economic inequality. Segregation in post-Soviet regions has historical differences compared to Western countries, but since the 1980s it seems to have similar tendencies to those in Western Europe (Tammaru *et al.* 2018).

Language groups of people identifying with each other based on common ancestral, social, cultural or shared norms and values are under consideration in this study. While an ethnic minority community identity may be defined, embodied and accessed through language (Alexander *et al.* 2007), language can also serve as a key marker of cultural difference and a symbol of ethnicity. In particular, language rather than ethnicity is the main marker of the social groups in Estonia that indicates structural 'community' differences (Masso & Soll 2014). Both language groups are distinguishable in terms of historical background in residential housing separation (Marcińczak *et al.* 2017) and of separate Estonian and Russian-speaking basic education systems (Masso & Soll 2014). These differences have remained largely unaltered and have continued to influence socio-economic delineations – a limited level of inter-marriage (Ham & Tammaru 2011); language-based differences in residential mobility (Tammaru *et al.* 2013); and income differences (Leping & Toomet 2008).

The existing literature on activity space segregation in Estonia has found that members of the Russian-speaking group have significantly smaller activity spaces, whereas their activity locations are spatially more concentrated in specific geographical areas than members of the majority group (Järv *et al.* 2015; Silm *et al.* 2018). Findings also reveal the variation of ethnic segregation over time and when going beyond everyday activities (such as leisure time and holidays), segregation between ethnic groups increases (Mooses *et al.* 2016; Silm & Ahas 2014).

METHODOLOGY

Data sources – We analysed ethnic segregation based on spatial mobility of people during a one-year study in 2014, using two datasets: (1) the territorially representative self-administered questionnaire survey (hereinafter *survey*); and (2) phone call detail records of mobile phone users (hereinafter CDR data).

The 5th round of the country-wide survey 'Me. The World. The Media' was carried out in 2014 using a random probability sampling according to a proportional general population model (gender, age, ethnicity and region). We used questions about subjective self-estimated social status and spatial visits within Estonia with extensive personal background information (age, gender, mother tongue, home and work location). Spatial mobility in the survey was self-reported by filling in visitations of predefined spatial units (Figure 1B) during the ongoing study year, and the visit frequency: daily; once a week; once a month; several times a year; once a year. Data were collected retrospectively (not like a travel diary) and some minor biases may have occurred regarding the ability to remember and associate the locations visited by a respondent to predefined locations they visited and the frequency (e.g. unintentional memory gaps, intentional mistakes). Thus, we used CDR data to compare spatial mobility indicators derived from the survey.

CDR data are a form of metadata on mobile network service usage (call activities) for each mobile phone collected for billing purposes by the mobile operator and were not collected for the purposes of this study. All call activities initiated by phone users (phone calls, messaging) include the following attributes: a unique phone user ID (randomly generated by the operator), time, and the geographic coordinates of the network base station that provided network signal (Figure 1A). The operator while preserving anonymity provided additional information about mobile phone users' age, gender and preferred communication language with the operator (Estonian or Russian). Hence, respondents of CDR data cannot be directly linked to respondents of survey data. CDR usage and processing in this study was in accordance with EU legislation. We assumed that the communication language with a mobile operator was a reflection of ethnolinguistic affiliation (hereinafter language) and took it as a proxy for ethnicity in case of the CDR data.

