Journal of Geographical Systems (2019) 21:295–318
https://doi.org/10.1007/s10109-019-00297-z

ORIGINAL ARTICLE

How much does geography contribute? Measuring inequality of opportunities using a bespoke neighbourhood approach

Umut Türk[1] · John Östh[2]

Received: 7 July 2018 / Accepted: 21 March 2019 / Published online: 30 March 2019

Abstract
To what extent an individual is successful in a variety of outcomes is the result of multiple factors such as (but not limited to) parental background, level of education, discrimination and business cycles. Factors like these also indicate that the success in life can be attributable to factors that both take individual-level merits into account but also to structural factors such as discrimination and contextual effects. Over the last decades, a growing interest in decomposing and categorising factors that affect the life chances of individuals has led to the formation of inequality of opportunity as a research field. This paper builds upon this growing literature, which amounts to quantify the contribution of factors that lie beyond the control of individuals to the total inequality observed in different spheres of life. Using rich Swedish longitudinal register data, we are able to follow individuals over time and their educational attainment during upbringing and later labour market outcomes. In difference from other inequality of opportunity studies, we make use of an egocentric neighbourhood approach to integrate the socio-economic composition of the parental neighbourhood in an inequality model and illustrate its contribution to the total inequality in both outcomes quantitatively. Using multilevel regression analyses, we show that the parental neighbourhood is highly influential in educational attainment and remains so for market outcomes even years after exposure.

Keywords Inequality of opportunity · Neighbourhood effects · Multilevel model · k-nearest neighbour

✉ Umut Türk
umut.turk@agu.edu.tr

John Östh
john.osth@kultgeog.uu.se

[1] Department of Economics, Abdullah Gül University, Sumer Campus, 38030 Kayseri, Turkey

[2] Department of Social and Economic Geography, Uppsala University, Box 513, SE-751 20 Uppsala, Sweden

JEL Classification R23 · J62 · D31 · D63

1 Introduction

In recent years, the equality of opportunity concept has often been mentioned in discussions concerning distributional disparities. It is almost a universally accepted principle developed recently by Roemer (1998) and already with numerous empirical applications (see Ramos and Van de Gaer 2012; Roemer and Trannoy 2016; Brunori et al. 2013, for reviews). In this framework, the overall inequality observed in different spheres of social life is decomposed into two major components: ethically acceptable (fair) components and offensive (unfair) components. *Circumstances* representing unfair sources of inequality are predetermined in their nature and go as such beyond people's controls, including factors such as gender, race and family background (Roemer 1998; Roemer and Trannoy 2016). On the other hand, acceptable (fair) sources of inequality are defined as *effort* for which individuals are held responsible. The inequality that is due to *circumstances* is defined as inequality of opportunity.

The inequality of opportunity is a product of several underlying inequalities, such as inequality due to differences in social treatment (based on gender, ethnicity, etc.), inequality of access to basic opportunities and inequality due to parental resources and location (de Barros 2009). A number of empirical studies seek to disentangle these underlying inequalities in opportunities through a set of variables as proxies of individuals' *circumstances*. To assess the opportunity share accurately, analyses thus need to take a comprehensive approach to the variables employed. However, most existing studies have been limited to accounting for inequalities due to parental resources and social treatment, with such variables as gender, race, parental income and education as typical predictors of *circumstances*. So far, however, there has been little discussion of the spatial sources of inequality of opportunity and none for inequalities due to the characteristics of residential locations.

It has already been suggested that residential location may generate unfair inequalities, especially for children (Ross and Iannotta 2002; de Barros et al. 2008). However, the empirical studies that have sought to evaluate inequality of opportunity, include geography either as a reference to a general Urban/Rural division of birthplace (Ferreira et al. 2010), or as large administrative units, for instance, regions (Peragine and Serlenga 2008; Checchi et al. 2010; Singh 2012). However, on such a scale geography loses the variation within boundaries and does not represent the residential characteristics to which individuals are exposed in everyday life. Therefore, a more specific characterisation of spatial patterns that communicates the current and past residential environment of individuals, as well as the potential interaction between individuals in neighbourhoods must be included in analyses to better encompass the spatial dimensions of inequality of opportunity.

The paper aims to go beyond the analysis of traditional sources of inequality by linking the equality of opportunity literature to the literature investigating the neighbourhood effects on various outcomes of individuals. Neighbourhood studies offer empirical evidence of the link between the local community and the opportunities of residents that traditional equality of opportunity literature does not consider. As a departure for our study, neighbourhood studies have made great contribution to increase knowledge on the neighbourhood effects on children's outcomes (see Leventhal and Brooks-Gunn 2000; Sharkey and Faber 2014; Van Ham et al. 2012, for reviews), individual opportunities on the labour market and in terms of economic outcomes (see Vartanian 1999) and also spatial mismatch implications (for a review, see Kain 1992) and the ability of individuals to shift spatial outcomes in the housing market (Brazil and Clark 2017).

The aim of the present work is to single out the contribution of neighbourhoods to inequality of opportunity in both educational and earnings outcomes of the whole 1985 cohort in Sweden. The estimates are carried out in two data points. We use a multilevel modelling strategy to disentangle the influence of *circumstances* in relation to the parental neighbourhood on educational attainment when living with parents and parental and own-neighbourhood characteristics influencing disposable income when living independently of parents. We use the longitudinal register database from Sweden. The database provides family background variables such as parental education, employment, marital status and national origin, and provides information on individuals' disposable incomes and compulsory school examination marks that are taken as dependent variables. Since residential coordinates on 100 m × 100 m level are available for each individual as well as over time, geographical information on residents is used to construct bespoke neighbourhoods for each individual with the aim of channelling several characteristics of residential locations based on a k-nearest neighbours approach (Östh et al. 2015). In addition, we include a measure of physical environment surrounding the parental neighbourhood derived from the Corine (coordination of information on the environment) database and a measure of job/housing balance in own-neighbourhood. Based on these variables, we construct a model to perform a comprehensive investigation of inequality of opportunity with particular attention to the spatial sources of inequality. As in Bourguignon et al. (2007) and Ferreira and Gignoux (2011), we formulate a situation where the within-group inequalities are eliminated so that the overall inequality in both educational attainment and disposable income is decomposed into *circumstance* (inequality of opportunity) and *effort* components. As it is the foremost aim of this study, we also decompose *circumstances* and *effort* into spatial and aspatial components.

The results of the model show that even though Sweden is characterised by lower levels of inequality in the life chances of individuals, a larger part of inequality of opportunity can be identified by quantifying neighbourhoods.

This study makes several contributions to the existing research: (i) via the comprehensive register data we cover a large set of *circumstance* variables, often not available due to data restrictions; (ii) using several bespoke neighbourhood characteristics provides robust, externally valid and policy-oriented identification of the spatial factors as affecting opportunities; (iii) the measure of inequality of opportunity is associated with parental neighbourhood characteristics for the first time in this study, and through a multilevel modelling strategy the results are robust with respect to previous studies where problems such as spatial autocorrelation have been ignored.

