Residential Urban Overcrowding in Alexandria, Egypt: A Spatial Econometrics Analysis

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Although residential crowding has various impacts on household socioeconomic and health circumstances, there has been a dearth of research investigating and predicting spatial patterns of overcrowding in Arab nations. In this work, analytical modeling techniques are applied to investigate the interrelationships between residential overcrowding and other explanatory variables in Alexandria, Egypt. Global (Ordinarily Least Squared) and local (Autoregressive, Error Term and Geographically Weighted regression) models are employed to conduct the analysis. As global model, OLS assumes homogeneity among spatial predictors and it fails to account for spatial non-stationary. In contrast, the proposed local spatial econometric models can easily model spatial autocorrelation and spatial heterogeneity. Population density and one-room-dwelling were found to be positively and significantly associated with overcrowding, while higher education of residents and five rooms dwelling were negatively related to residential overcrowding across Alexandria districts. Significant implications ranging from governmental subsidy to planning public housing are discussed.

INTRODUCTION

Residential overcrowding has recently become a major public policy issue (Gooding, 2016; Cobbinah & Aboagye, 2017). Although there are currently more than one billion people worldwide living in inadequate housing conditions, this number has been growing rapidly as a result of urban growth trends and sprawling (UN-Habitat, 2004). In most cities of developing countries, there has been an expansion of slums and unplanned residential areas. Such areas are generally characterized by a lack of access to basic daily needs such as potable water, electricity and sanitation facilities (Brueckner, 2000). For example, it is estimated that African countries need approximately 4 million housing units per year in urban areas where over 60 % of housing demand is reported (UN Habitat, 2015). Similarly, in New Zealand it is estimated that 10.5% of households are exposed to housing overcrowding (1+ bedroom deficit). Analyzing census data indicated the prevalence of this phenomenon worldwide (Baker et al, 2006; Gilbert, 2014; Olmos & Garrido, 2007).

High housing price in both developing and developed countries is regarded as a major cause of household overcrowding. For example, in the USA and Canada, higher rates of housing overcrowding are reported in clustered urban zones (Haan, 2011). In developing nations, demographic conditions such as population growth and dynamic urbanization have led to a significant impact on residential overcrowding (Dhonte et al., 2000). In Egyptian urban areas, unplanned settlements have been predominantly expanding in most neighborhoods and districts of major cities. A recent study addressing accessibility to infrastructure services in an Egyptian urban area found that local residences lack basic services due to residential overcrowding (Bremer and Bhuiyan, 2014).

Previous research investigating residential overcrowding has focused on countries as diverse as the U.S.A. (Haan, 2011), New Zealand (Arbury, 2005), Nigeria (Barredo and Demicheli, 2003), Mauritius (Gooding, 2016), Spain (Olmos and Garrido, 2007), and China (Zhang and Chen, 2014). However, to the best of our knowledge, no previous studies have been conducted to investigate residential overcrowding in Egypt. In this research we fill this research gap by assessing the effect of salient demographic factors related to residential overcrowding in Alexandria, Egypt. Thus, we aim to contribute significantly to the growing literature on residential overcrowding since research findings "can be important if they confirm or disconfirm a theoretical principle" (Rossiter, 2003, p. 86). More specifically, we aim to extend the existing debate regarding residential overcrowding in two ways: first, we investigate residential overcrowding in the second largest city in Egypt, which makes it possible to generalize results to other Middle East cities. Second, we use several spatial econometrics modeling approaches to check the robustness of our finding. We also compare traditional OLS results against established spatial models such as SAR, SEM and GWR models.

This paper is organized as follows. Next section reviews relevant literature and develops research hypotheses. Methodology used to conduct the research follows. Section four presents spatial econometrics results, while the final section presents a general discussion focusing on research implications, limitations and directions for future research.

