SPATIAL SEGREGATION OF IMMIGRANT HOUSEHOLDS IN MESSINA

*Segregazione spaziale delle famiglie di immigrati nella città di Messina*

Angelo Mazza and Massimo Mucciardi

**Abstract** We investigate spatial segregation of the most representative groups of foreign immigrants in the city of Messina.

We use spatial modeling with point level data to assess attraction among migrants’ households of the same ethnicity while adjusting for spatial inhomogeneity in the cost of housing, job availability and other factors. This work is still in progress; first results show more dispersed settlements patterns for ethnicities more involved with household services than for those devoted to commerce and peddling.

**Abstract** *In questo lavoro vengono analizzati i modelli insediativi dei gruppi di immigrati più rappresentativi nella città di Messina. Attraverso l’impiego di modelli spaziali per dati puntuali misuriamo l’attrazione tra nuclei familiari della stessa etnia, al netto delle eterogeneità spaziali nel costo degli affiti e nella disponibilità di lavoro. Il lavoro è ancora in progress; i primi risultati mostrano modelli insediativi meno concentrati per quei gruppi etnici maggiormente coinvolti nei servizi alle famiglie rispetto a quelli maggiormente impegnati nel commercio e nella vendita ambulante.*

**Keywords:** Spatial Clustering, Voluntary Segregation, Migrant Households

Introduction

Ethnic residential segregation has long been investigated in the USA and South Africa; however, only recently this topic has become prominent in Europe as well, following from a debate that links segregation with the perceived failure of integrating immigrants into host societies (Kalandides and Vaiou, 2012, Andersson, 2013). A minority ethnic group is segregated when the arrangement of minority households departures from expectations based upon a random spatial allocation. Following Schelling (1971), we distinguish two sources of spatial segregation. The first is mostly economically induced, and it is mainly ascribed to within-city inhomogeneity in the price of residential property, and in the availability of jobs. The second is attraction, i.e., individuals prefer living in areas where their group is a majority or near-majority (Clark and Fossett, 2008). Moreover, newly arrived minority migrants may benefit from positive spillovers in settling close to their compatriots, and transnational social networks play an important role in channeling arriving migrants into specific neighborhoods.

Whereas economic induced segregation might explain some initial degree of segregation and raises questions of social equity, the Schelling (1971) model highlights the importance of individually motivated segregation and posits that even mild preferences for living with similar neighbors carry the potential to be strong determinants for residential segregation (Clark and Fossett 2008).

From a methodological point of view, traditional indices of spatial segregation rely on data aggregated by areal unit, typically census tracts (Mazza and Punzo, 2015; Mucciardi, Mazza and Altavilla, 2017); however these analyzes could suffer from the modifiable area unit problem (i.e., alternative zoning or a different scale may yield different results; see Openshaw, 1984 and Wong, 2009) and do not allow to distinguish between the two sources of segregation. Instead, in this paper, we use individual point data, and we apply the inhomogeneous K-function (Baddeley et al., 2000), which allows assessing spatial attraction among migrants while adjusting for spatial inhomogeneity (Mazza and Punzo, 2016). To avoid the risk of confounding the two sources of clustering, spatial inhomogeneity is estimated following a case-control approach. Cases will be, in turn, migrants of each nationality, while the controls will be a random sample of native household locations.

The model: the inhomogeneous K-function

The spatial distribution of household locations may be represented by a point pattern. The simplest theoretical model for a spatial point pattern is the homogeneous Poisson process (HPP), in which the expected number of events occurring within a unitary region $u\in R$ follows a Poisson distribution, whose intensity $λ\left(u\right)$ is uniformly distributed over R (Diggle, 2003). The inhomogeneous point process (IPP) is a generalization of the HPP obtained replacing the constant intensity $λ$ by a spatially varying intensity function $λ\left(u\right)$; clustered patterns occur, with regions where $λ\left(u\right)$ is higher receiving a higher number of events. Ripley’s *K*-function, usually denoted with $K\left(d\right)$, is used to detect clustering (or inhibition) in point processes with constant intensity; at every spatial distance $d$, $λ$ $K\left(d\right) $is the expected number of additional points of the process X located in a circle $b$ of radius $d$ surrounding an arbitrary event $x$. Baddeley et al. (2000) generalized Ripley’s K-function to non-homogeneous point processes, by weigthing each point$ x\_{j} $by $w\_{i}=\frac{1}{λ\left(x\_{i}\right)}$ . The inhomogeneous K-function is defined as

$ K\_{inhom}\left(d\right)=E\left[\sum\_{x\_{j}\in X}^{}‍\frac{1}{λ\left(x\_{j}\right)}1\left\{0<\left‖u-x\_{j}\right‖\leq d\left|\right.u\in X\right\}\right]$ (1)

where $\left‖u-x\_{j}\right‖ $is the Euclidean distance between points $u$ and $x\_{j}$ and 1{…} is the indicator function. Clustered point patterns arise from the joint action of spatial inhomogeneity and spatial attraction. To distinguish between these two sources is challenging task, since many spatial processes are “equifinal”, i.e. one realization of a point process may be consistent with underlying processes involving clustering due to either spatial inhomogeneity or spatial attraction (Harvey, 1966). Mazza and Punzo (2016) deal with this issue using a case-control approach. In case-control studies, data consist of a realization of two spatial point processes, one representing cases of a condition of interest and the other representing controls drawn at random from the population at risk. Assuming that the size of the population at risk tends to infinity and the sampling fraction to zero, the controls constitute a realization of an IPP with intensity $λ^{\*}(u)$; the cases form a second, independent, point process – which may or may not be a Poisson process – with intensity $λ(u)$. The question of interest is whether the cases form an IPP with intensity proportional to that of the controls, i.e., $(u)=ρλ^{\*}(u)$, or whether they exhibit additional spatial structure.

Diggle et al. (2007) propose that the ratio between the intensity functions may be modeled to depend on a vector of m spatially referenced covariates

$ z\left(u\right)=\left(z\_{1}\left(u\right),…,z\_{m}\left(u\right)\right)^{'}$, i.e. ; $λ(u)=λ^{\*}\left(u\right)f\left(z(u);θ\right)$ (2)

where $f\left(⋅\right)$ is any nonnegative function, either nonlinear parametric with parameters θ as in (2), or nonparametrically specified.

Our controls are a random sample of native household locations, and economic constraints are taken into account through explanatory spatial covariates related to the cost of residential property and job availability.

Data at hand come from the administrative register of the city of Messina, at December 31, 2016. Register data have been integrated within a geographical information system, and all the residential addresses geocoded. Other data used are the rent cost per square meter for private residential properties, as collected by the Italian Revenue Agency (OMI database). Computations are carried out by means of the spatstat package (Baddeley and Turner, 2005) for the R computing environment (R Core Team, 2017).

Main results

Our investigation will cover the most representative groups of foreign immigrants in the city of Messina. We expect a differentiated spatial trend for the different nationalities, with higher values in the more central parts of the city for those groups involved mainly in retailing and peddling activities. We will compute the estimates for the inhomogeneous *K*-function at various distances $d$. We will also report confidence envelopes based on Monte Carlo simulations for the null hypothesis of absence of interaction. First results show more dispersed settlements patterns for ethnicities more involved with household services than for those devoted to commerce and peddling.Furthermore*,* a higher spatial attraction emerges for those groups for whom the effects of chain migrations and family reunifications have been stronger.

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