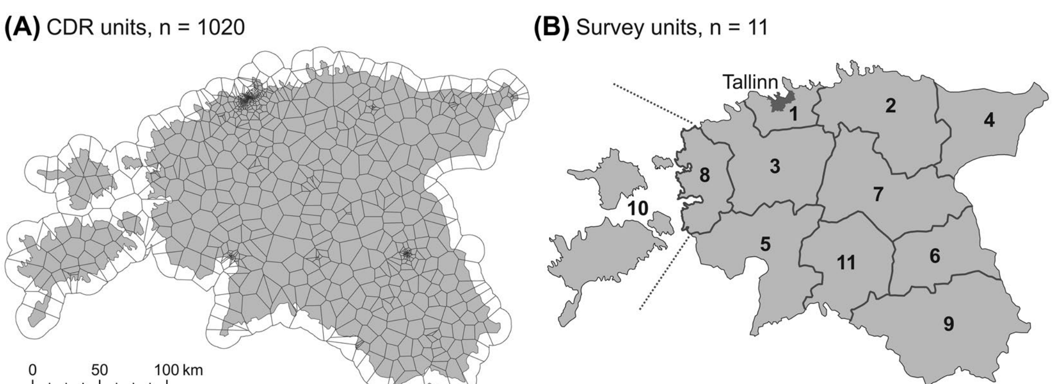


Figure 1. *The spatial accuracy of locations visited regarding the spatial units of CDR data (A) and the survey (B). Numbers in map B indicate spatial unit code.*

In comparing the two data sources from the spatial mobility perspective, CDR data provide spatially more accurate information as Estonia is divided into 1,020 spatial units (i.e. mobile antenna coverage areas) compared to 11 pre-defined spatial regions in the case of the survey. While the survey data were collected retrospectively, the CDR data was collected automatically when a phone was used, and thus making visit frequency more accurate in time. Relying on existing research on CDR data, we consider individual spatial mobility derived from CDR data to be more accurate than survey data that may include some subjectivity bias.

Sample – The study sample in both datasets was limited to the economically active population (aged between 20 and 64) who both live and work in Tallinn – the capital of Estonia. In total, 326 respondents from the survey fulfilled these criteria. For CDR data, the anchor point model by Ahas *et al.* (2010) was applied to reveal phone users' home and work locations within Tallinn, and further random sampling was applied to preserve the language division concurrent in the 2011 census data. In total, 7,056 mobile phone users were included. Personal characteristics of the sample were in line with both datasets while coinciding with census data (Table 1).

Measuring segregation – The comparison of both data sources required a comparable spatial division. Thus, the initial spatial accuracy of CDR data was interpolated in the survey units. The visit frequency of each unit for each respondent was interpolated according to the five visiting frequency classes of the survey, as follows: everyday (weight 5); at least once a week (4); once a month (3); several times a year (2); once a year (1). Weighting allowed us to obtain a more realistic temporal presence of people in the spatial units they visited.

First, a straightforward place-based relative presence method was used to explore the distribution of visits to each spatial unit while considering visit frequency as a weight. It is input to measure the latter against segregation indices of evenness and exposure (Massey & Denton 1988).We applied both non-spatial and spatial dissimilarity, and entropy (Theil's H) indices indicating differences in the distribution of the ethnic groups studied. Interaction and isolation indices were applied to indicate the potential interaction between two ethnic groups.

Second, from a person-based perspective, ethnic differences in spatial mobility were examined by measuring the extent of annual individual activity space. Based on the spatial units visited by a respondent and using the frequency as a weighting measure, the spatial extent of one's activity spaces is assessed using the standard deviational ellipse (SDE) technique, similar to Järv *et al.* (2015). The SDE is the smallest possible area in which the centre locations of each spatial unit visited are found with a probability of 95 per cent.

Individual spatial behaviour across ethnic groups was examined using SPSS for univariate general linear modelling (GLM) in which the size of an individual SDE was the dependent variable. The explanatory power of the model and the effect of the explanatory variables were determined by the partial eta-squared. We ran a three variable ANOVA model (age, gender, language) with a full factorial interaction model using the GLM for the survey data (Table 2). Interaction effects were included to improve control of the main effects and reveal the interactions that potentially influence the spatial behaviour of people (Garson 2012). For the CDR data, two additional independent variables (covariates) were included to control better for personal peculiarities of mobile phone usage (Järv *et al.* 2014): – the proportion of CDRs generated outside one's home and work location (non H-W), and the mean number of CDRs per day per person (avg CDRs).