LITERATURE REVIEW AND HYPOTHESES

The rapid expansion of urbanization and its influence on housing overcrowding has been extensively investigated in the literature (Cohen, 2004; Zhang and Chen, 2014; Barredo, & Demicheli, 2003). Much attention has been paid to socioeconomic indicators influencing residential overcrowding (Arbury, 2005; Sudhira et al. 2004; Goux & Maurin, 2005, Wan & Su, 2016; Yeh & Xia, 2001). Factors investigated also included urban population densities, educational level, number of rooms per dwelling, production and consumption economies of scale, car usage, etc. (Alig et al., 2004; Kasanko et al., 2005; Oh et al., 2005; Tan et al., 2008).

Fu (2001) argues that population density represents an important concern for both policy makers and academic researchers. It is generally acknowledged that American and European urban densities are lower than their African or Asian counterparts (Tan et al. 2008). Although there is a large variation in the definition of urban population density, researchers in fields as diverse as regional economics, urban planning, geography and land use policy have constantly reported a positive and significant relationship between urban population density and overcrowding (Li, Sato & Zhu, 2003; Camagni, Gibelli & Rigamonti, 2002; Williams, 1999). Densely-populated urban areas have been linked also to overcrowding, excessive congestion and social problems (Chan, Tang & Wong, 2002). In an empirical study conducted in China, Chen and Lotspeich (1988) found that urban population density in cities such as Shanghai and Beijing is responsible for dwelling overcrowding, serious traffic congestion and various environmental problems such as water shortage, water and air pollution.

The most compelling evidence linking educational level to urban overcrowding is found in studies conducted by Manjengwa, Matema & Tirivanhu (2016) and Mugisha (2006). In the first study, the authors argue that densely-populated urban areas are generally linked to low educational attainment and poverty. The authors also argue that higher educational levels increase the likelihood of moving to less crowded areas as education allows people to get quality employment with better remuneration usually not found in densely populated urban areas. The authors also reported a positive relationship between illiteracy and "the likelihood of a household falling into poverty" (Manjengwa, Matema & Tirivanhu, 2016, p. 33). Mugisha (2006, p. 472) found that people living in densely-populated urban areas usually do not “benefit from the urban advantage” because of the lack of quality public amenities such as health facilities and schools.

Previous research has also reported a positive correlation between densely-populated urban areas and small dwelling size (Burton, 1997), which could have a negative impact on the general quality of life (Dave, 2011; Troy, 1996; Millward & Mostyn, 1989). In a recent empirical study conducted in England, McCulloch (2012) found that areas characterized by low overcrowding rate enjoy more spacious dwellings with large number of rooms. The author also found a negative correlation between density and satisfaction among families with young children. In the former study, the author measured housing density by dividing the number of household spaces by the spatial area. In our study we use one-room dwelling as a proxy for high housing density and five-room dwelling to represent low housing density. The discussion presented above suggests the following hypotheses:

H1: Neighborhoods that exhibit higher population density are more likely to suffer from residential overcrowding.

H2 a: Household members with no formal educational level are more likely to live in more overcrowded dwellings.

H2 b: Household members with higher educational level are more likely to live in less overcrowded dwellings.

H3 a: The smaller the number of rooms in each dwelling, the higher the overcrowding rate.

H3 b: The larger the number of rooms in each dwelling, the lower the overcrowding rate.

METHODS

Ordinary Least Squares (OLS)

Assuming a stationary relationship across the study area, OLS regression is a global linear technique that is used to estimate the relationship between a dependent variable and explanatory variable/s. This model can be represented by equation (1) as follows:

$$Y= b_0 + b_1 x_1 + b_2 x_2 +\ldots + b_n x_n + e \quad (1)$$

Where Y is the response variable, X_n represent the set of one or more independent variables, b_0 is the intercept and b_1 is the parameter estimate for variable 1. Within an OLS context, Moran’s I can be used to detect spatial dependency. Moran’s I statistic can be computed using equation (2) as follows:

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (2)$$

where $\bar{x}$ is the mean of the x variable, w_{ij} represent the weight matrix elements and S_0 represents the sum of the elements of the weight matrix ($S_0 = \sum_i \sum_j w_{ij}$).