2 Previous work

Despite the increasing number of empirical papers assessing the degree and nature of inequality of opportunity in different contexts none, to the best of our knowledge, includes parental neighbourhood into typically used parental background attributes. Some associate geography-of-birthplace as a *circumstance*, but this is often limited to Urban/Rural classifications (see Ferreira et al. 2011) or to very large administrative units such as regions (see Cogneau and Mesplé-Somps 2008; Singh 2012). Others partition the study area into fewer but bigger macro-regions and evaluate inequality of opportunity separately (Peragine and Serlenga 2008; Checchi and Peragine 2010). In a recent study, Türk (2019) defines the province of parental residence as a *circumstance* generating inequality of opportunity in spatial access to higher education in Italy.

As is often underlined by the scholars proposing variants of the equality of opportunity approach, children should not be held responsible for their choices in any way (de Barros 2009; Björklund et al. 2012). Such a view can be extendable to include the residential decisions of parents on behalf of their children. Therefore, given the context of equal opportunities literature, there should be no objections to defining the parental neighbourhood as a *circumstance*.

Considerable effort has been put into providing a proper definition of neighbourhoods, and causal relations with their observed effects (see Ellen and Turner 1997, for a review). Several empirical studies investigate the effects of neighbourhoods on educational attainment (Garner and Raudenbush 1991), drop-outs (Crane 1991) and outcomes such as reading, maths achievement (Ludwig 1999) and higher education participation (Andersson and Malmberg 2015). For the Swedish context, the relationship between neighbourhood compositions and several individual outcomes is studied by a number of papers. For instance, Andersson (2004) shows a significant relationship between individuals' neighbourhood composition—in relation to socio-economic and physical characteristics—and their educational outcomes and subsequent occupational status. Similarly, Andersson and Subramanian (2006) find that educational outcomes are negatively influenced when exposed to neighbourhoods with higher concentrations of single mothers, individuals benefiting social allowances and of persons who born outside of Sweden. In a study on Stockholm area, Urban (2009) concludes that a small variation in individuals' market outcome is explained by neighbourhood characteristics and that economic segregation appears to be more influential than ethnic segregation. Using a longitudinal dataset including all working age individuals in Swedish metropolitan areas, Galster et al. (2008) show a significant and nonlinear impact of neighbourhoods on market outcomes, which vary with gender and occupation type (part time or full-time occupation).

In Sweden, earlier research in the field of neighbourhoods effects on various outcomes indicate a significant relationship both while exposure is ongoing and after it has ended. However, the extensive body of neighbourhood literature shows no consensus on the durability of neighbourhood effects especially in the US context. While a number of earlier and recent studies present a similar subsequent outcomes for once neighbouring children (Page and Solon 2003) and improved educational and market outcomes for those who were exposed to better neighbourhoods (Chetty et al. 2015), others find no impact Ludwig et al. (2013) or declining neighbourhood effects on earnings and educational attainment as years go by (Raaum et al. 2006). An explanation to these mixed findings is given by "stickiness" arguments that failing to consider the persistence of neighbourhood residence may lead to biased findings (Glass and Bilal 2016). Other explanation relates to the scale at which neighbourhoods are defined.

Although the above papers differ in important respects in how they study neighbourhood effects, they all identify a neighbourhood as an area comprising a predefined administrative unit. Galster (2001) argues that the neighbourhood is a multidimensional phenomenon, in which four actors (households, businesses, property holders and local government) act both as consumers and producers in shaping the structural, demographic and social-interactive characteristics of neighbourhoods (Galster 2001). In the light of this definition, it becomes clear that an arbitrary definition of neighbourhoods may suffer from misspecification in a crudely defined model, both from a geographical perspective (the modifiable areal unit problem (MAUP) (Openshaw 1984)-related issues) and a functional perspective (how size and composition of re-enacted neighbourhoods may vary between population groups). From a modelling perspective, it becomes important to treat neighbourhoods as the environment surrounding residents where its scale is based on the potential interaction between individuals. This means that individual-centred and differently sized neighbourhoods need to be designed. A number of recent and earlier studies make use of bespoke–individualised neighbourhood units (Johnston et al. 2004). Musterd et al. (2003) study whether the weak economic position of neighbours (within a circle drawn around households) influences the social mobility of households and shows that while the impact is minor for the benefit-dependent households, those with a paid job face greater risks of losing their job in an economically distressed neighbourhood in the Netherlands. Using the same approach to define neighbourhoods, Musterd and Andersson (2006) conclude that exposure to a higher concentration of the unemployed has negative consequences of one's own employment chances. Andersson and Musterd (2010) examine how varying neighbourhood sizes impact individuals social position and find that especially the smallest environments impact work income in Sweden. Van Ham et al. (2014) use k-nearest neighbour method in a study on the Stockholm metropolitan area and show that the adverse effects of neighbourhoods are both inherited and persistent over time. Similarly, when investigating a population of parental home-leavers in Stockholm, Hedman et al. (2015) observe negative effects of exposure to a poverty-concentration parental neighbourhood even after 17 years of living away from parents. In a recent study, Östh et al. (2018) combine k-nearest neighbour method to define neighbourhoods with a fine-grained mobile phone data to show how segregation experiences of individuals vary according to their daily mobility patterns.

This study seeks to bridge the gap between the literature dedicated to the theory and methods of equality of opportunities and to neighbourhood effects. We aim to incorporate neighbourhood characteristics in an inequality measure and quantitatively illustrate their contribution to the total inequality of opportunity in Sweden.

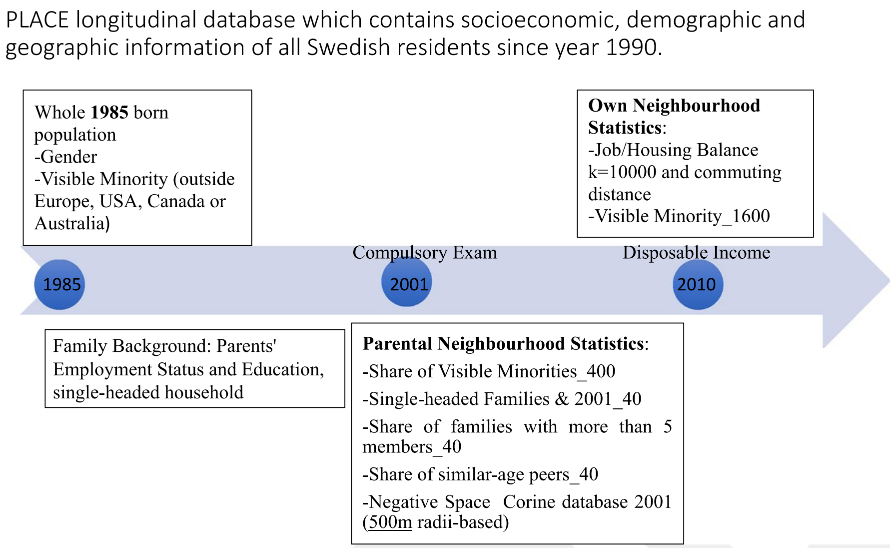

Fig. 1 Data points

For the educational inequality of opportunity we start from previous empirical studies on neighbourhood effects, and for the income inequality of opportunity we first show how the neighbourhood histories of individuals exert persisting effects on life chances.