Finally, in case of the survey data, we included socio-economic variables in the GLM models. Six GLM models were applied with a step-wise inclusion of the three variables as indicators of SES (Table 1): objective measures of self-reported education and income, and a subjective measure of self-estimated affiliation to social status (Table 3). In the last model ($M5_{weight}$), the survey data were weighted according to the actual spatial mobility index derived from mobile phone data to downplay potential biases related to filling in the survey and the possible differences between actual

Table 1. *The proportion of both CDR data and survey sample by personal characteristics, and in comparison to Population and Housing Census 2011.*

Variable		CDR	Survey	Census
Language	*Estonian*	51	52	51
	Russian	49	48	47
	Other	0	0	2
Ethnicity	*Estonian*	-	51	54
	Russian (other Slavonic)	-	49	43
	Other	-	0	3
Gender	*Male*	37	42	47
	Female	63	58	53
Age	*20–29*	4	20	27
	30–39	24	18	24
	40–49	36	22	19
	50–64	36	40	30
Residence by district of Tallinn	*Lasnamäe*	31		29
	Mustamäe	13		15
	Põhja-Tallinna	12		14
	Kesklinn (c)	14		13
	Kristiine	7		7
	Haabersti	9		10
	Pirita	6		4
	Nõmme	8		8
Household monthly net income by person	*< 250 EUR*		11	
	251 - 400 EUR		26	
	401 - 600 EUR		36	
	> 600 EUR		27	
Education level	*Primary or below*		6	9
	Secondary		56	62
	Higher		38	29
Social status (subjective)	*Low*		21	
	Low-Middle		17	
	Middle		25	
	Middle-High		20	
	Higher		17	
Total (%)		100	100	100
N		7,056	326	254,317

and self-estimated mobility. For the index, first the mean normalised mobility scores were calculated for all categories of comparable variables (language, gender, age). Second, the scores for each variable were assigned to each survey respondent according to the category, whereas given scores were summed as a compound index.

RESULTS

Place-based perspective – A distribution of respondents' relative presence in pre-defined geographical units by ethnicity was similar in both the survey and CDR data (Figure 2). In general, these distributions between the two ethnic groups coincided with previous studies from Estonia (Silm & Ahas 2014; Mooses *et al.* 2016). In general, both data sources indicated higher mobility outside one's home region (unit 1) for Estonian speakers; their relative presence there was around 40 per cent. In contrast, Russian speakers were more concentrated in the home region (around 60 per cent) and to its vicinity (units 2 and 3 in Figure 1). As expected from previous studies, Russian speakers showed higher rates of visiting the north-east of Estonia (unit 4), in

Table 2. *The comparison of GLM models examining the effect of personal characteristics on the spatial extent of individual activity space between the survey and CDR data.*

Independent factors		CDR F	CDR Partial eta squared	Survey F	Survey Partial eta squared
Corrected model		291.58***	0.242	5.44***	0.209
Language		1988.85***	0.127	36.62***	0.106
Gender		23.35***	0.002	0.00	0.000
Age		36.03***	0.008	2.42[a]	0.023
Gender × Age		3.47*	0.001	2.73*	0.026
Language × Age		8.52***	0.001	0.80	0.008
Language × Gender		0.03	0.000	0.56	0.002
Language × Gender × Age		3.96*	0.001	2.77*	0.026
Phone usage	avg CDRs	1781.54***	0.115		
	non H-W	2.38	0.000		

[a]*p* < 0.1, ****p* < 0.001, ***p* < 0.01, **p* < 0.05.

contrast to Estonian speakers. Interestingly, in the case of Russian speakers, some marked visiting differences occurred between the two datasets regarding the neighbouring regions of Tallinn (units 2 and 3).

Conventional segregation indices showed strong similarities for both data sources. In the case of the exposure dimension, the interaction index was 0.47 for the survey and 0.48 for the CDR data whereas the isolation index was 0.53 and 0.52, respectively. In the case of the evenness dimension, the entropy index was 0.07 for the survey and 0.05 for the CDR data. Only the dissimilarity indices showed marginal differences between the two data sources – the non-spatial dissimilarity index based on survey data was 0.29 compared to 0.22 for CDR data, and for the spatial dissimilarity index, the results were 0.27 and 0.20, respectively. Interestingly, the dissimilarity indices coincide with findings by Silm *et al.* (2018), despite the fact that they had significantly better spatial accuracy (n = 247) than in this study.

