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The association between neighborhood characteristics and mental health in old age – register based study of urban areas in three European countries

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Abstract

This study aimed to fill the gap in research regarding the longitudinal studies on the association between urban neighborhood characteristics and mental health of older populations. Individual level register-based data sets from Finland (10 largest cities), Sweden (Stockholm), and Italy (Turin) including satellite based land cover data were used. The data included sociodemographic individual information on population aged 50+, their antidepressant purchases, and socioeconomic and physical characteristics regarding area of residence. We followed individuals for antidepressant purchases for 5 years in 2001-2015, depending on dataset, and used hierarchical negative binomial models to assess whether there was an association between social and physical area characteristics and antidepressant use and to what extent was this association attributable to individual sociodemographic characteristics of the residents and whether the findings were consistent across countries. We found weak and inconsistent evidence of high levels of area characteristics related to dense physical urban structure being predictive of increased antidepressant use in ages above 50. However, generally the extent to which antidepressant use was clustered by areas in the studied contexts was minimal.

Introduction

The study of the effects of neighborhood characteristics on health and mental health has been extensive and growing in recent decades. Many of the studies on the topic have used neighborhood socioeconomic indicators aggregated from individual level as a proxy for specific social or physical features of neighborhoods. The evidence of spatial patterning of poor mental health by aggregated socioeconomic neighborhood characteristics is relatively clear but the results regarding the causality of the association have been inconclusive. (Diez Roux and Mair, 2010; Mair et al., 2008; Richardson et al., 2015) Majority of the studies on neighborhood characteristics and mental health are hampered by cross-sectional designs and even those with longitudinal designs show inconsistent results. However, particularly longitudinal studies with at least five years of follow-up suggest that there is no independent association between depression and neighborhood socioeconomic characteristics after individual sociodemographic characteristics are accounted for, while studies with shorter follow-up have reported a significant association (Richardson et al., 2015).

In recent years, instead of using neighborhood characteristics aggregated from population, studies have explored the associations more directly between physical characteristics of urban environment and mental health or psychological distress. (Generaal et al., 2019; Gong et al., 2016; Houlden et al., 2018; James et al., 2017) Measuring objective physical urban environment is difficult in survey settings but studies using register or satellite-based land use data suggest that green space in the neighborhood is beneficial to mental health although the findings are not always consistent. (Alcock et al., 2014; Astell-Burt et al., 2014; Gong et al., 2016; James et al., 2015) Evidence regarding land use mix or walkability is also mixed and inconclusive (Gong et al., 2016; James et al., 2017; Saarloos et al., 2011). It is suggested that the heterogeneity in the measurement of mental health outcomes, neighborhood characteristics and confounders explain the inconsistency of findings in different settings. (Generaal et al., 2019) It is also possible that to some extent the findings are dependent on national contexts or factors that affect the interaction of the residents with their urban surroundings as climate or cultural traditions regarding behaviour in public spaces.

Only few longitudinal studies have concentrated specifically on older population segments (Bierman, 2009; Mair et al., 2009; Moore et al., 2016; Wight et al., 2009), although it has been theorized that particularly older population may be more susceptible to neighborhood factors than other adults (Julien et al., 2012). These studies also reported mixed findings as three found no association between neighborhood social characteristics and depressive scores or changes in depressive scores (Mair et al., 2009; Moore et al., 2016; Wight et al., 2009) and the one found an association between neighborhood disorder and change in depression status among the non-married older population after two-year follow-up. (Bierman, 2009)

The vast majority of the studies exploring the association between mental health and urban environment in adult populations have used various validated survey questions to identify mental health outcomes and only few studies have taken advantage of register data, specifically individual level hospital discharge records for psychiatric care for the total population (Lofors and Sundquist, 2007; Sariaslan et al., 2015). However, to our knowledge only two studies have used individual-level register-based medication prescription data on antidepressants or anxiolytic medication as a proxy for mental health status of the individuals. Although neither of these studies specifically focused on the older population, one study with a cross-sectional design showed an association between mental health and presence of a segregating wall in the neighborhood (Maguire et al., 2016). The other study using longitudinal design showed that urban density and accessibility by public transport were slightly protective factors against antidepressant drug consumption. (Melis et al., 2015)

