Location matters: unraveling the spatial dimensions of neighborhood level housing quality in Kolkata, India

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Abstract

Amidst increasing urbanization and rising socioeconomic inequality, the availability and accessibility of adequate, affordable and quality housing has become challenging in urban India. Despite numerous policy reforms, the implemented programs have mostly failed to deliver as envisaged due to a lack of continuity and interconnectedness between them, thereby precipitating a high level of housing poverty for a significant proportion of households. This study explores the plausible spatial dependencies and heterogeneities in the relationships between neighborhood-level housing quality and its related demographic and socioeconomic parameters in the eastern Indian metropolis of Kolkata. A-spatial and spatial regression model based analyses reveal that the linkages between housing quality and its driving forces are not spatially invariant in terms of their strength, magnitude and direction across the cityscape at the neighborhood level, being governed by place-specific attributes. The importance of inculcating spatial dependence and heterogeneity analyses in similar research and policies is thus highlighted.

Keyword(s): housing and environment, housing choice, neighborhoods, urbanization, spatial dependence and heterogeneity, geographically weighted regression

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Main Text

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Introduction

Housing quality research has garnered much attention among those investigating urban areas but these have mostly been for urban locales in developed countries (e.g. Crook *et al.*, 2016; Memken & Canabal, 1994; Saari & Tanskanen, 2011; Shinnick, 1997). In the last two decades however, the focus on quality housing consumption patterns and its determinants across developing countries has also increased (e.g. Aribigbola, 2008; Fiadzo, 2004; Ibem, 2012; Jiboye, 2011, 2014; Lanrewaju, 2012; Meng & Hall, 2006; Morenikeji *et al.*, 2017; Moughalu, 1991; Opoko *et al.*, 2016; Pan, 2004; Sengupta & Tipple, 2007). A prime reason has been the burgeoning worldwide evidence linking housing quality to the occupants' satisfaction and their desired quality of life and basic well-being (Diener & Suh, 1997; Jiboye, 2014; Teriman et al., 2010), health and economic development (Dujardin & Goffette-Nagot, 2007), including successful family rearing and childhood development (Bratt, 2002).

Amidst increasing urbanization and the already marked socioeconomic inequality, the accessibility and affordability of quality housing has become ever more challenging in the cities of developing nations like India. Since her independence in 1947, India's urban housing sector has experienced several reforms at the policy level but most of the implemented programs have failed due to a lack of continuity and interconnectedness among them. Consequently, a significant proportion of households (HHs) now experience a high level of housing poverty across India's cities[i] and the eastern metropolis of Kolkata is no exception to this rule. Due to this city's conspicuous and surmounting housing problems, in the 1990s (post the economic liberalization reforms) the Government of West Bengal undertook an ambitious four-pronged reform initiative to revitalize the housing sector through *public private partnership in housing financing and delivery, deregulation of housing finance, privatization of government rental housing sector and the development of new townships* (for a detailed review, see Sengupta, 2006, 2007). While, these much hyped programs provided an impetus towards rejuvenating the housing sector, especially through inviting large investments from both private and international agencies and the construction of housing for the middle and higher income households, they failed to address the larger social agenda of housing the poor, thereby leaving a substantial portion of the poor residents bereft of the advantages accrued from these so called 'new housing reform measures' (Sengupta, 2007). Further research in this regard had also underlined the above scenario by showcasing the government's exclusionary role and 'poor blindness' *modus operandi* towards investment in housing and policy implementation, through a cut in public capital investment and noting the private sector's reluctance to deliver housing for the low-income populace (LIP) or economically weaker section (EWS), who made up 80% of the city's dwellers (Sengupta, 2010). The socio-spatial and financial distance between the urban poor and those socioeconomically better off thus became mirrored in the meager opportunities accorded to the former for finding a decent shelter in the city, thereby producing an extremely unequal and segregated distribution of housing quality among different population subgroups across the cityscape.

The most adverse impact of the failure of such housing polices has resulted in supply shortages and marked housing inequities in cities of the Global South (Mishra 2018), as is reflected by the numerous slums within the city limits and Kolkata is a standout example of this juxtaposition of slums and skyscrapers (Sengupta, 2007). Today, about 31.35% (1.41 million) of Kolkata's population resides in 5600 slums (GOI, 2015), with critically unequal access to essential civic services and living in a dangerously congested, residentially segregated, severely unhygienic and socially unacceptable housing environment. This endemic *spatial poverty* can be construed as the catalyst for a complex poverty trap that exerts huge stress on the health, earning capacity and general well-being of the resident individuals through their life course (Andersen, 2003). Effective policy interventions are thus required to bridge the gap created by market-based housing supply shortages in Kolkata in order to provide adequate, safe and affordable quality housing, in tune with the agenda outlined by the *Sustainable Development Goals (SDG) 11*.

With the above context and given the scant efforts so far to decipher the housing quality dynamics in Indian cities, (primarily due to the paucity of detailed data required to conduct such a quantitative analysis), this article develops a spatial conceptual framework to assess the housing quality aspects in Kolkata. Towards this, we construe three lines of enquiry- (1) is there a spatial distribution in the level of quality housing consumption in Kolkata, how may its pattern be deciphered and does location play any role in molding such intra-city housing quality differentials, (2) how might the determinants of neighborhood-level housing quality across Kolkata be analyzed spatially, given that spatiality is an inherent characteristic of housing economics, and (3) does any spatial dependence/ or heterogeneity exist in the relationship between the neighborhood-level housing quality outcomes and its determinants? This last line of enquiry question is pursued based on the surmise that housing quality is a composite and spatially heterogeneous good, because of its immovability (Fiadzo et al., 2001; Rothenberg, 1991) and its attributes include not just a particular dwelling's structural aspects but also several location-based or neighborhood settings, its accessibility, proximity externalities, amenities and services (Basu & Thibodeau, 1998). Therefore the relationships between housing quality outcomes and its determinants are likely to be non-stationary and differ geographically and such spatial dependence and/or heterogeneity effects that imbue most geographic cross-sectional data should not be overlooked. In addressing the above three points, this paper is one of the first such endeavors in the realm of housing studies in the Indian context, and elicits a more nuanced understanding of the spatial dimensions of neighborhood-scale housing quality outcomes by using some novel spatial econometric approaches.

Spatial effects and neighborhood-scale housing quality outcomes: a theoretical framework

Of late, a plethora of studies have surmised that spatial dependence does indeed influence social issues and behavior, including demographic, socioeconomic outcomes and political changes (Boumont, 2009; Crowder & South, 2008; Millward, 2008; Morenoff & Sampson, 1997; Morenoff *et al.*, 2001; Noonan, 2005; Swaroop & Morenoff, 2006; Taiwo & Ahmed, 2015; Wang & Chi, 2017). Location plays a vital role in producing spatial effects like spatial autocorrelation and heterogeneity during geographical data analysis (Yu *et al.*, 2007). This spatial autocorrelation refers to the coexistence of locational similarity with value similarity (Anselin, 2001). In an urban housing market, therefore, houses located close to each other are likely to have similar attributes and prices, thus revealing how the real-estate market functions. Due to their proximate spatial location, a house owner is also likely to perform or pursue activities similar to his/her neighbors, thereby yielding similar housing attributes (house dimension, age, architectural style and external and interior decoration). They may also mutually avail of or access common site-specific services and amenities within that neighborhood, especially public ones [Basu & Thibodeau, 1998; Militino *et al.*, 2004 (cited in Yu *et al.*, 2007)], e.g., schools, banks, health centers, police station, transportation facilities, parks, markets and other civic services (water, sanitation and sewerage facilities). Often across an urbanscape, neighborhoods of similar socioeconomic/demographic attributes (e.g., education, income, job rank, family structure, stages of life course) cluster together, giving rise to spatial autocorrelation in terms of neighborhood externalities and spatial diffusion. In a like manner, it could be hypothesized that neighborhood housing quality outcomes might well be influenced by similar spatial spill-over effects and spatial diffusion. As surmised in Byun & Esparza (2005), such a residential spill-over can also be shaped by a demand and supply mismatch in the urban housing market.

Contrastingly, spatial heterogeneity implies a non-stationary mechanism over the geographic space. Therefore, it exhibits housing-market processes wherein neighborhoods having similar socioeconomic/demographic attributes may however have different housing quality outcomes, based on their differing geographical locations in the study area (Bailey & Gatrell, 1995; Fik *et al.*, 2003; Fotheringham *et al.*, 2002; Theirault *et al.*, 2003). While contemporary metropolitan housing markets are often comprised of many housing sub-markets that are location, land-use pattern, tenure status, price, house type and quality based and are therefore of a segmented and heterogeneous nature, several attributes like the dwelling size/area, essential amenities, neighborhood conditions and externalities may not be substitutable (Yu *et al.*, 2007). This segmentation occurs when specific neighborhood/structural characteristics are desired by a comparatively large population (Schnare & Struyk, 1976). Besides this, metropolitan neighborhoods are usually heterogeneous in terms of their socioeconomic and demographic characteristics, including public resource endowments and this crucially affects its housing market segmentation (Can, 1990). Furthermore, both historical context and geographical setting may also affect a neighborhood's housing outcome. Thus, it is important to consider spatial effects (spatial autocorrelation/heterogeneity) in housing quality studies.

Though conceptually and empirically informed housing quality research has not been conducted in Indian context until recently, several studies elsewhere that have similarly assessed the quality dimensions of housing have used the conventional Ordinary Least Square (OLS) model to estimate the coefficient with the basic assumption of independent observation (e.g. Fiadzo, 2004; Ibem, 2012; Pan, 2004). They did not, crucially however, consider those aspects that are embedded in the spatial dimension and how the location affects such relationships. Given that spatial dependence and heterogeneity in housing quality is a fundamental aspect of housing economics, ignoring such spatial dependence/heterogeneity could result in statistical problems for an empirical investigation. If spatial autocorrelation is neglected while running a conventional OLS model, the standard errors are biased downward- therefore the estimated coefficients may be erroneous or deceptive (Anselin, 1988). To overcome this, one can use both the Spatial Lag (SLM) and the Spatial Error autoregressive (SEM) models that are likely to alleviate any spatial effects occurring on the coefficients (Yu, *et al.*, 2007). For addressing the spatial heterogeneity issue and spatial non-stationarity in housing quality analysis, the Geographically Weighted Regression (GWR) local model (Fotheringham *et al.*, 2002) can also be applied. The GWR considers spatial locations in the regression model in accordance with the '*First Law of Geography*'- nearer things are more related among themselves than with distant things' (Tobler, 1970), thus accounting for spatial heterogeneity in a more nuanced manner. In particular, considering the glaringly evident structural duality (formal and informal) and hybrid urban and housing contexts coupled with prolonged socioeconomic inequalities of Kolkata (Sengupta, 2010), the aforementioned theoretical underpinnings sets the context within which the trajectories of neighborhood-scale housing quality outcomes can be best understood spatially.