Activity space-based perspective – At the individual level, ethnic differences in human spatial mobility coincide well between the two data sources – both the distribution of activity spaces by its spatial extent and descriptive statistics indicated similarities (Figure 3). Both data sources indicated a clear ethnic difference – the median size of an individual activity space for Estonian speakers was 23,223 km^2 (survey) and 18,575 km^2 (CDR), whereas for the Russian speakers it was 7,544 km^2 and 7,543 km^2, respectively. Thus, the annual activity space of the average Estonian speaker was almost double that of the average Russian speaker.

Further, the distribution pattern of respondents according to the spatial extent of individual annual activity space indicated by both data sources showed a more-equal distribution for Estonian speakers regarding the extent of annual activity space. In contrast, most of the Russian speakers had smaller activity spaces and only a small proportion had larger activity spaces to indicate a concentrated use of space.

Finally, statistical models revealing how social attributes explain the size of the annual activity spaces at the individual level show clear similarities between the two data sources (Table 2). The model based on survey data had explanatory power to explain 21 per cent of the total variance for yearly individual activity space, while it was 24 per cent in the case of CDR data. In both models, language as a proxy for ethnicity remains by far the most important variable while explaining around half of the total variance of the size of activity spaces in given models.

Explaining ethnic segregation through socio-economic characteristics – The findings presented above show that the measured

Table 3. *A step-wise inclusion of socio-economic variables to GLM models examining the effect of personal characteristics on the spatial extent of individual activity space derived from survey data.*

	M1		M2		M3		M4		M5		$M5_{weighted}$	
	F	Partial eta squared	F	Partial eta squared	F	Partial eta squared	F	Partial eta squared	F	Partial eta squared	F	Partial eta squared
Corrected model	13.75***	0.178	5.44***	0.209	6.86***	0.243	4.11***	0.252	2.17***	0.371	2.55***	0.420
Language (Lang)	46.29***	0.127	36.62***	0.106	20.76***	0.044	13.10***	0.043	10.31***	0.040	1.05	0.004
Gender	0.30	0.001	0.00	0.000	0.02	0.000	0.03	0.000	2.90[a]	0.012	5.48*	0.022
Age	4.13**	0.038	2.42[a]	0.066	3.79**	0.006	2.20[a]	0.022	2.59[a]	0.031	0.88	0.011
Gender × Age			2.73*	0.044			1.94	0.019	1.51	0.018	2.38[a]	0.029
Lang × Age			0.80	0.008			0.39	0.004	1.41	0.004	1.59	0.019
Lang × Gender			0.56	0.002			0.32	0.001	0.72	0.000	0.00	0.000
Lang × Gender × Age			2.77*	0.026			2.37[a]	0.024	1.55	0.019	1.53	0.018
Education					0.99	0.007	1.28	0.009	0.82	0.007	1.22	0.010
Income					1.31	0.013	1.76	0.018	1.51	0.018	0.54	0.007
Social status (SS)					2.94**	0.038	2.42*	0.032	1.79	0.028	3.24*	0.051
Lang × Income									0.07	0.000	0.56	0.007
Lang × Education									0.90	0.011	0.16	0.001
Lang × SS									2.51*	0.039	2.94*	0.046
Gender × Income									2.80	0.018	0.26	0.003
Gender × Education									1.57	0.019	3.06*	0.025
Gender × SS									0.42	0.007	0.47	0.008
Age × Income									0.30	0.005	2.31*	0.079
Age × Education									0.98	0.035	0.43	0.010
Age × SS									0.42	0.020	1.07	0.050