Spatial Autoregressive Regression (SAR) and Spatial Error Model (SEM)

In contrast to OLS, both SAR and SEM can deal with spatial autocorrelation and heterogeneity. This can be achieved by incorporating spatial lags into the model. A spatial lag is simply a weighted average of each data points with neighbors. The weight matrix, which plays an important role in accurate estimations, is based on the spatial lag concept (Plumper & Neumayer, 2010). Following Klemm and Van Parys (2012), the reciprocal geographic distance between two neighbors i and j was used to build the spatial weight matrix.

Formally, a SAR model is expressed in a matrix notation as shown in equation (3)

$$y = \lambda \mathbf{W} y + X\boldsymbol{\beta} + \varepsilon \quad (3)$$

while a SEM regression maybe written as:

$$y = \mathbf{X\beta} + \mathbf{u} \tag{4}$$

$$u = \rho\mathbf{Wu} + \varepsilon \tag{5}$$

where y is a dependent variable vector, $\boldsymbol{\lambda}$ is a spatial lag parameter to be estimated, **Wy** is a vector of spatial lags of the dependent variable y, **X** is a vector representing the independent variables in the model, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, $\boldsymbol{\varepsilon}$ and **u** are error term vectors, ρ is a spatial lag regression parameter to be estimated and **Wu** is vector representing spatial lags of the disturbance term **u**.

Geographically Weighted Regression (GWR)

Unlike OLS which assumes that spatial processes are stationary, GWR approach can be used to estimate local regression parameters (Fotheringham et al. 2003). It thus corrects for a major problem in OLS models which assume stationarity and thus their results can "mask the processes being studied because they give an average picture of the relationship between the predictor and the response factors" (Osborne, Foody, & Suarez-Seoane, 2007, p. 314). GWR is likely to attain higher performance/explanatory power compared to OLS and it can also lead to a new interpretation of the study phenomena. The GWR model is defined by equation (6).

$$y = \sum \beta\,(\rho_i) + \varepsilon \tag{6}$$

where ρi is the geographic location of observation i. In GWR, each parameter is expressed in terms of its spatial location.

RESULTS

SAR and SEM Models

We commenced the analysis by conducting a traditional OLS Regression. We examined the OLS residuals for spatial autocorrelation using Moran's I statistic. The value obtained (0.380, $p < 0.001$) is sufficient to cast doubt over the standard OLS estimates. To correct for this, we implemented both a spatial autoregressive regression (SAR) and a spatial error model (SEM). The two models are the most widely used among spatial econometric models (Hao & Liu, 2015; Voss, Long, Hammer, & Friedman, 2006).

Coefficients of OLS, SAR, and SEM regressions are shown in Table 1. Moran's I statistic for SAR and SEM residuals were not significant (0.052, $p = 0.808$) indicating that spatial econometric models have accounted for spatial autocorrelation. Since the comparison between AIC values is the basis for selecting a spatial model (Anselin, 1988), the SEM seems to outperform the SAR model as indicated by a lower AIC value in Table 1. Figure 1 compares the OLS, SAR, and SEM residuals. From this graph we see that whereas there is a clear pattern of spatial autocorrelation in the OLS residuals, there is negligible spatial pattern in both the SAR and the SEM residuals. However, it should be noted that there is a strong correlation between the OLS, SAR, and SEM residuals.