3 Data

The present study uses the PLACE longitudinal database (located at the Department of Social and Economic Geography, Uppsala University) which contains socio-economic, demographic and geographical information for all Swedish residents since 1990. Following the same individuals over time, we investigate the distribution of compulsory school examination marks in 2001 and the distribution of disposable incomes in 2010 for the whole 1985 cohort as our variables of interest. Two sets of independent variables are considered in the model: *circumstances* as measured by parental background and parental neighbourhood characteristics and *effort* as measured by educational level and own-neighbourhood characteristics. The PLACE is used to extract information at three data points as shown in Fig. 1. The first point relates to the inherited *circumstances* by birth, the second point corresponds to the year 2001 when individuals graduate from compulsory school (this is also when and where parental neighbourhood statistics are created). The last data point is considered when the individuals are at an employable age and exposed to their own neighbourhoods.

For each individual, we use spatial and aspatial information from the dataset (Table 1 and Fig. 1). The aspatial set of variables includes several covariates typically used in equality of opportunity studies that are informative of the family

Table 1 Variables

	Variables	Description
First Level		
Individual	Gender	1 = Female, 0 = Male
	Visible minority	1 = VM, 0 = Not a VM
	Compulsory school marks	
	Family background	Parents' employment status and education, single-headed household
Bespoke neighbourhoods	Share of visible minorities	2001 (k = 400) and 2010 (k = 1600)
	Single-parent families	2001 (k = 40)
	Share of families with 3 or more children	2001 (k = 40)
	Share of same-age peers	2001 (k = 40)
	Negative space	Corine database 2001 (500m radii-based)
	Housing/job market balance	2010 k = 10000 and commuting distance
Second level		
	Municipality	290 Swedish municipalities

background and other inherited *circumstances*. Six such variables are used: gender, compulsory school examination marks, disposable income for 16-year-olds residing in the household of upbringing (measured as part of household disposable income), whether or not a visible minority (VM, here understood as all individuals born outside Europe, USA, Canada or Australia), parent's marital status (single-parent or dual-parent households), parental education and employment status. The parental educational level is measured as the highest educational level reached by either of the biological parents. In order to take returns-to-education in account parental education level interacts with ten city classes accounting for different degrees of industrialisation in cities as well as functions in terms of population density, commuting and remoteness following a classification of municipalities provided by SALAR (Swedish Association of Local Authorities and Regions)[1]. Employment status is measured as each parent working or not working in 2001.

The spatial set of variables includes parental neighbourhood characteristics in 2001 and the own-neighbourhood of the same individuals in 2010. We channel the following parental neighbourhood characteristics from 2001: the share of similar-age peers among the nearest 40 neighbours account for socialisation and network patterns, the share of visible minority neighbours among the nearest 400 neighbours shows the degree of segregation and deprivation, the share of single parents and families with 3 or more children (large families) among the nearest 40 neighbours accounts for household and housing characteristics. We use smaller k levels for the

[1] Source: https://www.scb.se/Grupp/Hitta_statistik/Regional%20statistik/Kartor/_Dokument/SKL-Kommungrupp.pdf.

year 2001 as the potential interaction with the neighbourhoods might be limited compared to 2010 (since children have limited activity spaces compared to adults).

In addition to these bespoke neighbourhoods, the negative environment surrounding the parental neighbourhood is constructed based on Corine (coordination of information on the environment) data, which is available as 100-metre pixel raster images. ArcGIS software is used to match the land cover data to the coordinates of individuals (both available as 100×100 geo-coordinates) and after a classification of good/bad elements of Corine, the exposure to negative surroundings within a 500-m radios is imported into the data as a column vector (negative space includes factors such as dumps and industrial areas).

The own-neighbourhood in the year 2010 is defined as the share of visible minorities among the nearest 1600 neighbours, and a measure of job/housing balance is computed for 2010 as follows: we first classify individuals according to their level of education and the jobs available to them under three categories: low, intermediate and high. Then for each residential location, the nearest 10,000 jobs are computed by EquiPop. The assumption is that individuals seek jobs that correspond to their level of education. Thus for a lower educated person, this method computes the share of low skill requiring jobs among a total of 10,000 job opportunities. Since the spatial mismatch hypothesis first advanced by Kain (1968), there has been great interest in understanding differences in unemployment and job search success rates, job accessibility and job/housing mismatch (see for example Kain 1992; Van der Klaauw and Van Ours 2003; Houston 2005). We are unaware of any application of job/housing (mis)match using the k-nearest neighbour algorithm, which in return accounts for both residential location-driven and skill-based job accessibility.

Finally, we include a commuting measure based on the observed distance to reach the workplace. The observed Cartesian distance between home and work can be used as a crude measure of job accessibility at any location i. However, since some of the studied individuals were not in employment in 2010 and others may have travelled distances that are considerably different from others residing in close proximity, data from near neighbours need to be interpolated. In order to depict a local commuting distance that renders potential commuting distances for non-commuters and renders commuting distances that reduce outlier effects for individuals with very short or long distances, we employ a Kriging strategy where the 12 nearest neighbours constitute the search radius for the commuting distance interpolation surrounding any location where a population member resided in 2010. The smoothed interpolation expresses a commuting distance used as a representation of the potential commuting distance at any location i.[2].

[2] Kriging was conducted in ARCInfo using the ordinary spherical semivariogram method, $k = 12$

4 Analytic framework

We assume that a function of *circumstances*, *effort* and unobserved factors generates the outcomes of individuals. Estimating and partitioning this function permit us to identify the degree of inequality attributable to the factors that are beyond individual responsibility (due to *circumstances*) and to those that are within individual responsibility (due to *effort*). In this paper, we use a parametric method (Ferreira and Gignoux 2011) to partition inequalities in the distributions of educational success and income. The method amounts to compare the actual inequality with the inequality that would result if there were no differences between individuals with different socio-economic backgrounds such that only variation left is attributed to *effort*. Our objective differs from previous studies in that we also partition *circumstances* and *effort* into spatial and aspatial components. Moreover, while in most of the previous studies the functions of individuals' outcomes are estimated by OLS regressions (see Bourguignon et al. 2007; Ferreira and Gignoux 2011), we employ a multilevel model with linear specification. There are several ways to justify our choice. The first reason is that we consider observations nested under a higher hierarchical geographical unit: municipalities, and under these settings OLS models underestimate standard errors and overestimate test statistics, while multilevel models are designed specifically to analyse variables from different levels simultaneously (Snijders and Bosker 1999). Moreover, contextual variables are of main interest and for this reason we need to specify a model that caters for the spatial patterns of variation that may lead to erroneous inferences due to spatial autocorrelation problem. By employing the Moran's I test on the regression residuals, we can test if there are any spatial dependencies not catered for in the specified models (Moran 1950). In other words, we test whether a residual at any location is correlated to other residuals at nearby locations which violates the assumption that residuals are identically and independently distributed.