The study area

Kolkata, the world's 14th largest city (UN DESA, 2016), was India's first metropolitan entity and is the prime commercial, cultural and educational hub of the state of West Bengal as well as Eastern India. Unprecedented and unplanned population growth due to cross-border migration, first during the 1947 Indo-Pak partition and then during the formation of Bangladesh in 1971, put enormous pressure on the then existing housing and infrastructure bases, transforming the city into a '*premature metropolis'* (Bose, 1973). Furthermore, being the only mega urban centre of Eastern India, Kolkata had enjoyed lot of geopolitical importance since the colonial era and served as a favorable livelihood destination for rural migrants from the states of Uttar Pradesh, Bihar and Orissa and from the hinterland of West Bengal. Though, attempts were made to decentralize the urbanization and industrialization processes to other parts of the state by developing some secondary cities like Siliguri, Asansol and Durgapur, this onslaught of migration remained unchecked (Sengupta, 2010). Consequently, the rise in urban poverty became glaringly evident in respect of the quality of housing stock available, accentuated further by and local and state governments' failure in successfully addressing this massive demand for adequate housing and infrastructure. Presently, the city suffers from an acute spatial poverty in terms of housing and civic services with the most recent census of 2011 reporting that about 31.35% of its total residents were slum dwellers. Overall, only 65.3% and 58% of HHs respectively have their dwellings in good condition or whose homes have a concrete roof respectively, followed by nearly 42.5% of HHs being comprised of only one room (RGI, 2011). Dutt and Halder (2007) have observed that while non-slum HHs enjoy more than 500 sq.ft. of space within their homes with two/three rooms of living space, the majority of the slum HHs reside in a space of less than 200 sq.ft. Recent research has also surmised that some particular neighborhoods with a disproportionate concentration of socioeconomically deprived residents enjoy a significantly lower level of basic amenities and services as compared to the city average (Haque, 2016). By and large, sustained exposure to such housing poverty not only adversely affects the health, childhood development, education and political participation among the residents but also impacts on their employability and income outcomes and this is clearly manifested in the city's chronic 'economic poverty', with 80% of its population who earn below Rs.5000 monthly comprising of LIP and EWS (Sengupta, 2010). Basically the poor neighborhoods are victims of severe income and housing deficiencies, with most residents engaged in unregulated informal economic activates that are characterized by low wage rates, ill-treatment and job uncertainty. The prevailing socioeconomic, political and policy conditions set the context within which the challenges pertaining to housing affordability, poor quality housing outcomes and mismatches between housing demand and supply can best be understood in Kolkata.

Materials and methods

Data

The most recent Indian Population Census of 2011 contains, for the first time, details of housing conditions and access to or ownership of amenities and assets at the neighborhood level for urban areas. The relevant data for all 141 neighborhoods of Kolkata was accrued by combining the House Listing Primary Census Abstract (HLPCA) and the Primary Census Abstract (PCA) databases. The HLPCA contains data on housing conditions and essential household amenities and assets owned, for each household (Figure 1), while the PCA reports individual level data regarding demographic aspects like the population size by residence, sex, number of children, caste and literacy status, including their employment details. The statistics for the individual neighborhoods' poverty rate (% BPL households) and the voting turnout in municipality elections were sourced, respectively, from the Kolkata Municipal Corporation and from the Election Commission of West Bengal for the years 2012 and 2015.

Measure

Housing Quality- definition and measure

A normative definition of housing quality refers to *the level of acceptability of housing units, and their related and surrounding housing environment, including design and serviceability of dwelling structures, construction materials utilized, availability of internal and external space related to the units, housing amenities and provisions of civic services* (Meng & Hall, 2006). However, the concept of housing quality has been recognized as complex in respect of the wider socio-cultural and economic considerations, incorporating both qualitative and quantitative aspects of housing units, their proximate environments and the occupants' satisfaction. Furthermore, the housing quality concept is relative since it is more associated with local norms and conditions (Meng & Hall, 2006). Therefore, its definition varies according to the study's context (e.g. formal and informal housing, developed or developing countries, rural or urban- Sengupta & Tipple, 2007). In this paper, following the concept of adequate housing as postulated by UN-Habitat (2006), we define housing quality to be a good, if it is structurally sound and durable and having access to essential civic amenities and services (water, electricity, drainage), while being located in an area that enjoys good connectivity with the rest of the city. Housing studies literatures recognize these multiple dimensions of housing quality [quantitative (physical and economic: structural, material and social/economic); qualitative (cultural): comfort/quality of life] and they are difficult to measure (Casey, 1980; Meng & Hall, 2006; Goodman, 1978; Myers et al., 1996; Kutty, 1996; Buckley & Tsenkova, 2001; Fiadzo et al., 2001). For our purpose here, following Meng & Hall (2006) and Mohit et al. (2010), the housing quality is measured as a composite of 18 best-reflective and commonly used objective aspects of housing quality indicators which can be clubbed into four broad dimensions of, a) Physical Sustainability, b) Spatial Deficiencies (Overcrowding), c) Housing Services, and d) Extra Amenity (assets owned) (Figure 1 and Table 1) (for detailed definitions of indicators, see Supplementary Table S1). *First*, for the respective dwellings' physical sustainability measure, the census houses with good condition, concrete roof, concrete/burnt brick wall and concrete floor materials are considered to be the most vital indicators compared to other facets of sustainability of dwelling structures. *Second*, for spatial deficiency/overcrowding dimension, the HHs having at least two living rooms and separate kitchen for cooking are taken into consideration on the grounds that these two indicators best reflect the characteristics and requirements of a living space/home for maintaining privacy and health. Especially overcrowding is typically associated with poor quality housing with 42.5% of Kolkata's HHs being comprised of only one room while 28% of HHs do not have separate kitchen (RGI, 2011). *Third*, seven essential services, namely, electricity, access to treated tap water, access to drinking water within the premises, clean fuel, improved latrine, bathing facility within the premises and sewerage connection (covered drain) are used to measure 'housing services', which has been widely recognized as a significant factor in denoting the housing quality in many previous studies (Table 1). *Finally*, five indicators are taken to encapsulate the 'extra amenity' dimension. These variables comprise access to finance and ownership of utilities/devices like television, computer/laptop, two wheelers and cars.

Apart from this, the share of formal housing (legally protected), the average house age and the average housing space per dwelling have a bearing on the multi-faceted nature of the housing quality. Since the census does not provide this data, we were not in a position to include these indicators and acknowledge the inherent limitations as a result.

For developing an area based HQI (Housing Quality Index), we follow a methodology which is a revised version of the principal components analysis where a dimension reduction process was performed to generate weighted linear combinations of the characteristics under consideration (Krishnan, 2010; Vyas & Kumaranayake, 2006- the detailed procedure of index calculation can be found in the related supplementary document). Finally, the index is standardized to a scale of (0, 100) to make it comparable with other variables of interest, with higher index values denoting better quality housing. The internal consistency of the scale of measurement applied in this housing quality measure is examined through the Cronbach's alpha test which shows a robust Cronbach's alpha value of *0.892* ($p<0.000$) for the select 18 indicator variables considered for assessing the neighborhood level housing quality. The HQI scores serve as the dependent variable in our econometric estimations.