TABLE 1
OLS, SAR, AND SEM COEFFICIENTS
OLS

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.095000	0.002974	36.819	< 0.001
Density	0.000004	0.000001	2.650	0.009
Illiteracy	0.003821	0.000914	4.180	< 0.001
Higher Ed	-0.005535	0.000906	-6.107	< 0.001
One room	0.008785	0.000151	5.789	< 0.001
Five room	-0.003603	0.000440	-8.178	< 0.001

R^2 = 0.758

SAR

Coefficients	Estimate	Std. Error	Z value	Pr(>|Z|)
(Intercept)	0.654850	0.008197	7.988	< 0.001
Density	0.000005	0.000001	3.242	0.001
Illiteracy	0.002978	0.000817	3.645	< 0.001
Higher Ed	-0.003789	0.000849	-4.461	< 0.001
One room	0.009886	0.000134	7.334	< 0.001
Five room	-0.002668	0.000421	-6.35	< 0.001

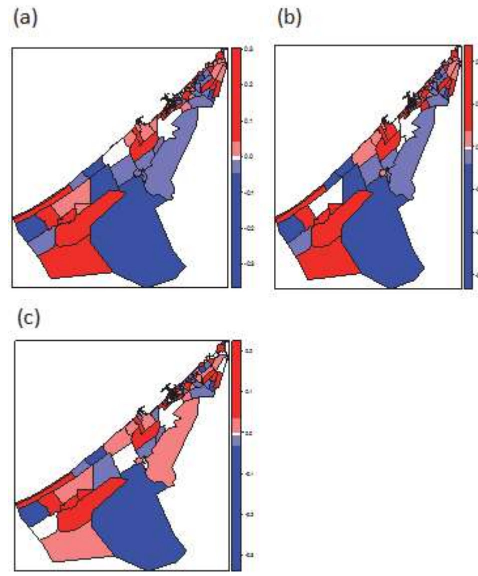
Rho = 0.3778
AIC = -318.35 (AIC for OLS = -292.97)
Log likelihood = 167.17

SEM

Coefficients	Estimate	Std. Error	Z value	Pr(>|Z|)
(Intercept)	1.111600	0.003104	35.812	< 0.001
Density	0.000007	0.000001	1.525	0.009
Illiteracy	0.002895	0.000777	3.723	< 0.001
Higher Ed	-0.004686	0.000925	-5.065	< 0.001
One room	0.009936	0.000123	8.056	< 0.001
Five room	0.003968	0.000581	-6.826	< 0.001

Lambda = 0.616
AIC = -330.97 (AIC for OLS = -292.97)
Log likelihood = 173.49

FIGURE 1
OLS RESIDUALS (A), SAR RESIDUALS (B), SEM RESIDUALS (C)



From Table 1 it is also clear that almost all coefficients for study variables are smaller in spatial regression models compared to the traditional OLS model. This implies that ignoring land prices' spillovers in adjacent districts can falsely inflate the exogenous variables impact. In fact, it is well-documented that OLS coefficients are biased in the existence of spatial autocorrelation (Goffette-Nagot, Reginster, & Thomas, 2011).

GWR Model

To check the robustness of our findings we also conducted a geographically weighted regression (GWR). This modeling method allows parameter estimates to vary over space (Bitter, Mulligan, & Dall'erba, 2007). Following Megler, Banis, and Chang (2014), we use an adaptive Gaussian kernel bandwidth since crowding rates in Alexandria are not evenly distributed over space. Figure 2 maps the GWR resulting coefficients for the variables used in the study. Figure 3 plots the R^2 which ranges from 0.75 to 0.84. As expected this is higher than the R^2 obtained from OLS as shown in Table 1. Figure 4 shows actual and predicted crowding rate values. From this graph we see that although there are some differences in the absolute versus predicted values, the overall pattern is very similar. This is confirmed in Figure 5 which shows the GWR prediction error. Table 2 shows the GWR empirical results. From Table 2 we see that the medians from GWR are relatively similar to those for OLS. However, the minimums and the maximums vary considerably. This lends strong support to the spatial non-stationarity in study variables.