This study aims to fill the gap in research regarding the lack of longitudinal studies on the association between urban neighborhood characteristics, both socioeconomic and physical environment, and antidepressant use of older populations. The current study is conducted using register or census data sets from Finland (covering 10 largest cities in Finland: Helsinki metropolitan area [incl. Espoo, Kauniainen & Vantaa], Turku, Tampere, Oulu, Jyväskylä, Kuopio, Lahti), Sweden (Stockholm metropolitan area), and Italy (City of Turin). We aim to assess whether there is an association between socioeconomic and physical area characteristics and antidepressant use and to what extent is this association attributable to individual sociodemographic characteristics of the residents and whether the findings are consistent across countries.

The contribution to the knowledge regarding the topic is threefold. Firstly, when identifying mental health outcomes from linked medication registers covering the total population the problems related to self-rated mental health are absent (e.g.(Levinson and Kaplan, 2014)) as well as the non-response to surveys among the deprived and depressed population segments. Furthermore, problems arising from the recall bias, preferential reporting and loss to follow-up are absent in the measurement of individual level characteristics in these register data. Secondly, we can compare the prevalence of mental health outcomes in urban areas in various national contexts and to study whether the neighborhood characteristics are of differing relevance as predictors of mental health across countries. Thirdly, we have robust register based information on not only socioeconomic characteristics of the areas but also physical characteristics measured in a uniform and objective manner not suffering from same-source bias over several cities and national contexts by using European Urban Atlas and CORINE Land Cover project satellite imaging data. In sum, this study explores the association between antidepressant use and urban socioeconomic and physical environment using longitudinal design and large sets of register-based data including uniform measures on exposure, outcome and confounders in three national settings thereby overcoming problems stated in previous studies. (Generaal et al., 2019; Gong et al., 2016; Julien et al., 2012)

Data and methods

We use register-based data sets including individual level information on purchases or prescriptions of antidepressants as a proxy for the mental health disorders and area level data on neighborhoods' sociodemographic, economic and physical characteristics. The Finnish dataset is a nationally representative 11% random sample of all persons residing in Finland in at least one of the years between 1987 and 2007. The data combines information from various administrative registers and data on antidepressant drug purchases for years 1995-2012, which were obtained from the Finnish Social Insurance Institution's Prescription Register. Swedish data includes all persons residing in Stockholm urban area (Stockholm and 11 adjacent municipalities) in 2010 linked to registers including the Swedish medication register in 2011-15. Italian data originates from Turin Longitudinal Study (TLS) based on census records covering the total population of city of Turin in 2001 census and linked to prescription registers in 1998-2013. The analysis is limited to individuals aged 50+ and measure the individual characteristics in the baseline year. Physical-environmental characteristics of the areas are based on the European Urban Atlas (UA) and the CORINE Land Cover project (CLC) (Copernicus Land Monitoring Service, 2018). Data on the amount of green areas, land use mix, and urbanicity grade were derived from these databases and aggregated to the relevant neighborhood levels using a Geographic Information System (GIS). These characteristics were measured in in 2006 for Turin and 2012 for Stockholm and Finland.

Individual level variables

The outcome variable was defined as number of years individual had at least one purchase of antidepressants after baseline. In Finland the individuals were followed after baseline of 2003 for years 2004-2008, in Turin baseline was 2001 and follow-up 2002-2006 and in Stockholm baseline 2010 with follow-up of 2011-15. We included codes N06A in the Anatomical Therapeutic Chemical Classification (ATC). In order to focus on depression, tricyclic antidepressants (codes N06AA but not N06AA22) were excluded as they are often used for non-psychiatric indications at older ages (Gardarsdottir et al., 2007).