[a]*p* < 0.1, ****p* < 0.001, ***p* < 0.01, **p* < 0.05,

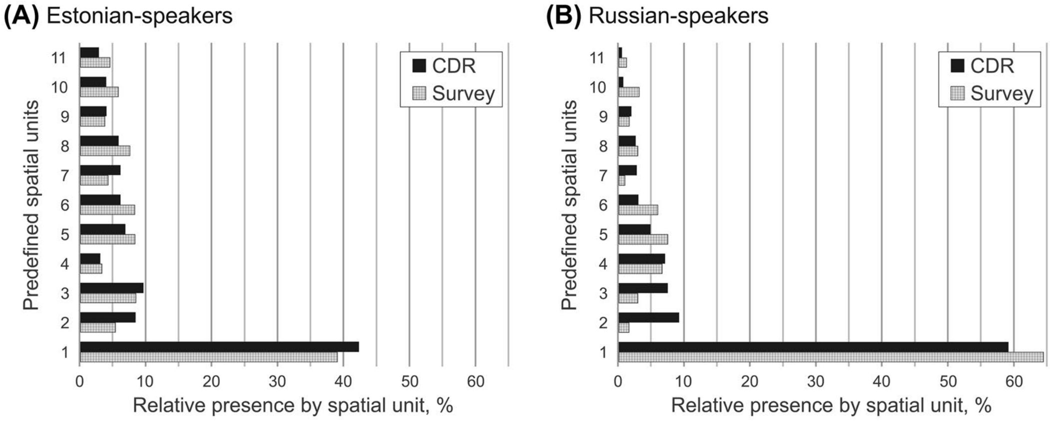
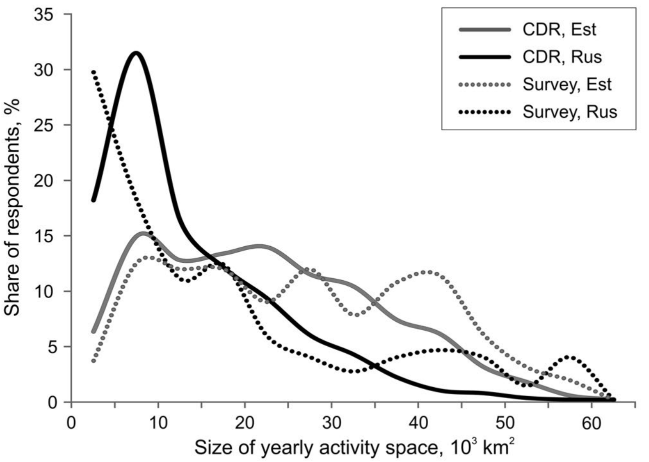


Figure 2. *The spatial distribution of relative presence of respondents by ethnicity in case of two data sources at predefined spatial unit level (see, Figure 1).*



		CDR	Survey
Mean	Est	19,926	23,966
	Rus	11,067	14,892
SE. of mean	Est	211	1,099
	Rus	163	1,254
Std. Dev.	Est	12,705	14,324
	Rus	9,578	15,656
Kurtosis	Est	0,65	0,98
	Rus	1,19	0,34
Skewness	Est	0,43	0,22
	Rus	1,27	1,22
Q1	Est	9,084	11,944
	Rus	3,449	1,924
Median	Est	18,575	23,223
	Rus	7,543	7,544
Q3	Est	29,156	36,264
	Rus	16,590	20,973
N	Est	3,614	170
	Rus	3,442	156

Figure 3. *The comparison of distribution (A) and descriptive statistics (B) on the spatial extent of individual yearly activity spaces between two ethnic groups and the two data sources.*

spatial mobility of individuals based on the survey data corresponded to the findings based on the CDR data. This gives us confidence that the survey data ought to be reliable in examining ethnic differences in human spatial mobility, and to examine further the underlying causes behind the differences. As a final step, we focused only on the survey data to explain how socio-economic background is linked to ethnic differences in activity spaces regarding a step-wise inclusion of three additional socio-economic variables (Table 3). Including more variables and interaction effects improves the explanatory power of a model, but with better-controlled models the explanatory power of language (ethnicity) decreases from M1 to M5. Nevertheless, language remains one of the more significant variables in each model to explain the total variance of the extensity of individual activity spaces.