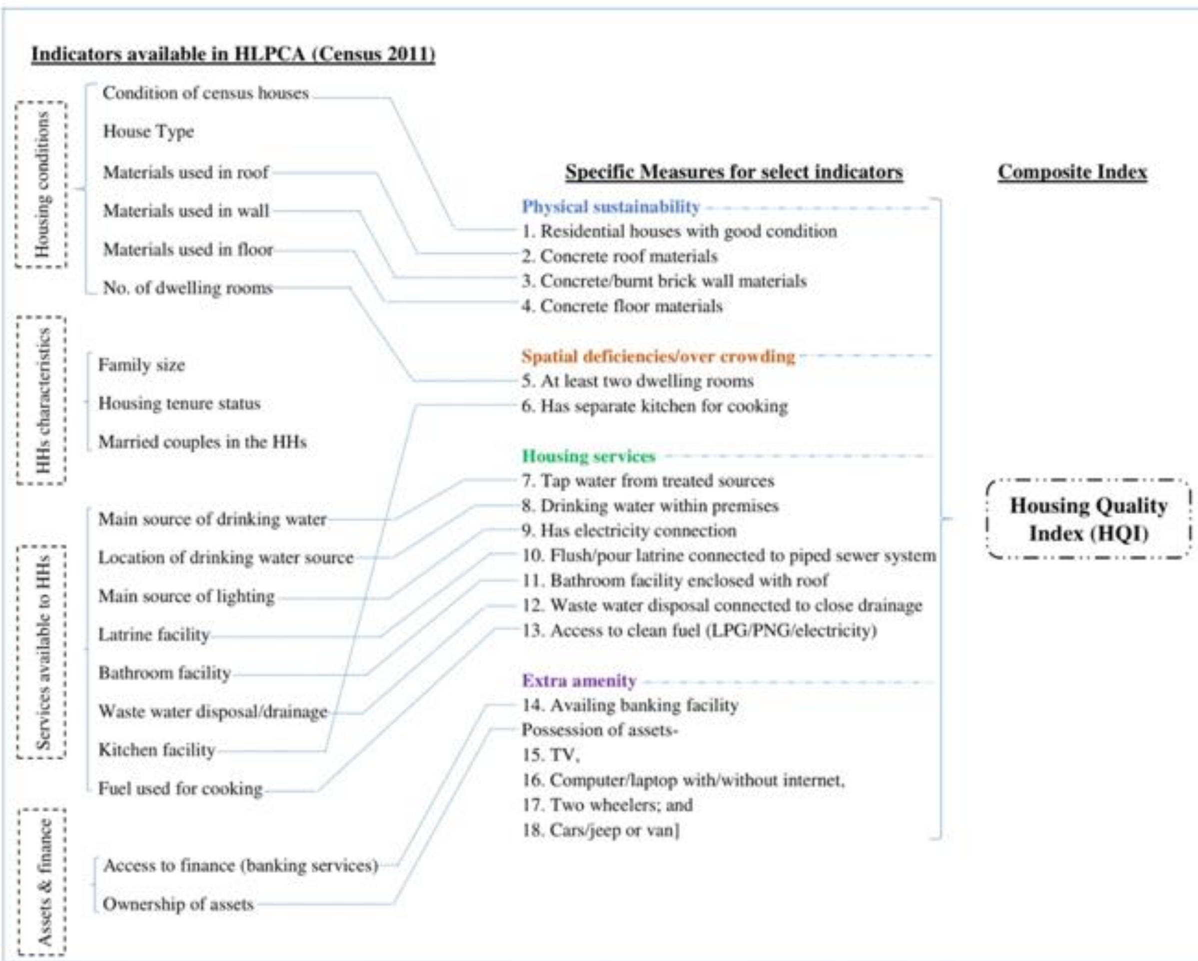


Figure 1: Structure of an area-based housing quality index for Kolkata

Independent Variables

Despite the varying definitions and conceptualizations of housing quality measures as outlined before, in common parlance, the housing quality is broadly determined by the HHs' socioeconomic characteristics, neighborhood conditions, tenure structure, proximity externalities, dwelling structure and age, family composition, stages of life course and space adequacy (Kain & Quigley, 1970; Ibem, 2012; Pan, 2004; Fiadzo et al., 2001; Morris &Winter, 1997; Yust et al., 1997). Based on them, some relevant socioeconomic, demographic, housing and political indicators were considered as independent variables in the regression analysis (Table 1). Previous research has also recognized race, ethnicity, and minority status as crucial predictors of housing quality outcomes (Spain, 1990; Memken & Canabal, 1994). In the Indian context, caste hierarchy plays a vital role in shaping various life outcomes, including housing and access to basic public goods (Banerjee et al., 2015; Haque, 2016). Therefore, the neighborhood caste composition, as measured by the proportion of *'SC/STs'* [Schedule Caste (SC) and Schedule Tribes (ST)] (Haque, *et al.*, 2018) is taken to incorporate the effect of social exclusion by caste in housing quality outcomes[ii]. We hope to see a negative relationship between the housing quality and SC/STs in the global models. The proportion of '*Literate females'* has been taken as a proxy of social development (Bilance, 1997) as households with women who have studied beyond the secondary level are more likely to be better aware about their home environment quality, especially in the context of maintaining a hygienic and healthy habitation. Similarly, '*Females WPR'* (proportion of females in the main workforce) is also incorporated, assuming that higher is the female participation in economic activities, the higher would be that household's monetary strength and level of female empowerment and say in taking household and family planning decisions, which may then influence its housing outcome. We expect both these variables to positively impact the housing quality. Since the Indian Census does not provide household-level income data, the proportion of BPL households (measure of '*Poverty*'), is used as its indirect measure. As listed in Table 1, earlier studies too surmised the strong income effect on housing quality outcomes. As housing variables we include- the percent of households living in slums ('*Slum housing'*), '*Homeownership*' rate and housing status, as these factors may influence the neighborhood scale housing quality. Since slums usually lack proper building design, quality building materials and scarcely receive basic amenities and services, the HQI can be expected to relate negatively with slum housing. Owned dwellings are more likely to be of better quality because people generally improve the building design and features of their own houses but not if they live in rented accommodations (Fiadzo, 2004; Stefanie *et al.*, 2017). Similarly, people living in permanent houses ('*Permanent Housing'*) are more likely/able to upgrade their homes compared to temporary habitation residents, and hence housing quality correlates with housing status. We examine if these two covariates will positively affect the housing quality in our global models. The percentage of households having more than four members ('*HH Size'*) and at least two married couples ('*Married Couple'*) are also incorporated as independent variables (congestion factors). Larger households prefer more sleeping rooms instead of opting for a higher quality of living (Pan, 2004). Though, the mean household size in India is five, we consider households with more than four members in the disadvantaged group, since very low fertility rates prevail in Kolkata, fostering a lower mean household size (Ghosh, 2016). Furthermore, we expect married couples to endeavor to own better houses (Mulder, 2013), since getting married is a vital stage of life course transition and such HHs initially enjoy a relatively higher quality of housing which then diminishes over time (e.g. retirement), thereby revealing a curvilinear relationship (Morris & Winter, 1997). Finally '*Voting turnout'* is included to consider the degree of political inclusion/access to political citizenship of an area, surmising that an individual's degree of citizenship plays a vital role in determining their access to goods and services (Bertorelli *et al.*, 2017). Furthermore, the ward committee or the Urban Local Body may influence housing outcomes through differential resource allocation and service delivery of essential amenities (for detailed definitions of variables, see Supplementary Table S2).

Analytical strategy

We have used several analytical strategies to decipher the spatial dimensions of neighborhood-scale housing quality outcomes in Kolkata. For understanding the nature of each variable's distribution across the study area, their respective univariate descriptive statistics were initially computed. We then mapped all the sample variables to garner a better understanding of their spatial distribution patterns (see Appendix-1). Secondly, the Moran's *I* statistics along with the Local Indicators of Spatial Associations (LISA) cluster maps were prepared to assess the univariate global and local patterns of spatial dependence, respectively, for the neighborhood housing quality outcomes and its predictors (Anselin, 1996; Bivand & Piras, 2015).

We ran some spatial econometric regression analyses to ascertain whether spatial effects (spatial autocorrelation and heterogeneity) exist in the relationship between the neighborhood level housing quality outcomes and its predictors. We first estimated the global coefficients for the independent factors by using both aspatial OLS and spatial autoregressive models (SLM and SEM). For spatial modeling, a spatial weight matrix, ***W***, that considered the spatial structures of neighborhoods was generated by considering different types of spatial structures, i.e., a contiguity through a common boundary (the rook criterion) or vertices (the queen criterion) and k-nearest neighbors (Anselin, 1992). While the selection of the weight matrix was crucial for spatial regression analysis in accordance with the contextual background of the study area and the objectives being pursued (Anselin, 1988), there is little theory on the weight matrix selection type in practice [Chi & Zhu, 2008 (cf. Jun, 2017)]. Therefore, following Jun (2017), we compared the degree of Moran's I values (a common measure of spatial autocorrelation) as calculated from the various spatial weight matrices of the queen's case, rook's case and k-nearest neighbor, with the k ranging from four to seven neighbors. As surmised in Voss & Chi (2006) and Jun (2017), we used the spatial weight matrix that yielded the highest Moran's I values, which was the k-nearest neighbor case (k=4). In the final step, the local coefficients were estimated by using the GWR model and we then compared and examined the performance and predictive accuracy of these three models respectively. We have used the respective statistical packages of GWR (version 4.0), GeoDa (version 1.8), and ArcGis10.1 for these spatial and statistical analyses. The detailed model specifications can be found in Appendix-2.

Results and discussion

Spatial patterns of quality housing consumption

Our initial excercise used principal component analysis to build a composite HQI using the latest neighborhood-level disaggregated housing data. The obtained HQI score for each neighborhood allowed their comparison across the study area, with the descriptive statistics for the HQI and selective covariates showing huge variations (Table 1). More than half the examined neigbourhoods (52%) were noted to suffer from severe housing quality deprivation, with the below average HQI scores denoting a stark spatial inequality in quality housing consumption (the relevant table is not given here but may be provided upon request).

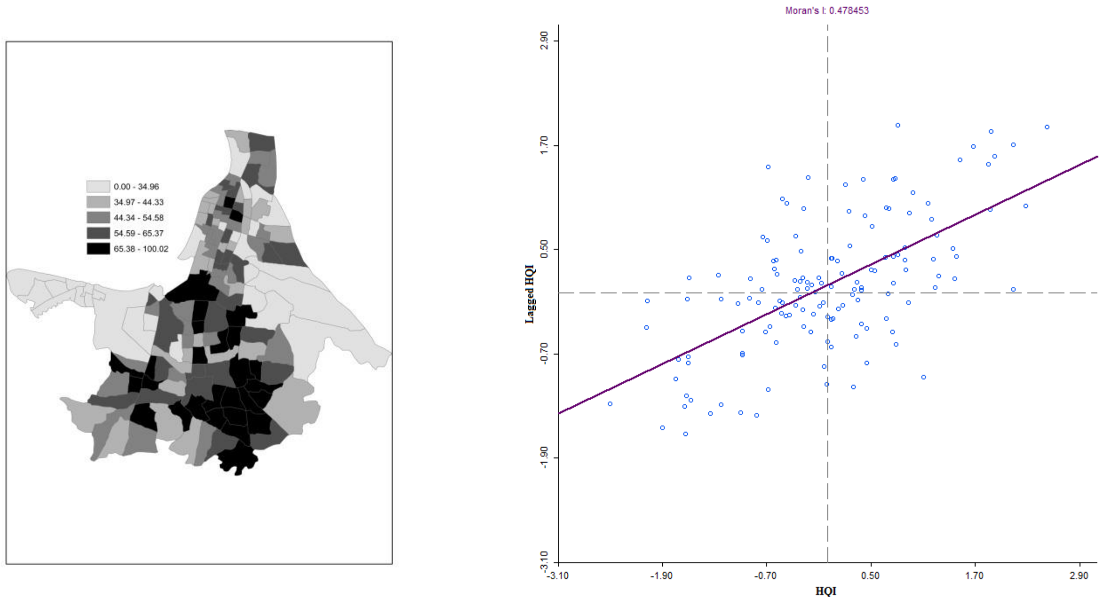
Table 1: Descriptive summary of the study variables (N=141)

Variable	Mea n	SD	Moran's *I*	References
Dependent variable				
HQI	48.71	20.25	0.478***	
Physical sustainability				Fiadzo et al., 2001; Meng and Hall, 2006

Spatial deficiency/overcrowding				Spain, 1990; Cook and Bruin, 1994; Meng and Hall, 2006; Pan, 2004
Housing services				Memken and Canabal, 1994; Sengupta and Tipple, 2007; Meng and Hall, 2006; Pan, 2004
Extra amenities				Meng and Hall, 2006; Memken and Canabal, 1994
Independent variables				
Neighbourhood composition (SC/STs)	4.75	4.83	0.360***	Zey-Ferrel et al., 1997; Spain, 1990; Memken and Canabal, 1994
Education (Literate Females)	84.56	6.69	0.429***	Ibem, 2012; Cook and Bruin, 1994; Pan, 2004; Fiadzo et al., 2001
Employment (Females' WPR)	13.3	4.31	0.665***	Fiadzo et al., 2001; Pan, 2004; Zey-Ferrel et al., 1997
Income (Poverty rate)	20.92	11.74	0.392***	Cook and Bruin, 1994; Memken and Canabal, 1994; Pan, 2004; Ibem, 2012
Location (Slum housing)	27.29	27.48	0.577***	Ibem, 2012; Fiadzo et al., 2001; Yust et al., 1997; Cook and Bruin, 1994
Household size	36.74	11.52	0.725***	Spain, 1990; Pan, 2004; Fiadzo et al., 2001; Ibem, 2012
Marital status (Married couple)	14.73	2.49	0.422***	Ibem, 2012; Fiadzo et al., 2001; Memken and Canabal, 1994; Cook and Bruin, 1994; Spain, 1990; Morris and winter, 1997
Tenure (Homeownership rate)	52.04	20.87	0.783***	Zey-Ferrel et al., 1997; Cook and Bruin, 1994; Yust et al., 1997; Pan, 2004; Fiadzo et al., 2001; Ibem, 2012
Housing status (Permanent Housing)	93.71	4.87	0.090**	Daniere, 1994
Political factor (Voting turnout)	67.48	8.14	0.407***	Chan et al., 2006; Ibem, 2012

Note: SD denotes Standard deviation; Level of significance: **p<0.01; ***p<0.001
Moran's *I* is calculated based on the k-nearest neighbour (k=4) weight matrix. The significance levels are based on 999 times of permutations.
Source: Computed by the authors

It is pertinent to mention that we are not comparing the absolute degree of housing quality or other such variables of interest here but merely analysing the level of variation within each. Furthermore, these are the inequalities among neighborhoods, not individual households. However, even this initial level of disaggeration provided some insights on housing quality distribution across Kolkata. An added benefit of this exercise was that it allowed comparison across neighborhoods lucidly, since it measured variation instead of absolute levels. Our findings revealed that the studied variables were spatially unequally distributed in varying magnitude across Kolkata's neighborhoods. What these measures of variations did not reveal, however, was the pattern of the distribution of this variance. Therefore, we mapped the HQI score for each neighborhood and the emergent patterns became self evident, denoting some clusters of deep deprivation and impoverishment as regards to the quality housing consumption (Figure 2a). This is further highlighted by the concentration of better quality housing in the central and southern tracts of the city side-by-side with the relative impoverishment of the entire north-eastern and western peripheries.



a. Housing Quality distribution b. Moran scatterplot: Neighbourhood HQI

Figure 2: Neighborhood housing quality and spatial autocorrelation

Spatial dependence in neighborhood housing quality outcomes

Global patterns

The global patterns of spatial dependence in neighborhood housing quality could be assessed by Moran's I statistics (Moran, 1948). It measured the linear relationship bewteen the values of an indicator and the spatially weighted values of its neighbouring indicator (Anselin, 2005). Thus, the Moran's I statistics could be explained as the regression slope of a variable on the spatially weighted average (Pacheco & Tyrrell, 2002). Based on the k-nearest neighbour spatial weights matrix, Table 1 (4^{th} column) reports the Moran's I statistics for all the variables and we found a relatively higher positive spatial autocorrelation except for the '*Permanent housing*' variable, implying strong spatial patterns for both neighborhood housing quality and its driving forces. Particularly, this indicates that neglecting the spatial dependence in such analyses could result in a severe bias in estimates and standard errors.