Individual level characteristics accounted for at baseline include sex, age, education (high [International Standard Classification of Education ISCED 2011 levels 5-8], intermediate [ISCED 3-4], and basic [ISCED 0-2]), economic activity (employed, unemployed, retired, other), marital status (married, single, divorced, widowed), housing tenure (owner, renter, other), household composition (living alone, others).

Area level variables

The area level used in the analysis is postal code (zip-code) area or equivalent with median population between 4252 (IQ range 2079-7156) of Finland and 6944 (IQ range 2553-12962) of Turin. In the Finnish data set the included urban areas consist of 380 postal code areas, in Stockholm metropolitan area there are 244 'city parts', and in Turin 94 statistical zones. All areas are based on administrative boundaries. In Turin four areas were excluded from the analysis as they had very low number of residents aged 50+ (<100).

Measured characteristics of these areas include aggregated information from register or census data on sociodemographic composition of population: proportion of residents with only basic education, proportion of households living in rented dwelling and unemployment rate. The physical characteristics of the areas derived from UA and CLC data sets consist of following variables: proportion of green areas (forests and parks) of the total area of neighborhood, proportion of continuous urban fabric of neighborhood, population density (residents per square kilometre) and land use mix (LUM) indicated by entropy index which varies between 0 when the area has only one use and 1 when all uses are evenly present in the area.

$$LUM = -\sum_{i=1}^{k} \frac{P_i \times \ln(P_i)}{\ln(k)}$$

, where k is the number of land-use categories and p is the proportion of use i in the area. (e.g. (Cervero and Kockelman, 1997))

These variables are used in the analysis as dichotomized with median as cut point. Therefore both categories contain same amount of areas. In addition, the Finnish models include covariate for city to account for differences between the ten cities included in the analysis

Statistical methods

We estimated negative binomial models with number of years during follow-up that individual had at least one antidepressant purchase as the outcome. The exposure variable was the number of years present in the population from baseline year until latest year with information or being censored due to death or emigration. The used models were random intercept multilevel models in which the individuals were nested in areas. We estimated incidence rate ratios (IRR) for area level socioeconomic and physical environment indicators from models including 1) only each area indicator, 2) each area indicator including individual level covariates , 3) full model with all area and individual covariates. In order to assess the magnitude of clustering of mental health problems across areas, and not only the associations of specific area characteristics, we also estimate median incidence rate ratios for these models. This metric describes the median relative change in the incidence rate when comparing two identical individuals from two random areas that are ordered by areal incidence rate. (Austin et al., 2018; Merlo et al., 2018)

Results

The age-adjusted incidence rates for antidepressant purchases are roughly similar in Turin and Finland with females having higher rates than men (Table 1). Results regarding Stockholm were not yet ready for reporting in this manuscript version. The patterning of the rates by sociodemographic factors is clear in Finland whereas in Turin groups like basic educated, unemployed and renters have lower rates than more privileged groups.

Socioeconomic area characteristics in Turin show bivariate associations with confidence intervals not overlapping IRR 1.00 for unemployment rate and proportion of persons with only basic education in the area (Figure 1). After adjustments both remain statistically significant and show that in the areas with high proportion of basic educated the IRR for antidepressant use is 0.95 (95% CI: 0.90-0.98) and for unemployment the IRR is 0.94 (95% CI: 0.90-0.98). In Finland the IRR for proportion of renters was 1.15 (1.10-1.21) before adjustment but when individual characteristics were included the IRR was bordering on being significant 1.05 (1.00-1.10). However, after individual adjustments areas with high unemployment rate and proportion of basic educated had lower AD use with IRRs of 0.95 (0.91-0.99) and 0.94 (0.90-0.98), respectively. After including all individual and area characteristics the IRR for education remained statistically significant at 0.94 (0.89-0.99).