TABLE 2
GWR COEFFICIENTS

Coefficients	1st quart.	Median	3rd Quart.	Maximum
(Intercept)	1.073000	1.074000	1.075000	0.135000
Density	0.000004	0.000004	0.000004	0.000006
Illiteracy	0.001957	0.005153	0.005281	0.005642
Higher Ed	-0.004410	-0.004323	-0.004133	0.003370
One room	0.005659	0.005958	0.006134	0.012204
Five room	-0.005033	-0.004821	-0.004736	-0.002734

FIGURE 2
COEFFICIENT MAPS OF GWR VARIABLES

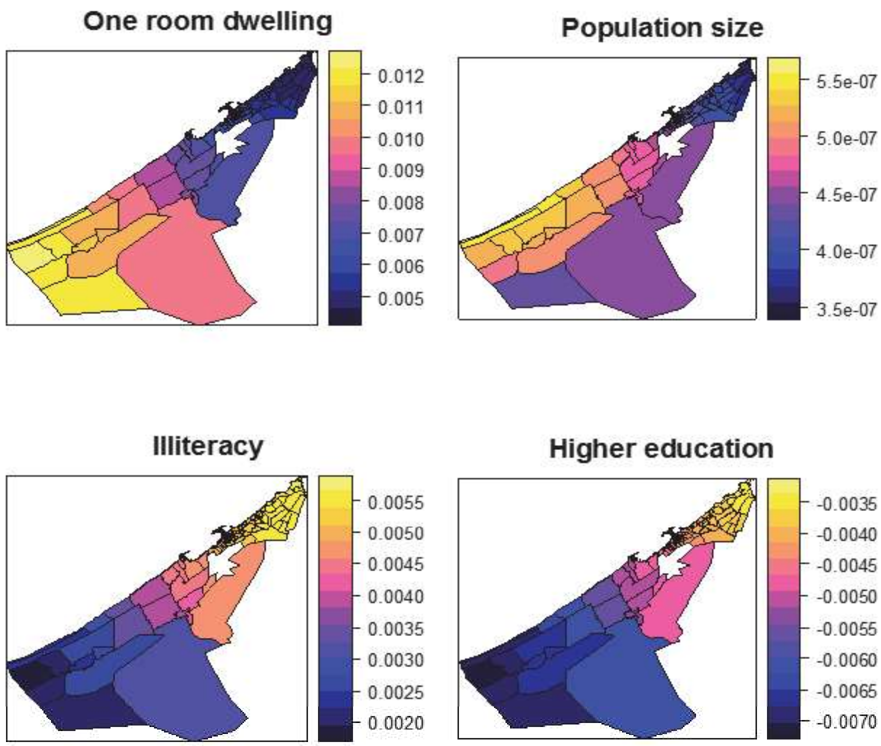


FIGURE 3
GWR R2 MAP

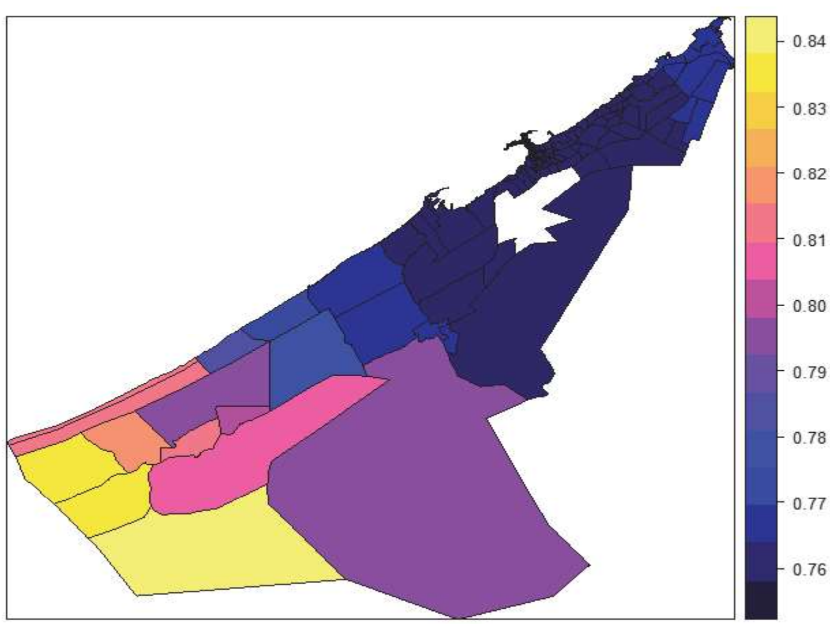
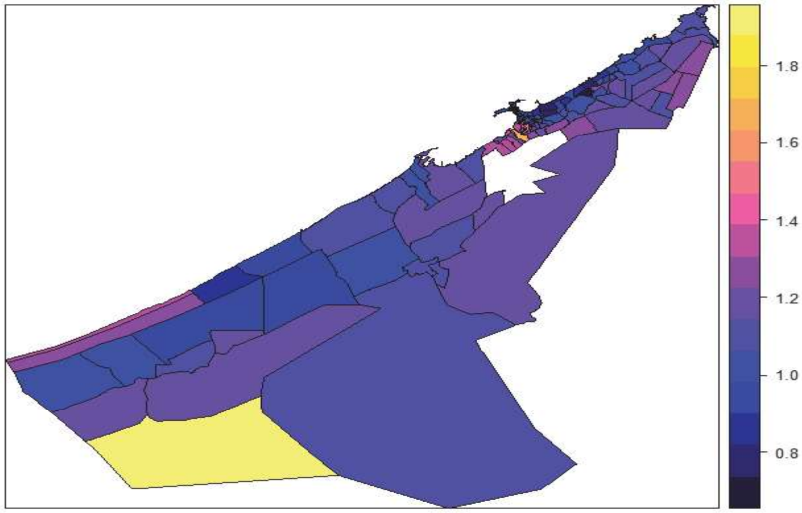


FIGURE 4
GWR OBSERVED VERSUS PREDICTED CROWDING RATE MAP



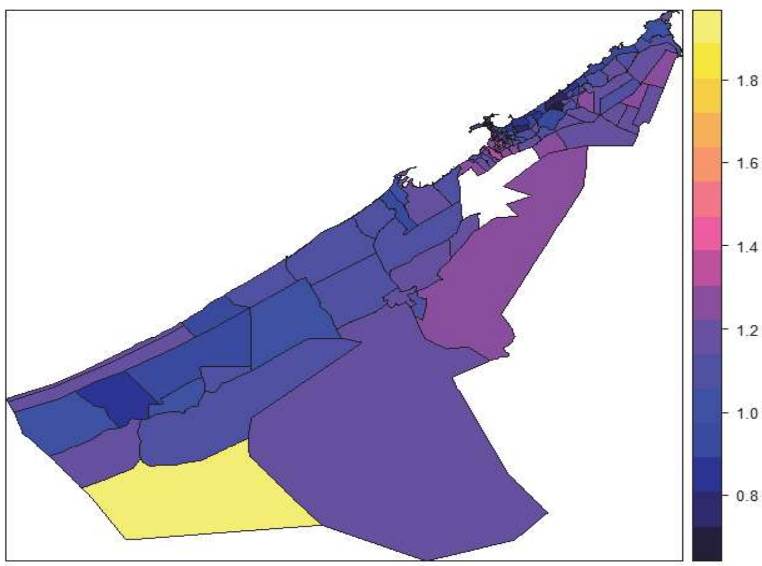
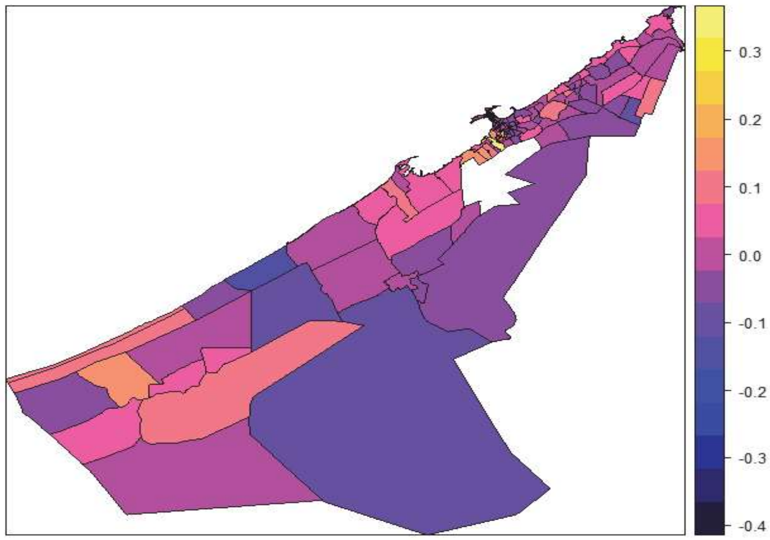