For a more nuanced econometric understanding of the spatial autocorrelation, Moran scatter plots were prepared. As surmised by Anselin (1996), they visually interpret the distribution of housing quality for each neighborhood on the horizontal axis in relation to the spatial lag (standardized spatially weighted average) on the vertical axis (see also Jun, 2017). The Moran scatter plot has four distinct quadrants related to the four varieties of local spatial relationships among neighborhoods and their geographically proximate neighbours, such as: high-high (or, high quality housing neighborhoods bordered by other high quality housing neighborhoods, low-low (or, low quality housing neighborhoods adjacent to other low quality housing neighborhoods), high-low (or, high quality housing neighborhoods surrounded by low quality housing neighborhoods), and low-high (low quality housing neighborhoods surrounded by high quality housing neighborhoods). Here, the high-low and low-high neighborhoods were the spatial outliers that lowered the Moran's I value.

Figure 2b shows the Moran scatter plot of the neighborhood level housing quality in Kolkata (Moran scatter plots for all independent variables were also prepared and are available on request). Consistent with the relatively high Moran's I value for the neighborhood housing quality, a greater proportion of neighborhoods i.e. 35.5 percent and 33.3 percent, lay in the high-high and low-low quadrants respectively. We also found that comparatively, there were markedly fewer high-low (12.8 percent) and low-high (18.4 percent) cases.

Local patterns

Moran's I statistics showcases the overall patterns but does not reveal the local patterns of spatial dependence, which may be assessed by using LISA statistics (Anselin 1995). LISA explains the local spatial autocorrelation functionability and helps identify particular locations of spatial clusters. Figure 3 showcases conspicuous local patterns of spatial dependence in the neighborhood housing quality and its driving forces in Kolkata. These maps illustrate local spatial autocorrelation in the variables of interest, considering a five pronged classification scheme: high-high, low-high, high-low, low-low and not significant neighborhoods. Those in the 'not significant' group were neighborhoods that reflected no significant autocorrelation with proximate neighborhoods and therefore were neither clusters nor outliers (Jun, 2017). Neighborhoods with high quality housing that were surrounded by other high quality housing neighborhoods (high-high) were mainly clustered in southern and western Kolkata, while neighborhoods with low quality housing (the 'low-low' class) mostly clustered along the eastern and western fringes. This dominance of neighborhoods with high-high and low-low clusters confirmed the overall positive spatial autocorrelation in neighborhood housing quality outcomes. Some spatial outliers with high-low and low-high neighborhood combinations were present, with the high-low neighborhoods being gentrified locales in the north-central part of the city, while the low-high neighborhoods tended to cluster around other better-off neighborhoods (Figure 3, Map-HQI). Overall, the LISA map demonstrated that the distribution of quality housing differed significantly across the city space and highlighted the neccessity of considering spatial heterogeneity in neighborhood housing quality studies.

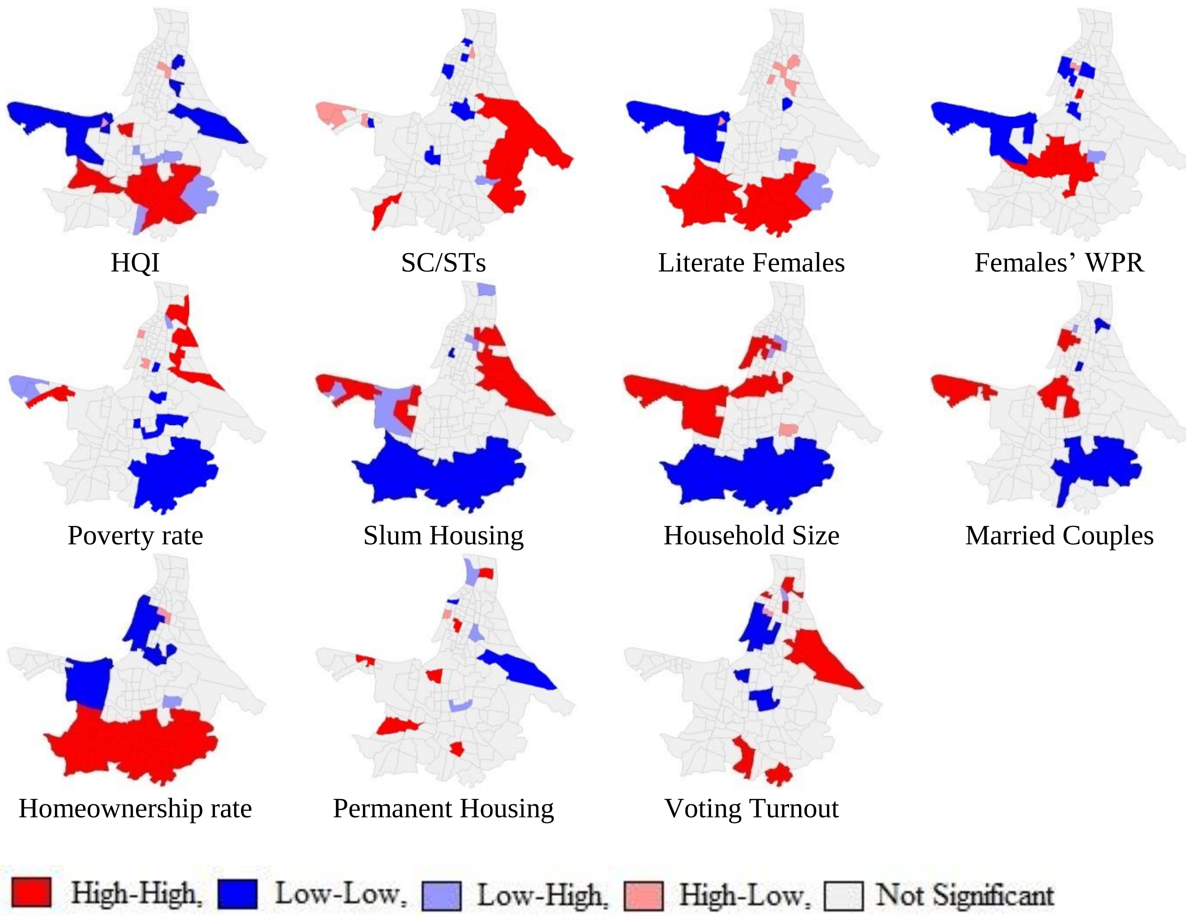


Figure 3: Local Clusters and Outliers of the Neighbourhood scale housing quality outcomes and its driving forces (Kolkata, 2011)

Findings from multivariate analysis

The estimations from the different models, particularly the OLS, SLM and SEM are presented in Table 2 and the GWR local coefficients and goodness-of-fit values (local R^2 and standardized residual) are displayed in Figure 4 and Figure 5 respectively. The summary of GWR estimates and the respective performance measures (AICc) along with the accuracy of the prediction measures (RMSE/RE) of all the models are reported in Table 3 and Table 4 respectively.

Global regressions results

Our global (OLS and SLM/SEM) models showed that only four out of the total selected predictors [(Literate female (+), Slum housing (-), Permanent housing (+) and Voting turnout (-)] were statistically significantly related to the housing quality in Kolkata, in all the three models. Contrarily, 'Poverty' seemed to have a significantly negative impact on the neighborhood quality housing in the OLS and spatial lag models only but not in the error model. Likewise, the 'SC/STs' reported a significant negative impact on housing quality only in the OLS and error models. The ρ and λ tests in Table 2 implied that a significant autocorrelation existed between the housing quality scores and its error terms. Furthermore, a considerable variation existed between the aspatial OLS and the SLM/SEM models in terms of their degree of estimations (*β* coefficient value).

Table 2: Estimates from global OLS and spatial (SLM & SEM) regressions (N=141)

Variables	OLS	SLM	SEM
SC/STs	-0.37 (0.22)*	-0.31(0.21)	-0.42 (0.21)**
Literate Females	1.56 (0.25)***	1.49 (0.24)***	1.31 (0.23)***
Females WPR	0.35 (0.28)	0.26 (0.26)	0.03 (0.29)
Poverty rate	-0.16 (0.09)*	-0.15 (0.08)*	-0.11 (0.09)
Slum housing	-0.07 (0.04)*	-0.05 (0.04)*	-0.11 (0.05)***
Household size	-0.19 (0.19)	-0.15 (0.18)	-0.26 (0.19)
Married couple	-0.34 (0.46)	-0.22 (0.44)	-0.05 (0.50)
Homeownership rate	0.06 (0.06)	0.06 (0.05)	0.12 (0.08)
Permanent Housing	0.65 (0.23)***	0.66 (0.22)***	0.76 (0.21)***
Voting turnout	-0.32 (0.12)***	-0.33 (0.11)***	-0.39 (0.11)***
Constant	-109.79***	-116.71***	-97.12***
Mean VIF	2.89		
F statistic $_{(10, 130)}$	53.27***	-	-
Log likelihood	-506.209	-504.041	-498.376
ρ	-	0.156 (0.05)***	-
λ	-	-	0.511(0.56)***
Likelihood Ratio test	-	4.336**	15.666***

Notes: Level of significance: *** p<0.01, ** p<0.05, * p<0.1; Standard errors appear in the parentheses.
Source: Same as Table 1

Table 3: Models' performance and their prediction accuracy assessment[a]

Parameters	OLS	SLM	SEM	GWR*
Adjusted R^2	0.641	-	-	0.845
AICc	1034.42	1027.3	1007.98	998.229
AICc reduction	-	7.12	26.44	36.191
RMSE	8.769	8.615	8.058	6.025 (31.29%)
RE	0.507	0.498	0.468	0.337 (33.35%)

Note: [a]All the abbreviations used in this table are specified in the text.
*Figures in parentheses indicate % increase of prediction accuracy in GWR estimation relative to OLS.
Source: Same as Table 1

Thus the spatial regressions (the SLM/SEM and the GWR local model) aligned far better with the data than the aspatial OLS regression. Among these, the GWR seemingly provided the best fit for the data with the least AICc (998.229), while the SEM performed marginally better than the SLM. The adjusted R^2 values also showed significant improvement in the GWR estimation ($R^2_{GWR} > R^2_{OLS}$).