Bivariate associations of physical area characteristics were all statistically significant at 95% level in Finland with higher proportion of green areas predicting lower AD use (IRR 0.93; 0.88-0.97) and higher levels of population density, urbanicity and mixed land use predicting higher AD use with IRR ranging from 1.18 (1.11-1.25) of population density to 1.10 (1.04-1.15) of land use mix. After adjusting for individual characteristics only population density and land use mix remained significant on 95% level with IRRs of 1.11 (1.05-1.17) and 1.05 (1.00-1.10), respectively. When all variables were included the population density had IRR of 1.08 (1.02-1.15).

The median incidence rate ratio for model without any explanatory variables was 1.010 in Turin and 1.011 in Finland meaning that incidence rate was on average 1% higher for individuals in areas with higher incidence rate for using antidepressants. When all individual and area variables were included in the model, MIRR decreased even further to 1.003 and 1.006 in Turin and Finland, respectively.

Discussion

We observed bivariate association between proportion of households in rented dwellings and antidepressant use in Finland and inverse associations between antidepressant use and unemployment rate and proportion of basic educated residents in the area in Turin. After individual and other area characteristics were accounted for the inverse associations remained in Turin and occurred also in Finland. Bivariate associations were observed for all physical environment characteristics in Finland so that higher levels of green areas decreased the rate for AD use and high population density, urbanicity and land mix increased AD use. After all adjustments only population density remained as the statistically significant predictor of AD use. No physical characteristics were associated with AD use in Turin. Despite weak to moderate associations of specific area characteristics with AD use, the extent to which antidepressant use was clustered by areas was very low. Residents of areas with higher rate of antidepressant use have only on average 1% higher incidence rate compared to areas with lower rate. It appears that even when the mental health status, individual and neighborhood characteristics were measured in a uniform manner in different urban and national contexts, the results regarding these associations are inconclusive. On the other hand, the only consistent finding across cities was that the clustering of antidepressant use by areas was very low.

High levels of physical area characteristics related to dense urban structure were predictive of more AD use in Finland. This was also observed in Turin but not statistically significantly. These findings are in line with previous studies reporting higher prevalence of depressive disorders in urban than rural areas and that population density is associated with depression among the elderly population (Peen et al., 2010; Walters et al., 2004). Higher land use mix has also been found to be associated with higher rates of depression among older men in Australia (Saarloos et al., 2011). On the other hand, contradicting results exist as well suggesting that urbanization or population density is not associated with poor mental health (Generaal et al., 2019; Saarloos et al., 2011). Most of the physical area characteristics included in this study were correlated with each other and accounting for all of them in the last model attenuated their associations with AD use. However, even after mutually adjusting for these characteristics, population density was the only characteristic that had an independent association in Finland and was bordering on being statistically significant on 95% level in Turin. This suggests that population density accounts for most of the association between urbanicity and mental health.

The inverse associations between AD use and area unemployment rate and proportion of basic educated observed in Turin are rather surprising. This inverse association between area socioeconomic characteristics and mental health status has not been reported using other mental health outcomes e.g. depressive scores. It may be that these area characteristics are either protective from poor mental health or that residents of these areas are less likely to seek treatment for mental health problems or that depression is not diagnosed or treated with antidepressants as likely as in other areas. The fact that the association between education and antidepressant use in the population aged 50+ when all characteristics are adjusted is also inverse on the individual level (results not shown here) implies that the process does not only originate from the area level. This suggests that individuals living in these areas are likely to have personal characteristics not adjusted for in this study that predict lower probability for either mental health problems or to seek or receive treatment for such problems.

No statistically significant effect of green areas was observed in the studied age group after accounting for individual level characteristics. This is partially in contrast to previous studies, many of which have reported such an association but often with different mental health outcomes and age ranges or small sample sizes (Gascon et al., 2015). However, the effect of green areas may differ along life course and be particularly pronounced in childhood and adolescence (Astell-Burt et al., 2014; Engemann et al., 2019). Elderly population has been thought to generally spend more time in their residential area so the absence of effects of green areas in these ages warrants more detailed studies on this issue. However, the fact that green area shows no bivariate association in Turin is possibly due to the less variance in the measure in

Turin. In Finnish cities and Stockholm there are more areas with high proportion of green areas whereas in Turin the green areas are less common in general.