Four models are tested: (1) full model OLS, (2) empty model MLM, (3) contemporary model MLM and (4) full model MLM. The first model represents the scenario where we employ OLS regressions as in previous studies. When working with multilevel model, so-called empty models lacking predictors (model 2) are widely used to consider the variance at the individual and contextual levels. The model (3) analyses the distribution of income where contextual variables from past are not included. Therefore, the model contains the contextual variables that individuals are presently exposed. Finally, full model (4) incorporates all the predictors. Moran's I tests reveal that the OLS and empty models fail to take the spatial autocorrelation into account. That the empty model fails to explain variation is expected since no parameters are included, but that the full OLS model lies comparatively close to the empty model and far from remaining models clearly indicates that using OLS does not cater for the spatial variation present in the dataset. Of the remaining two models, the contemporary model is the only model with no significant spatial autocorrelation, while the full model displays a weak but significant spatial autocorrelation. The chief difference between models

Table 2 Moran's I tests

	Full model OLS	Empty model MLM	Contemporary model MLM	Full model MLM
Moran's I	0.005457	0.005947	0.000181	0.00104
Expect I	– 0.000025	– 0.000025	– 0.000025	– 0.000025
z-score:	13.437288	15.425446	0.534853	2.98011
p-value:	0.00000	0.00000	0.592751	0.002881

explains why the full models show spatial autocorrelation. In the contemporary model, individual-level parameters as well as contemporary contextual variables are introduced. Variables and the multilevel approach account for the spatial variation in regression residuals. However, in the full model, contextual variables from the year 2001 are also included. The variables introduced improve the overall model fit (see Table 2) but also introduce a spatial bias related to the sorting of individuals during the years of upbringing. Consequently, we use Model 3 to analyse examination marks. However, in order to incorporate spatial influences from parental neighbourhood, we use Model 4 to examine income distribution despite a weak spatial bias.

We specify the empirical model of compulsory school examination marks with contemporary contextual variables (Model 3) as follows:

$$g_{ij} = a_0 + a_{1j}\,Aspatial\,Circumstances_{ij} + a_{2j}\,Spatial\,Circumstances_{ij} + a_j x_j + t_j + q_{ij} \tag{1}$$

where i and j index individuals and municipalities, respectively, and g_{ij} represents the log of compulsory school examination marks, and a_0 is the intercept, x_j represents municipality-level covariates, t_j is municipality-specific random effects, and q_{ij} is the residual term. *AspatialCircumstances* are individual-level covariates including family background and visible minority status. Finally, *SpatialCircumstances* represent a set variables accounting for neighbourhood characteristics computed for each individual by a knn approach. Generating a form of a scalable egocentric neighbourhood, knn approach departs from each residential location and begins counting in every direction until a threshold (k) is reached. It then relates the population involved to the total counted population. The method does not require the use of predetermined administrative units and thus provides an efficient, comparable and robust definition of place (Östh et al. 2015; Östh and Türk 2019). The computations were carried out using EquiPop software (Östh 2014), which sorts people (in this case) according to a georeferenced grid and generates contextual variables quantifying the share of a given attribute within their k-nearest neighbours. The neighbourhoods are quantified as follows:

$$Spatial\,Circumstances_i = \frac{N_{i,k}}{k} \tag{2}$$

where k is the total count of i's nearest neighbours and N_i, k is the number of individuals living closest to i and belonging to a specific group such as visible minorities (see Table 1).

The model of income is defined in a similar way to that of education. Additionally, a set of *effort* variables and contextual variables from the year 2001 are included as follows:

$$\begin{aligned} y_{ij} = \beta_0 + \beta_{1j}\, Aspatial\, Circumstances_{ij} + \beta_{2j}\, Spatial\, Circumstances_{ij} \\ + \beta_{3j}\, Spatial\, Effort_{ij} + \beta_{4j}\, Aspatial\, Effort_{ij} + \beta_j x_j + u_j + z_{ij} \end{aligned} \tag{3}$$

where y_{ij} is the log of disposable income, β_0 is the intercept, x_j and u_j are municipality-specific covariates and random effects, respectively, and z_{ij} is the residual. *AspatialCircumstances* and *SpatialCircumstances* are defined same as in (1). *AspatialEffort* represents the log of compulsory school examination marks and *SpatialEffort* is computed as in (2) and represents i's own-neighbourhood characteristics. Note that i is the same individual as in (2) but now lives independently of parents.

Different from (1) where only *circumstances* are included, in (3) the potential correlation between *circumstances* and *effort* needs to be examined. We follow Roemer (1998) in treating the *effort* variables. A fundamental aspect in this setting is the fact that the degree of how hard an individual tries may constitute the effects of inherited *circumstances* therefore may be endogenous to *circumstances*. Since a part of *effort* is beyond individual control, it is also considered as *circumstances*.[3]. The following models derive genuine *effort* by regressing each *effort* variable on *circumstances*.

$$\begin{aligned} Aspatial\, Effort_{ij} = & b_0 + b_{1j}\, Aspatial\, Circumstances_{ij} \\ & + b_{2j} Spatial\, Circumstances_{ij} + b_j x_j + v_j + aspatial\, effort_{ij} \end{aligned} \tag{4}$$

$$\begin{aligned} Spatial\, Effort_{ij} = & \gamma_0 + \gamma_{1j} Aspatial\, Circumstances_{ij} \\ & + \gamma_{2j} Spatial\, Circumstances_{ij} + \gamma_j x_j + v_j + spatial\, effort_{ij} \end{aligned} \tag{5}$$

where $aspatialeffort_{ij}$ and $spatialeffort_{ij}$ are the residuals of (4) and (5), respectively, and employed as measures of pure *effort* in the following model of income:

$$\begin{aligned} y_{ij} = \beta_0 + \beta_{1j} Aspatial\, Circumstances_{ij} + \beta_{2j} Spatial\, Circumstances_{ij} \\ + \beta_{3j} \widehat{aspatial\, effort}_{ij} + \beta_{4j} \widehat{spatial\, effort}_{ij} + \beta_j x_j + u_j + z_{ij} \end{aligned} \tag{6}$$

where $\widehat{aspatial\, effort}_{ij}$ and $\widehat{spatial\, effort}_{ij}$ are the residuals of (4) and (5).