The RE and RMSE measures implied that our GWR model outperformed the rest, with the other spatial models (i.e. SLM/SEM) lagging just behind (Table 3). Compared to the conventional OLS model, the local GWR model improved the prediction accuracy by more than 30%, implying that many of the un-captured housing quality predictors were strongly associated with their location. Therefore the GWR, with its inherent understanding of the natural mechanism of spatial heterogeneity that underlies the metropolitan housing market, emerged as the best predictive model for such estimation (Yu *et al.*, 2007).

Estimations of GWR local coefficients

Table 4 reports the summary results of the GWR model. All the select independent variables were spatially non-stationary and therefore, could be considered as local covariates (last column, Table 4). GWR local coefficients of all variables (significant at 5% level) were mapped in order to have a more nuanced interpretation of the results (Figure 4). We also mapped these local coefficients without showing significant levels (Appendix-3). In particular, the interpretation of the GWR local coefficients seemingly supported our assumption that the impact of select socioeconomic, demographic, housing, and political variables on the neighborhood housing quality outcomes was not spatially invariant.

Table 4: Estimates of the GWR model (N=141)

Variables	Min	Lower quintile	Median	Upper quintile	Max	Diff-of-criterion[a]
Intercept	-153.824	-134.538	-108.602	-72.412	-64.805	-584.610
SC/STs	-0.617	-0.541	-0.475	-0.351	-0.199	-1.111
Literate Females	0.699	0.933	1.519	1.867	2.149	-546.483
Females WPR	-0.343	-0.170	0.199	0.389	0.582	-14.335
Poverty rate	-0.243	-0.216	-0.175	-0.117	-0.100	-1.245
Slum housing	-0.162	-0.140	-0.082	-0.057	-0.042	-1.235
HHs Size	-0.352	-0.178	-0.065	0.086	0.208	-31.704
Married Couple	-1.123	-0.682	-0.193	0.629	0.839	-16.940
Homeownership rate	0.026	0.071	0.174	0.302	0.459	-22.276
Permanent Housing	0.507	0.558	0.613	0.656	0.772	-142.898
Voting Turnout	-0.433	-0.375	-0.293	-0.217	-0.207	-40.326
Adjusted R^2	0.845					
AICc	998.229					
Best Bandwidth	62					

Note: [a]Positive value of diff-Criterion implies non-spatial variability.
Source: *Same as Table 1*

Figure 4 further clarified the point of not all predictors being statistically significantly associated with the neighborhood scale housing quality across Kolkata, with their effects being varied spatially in terms of strength, magnitude and direction. In fact, all the independent variables significantly influenced the housing quality only in specific areas. For instance, the concentration of SC/STs in a neighborhood was a significant determinant of housing quality in the global model ($\beta=-0.37, p<0.1$), while the GWR local coefficient indicated that its influence differed substantially over the city space. In particular, it was strongly negatively related with housing quality in some northern, central and south-western neighborhoods. The north-central (old town and Central Business District (CBD) area) and entire western (port area) part of the city showed moderate to weak significant negative relationship between the housing quality and SC/STs (Figure 4a).

(a) SC/STs (b) Literate Females (c) Females WPR (d) Poverty rate

(e) Slum housing (f) HH size (g) Married couple (h) Homeownership rate

(i) Permanent housing (j) Voting turnout (k) Intercept

Note: All coefficients are significant at 5% level. The classes are determined using the natural breaks scheme of Jenks (Jenks and Caspall, 1971).

Source: Same as Table 1

Figure 4: GWR local coefficient at the Neighbourhood level (Significant areas only) (N=141)

The local coefficient of 'literate females' (Figure 4b) revealed the expected significant positive association between 'literate females' and housing quality everywhere in Kolkata. However, its degree of effect differed greatly across the examined space. Neighborhoods located in the southern suburbs of Kolkata indicated a relatively stronger significant positive relationship with the housing quality, while a larger tract of the south-eastern, central and western part of the city showcased a moderate to weak positive impact on the housing quality outcome. Relatively, the significantly higher coefficient values discerned in the entire southwestern part of the city could feasibly be manifested by a greater concentration of literate females therein who might have enjoyed various housing benefits like affordability, wider tenure choices, location and overall quality (Apendix-1).

Similarly,the ‘Females WPR’ variable flagged a positive impact on the housing quality in the global models though this was statistically insignificant. On the contrary, our GWR estimation unearthed an interesting picture (Figure 4c). The ‘Female WPR’ was strongly significant and positively associated with the housing quality, in only four neighborhoods situated in the extreme south of the city, while some other neighborhoods proximate to these four localities also exhibited a comparatively moderate to weak positive impact of this variable on the housing quality. This may be the reflection of a higher concentration of educated females, possibly engaged in more remunerative employment, since a greater concentration of literate females was already discerned previously in this area. Apart from this, a large number of neighborhoods located in the central and north-eastern part of the city flagged a negative relationship between the ‘Females WPR’ and housing quality, though this was statistically insignificant (see Appendix-3).

As expected, Figure 4d showed a spatially varying significant negative relationship between the ‘poverty rate’ and housing quality. A few eastern and central wards and the majority of the western (port area) neighborhoods reported its strong negative effect on the housing quality outcome, reflective of their marked poverty concentration. In contrast, the entire south-eastern periphery and south-central Kolkata displayed a moderate to weak negative relationship, respectively, between the same parameters. Since this was a proxy measure of the household income, neighborhoods having more households in poverty exhibited lower quality housing and vice-versa. Such spatial dynamics in housing quality outcomes can be partly attributed to the glaringly evident income defieciencies across and even within neighborhoods in Kolkata.

Residential locations thus determine the housing quality and thereby feasibly influence the access to essential amenities. Therefore, slum and non-slum households within the same city could reasonably be assumed to have differing access to housing options and other basic services. Our global model indicated that households in slum areas were likely to have poorer quality housing (β=-0.07, p<0.1). GWR local coefficients however inferred that while it was a significant locational determinant of housing quality, the impact of ‘Slum housing’ varied greatly over the cityscape. It recorded a significantly higher negative effect on housing quality in the neighborhoods located across the western suburbs to central and eastern alignments (Figure 4e),while the entire eastern, central CBD area and nothern Kolkata demonstrated a relativly lesser negative influence. This spatial dynamic in the interrelationship between slum households and housing quality could arise from the entire northeastern part of the city and some neighborhoods (e.g. Ayub Nagar Basti, Rajabagan, Metiabruz, Khiderpore port area) in the western part being concentrated with poverty/slum households that obviously have limited access to basic household services and amenities (see Appendix-1).

On examining the relationship between ‘HH Size’ and housing quality (Figure 4f), we found that only two northern Kolkata neighborhoods (CIT Road area and Belgachia) showed a significantly negative effect of the ‘HH size’ on the housing quality outcome. A higher concetration of ‘bigger HH size’ in these neighborhoods may have possibly induced their poorer housing outcomes. Although the coefficients were insignificant, the whole of southern Kolkata showed a positive relationship between the ‘HH size’ and the housing quality, possibly due to a greater concentration of smaller HH sizes and better access to jobs, threreby leading to an overall improvement in neighborhood conditions (see Appendix-3).

In the global models, no significant relationship between ‘married couple’ and housing quality was observed, while its local coefficients displayed significant negative effects on the housing quality, with it differing considerably across the study region (Figure 4g). Only a few southern Kolkata neighborhoods reported any significant negative effect of this variable on the housing quality. Multicoliniearity was detected between the ‘married couples’ and ‘HH size’ variables and none of them were significant in the global models. However, in our local model, both these covariates seemed to reflect a significant impact on the neighborhood housing quality outcome. We found a significant negative effect in the southern part of the study area, possibly due to some concentrations of households with married couples (Appendix-1). This supported our intial assupmtion that households with married couples were more likely to upgrade their housing quality, possibly in light of their social status. Contrastingly, a positive but insignificant relationship was observed between ‘married couples’ and housing quality in the northeastern part of the city (Appendix-3). This reverse causation requires further indepth research to understand the ambient socio-cultural or tradition-religious factors that are precipitating such a condition.

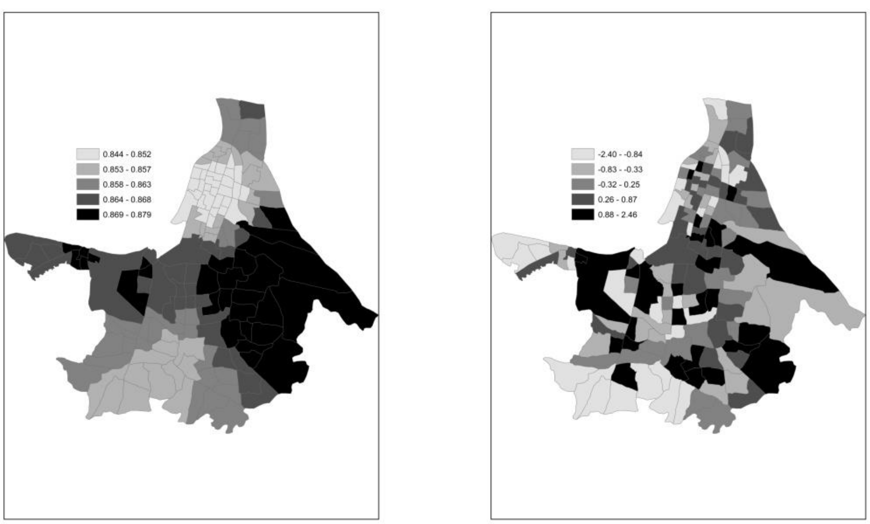
Consistent with the global estimates, Figure 4h shows a positive relationship between ‘Homeownership rate’ and housing quality, with a varying spatial magnitude. A significant positive cluster with higher coefficient value was discerned in the northeastern part of Kolkata. On the other hand, the remaining part of northern Kolkata, the eastern periphery and central Kolkata exihibited a comparatively moderate to weak impact, stressing the place-specific relationship between ‘Homeownership rate’ and housing quality outcomes.

Similar to the homeownership rate, the ‘permanent housing’ status was an important determinant of the neighborhood-level housing quality in the global (β =0.65, p<0.01),and local models. Local coefficients from GWR estimation, however, inferred a substantial locational variability ranging from 0.507 to 0.772 (Figure 4i). In particular, there was a significant highly positive cluster in the eastern and south-eastern part of the city. The northern, central (old city and CBD areas) and entire western-southwestern parts reported a relatively moderate to weak explanatory power of ‘permanent housing’. Such conspicuous spatial dynamics in the relationship between ‘permanent housing’ and housing quality suggested that, all else being equal, a higher prevalence of permanent housing status was related to better housing quality outcomes.

Quite unexpectedly, our last variable, political inclusion/access to political citizenship, measured by the ‘voting turnout’, showed a negative effect on housing quality outcomes (Figure 4j). Local coefficients showed that its impact varied significantly in terms of its magnitude across the locations, within the range of -0.433 to -0.001. Barring a few neighborhoods in the northern part of the city, a negative relationship was found across the entire study area. In particular, neighborhoods located in the extreme north and in some central and eastern parts were found to report a strong negative significant effect on the housing quality. Contrarily, large tracts of the eastern, central, southeastern and the entire western part of the city showed a moderate to weak negative effect of ‘voting turnout’ on the housing quality. Seemingly,the degree of access to political citizenship may not be commensurate with the neighbourhod-level housing quality consupmtion and other life opprtunities in Kolkata. A recent study in India's capital New Delhi had also surmised that the urban poor, residing in under-priviledged neighborhoods voted more than their richer counterparts (Joshi *et al.*, 2016). Possibly such groups are being mobilized more effectively for electoral turnouts by political parties on the pretext that they would get better material benefits and services in return (Ahuja & Chhibber, 2012).