Strengths and limitations

When identifying mental health outcomes from linked medication registers covering the total population the problems related to self-rated mental health are absent e.g. (Levinson and Kaplan, 2014) as well as the substantial non-response to surveys among the deprived and depressed population segments. Furthermore, problems arising from the recall bias, preferential reporting and loss to follow-up are absent in the measurement of individual level characteristics in these register data.

Whether the antidepressant prescription or purchase is an accurate proxy of individual's mental health status is dependent on various factors. Differential access to antidepressants (access to mental health care, cost of medication, reimbursements) in countries and areas may affect the willingness to seek treatment for mental health issues. However, reduced access to health care is unlikely to have major effect on our measurement of mental health given that all the studied countries have universal healthcare and the cost of the medication is either heavily subsidized or completely free. Determining area unit most relevant for individual perception of neighborhood is challenging and it is likely that administrative areas used in this study do not coincide to the residents' perceptions of their area of residence. This is likely to dilute the real effects of the area characteristics and result in conservative estimates being reported in this study.

Determining the causality of the observed associations is not possible with these data. The onset of depression occurs often much earlier in life than after age 50, therefore those using antidepressants in this study may have had spells of mental health problems already before baseline. Previous spells may affect the location of residence as individuals with mental health issues are likely to end up living in more dense neighborhoods because they have less financial resources to begin with or due to their condition. Or specific personal characteristics (personality traits, genetic predispositions) may increase probability of both residing in areas with high population density and being more susceptible to depression (Jokela et al., 2015; Klein et al., 2011). We may have not been able to account for all individual level confounders of the association in this comparative analysis. We conducted a sensitivity analysis with the Finnish data in which we included more individual level characteristics, such as retrospective occupational social class, income level at baseline, and health status (measured with hospital discharge records 5-years before baseline).[This analysis has not yet been conducted for this manuscript]

Our study population includes also persons who have not yet retired from employment and may be less exposed to the area of residence. To account for this we conducted sensitivity analysis with only population aged 65+ with all datasets. The results didn't change much but due to wider confidence intervals some associations, e.g. inverse association with education, were non-significant.

Conclusions

We found weak but inconclusive evidence of area characteristics related to dense physical urban structure being predictive of higher antidepressant use in ages above 50. However, generally the extent to which antidepressant use was clustered by areas in the studied contexts was minimal. The study also showed that the origin of mixed findings regarding mental health and socioeconomic and physical area characteristics go beyond the uniform measurement of exposure, outcome and confounders.

Table 1. Proportions of persons at baseline and age-adjusted incidence rates (per 1000) for antidepressant purchases by individual characteristics in Turin, Finland, Stockholm and Turin

		% of persons			Rate		
		Turin	Finland	Stockholm	Turin	Finland	Stockholm
Age (average)		66.1	67.9				
Sex							
Male		43	42		80.6	85.8	
Female		57	58		139	131.3	
Education							
Basic		73	44		113.7	115.2	
Intermediate		17	26		116.3	113.0	
High		10	30		115.3	109.3	
Marital status							
Never-married		8	12		106.2	107.2	
Married		66	55		111.4	100.8	
Divorced		20	19		127	135.2	
Widowed		6	15		127.6	136.9	
Household composition							
Living alone		26	32		124.8	135.8	
Other		74	68		111.6	102.3	
Housing tenure							
Owner		71	70		114.4	105.4	
Renter		25	26		112.3	135.9	
Other		4	6		121.5	120.2	
Economic activity							
Employed		21	38		97	72.3	
Unemployed		2	5		74.2	105.5	
Retired		52	53		109.2	160.2	
Other		26	3		141.5	92.1	
N		347647	94345				
Unemployment	Low				119.4	114.2	
	High				109.7	112.5	
Basic education	Low				119.9	114.2	
	High				110.9	112.0	
Households renting	Low				114.8	106.1	
	High				113.7	116.1	
Population density	Low				111.8	101.9	
	High				115.1	116.2	
Green areas	Low				115.3	114.7	
	High				113.1	111.1	
Urbanicity	Low				112.2	108.2	
	High				115.2	115.5	
Land use mix	Low				113.9	110.0	
	High				114.5	115.0	