Results indicate that education and income do not explain individual spatial mobility (M4). However, subjective assessment of

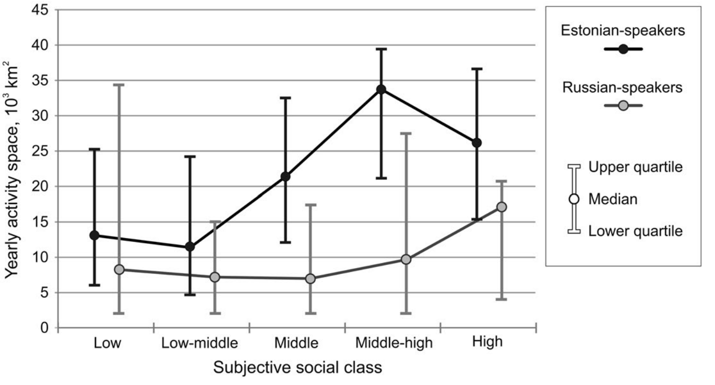


Figure 4. *The spatial extent of individual yearly activity spaces derived from the survey data by ethnicity and subjective social status.*

one's subjective social status clearly explains the variance. By including two-way interaction variables in the model (M5), the interaction between language and social status has almost the same explanatory power as language, whereas social status becomes a non-significant factor. Thus, individuals' social status influences on ethnic differences in spatial mobility.

Finally, we added the actual spatial mobility index derived from mobile phone data as weights in the model ($M5_{weight}$). Interestingly, the final model suggests social status to be a significant factor, rather than ethnicity. Some interesting results occur. First, language as such is not a relevant factor for explaining spatial differences, but rather the interaction between language and self-estimated social status is. Second, social status as a major factor has the strongest explanatory power rather than ethnicity. Third, the interaction of age and income emerged as the strongest explanatory power in the model.

The examination of the two-way interaction between language and social status in more detail revealed that the largest differences in individual annual activity spaces between ethnicity occurred among people who considered themselves to be in the middle of the social status ladder (Figure 4). The extent of Russian speakers' annual activity spaces did not have a linear association with the subjective social status – only those who considered themselves to be in the highest social status category had clearly larger yearly activity spaces. For Estonian speakers the spatial extent of individual activity space and subjective social status were positively associated, except those who considered themselves to belong to the highest social status category.

DISCUSSION AND CONCLUSION

In this study, we were striving to contribute to the seminal topic of debate on ethnic segregation resulting from differences in socioeconomic factors by using an activity space approach with mobile phone positioning and survey datasets.

The results of the study demonstrated that individuals from the ethnic minority group (using the Russian language as a proxy indicator) in Estonia have concentrated annual activity spaces, whereas language is the main variable explaining differences in spatial behaviour. These results are in line with earlier activity space-based segregation research using mobile phone data in Estonia. From a conventional place-based perspective, segregation indices coincided with previous segregation research (Silm *et al.* 2018), whereas from an activity space perspective, the extent of activity spaces are significantly smaller for Russian speakers than for Estonian speakers (Järv *et al.* 2015). The comparison between two different datasets – a questionnaire survey and mobile phone data – showed that ethnic differences are similar in both data sources, in both place-based and activity space-based segregation perspectives.

By considering mobile phone data as the best available information about the spatial mobility of individuals, gave us confidence to conduct the second part of the study – using survey data for examining the impact of SES on ethnic differences in individual activity spaces. The findings suggest that differences in individual spatial mobility are not related to a position in the economic (income) nor knowledge (education) hierarchy, but rather as a socially perceived phenomenon – how individuals positions themselves in a social layer. However, ethnicity remains an important variable in explaining differences in human spatial mobility while also controlling for the variables of SES and interaction effects (Table 3). The findings do not indicate whether the underlying main factor explaining the variation in individuals' spatial mobility is ethnicity or self-estimated affiliation to social status. In contrast, findings indicate that it is the interaction between ethnicity and self-estimated social status, which matters. This indicates that ethnic inequality in human spatial behaviour is not a straightforward phenomenon but is linked to how individuals position themselves in a society. Thus, SES information should be included in future ethnic segregation research that implements an activity space approach.