GWR model fits

The GWR estimations inferred a reasonable spatial heterogenity in the interlinkages between housing quality and its economic and socio-demographic determinants at the neighborhood scale. With respect to the model goodness-of-fit, our local model (R^2=0.845) elucidated a much higher reliability of the relationship as opposed to what is demonstrated by the global OLS regression (R^2=0.641).To examine how the GWR best fit our data, we mapped the local R^2 and local residual (Figure 5). The local R^2 ranged from 0.844 to 0.879. We found that in the eastern and western flanks of the city, which both suffer from housing quality deprivation (Figure 2a), our dependent variable (HQI) was better explained by its predictors than by their counter parts.



(a) Local R^2 (b) Standardized Residual

Figure 5: GWR model fit

Conclusions

Through this detailed paper we have elicited useful insights into the spatial dimensions of neighborhood-scale housing quality outcomes in India's oldest metropolitan city, Kolkata, using the most recent housing datasets. This paper has also developed a spatial theoretical framework to decipher the intricacies of neighborhood-level housing quality outcomes, given that spatiality is an inherent characteristic of housing economics (Arnott et al., 1995). Some key reflections from the analyses performed are as follows:

We have found that a significant number of neighborhoods suffer from acute housing quality deprivations, with their very poor HQI scores reflecting a colossal spatial inequality in the pattern of quality housing consumption across Kolkata. Similar intra-urban spatial inequality in housing quality distribution was evident in other big Indian cities as well (Bhan and Jana, 2015). Univariate spatial statistics (Moran's I and LISA) further confirmed that an admixture of neighborhood externalities, spatial spill-over effects and spatial diffusion were at play in producing relatively higher positive spatial autocorrelation for both neighborhood housing quality and its driving forces. Through the multivariate analysis, we deciphered that the GWR local model best fit the data compared to all other global models, further stressing that there existed statistically significant spatial effects intricately woven with the neighborhood-level housing quality. The estimates from these spatial models suggested that earlier studies which did not factor in or account for such spatial effects may have erroneously discerned or overestimated the effects of neighborhood-level housing quality determinants. The GWR based local estimates clearly demonstrated that the relationships between the neighborhood-level housing quality and socioeconomic, demographic and political factors were not only spatially invariant but also differed spatially in terms of their magnitude, direction and intensity. In particular, all the selected independent variables appeared to have statistically significant but place-specific varying effects on the housing quality, hinting at the complex nature of spatial dynamics that shape such neighborhood-level housing quality outcomes in Kolkata. The best fits of the GWR model were in the eastern and western parts of the city, marking them as poor quality housing locales while the selected ten predictors explained these differentials quite lucidly. The northern and southern parts of the city however flagged poorer model fits, implying that these independent variables could not sufficiently explain the dynamics at play reagarding the housing quality outcomes therein. Therefore our results speak directly to location-specific and context-specific research on housing quality in urban India, clearly demonstrating how identified relationships alter from one neighborhood to another and the degree to which these local dynamics might be masked in global measures. This particular finding is new, quite unique and unlike those garnered from previous housing quality studies done elsewhere (e.g. Yust et al., 1997; Fiadzo, 2004; Ibem, 2012; Linneman, 1981; Pan, 2004; Spain, 1990; Memken and Canabal, 1994; Cook and Bruin, 1994).

The above findings have some crucial implications that need elucidating further. *Firstly*, it becomes evident that quality housing distribution in Kolkata is characterized by stark spatial inequality across the cityspace as well as across different socioeconomic rungs. Therefore, policymakers and housing developers should ideally accord utmost priority to the more deprived neighbourhods with a better provision of basic services and amenities, for balanced residential quality outcomes. Not doing so may lead to the spatial reproduction and inter-generational transmission of housing proverty. *Secondly*, formulation of more targated and *place-based housing schemes* that seek to abate the evident local level spatial and social class/caste based inequalities in quality housing consumption are sorely required to ensure its accessibility and affordability equitably for all residents. For this [as surmised by Sengupta (2007)], provisions like self-help housing, greater tenure security and income generation for low-income groups should be recognized as useful policy options. *Thirdly*, Housing quality is largely found to be determined by the HHs' income and financial well-being and tenure security in Kolkata. The Government of India has undertaken some *singular-minded* ownership-based housing policies [e.g. Pradhan Mantri Awas Yojana (Urban), 2015] to cater for the unmet housing need. Unfortunaly, the sheer proportion of HHss that are financially incapable of affording ownership-based quality homes renders such programs quite ineffectual in many areas. Therefore, rental housing as an affordable, accessible and viable option, especially for the EWS and LIP, needs to be developed to ensure equitable quality housing consumption in Kolkata. *Fourthly,* while GWR based studies that have deciphered similarly spatially varying effects of the independent variables are abundant in the literature, to our knowledge, this is one of the firsts such studies in an Indian context that has sought to enhance the conceptual and empirical understanding of geographical non-stationary association between the neighborhood-scale housing quality and its determinants, using the disaggregated neighborhood-level housing quality data provided for thr first time by the Indian Census. *Fifthly*, a significant negative relationship between the access to political citizenship and housing quality outcomes was unearthed, requiring further investigation into the existing socio-political forces operating in Kolkata's neighborhoods, to gauge how resources, services and financial assistance are controlled, organised and distributed in order to manifest such space-power relations.

Despite some data constraints and limitations of the measures used, this detailed study offers some interesting and new insights into the spatial dimensions of neighborhood level housing quality dynamics in an Indian context. It is hoped that others shall utilize the approach adopted in this paper and further examine the changes in trajectories of such spatial dimensions in housing quality outcomes over time along with their respective trends, across other cities, using longitudinal data. This would then certainly provide policymakers and housing developers with a holistic understanding of the interplay of causative factors determining the residential character of urban areas.

Declaration of interest and disclosure statement

No financial interest or benefit has arisen for any of the authors from the direct applications of the research undertaken in this article.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

Supplementary information

Supplementary data tables are available for this article.

Data availability and data deposition

The data on which this paper is based can be found freely online, at the Census of India website of the Office of the Registrar General & Census Commissioner, India (http://www.censusindia.gov.in/2011-Common/CensusData2011.html). All the tables and information generated from these datasets are fully included within this manuscript in the main text and supplementary information sections.

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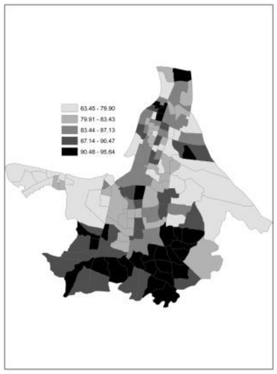
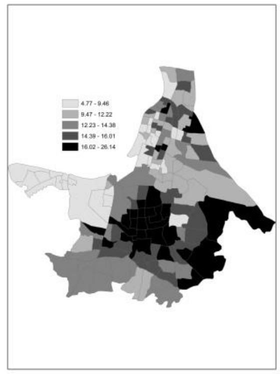
Appendices

Appendix-1: Spatial distribution of select variables (N=141)

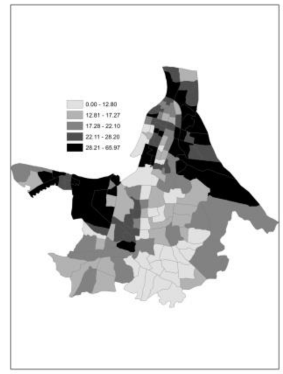
SC/STs



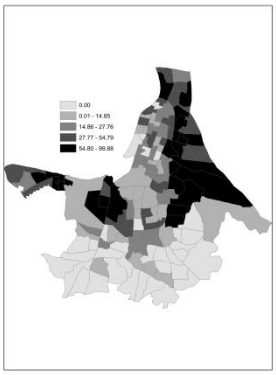
Literate Females



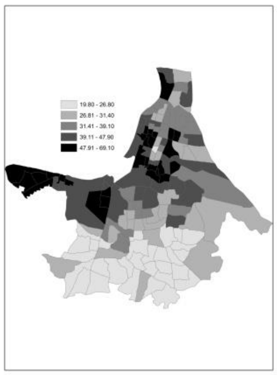
Females WPR



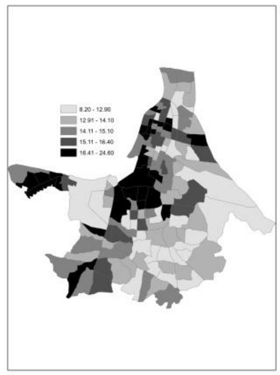
Poverty rate



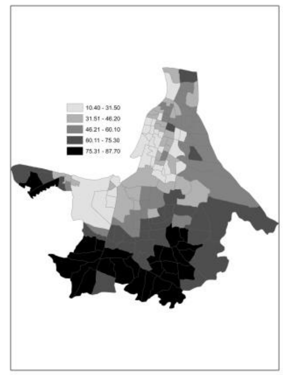
Slum housing



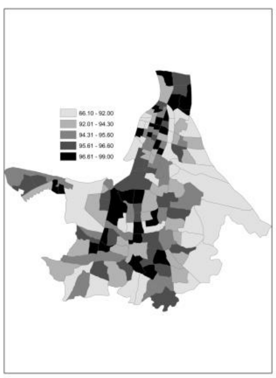
HH Size



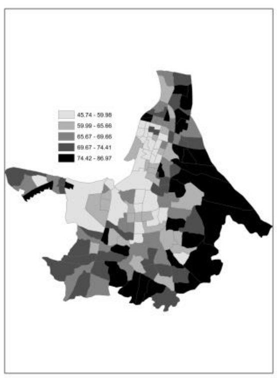
Married couples



Homeownership rate



Permanent housing



Voting turnout

Note: Values are presented in quintile scales.

Source: Same as Table 1.

Appendix- 2: Model specification

Model specification

***OLS**:* Our basic OLS model is defined as:

$$Y_{(\mathrm{HQI})i} = \beta_0 + \sum_{i=1}^{10}(\beta_i X_i) + \varepsilon_\mathrm{i} \qquad \text{(Eqn. 1)}$$

where the dependent variable $Y_{(HQI)i}$ is the HQI score of the i^{th} neighborhood. X_i denotes the vector of select independent variables of the i^{th} neighborhood which includes the following: *SC/STs, Literate females, females' WPR, Poverty, Slum housing, HH size, Married couple, Homeownership, Permanent Housing and Voting turnout.* $\beta_{0.}$ and β_i denotes the intercept and regression coefficients respectively. $\varepsilon_i$is an *i.i.d* error term. The Variance Inflation Factors (VIF) measure was also employed for the post-estimation test and the mean VIF appears to be 2.89. No potential multi-collinearity was found among the independent variables in the regression.