Figure1. TURIN IRRs for area level characteristics (<u>the half below median is always the reference category</u>) from three models 1: Only each area variable in the model 2: each area variable and all individual characteristics 3: all area and individual characteristics

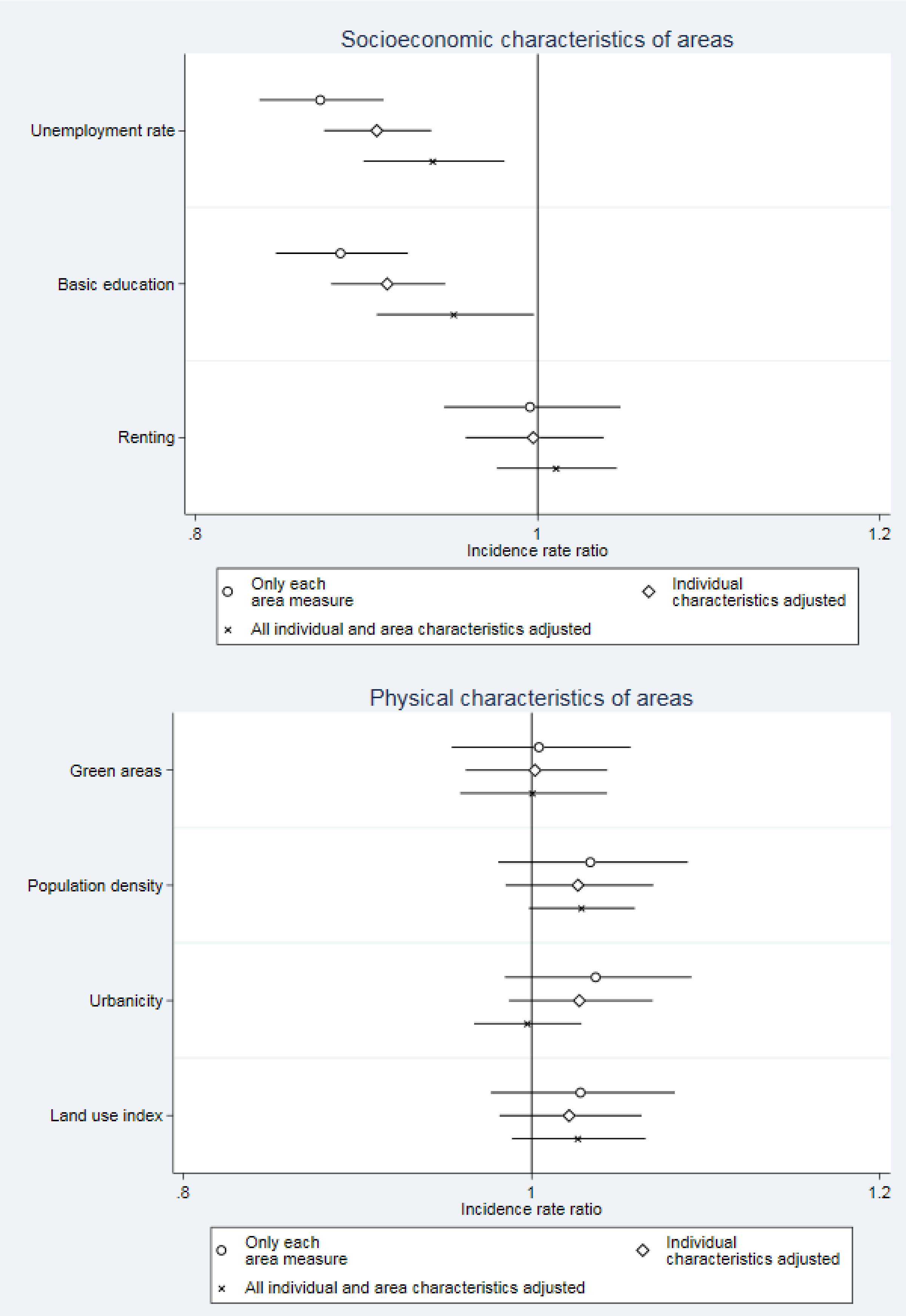
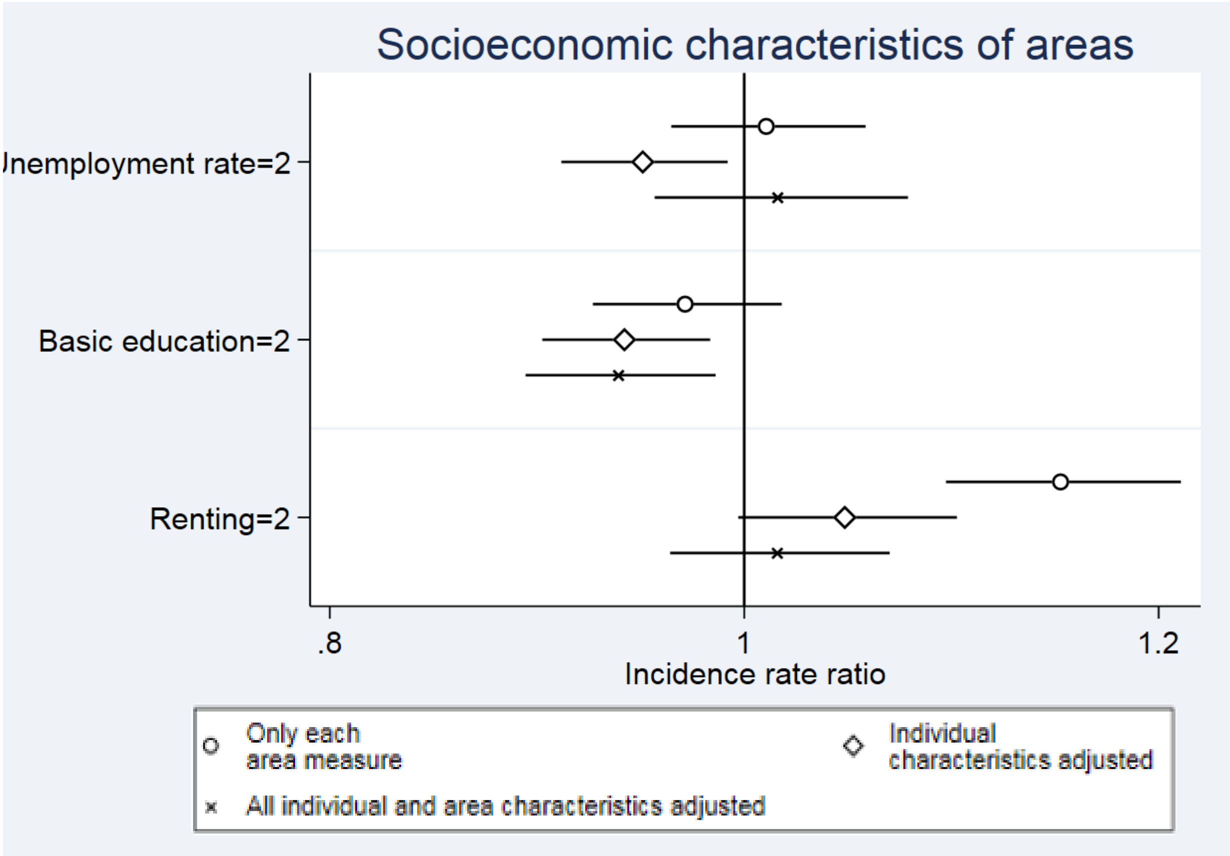
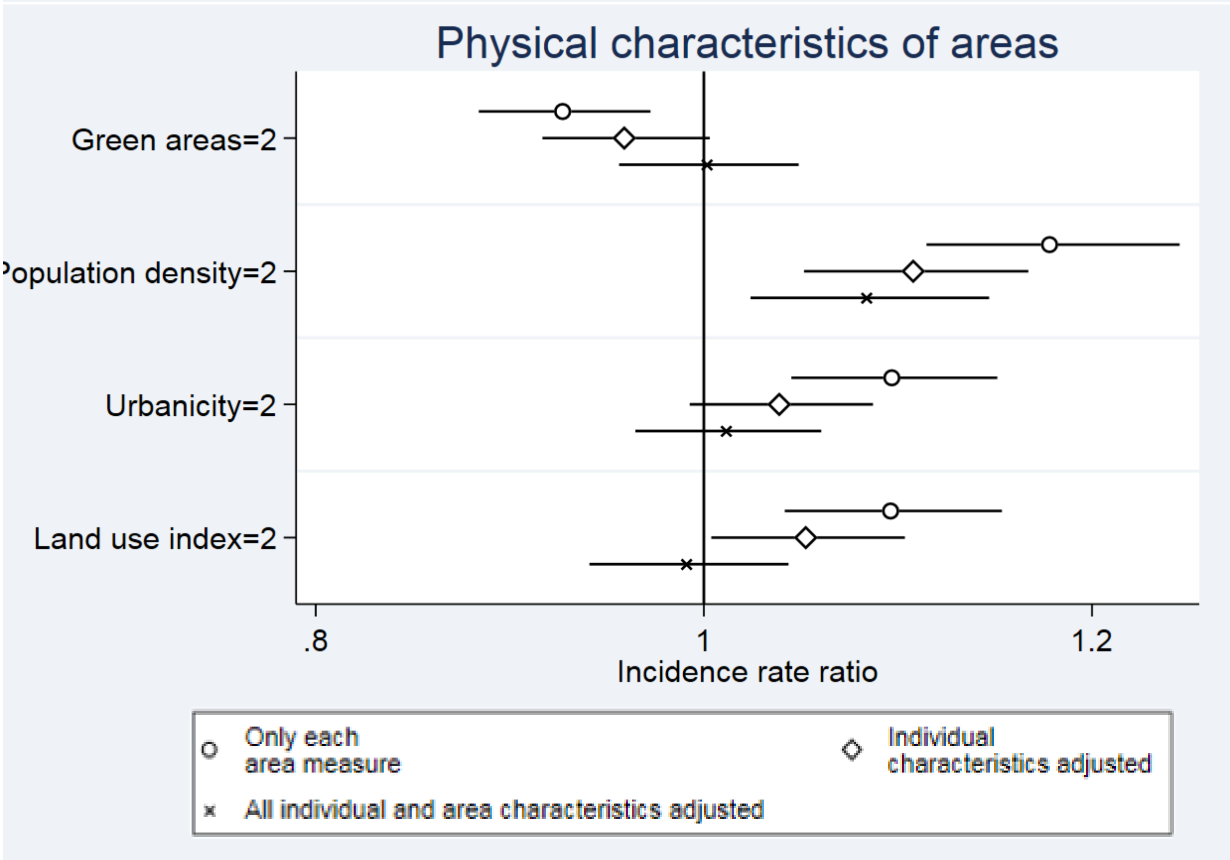


Figure 2. FINLAND IRRs for area level characteristics (<u>the half below median is always the reference category</u>) from three models 1: Only each area variable in the model 2: each area variable and all individual characteristics 3: all area and individual characteristics





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