In this study, the most significant ethnic differences in activity space occurred among those who self-defined their social affiliation as middle and middle-high social status in Estonia – Russian speakers had a more limited extent of spatial mobility during the one year study period within Estonia than Estonian speakers did. If ethnic differences are the least among people positions themselves in low and lower-middle class in a society due to limited resources and/or interest to be mobile and to seek new places, then why aren't Russian speakers positioning themselves in the middle and middle-high classes mobile? We can't explain the reasons behind this, but this is a significant finding in itself – for some reasons the middle-class minority population is not using its resources and/or do not have any interest to discover society beyond their concentrated (segregated) daily life. This means that the crucial middle class of the ethnic minority group has limited potential exposure to encounter and possibly interact with members from the majority group. Put differently, their limited and concentrated activity spaces indicates that there are fewer chances to establish the crucial weak ties with the majority population (Granovetter 1973) and to achieve upward social mobility (Faist 2013). Certainly, the middle class could potentially be more mobile in travelling abroad (e.g. to Russia in our case) instead of discovering the society. However, this does not reduce the finding that the middle class minority population seems to have fewer opportunities to be integrated into the society and tackle ethnic segregation.

So far, we have not reflected critically the quality and applicability of the data sources used in this research, as it was not the focus of this study. Both data sources certainly have drawbacks we should highlight. For example, mobile phone data do not represent the whole population; for various reasons, not everyone uses mobile phones (e.g. young children, the elderly, members of marginalised socio-economic groups) (Masso *et al.* 2019). Also, as addressed in Järv *et al.* (2014), the habits and patterns of using one's phone in space and time vary due to individual characteristics, which influenced the spatial analysis outcomes derived from the CDR data if they are not taken into account. For example, a social subgroup may have smaller activity spaces due to their less frequent phone usage pattern rather than due to their social background. We mitigated this bias by including phone usage variables in our model (Table 2). However, the CDR data can capture the spatial behaviour of people within an accuracy level of a city block every hour over a longer time and provide more nuanced understanding on (ethnic) segregation than we examined here. With survey data, the main issue is how people recall where they had been and how often (unintentional memory gaps) and how objectively they fill in surveys (intentional mistakes). However, we expect that biases have not had a significant influence on our empirical findings. At least the spatial mobility of individuals based on the survey data corresponds with findings based on the CDR data. Then again, a survey allows for better data capture on (ethnic) segregation while controlling for other social factors and interacting relations.

In conclusion, this study provides methodologically a fruitful step forward in studying ethnic differences in human spatial mobility from a person-based perspective. First, the dataset comparison confirms the suitability of both datasets in (ethnic) segregation research, and addresses the need for new data sources in the segregation domain in addition to census and register data (Shelton *et al.* 2015; Wang *et al.* 2018a). Second, findings indicate the need for future segregation studies to combine and take advantage of the strengths of both methods – mobile phone positioning for capturing accurate spatio-temporal mobility information, and a survey for collecting comprehensive social information. Third, additional variables and their interaction effects are needed to control the main segregation effect better, as we showed in our case that ethnic differences in human spatial behaviour is not straightforward and other underlying factors also have an influence (Table 3). Finally, findings indicate that ethnic differences in individual spatial behaviour are partly explained by socio-economic inequality. Thus, it confirms socio-spatial segregation thesis about the link between ethnic spatial segregation and socio-economic inequality. However, the link is not linear and depends on socio-cultural context. In the case of Estonia, it seems that ethnic inequality in human spatial mobility is interlinked with the subjective self-estimated affiliation to a perceived social layer.

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