***Spatial autoregressive models**:* We have used two spatial autoregressive regression techniques so that spatial autocorrelation is inculcated into the model building- the lag (or as postulated in Anselin and Rey, 1991- the substantive) and error (or nuisance) autoregressive specifications. We specify our autoregressive lag (SLM) model as follows:

$$y = \rho W y + \beta X + \varepsilon \qquad \text{(Eqn. 2)}$$

where, ρ is the simultaneous autoregressive lag coefficient. *Wy* denotes the spatially lagged dependant variable for the spatial weight matrix *W*, X is a matrix with all the explanatory variables, ε is an *i.i.d* error term.

The spatial simultaneous autoregressive error (SEM) model, on the contrary, considers the autocorrelation in the error terms, and looks like:

$$y = \beta X + \varepsilon, \quad \varepsilon = \lambda W \varepsilon + \mu \qquad \text{(Eqn. 3)}$$

where, λ is the simultaneous autoregressive error coefficient, μ symbolises for an i.i.d error with the other parameters as defined above.

The maximum likelihood estimator (MLE) is generally endorsed as a powerful asymptotic option (Anselin, 1988). Accordingly, the standard OLS goodness-of-fit, i.e. adjusted R^2 becomes irrelevant and primarily the Akaike Information Criterion [AIC] (Akaike, 1974), a likelihood-based goodness-of-fit measure is utilized here for comparing goodness-of-fit of the model.

***Geographically Weighted Regression (GWR)**:* The GWR approach advances the concept of expansion regression technique, devised by Cassetti (1972), in spatial terms. To explore the varying associations between neighborhood housing quality outcome and its predictors, the GWR local model is used, following the method outlined by Fotheringham *et al.* (1998, 2002), Paez *et al.* (2002) and Yu *et al.* (2007). Within this GWR framework, the OLS model specified above was rewritten as:

$$y_{(HQI)i} = \beta_{0i}(u_i, v_i) + \sum_{j=1}^{k} \beta_{ij}(u_i, v_i) X_{ij} + \varepsilon_i \qquad \text{(Eqn. 4)}$$

where $y_{(HQI)i}$ is the dependent variable (HQI score) at neighborhood i, (u_i, v_i) refers to the coordinates of the centroid of neighborhood i, $\beta_{0i}$and β_{ij} denote the local intercept and the estimated local coefficient for indicator *j* for neighborhood *i*, respectively, *k* denotes the number of explanatory variables while the other notations are as specified earlier.

The GWR model estimates the coefficients for every location independently by using a locally weighted least square (WLS) scheme (Fotheringham *et al.*, 2002). More explicitly, in GWR every location has its own regression model. Accordingly, the vector of local coefficients of $\hat{\beta}$ can be derived by matrix form as follows:

$$\widehat{\beta_i} = (X' W_i X)^{-1} X' W_i y \qquad \text{(Eqn. 5)}$$

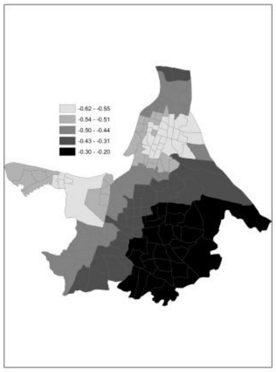
Notations X and y are as defined earlier. The estimator in equation (5) is a location-based weighted least squares (WLS) estimator where the weights differ depending on the location point of i. The literature on this provides a plethora of weighting methods for use (see Fotheringham *et al.*, 2002). We have used the adaptive bi-square Gaussian kernel function, a commonly applied option (Chi & Wang, 2017) for weighting. Therefore in equation (5), W_i is the (diagonal) weight matrix having its weight w_{ij} for i^{th} row and j^{th} column specified as:

$$w_{ij} = \{1 - (d_{ij}/h)^2\}^2 \text{ if } d_{ij} < h \text{ and zero otherwise} \qquad \text{(Eqn. 6)}$$

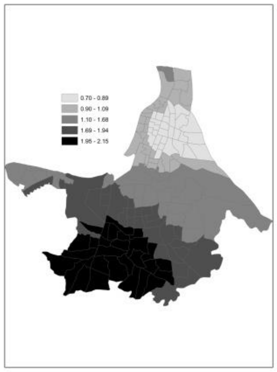
Here, d_{ij} is the measure of the Euclidean distance between i^{th} neighborhood at which the coefficient is estimated and a particular point in j^{th} location where the data is positioned (Fotheringham *et al.*, 2002), and h denotes the bandwidth size, i.e. the distance between every observation and their proximate location as defined by the spatial weights. As mentioned above, the adaptive kernel is used for bandwidth selection, since it is more appropriate for exhibiting the spatial heterogeneity dimensions in the area studied (Yu *et al.*, 2007).

The OLS, spatial autoregressive SLM/SEM and GWR models have been applied on the same dataset. Since the adjusted R^2 based OLS goodness-of-fit is not applicable in spatial models for comparing model performance, the AICc [corrected Akaike Information Criteria (Hurvich *et al.*, 1998)] is used for performance measure where a reduction (or difference) of >3 in the AICc value between two models would indicate a significant enhancement in the model's performance (Fotheringham *et al.*, 2002). To examine the model prediction accuracy, following Yu *et al.*, (2007), we have used two particular statistics, the RMSE (Root Mean Squared Error) and the RE (Relative Error).

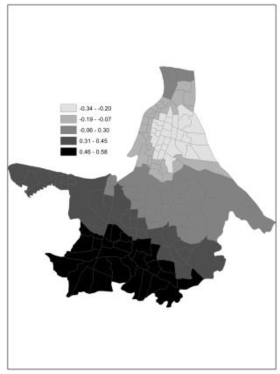
Appendix-3: GWR local coefficient (without presenting significance level) (N=141)



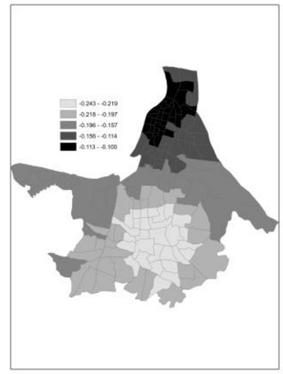
SC/STs



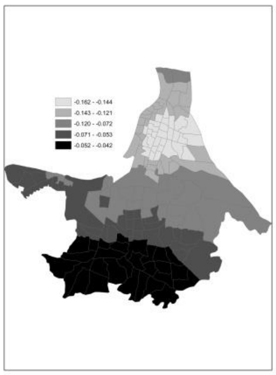
Literate Females



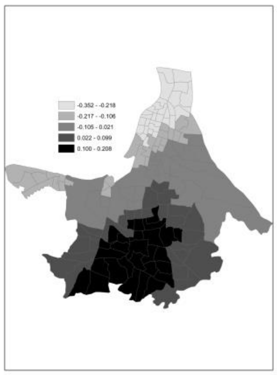
Females WPR



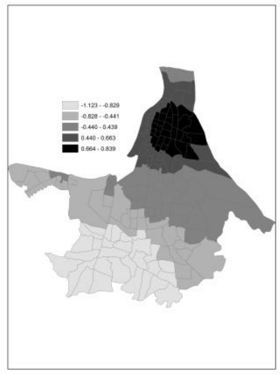
Poverty rate



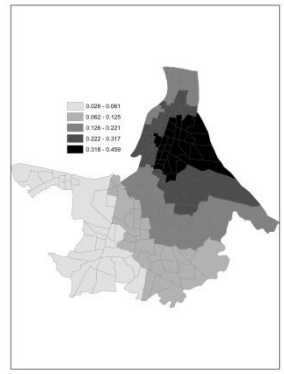
Slum housing



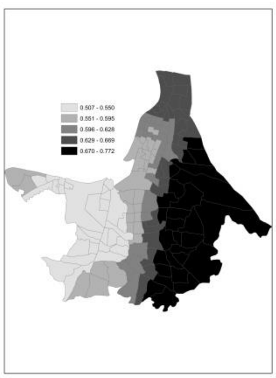
HHs size



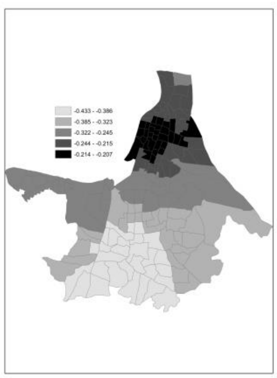
Married couple



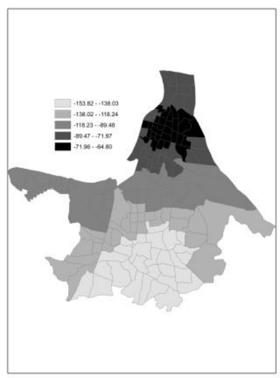
Homeownership rate



Permanent housing



Voting turnout



Intercept

Note: Local coefficients are presented in quintile scales.
Source: Same as Table 1.

Table Captions

Table 1: Descriptive summary of the study variables (N=141)

Table 2: Estimates from global OLS and spatial regressions (N=141)

Table 3: Models' performance and their prediction accuracy assessment[a]

Table 4: Estimates of the GWR model (N=141)

Figure Captions

Figure 1: Structure of an area-based housing quality index for Kolkata

Figure 2: Neighborhood housing quality and spatial autocorrelation

Figure 3: Local Clusters and Outliers of the Neighborhood level housing quality and its driving forces (Kolkata, 2011)

Figure 4: GWR local coefficient at the Neighborhood level (Significant areas only) (N=141)

Figure 5: GWR model fit

Appendices

Appendix Figure Captions

Appendix-1: Spatial distribution of select variables (N=141)

Appendix-2: Model specification

Appendix-3: GWR local coefficient (without presenting significance level) (N=141)

Supplementary Materials (only for Review)

Supplementary Tables Captions

Supplementary Table S1: Definitions of Indicators used in developing the Neighborhood level Housing Quality Index (HQI)

Supplementary Table S2: Definitions of variables used in the regression analysis

Supplementary Table S3: KMO and Bartlett's Test

Supplementary Table S4: PCA Result: Varimax Rotation Factor Matrix

Supplementary Figure S1: Correlation among original indicators

Supplementary Figure S2: Correlation among transformed indicators

Supplementary Figure S3: Scree plot of eigen values of factors

Supplementary Materials

Supplementary Table S1: Definitions of Indicators used in developing the Neighbourhood level Housing Quality Index (HQI)

Physical Sustainability

1. % of households (HHs) with good housing conditions including both residential and other uses in the total number of HHs
2. % of HHs having houses with concrete roof material in the total number of HHs
3. % of HHs having houses with concrete / burnt brick wall in the total number of HHs
4. % of HHs having houses with concrete floor in the total number of HHs

Overcrowding

5. % of HHs having at least two living dwelling rooms in the total number of HHs
6. % of HHs having separate kitchen for cooking facility in the HH

Housing Services

7. % of HHs having electricity as the main source of lighting in the total number of HHs
8. % of HHs with access to tap water from treated sources as the main source of drinking water in the total number of HHs
9. % of HHs having access to drinking water facilities within their own premises
10. % of HHs using clean (LPG, PNG and electricity) fuel for cooking
11. % of HHs having access to flush/pour flush latrine connected to piped sewer system in the total number of HHs
12. % of HHs having bathing facilities enclosed with a roof within their own premises in the total number of HHs
13. % of HHs with the facility of waste water outlet connected to a closed drainage system in the total number of HHs