Using the estimates from Eq. (1) and from the full model of disposable income (6), we construct a counterfactual distribution of compulsory school examination marks g_{ij} and of disposable income y_{ij} where all variation within *circumstance*

[3] see Jusot et al. (2013) for other approaches

groups is eliminated. This approach allows comparing the actual inequalities with the inequalities which would result with no differences in *circumstances*.

$$g_{ij}^{c} = exp[C_i \hat{a}_{ij}] \tag{7}$$

and

$$y_{ij}^{c} = exp[C_i \hat{\beta}_{ij}] \tag{8}$$

Subsequently, the absolute and relative inequality of opportunity measures are calculated both with a path-independent decomposable inequality index, namely the mean logarithmic deviation (MLD) and with the Gini index as $IO = I(g_i)$ and $IO = I(y_i)$. Following this procedure, we can see how much of the inequality is due to inequality in opportunities and the share attributable to *effort*.

$$EIOp = \frac{I(g_{ij}^{c})}{I(g_i)} \tag{9}$$

and

$$IOp = \frac{I(y_{ij}^{c})}{I(y_i)} \tag{10}$$

Using the same techniques, we further decompose the relative contributions of spatial and aspatial factors to both *circumstances* and *effort* partitions of inequality. This practice is able to pinpoint the extent to which neighbourhoods influence given outcomes.

$$EIOp_{spatial} = \frac{I(g_{ij}^{sc})}{I(g_{ij}^{c})} \tag{11}$$

In a similar manner for earnings inequality:

$$IOp_{spatial} = \frac{I(y_{ij}^{sc})}{I(y_{ij}^{c})} \quad \text{and} \quad IO_{spatial} = \frac{I(y_{ij}^{se})}{I(y_{ij}^{e})} \tag{12}$$

Therefore, $IOp_{spatial}$ quantifies the relative contribution of parental neighbourhoods to overall inequality due to *circumstances* and $IO_{spatial}$ indicates the relative contribution of own-neighbourhood to overall inequality due to *effort*.

5 Findings

This section presents the regression outputs of the multilevel models and related inequality decomposition by *circumstances* and *effort* and their respective decomposition by spatial and aspatial components.

We model compulsory school marks as a function of the following individual-level *circumstances*: gender, minority status (visible minority or not), the highest level of education attained by parents, the employment and marital status of parents, pupils' disposable income in 2001. The function also includes the share of the following attributes in the neighbourhood (k levels in parenthesis): single-headed families (k = 40), same-age children (k = 40), families with at least three children (k = 40) and visible minorities (k = 400).

When analysing disposable income, we add the variable gender to the model as an additional *circumstance* variable with the following *effort* variables: compulsory school examination marks, job/housing balance (k = 10000), observed commuting distance between job and home, and the share of visible minorities (k = 1600) in 2010. The highest educational level of parents is interacted with ten city classes to account for different degrees of industrialisation in cities as well as functions in terms of population density and commuting, and remoteness following a classification of municipalities defined by SALAR (Swedish Association of Local Authorities and Regions)[4]. We examine the correlation between *effort* and *circumstances* for all *effort* variables. This procedure guarantees that the *effort* variables reflect only pure *effort*, without the influence of observed *circumstances*. Then, we substitute the resulting residuals terms in Eq. (6). This means that the *circumstances* in (6) are expected to reflect both their direct impacts on the response variable and indirect effects on five *effort* variables.

An important result to note is that as we regress the visible minority concentration of own-neighbourhood in 2010 on the *circumstance* variables. Most of the variation is explained by the visible minority share of the parental neighbourhood. This indicates that the study population ended up in similar neighbourhoods as their parents. The observed residential immobility, or similarity in neighbourhood characteristics over time, points to long-term exposure to the effects neighbourhoods produce and a higher likelihood that these effects are transmitted to offspring. From the equal opportunities perspective, being locked-in parental neighbourhoods (or to those with similar characteristics to parental neighbourhoods) is clearly a factor influencing life chances. For this reason, even though we deem individuals responsible for their choice of neighbourhood, it seems reasonable to derive pure *effort* purged of the influence of parental neighbourhood and other *circumstances* by Eq. 5.

Tables 3 and 4 report the multilevel models of educational and income, respectively. In both regression outputs, the results concerning the aspatial regressors confirm the previous works in the literature. The family background shows the expected correlation with the educational and market outcomes of offspring. Highly educated and employed parents contribute to the life chances of offspring, while single parents show an opposite impact. Moreover, a higher disposable income in childhood is correlated with better educational success and higher income in adulthood. Meanwhile, belonging to visible minorities is negatively correlated with both outcomes,

[4] Multilevel regression showed a negative association with the disposable income of individuals and their parental education. To correct this, we used a classification that sorted municipalities by the degree of industrialisation, population density, commuting and remoteness

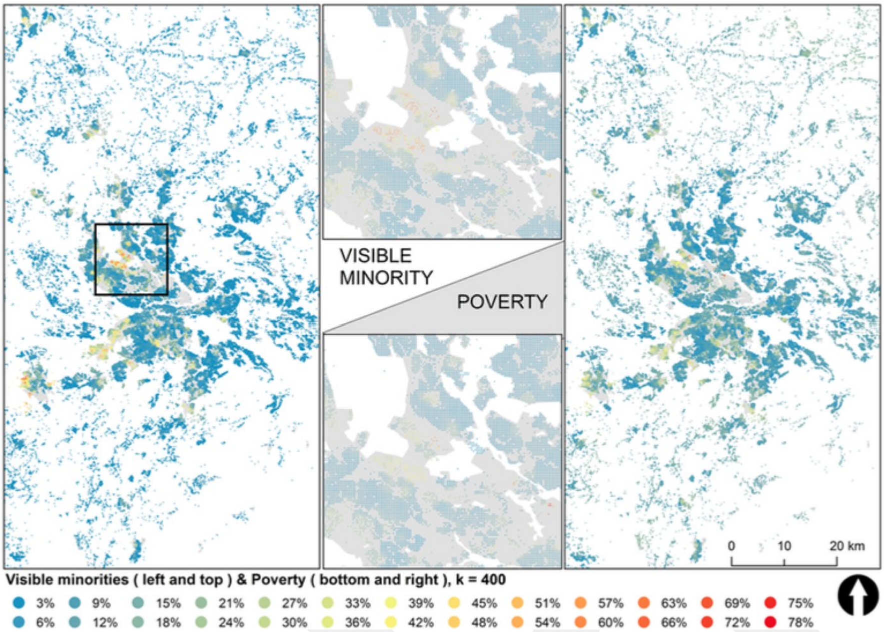

Fig. 2 Neighbourhoods

Table 3 Multilevel model: Log of marks (Compulsory school examination)

Fixed	Coef.	Standard error	P values
1. Individual			
Employment father	0.2361	0.0180	0.000
Employment mother	0.2614	0.0170	0.000
Parental education	0.1694	0.0123	0.000
Single parent	− 0.2322	0.0143	0.000
Visible minority	− 0.1702	0.0313	0.000
Disposable income (2001)	0.1310	0.0151	0.000
2. Neighbourhood			
Single-headed families (2001)_20	− 0.2323	0.0143	0.000
Large families (2001)_20	− 0.2253	0.0468	0.000
Same-age peers_20	−0.2399	0.1136	0.035
Negative space	− 0.2063	0.0411	0.000
Visible minority (2001)_200	− 1.0354	0.0937	0.000
Random effects parameters	Estimate	Standard error	
Municipality-level var (_cons)	0.0094	0.0020	
Var (Residual)	2.9919	0.0139	
Number of obs = 92674			