FIGURE 5
GWR CROWDING RATE PREDICTION ERROR MAP



CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

One of the main goals of this research was to investigate the spatial effects of various socioeconomic determinates on residential overcrowding rates in Alexandria, Egypt. Results of OLS, SAR, SEM and GWR indicate that the population density, illiteracy and one room dwelling variables are positively and significantly related to residential urban overcrowding, while higher education and five room dwelling are negatively related to overcrowding. On the other hand, GWR findings show that the spatial variation of socio-demographic variables on residential overcrowding across Alexandria is non-stationary. Consequently, the modelling techniques which assumes homogeneity of relationships between overcrowding and explanatory variables should be avoided when modeling spatial patterns of residential overcrowding. We also found that the overcrowding rate increases in south-western, the middle and in some districts located in the east parts of Alexandria. In the middle part of the city overcrowding rate is higher in the districts close to the city center as well as the eastern districts (e.g. al Montazah) where there are many slum areas encroaching on agricultural land. In contrast, lower overcrowding rates appear to follow a long strip starting from northern districts of the east and middle parts of the city. Similarly, some districts in western south show lower overcrowding rates. The findings indicate that population density has a significant impact on residential crowding.

To the best of our knowledge, there has been no studies investigating factors influencing residential urban overcrowding in Alexandria, Egypt. Thus, our findings might be important as they indicate the urban structure in the city, which is regarded as a useful metric in urban planning. Understanding how residential overcrowding is distributed spatially in Alexandria can help the decision maker in establishing transportation networks and zoning. Our results can also help policy makers in estimating the implicit value of “non-market attributes” of amenities such as residential land prices. The way residential urban overcrowding is clustered in Alexandria might be an indication of the existence of what is called in the literature “market segmentation”- a phenomenon that arise “when consumers’ demand for a particular structural or location-specific characteristic is highly inelastic and that the preference for this characteristic is shared by many other consumers” (Glaesener & Caruso, 2015).

Like other studies, this study is not without limitations. First, we have focused only on one type of overcrowding, namely residential urban overcrowding. Future research may replicate this study on other types of crowding such as sprawling to test the robustness of our findings. Although we focused on several socio-economic factors influencing residential urban overcrowding in Alexandria, Egypt, future studies may investigate the impact of other hedonic factors such as proximity to parks, views of green space, seaside, lakes and waterfalls on overcrowding. Since residential overcrowding might be the result of a complex interaction between socio-economic and hedonic variables, future research may also investigate the impact of such interaction on residential urban overcrowding. For example, future research may develop theoretical econometric choice models incorporating both "green amenities" and distance to "economic opportunities". It should also be noted that we investigated residential urban overcrowding in Alexandria, Egypt using a cross-sectional rather than a longitudinal design, which implies that much more emphasis has been placed on observing overcrowding behavior than in observing changes in such dynamic behavior. Thus, future research may employ a longitudinal approach to observe changes in residential urban overcrowding in Alexandria, Egypt over time. Finally, in this research we investigated factors influencing residential overcrowding in a single Egyptian city. It would be interesting to extend this kind of research to other cities in the Arab countries in order to see if our results hold.

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