Extra Amenities

14. % of HHs availing banking facilities in the total number of HHs
15. % of HHs possessing television in the total number of HHs
16. % of HHs having computer/laptop including both with/without internet connections in the total number of HHs
17. % of HHs possessing Two Wheelers (motorcycle, scooter or moped) in the total number of HHs
18. % of HHs with cars (car, jeep or van) in the total number of HHs

Supplementary Table S2: Definitions of variables used in the regression analysis

Variables	Definitions
Dependent variable	
HQI	Standardized composite HQI comprising 18 indicators of housing quality
Explanatory variables	
SC/STs	% of Scheduled Caste (SC) and Scheduled Tribe (ST) population in total population
Literate females	% of literate females in total female population
Females WPR	% of females engaged in main working activities in total female population
Poverty rate	% of HHs living Below the Poverty Line (BPL) in the total number of HHs
Slum housing	% of HHs residing in slum area in the total number of HHs
Homeownership rate	% of HHs with ownership housing status in the total number of HHs
Permanent Housing	% of HHs with permanent houses in the total number of HHs
Married couple	% of HHs with at least two married couple in the total number of HHs
Household size	% of HHs with at least five members in the total number of HHs
Voting turnout	% of vote polling turnout in the total number of voters

Supplementary material: PCA-based HQI calculation

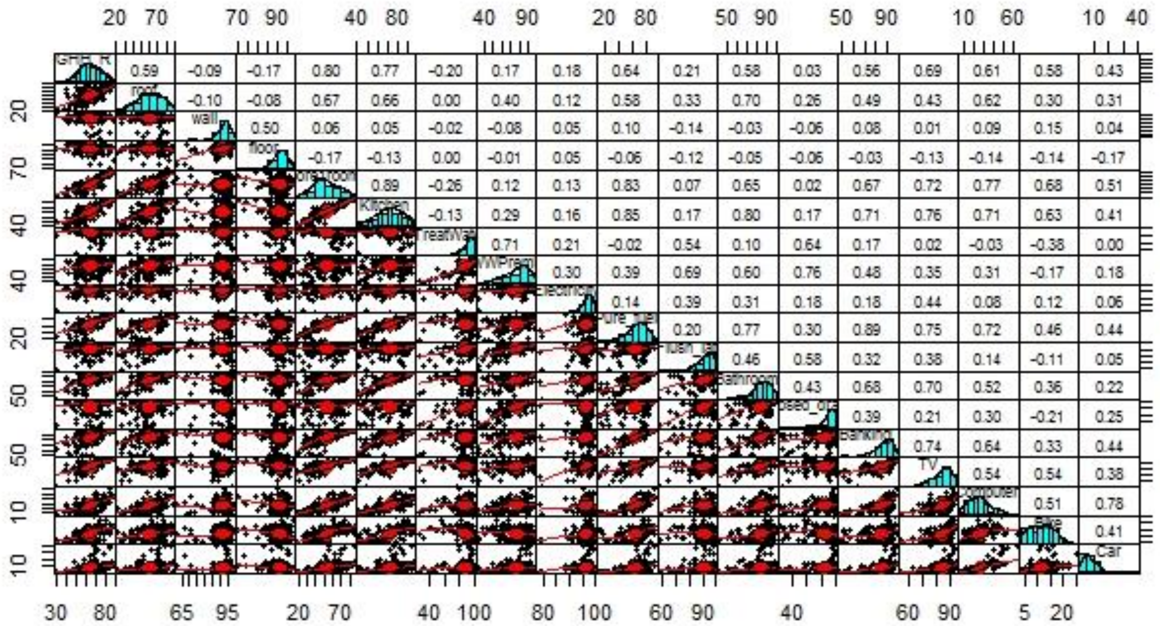
For developing an area based HQI (Housing Quality Index) for this paper, we used a revised version of the Principal Components Analysis (PCA) as suggested in Krishnan (2010) and Vyas & Kumaranayake (2006). Here, a data dimensionality reduction procedure is performed to generate the weighted linear combinations of the indicators under consideration, for instance: given x correlated indicators, we developed an index, I, that corresponded to the weighted combination of all principal factors (component), where, the weights for every factor was equal to the % of variance explained by that factor. Next, the index assigned a different weight, w_i, to every indicator, c_i, where w_i was the loading (eigen vector) corresponding to the indicator c_i. Actually, the weightage given to every indicator was equal to the sum of corresponding loadings, each in turn weighted by the % of variance explained by that factor. Finally, the index was standardized to a scale of (0, 100) to make it comparable with other variables of interest, with higher index values denoting better quality housing.

Computation: A 141 (neighborhoods) by 18 (indicators) data matrix was generated for the PCA with varimax rotation. Measures of Sampling adequacy, KMO test was performed to detect multi-collinearity among indicators, followed by Bartlett's Test of Spheriocity to check the strength of relationship among the indicators. Both the tests confirmed the suitability for these data for performing the PCA (see Table S3, Figure S1, S2). Four factors with Eigen value more than or equal to 1 were extracted (see Figure S3). Table S4 reports the PCA results in detail along with the % variance explained by each factor. The extracted factors were then saved as score variables in the data matrix. The final index was then computed as follows:

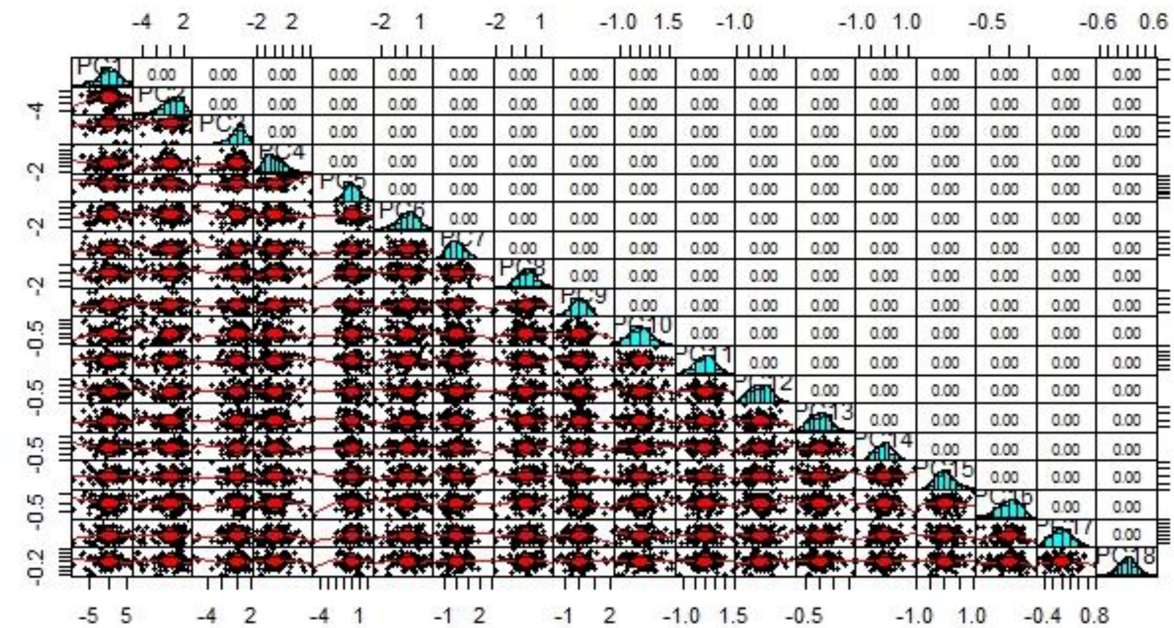
HQI= (42.50/76.26)(Factor 1 score) + (18.13/76.26)(Factor 2 score) + (8.69/76.26)(Factor 3 score) + (6.94/76.26)(Factor 4 score)

Supplementary Table S3: KMO and Bartlett's Test

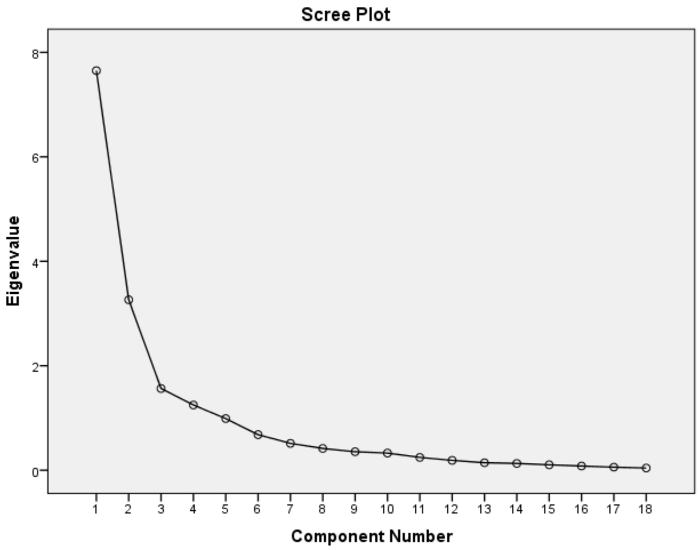
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.849
Bartlett's Test of Sphericity	Approx. Chi-Square	2403.406
	df	153
	Sig.	.000



Supplementary Figure S1: Correlation among original indicators



Supplementary Figure S2: correlation among transformed indicators



Supplementary Figure S3: Scree plot of eigen values of factors

Supplementary Table S4: PCA Result: Varimax Rotation Factor Matrix

Housing Quality Indicators	Factors*			
	Factor1	Factor2	Factor 3	Factor 4
1. Physical sustainability				
Good condition house	**0.837**	-0.087	-0.180	0.095
Concrete roof	**0.694**	0.219	-0.134	0.014
Concrete/burnt brick wall	0.071	-0.073	**0.873**	-0.068
Concrete floor	-0.131	-0.001	**0.832**	0.140
2. Spatial adequacy/overcrowding				
At least 2 living rooms	**0.947**	-0.129	-0.037	-0.057
Has Separate Kitchen	**0.939**	0.023	-0.018	0.050
3. Housing services				
Tap Water (treated)	-0.184	**0.857**	0.038	0.033
Water within Premises	0.263	**0.893**	-0.017	0.111
Electricity	0.229	0.237	0.085	**0.654**
Clean fuel for cooking	**0.887**	0.190	0.102	-0.050
Flush latrine	0.189	**0.721**	-0.175	0.375
Bathroom within premises	**0.770**	0.362	-0.020	0.286
Closed drainage	0.148	**0.879**	-0.018	-0.119
4. Extra amenity				
Access to Banking	**0.777**	0.350	0.119	-0.037
TV	**0.825**	0.141	-0.018	0.312
Computer	**0.811**	0.168	0.020	-0.427
Two-wheelers	**0.704**	-0.411	0.017	0.000
Car	**0.561**	0.144	-0.022	-0.584
% variance explained (76.26)	**42.50**	**18.13**	**8.69**	**6.94**

Note: *Higher loadings are in bold
Source: Authors calculation

[i]Presently 18.78 million HHs suffer from housing shortages in urban India and among them 95.62% HHs are from the LIP and EWS category (GOI, 2012).

[ii] These groups are the historically marginalized entities in India and were therefore accorded similar status and rights in her constitution through affirmative action policies. They are also residentially segregated across Kolkata (Haque, 2016). The '*SC/STs*' population are combined together for analysis due to the negligible proportion of STs in many neighbourhoods of Kolkata.