Table 4 Multilevel model: Log of disposable income

Fixed	Coef.	Standard error	P values
1. Individual			
Gender	− 0.1644	0.0030	0.000
Compulsory school examination marks	0.0188	0.0008	0.000
Employment father	0.0714	0.0047	0.000
Employment mother	0.0784	0.0044	0.000
Parental education			
x CityClass2	0.0634	0.0108	0.000
x CityClass3	0.0252	0.0081	0.002
x CityClass4	0.1121	0.0223	0.000
x CityClass5	0.0808	0.0151	0.000
x CityClass6	0.0508	0.0220	0.021
x CityClass7	0.1039	0.0144	0.000
x CityClass8	0.0968	0.0303	0.001
x CityClass9	0.0850	0.0135	0.000
x CityClass10	0.0845	0.0200	0.000
Single parent	− 0.0249	0.0037	0.000
Visible minority	− 0.1152	0.0081	0.000
Disposable income (2001)	0.1211	0.0041	0.000
2. Neighbourhood			
Large families (2001)_40	− 0.0382	0.0123	0.020
Single-headed families (2001)_40	− 0.0789	0.0113	0.000
Same-age peers_40	0.0790	0.0296	0.002
Negative space	− 0.0291	0.0107	0.007
Visible minority (2001)_400	− 0.3598	0.0248	0.000
Job/housing balance (2010)_10000	0.2074	0.0129	0.000
Commuting distance (2010)	− 0.0117	0.0007	0.000
Visible minority (2010)_1600	− 0.6481	0.0205	0.000
Random effects parameters	Estimate	Standard error	
Municipality-level var (_cons)	0.0024	0.0003	
Var (Residual)	0.2045	0.0009	
Number of obs = 91413			

and the results regarding gender indicate that the female population has lower disposable incomes.

At the bottom of each Table, individual and municipality-level variances are reported. Table 3 registers 0.3% intra-class variation (ICC) and Table 4 one per cent ICC for income. ICC indicates the variation of outcomes depending on the municipalities. Note that in the null models, 0.6% and 2% ICCs are displayed for education and income variation, respectively. These values are comparable with the findings of Andersson and Musterd (2010) in a study conducted for the income distribution in Stockholm, Malmö and Gothenburg in the period 1995–2002. They show that when the second level in the multilevel model communicates smaller locations, the variation attributed to random component becomes greater. In the present paper, we are able to explain half of the variation that is attributable to municipality-level effects by including individual level and spatial covariates. Regarding the spatial variables, neighbourhoods show significant effects on both outcomes. The concentration of single-headed and large families, visible minorities, and same-age peers in addition to negative surroundings show negative association with educational outcomes. Among the spatial variables, especially neighbourhoods with high concentrations of visible minorities show the strongest association with both outcomes. Table 4 reveals the same neighbourhood influences for disposable income, except in this table the share of same-age peers is positively correlated with income. The reason might be that the variable may reflect the positive effects that friendship networks have on market outcomes. Additionally, job/housing balance positively and commuting distance negatively impact earnings. The present paper employs this specific set of neighbourhood variables since they potentially perform as the proxies of other locational characteristics. For instance, the share of visible minorities in a neighbourhood might coincide with the poverty concentration and other possible adverse characteristics of the locality. This can be seen from the maps in Fig. 2, containing all residential coordinates aggregated to $100\,\mathrm{m} \times 100\,\mathrm{m}$ units for the greater Stockholm area, where on the left hand side the visible minorities population in the 400 nearest neighbours for the whole Stockholm population is shown and on the right hand side the poverty concentration [EU criteria (Bradshaw and Mayhew 2011)] among the 400 nearest neighbours is mapped for the whole Stockholm metropolitan area. These maps show how the two aspects of the locality are statistically entangled, so that almost the same pattern of segregation is observed for both attributes of neighbourhoods.

Furthermore, the variable for single-headed family concentration in neighbourhoods performs as a proxy of residential environment and housing conditions to which the study population is exposed: due to lower household income, these families might reside in poor neighbourhoods. A similar interpretation applies to large-family concentration. Since large apartments are not found in the central districts, large families reside in rural areas or areas with a rural character far from amenities. Moreover, if mothers with three or more children stop studying at an early age, large-family concentrated areas might be characterised by lower human capital accumulation.

Turning now to the discussion of the long-term effects of neighbourhoods, Table 4 reveals that parental neighbourhood characteristics significantly influence adult earnings even though a range of individual and household characteristics are present in the model. For this reason, we conduct the following inequality decompositions for both models reported in Tables 3 and 4.

The second and third columns of Table 5 illustrate the magnitude of income and educational inequality of the entire Swedish population born in 1985. Based on the estimated coefficients from Eqs. (1) and (6), the *opportunity* share in total inequality in income is computed as 8.05% and the *opportunity* share in educational inequality is 42.63% as measured by MLD. These findings indicate that almost half of the inequality in educational outcome is related to exogenous factors, hence inequality

Table 5 Inequality decomposition

	Income inequality				Educational inequality		
Total inequality (GINI)	0.2674				0.1749		
Total inequality (MLD)	0.1315				0.2667		
Inequality of opportunity (GINI)	0.0695				0.1528		
Inequality of opportunity (MLD)	0.0106				0.1137		
	Effort		Circumstances		Effort	Circumstances	
Contribution (%) to total inequality (MLD)	91.95%		8.05%		57.37%	42.63%	
	Aspatial (residual)	Spatial	Aspatial	Spatial		Aspatial	Spatial
Spatial/aspatial (MLD)	98.05%	1.95%	83.33%	16.66%	Residual	63.06%	36.94%

of opportunity. However, the *opportunity* share of income inequality is considerably smaller. Since the analyses follow the same cohort over time and inequality in both outcomes refer to the same individuals, we may conclude that a high social mobility characterises the country. That is the influence of family background and other *circumstances* decreases with equal earnings in later labour market.

Moreover, the relative decomposition of *circumstances* shows that spatial *circumstances* (parental neighbourhood) account for 16.66% of the inequality of opportunity. Meanwhile, spatial *effort* (own-neighbourhood) accounts for 1.95% of the total *effort*. The corresponding decomposition for educational inequality shows that the spatial *circumstances* (parental neighbourhood) represent 36.44% of total *circumstances*. Comparison between spatial *circumstances* indicates that neighbourhoods are more influential, while the exposure is ongoing. Nevertheless, from educational to income inequality of opportunity the influence of spatial *circumstances* does not decrease as much as the overall *opportunity* share in inequalities. This finding may indicate that the impact of neighbourhoods is more persistent compared to other *circumstances*.

We also conducted separate analyses for gender. The estimates of total inequality in education and income with related decompositions are shown in Table 6 for females and Table 7 for the male population. Higher income inequality of opportunity is observed among men compared to women. However, the relative income inequality of opportunity is almost identical for both. The latter result seems to be related to the spatial sources of inequality of opportunity. For women, the parental neighbourhood is more influential than for men (27.27% for women compared to 16.66% for men). On the other hand, spatial *effort* accounts more for men than for women with the shares 5.21% and 4.06%, respectively. Regarding the inequality of opportunity in educational attainment, overall *circumstances* explain a higher degree of variation for male students. Again this result seems to be related to parental neighbourhoods. For male students, 30.15% of the total *circumstances* pertains to spatial *circumstances*; it is only 13.75% for female students.

Comparing the results in Tables 6 and 7 concerning the effects of spatial *circumstances*, the parental neighbourhood seems to be more influential for the educational attainment of male students, hence during exposure. Once in employment, male students seem to be more successful in overcoming spatial-adverse effects by spatial *effort* compared to the female population. That is to say, the male population uses *spatial mobility* as an instrument to generate additional income and to decrease the gap with higher income groups. In line with the findings for the whole population, for men, the influence of parental neighbourhood proportionally decreases from 2001 to 2010. However, it is interesting to note that for the female population parental neighbourhoods cause a lower variation in marks during exposure and a higher variation in subsequent earnings. One interpretation of this pattern is that while being exposed to socio-economic characteristics of parental neighbourhoods, female students might manage to focus on their studies and reflect the adverse effects to a relatively lower degree to their marks. Yet, as females grow up, they might be building personal identities similar to that of the residents of their parental neighbours. This is a relevant interpretation especially given the fact that neighbourhood statistics for single-parent and large families mostly impact women. Another view relates

Table 6 Inequality decomposition female population only

	Income inequality (Female)				Educational inequality (Female)		
Total inequality (GINI)	0.2495				0.1657		
Total inequality (MLD)	0.1105				0.2552		
Inequality of opportunity (GINI)	0.0548				0.1436		
Inequality of opportunity (MLD)	0.0058				0.1091		
	Effort		Circumstances		Effort	Circumstances	
Contribution (%) to total inequality (MLD)	94.76%		5.24%		57.24%	42.76%	
	Aspatial (residual)	Spatial	Aspatial	Spatial		Aspatial	Spatial
Spatial/aspatial (MLD)	95.94%	4.06%	72.73 %	27.27%	Residual	86.25%	13.75%

Table 7 Inequality decomposition male population only

	Income inequality (Male)				Educational inequality (Male)		
Total inequality (GINI)	0.2729				0.1784		
Total inequality (MLD)	0.1423				0.2747		
Inequality of opportunity (GINI)	0.0623				0.1601		
Inequality of opportunity (MLD)	0.0082				0.1342		
	Effort		Circumstances		Effort	Circumstances	
Contribution (%) to total inequality (MLD)	94.02%		5.80%		51.12%	48.88%	
	Aspatial (residual)	Spatial	Aspatial	Spatial		Aspatial	Spatial
Spatial/aspatial (MLD)	94.79%	5.21%	50.00 %	16.66%	Residual	69.85%	30.15%

to mobility patterns. For the female population, parental neighbourhoods potentially become own neighbourhoods since they seem to be immobile.

6 Concluding remarks

A society is considered to be equal in opportunities if the life chances of individuals do not depend on the factors beyond their choice, and the systematic differences in outcomes as a result of exogenous factors are defined as inequality of opportunity. A number of studies show that parental backgrounds account for most of the inequality in the life chances of individuals. So far, however, there has been no discussion on the quantitative contribution of the parental neighbourhood in overall inequalities.

In this paper, we investigated the inequality in education and earnings opportunities in Sweden for the whole 1985 cohort. Different from other studies of inequality of opportunity, we included a set of variables communicating parental neighbourhood and *own*-neighbourhood characteristics in a model of inequality. We constructed bespoke neighbourhoods which constitute k number of neighbours with various socio-economic characteristics. In addition, the model included the share of negative components surrounding parental residence and a measure of housing/job market balance, the observed commuting distance between neighbourhoods and jobs. Instead of the standard OLS approach, we utilised a multilevel model, which overcame most of the spatial autocorrelation problem.

The findings indicate that while *opportunity* share of inequality accounts almost half of the variation in educational success, it decreases substantially in earnings distribution. Therefore, we observe a high social mobility in the country, that labour market outcomes are noticeably less dependent on socio-economic backgrounds. However, this may also indicate a lower economic resilience. That is if external shocks impact the economy of the country, the gap between advantaged and disadvantaged backgrounds may widen rapidly due to inequality of opportunity in educational outcomes. Moreover, our findings show that as well as the commonly used aspatial *circumstance* variables, parental neighbourhoods also strongly impact educational attainment and even years after exposure they remain influential for earnings distribution. Although the impact of spatial *circumstances* decreases from educational to income inequality of opportunity, the reduction is not as much as when aspatial *circumstances* are considered. This means that by employing spatial *circumstances* variables, we are able to identify more persistent *circumstances*, which may serve to policy makers and also civil society activists. Finally, our results show that the *opportunity* gap between individuals widens both for visible minorities and for the residents of visible minority-concentrated neighbourhoods. Therefore, in order to decrease inequality in opportunities, an effective policy must target the population belonging to the visible minority population and their residential environment.

We are aware that incorporating neighbourhood socio-economic characteristics as *circumstances* requires detailed information on geo-locations. But, the recent developments in data collection methods associated with "big data" significantly facilitate the collection of contextual variables. For instance, there is a vast quantity of information that is made freely available on the internet through open maps and the social-media data provides a wealth of information to researchers. Therefore, what is left is the proper handling of geography. The findings of this study recommend using bespoke neighbours to define an individual's residential environment. Creating individualised neighbourhoods based on the k-nearest neighbour algorithm enabled us to overcome problems associated with administratively defined areas, as the use of latter creates mixed findings concerning the long-term effects of neighbourhoods as presented in Sect. 2. Accordingly, by knn approach to neighbourhoods this paper has gone some way towards enhancing our understanding of the temporal effects of neighbourhoods.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Andersson E (2004) From valley of sadness to hill of happiness: the significance of surroundings for socioeconomic career. Urban Stud 41(3):641–659

Andersson E, Subramanian S (2006) Explorations of neighbourhood and educational outcomes for young Swedes. Urban Stud 43(11):2013–2025

Andersson Roger, Musterd Sako (2010) What scale matters? Exploring the relationships between individuals' social position, neighbourhood context and the scale of neighbourhood. Geogr Ann Ser B Hum Geogr 92(1):23–43

Andersson EK, Malmberg B (2015) Contextual effects on educational attainment in individualised, scalable neighbourhoods: differences across gender and social class. Urban Stud 52(12):2117–2133

de Barros RP (2009) Measuring inequality of opportunities in Latin America and the Caribbean. World Bank Publications, Washington, D.C

de Barros RP, Vega JRM, Saavedra J (2008) Measuring inequality of opportunities for children. World Bank, Washington, DC

Björklund A, Jäntti M, Roemer JE (2012) Equality of opportunity and the distribution of long-run income in Sweden. Soc Choice Welf 39(2–3):675–696

Bradshaw J, Mayhew E (2011) The measurement of extreme poverty in the European Union. European Commission, DG Employment, Social Affairs and Inclusion, Brussels

Brazil Noli, Clark William AV (2017) Residential mobility and dynamic neighborhood change during the transition to adulthood. Adv Life Course Res 33:1–10

Bourguignon F, Ferreira FH, Menendez M (2007) Inequality of opportunity in Brazil. Rev Income Wealth 53(4):585–618

Brunori P, Ferreira FH, Peragine V (2013) Inequality of opportunity, income inequality, and economic mobility: some international comparisons. Springer, Berlin

Checchi D, Peragine V (2010) Inequality of opportunity in Italy. J Econ Inequal 8(4):429–450

Checchi D, Peragine V, Serlenga L (2010) Fair and unfair income inequalities in Europe. IZA Discussion Paper No. 5025. Available at SSRN: https://ssrn.com/abstract=1634492

Chetty R, Hendren N, Katz LF (2015) The effects of exposure to better neighborhoods on children: new evidence from the moving to opportunity experiment. Technical Report, National Bureau of Economic Research

Clark WA, Ledwith V (2006) Mobility, housing stress, and neighborhood contexts: evidence from Los Angeles. Environ Plan A 38(6):1077–1093

Cogneau D, Mesplé-Somps S (2008) Inequality of opportunity for income in five countries of Africa. Res Econ Inequal 16:99–128

Crane J (1991) The epidemic theory of ghettos and neighborhood effects on dropping out and teenage childbearing. Am J Sociol 96(5):1226–1259

Ellen IG, Turner MA (1997) Does neighborhood matter? Assessing recent evidence. Hous Policy Debate 8(4):833–866
Ferreira FH, Gignoux J (2011) The measurement of inequality of opportunity: theory and an application to Latin America. Rev Income Wealth 57(4):622–657
Ferreira FH, Gignoux J, Aran M (2010) Inequality of economic opportunity in Turkey: an assessment using asset indicators and women's background variables. State Planning Organization of the Republic of Turkey and World Bank Welfare and Social Policy Analytical Work Program Working Paper (3)
Ferreira FH, Gignoux J, Aran M (2011) Measuring inequality of opportunity with imperfect data: the case of Turkey. J Econ Inequal 9(4):651–680
Galster G (2001) On the nature of neighbourhood. Urban Stud 38(12):2111–2124
Galster G, Andersson R, Musterd S, Kauppinen TM (2008) Does neighborhood income mix affect earnings of adults? New evidence from Sweden. J Urban Econ 63(3):858–870
Garner CL, Raudenbush SW (1991) Neighborhood effects on educational attainment: a multilevel analysis. Sociol Educ 64(4):251–262
Glass TA, Bilal U (2016) Are neighborhoods causal? Complications arising from the 'stickiness' of zna. Soc Sci Med 166:244–253
Hedman L, Manley D, Van Ham M, Östh J (2015) Cumulative exposure to disadvantage and the intergenerational transmission of neighbourhood effects. J Econ Geogr 15(1):195–215
Houston D (2005) Employability, skills mismatch and spatial mismatch in metropolitan labour markets. Urban Stud 42(2):221–243
Johnston Ron, Jones Kelvyn, Burgess Simon, Propper Carol, Sarker Rebecca, Bolster Anne (2004) Scale, factor analyses, and neighborhood effects. Geogr Anal 36(4):350–368
Jusot F, Tubeuf S, Trannoy A (2013) Circumstances and efforts: How important is their correlation for the measurement of inequality of opportunity in health? Health Econ 22(12):1470–1495
Kain JF (1968) Housing segregation, negro employment, and metropolitan decentralization. Q J Econ 82(2):175–197
Kain JF (1992) The spatial mismatch hypothesis: three decades later. Hous Policy Debate 3(2):371–460
Kunz J, Page ME, Solon G (2003) Are point-in-time measures of neighborhood characteristics useful proxies for children's long-run neighborhood environment? Econ Lett 79(2):231–237
Leventhal T, Brooks-Gunn J (2000) The neighborhoods they live in: the effects of neighborhood residence on child and adolescent outcomes. Psychol Bull 126(2):309
Ludwig J (1999) Information and inner city educational attainment. Econ Educ Rev 18(1):17–30
Ludwig J, Duncan GJ, Gennetian LA, Katz LF, Kessler RC, Kling JR, Sanbonmatsu L (2013) Long-term neighborhood effects on low-income families: evidence from moving to opportunity. Technical Report, National Bureau of Economic Research
Moran PA (1950) Notes on continuous stochastic phenomena. Biometrika 37(1/2):17–23
Musterd Sako, Ostendorf Wim, De Vos Sjoerd (2003) Neighbourhood effects and social mobility: a longitudinal analysis. Hous Stud 18(6):877–892
Musterd S, Andersson R (2006) Employment, social mobility and neighbourhood effects: the case of Sweden. Int J Urban Reg Res 30(1):120–140
Openshaw S (1984) The modifiable areal unit problem. Geo Abstracts University of East Anglia, East Anglia
Östh J (2014) Introducing the equipop software-an application for the calculation of k-nearest neighbour contexts/neighbourhoods
Östh J, Clark WA, Malmberg B (2015) Measuring the scale of segregation using k-nearest neighbor aggregates. Geogr Anal 47(1):34–49
Östh J, Türk U (2019) Integrating infrastructure and accessibility in measures of bespoke neighbourhoods. In: Musterd S (ed) Handbook on Urban segregation Edward Elgar. Edward Elgar Publishing, Cheltenham
Östh J, Shuttleworth I, Niedomysl T (2018) Spatial and temporal patterns of economic segregation in Sweden's metropolitan areas: a mobility approach. Environ Plan A Econ Space 50(4):809–825
Page ME, Solon G (2003) Correlations between brothers and neighboring boys in their adult earnings: the importance of being urban. J Labor Econ 21(4):831–855
Peragine V, Serlenga L (2008) Higher education and equality of opportunity in Italy. Res Econ Inequal 16:67–97
Quillian L (2003) How long are exposures to poor neighborhoods? The long-term dynamics of entry and exit from poor neighborhoods. Popul Res Policy Rev 22(3):221–249

Raaum O, Salvanes KG, Sørensen EØ (2006) The neighbourhood is not what it used to be*. Econ J 116(508):200–222

Ramos X, Van de Gaer D (2012) Empirical approaches to inequality of opportunity: principles, measures, and evidence

Roemer JE (1998) Theories of distributive justice. Harvard University Press, Cambridge

Roemer JE, Trannoy A (2016) Equality of opportunity: theory and measurement. J Econ Lit 5(4):1288–1332

Ross JL, Iannotta JG et al (2002) Equality of opportunity and the importance of place: summary of a workshop. National Academies Press, Washington, D.C

Sharkey P, Faber JW (2014) Where, when, why, and for whom do residential contexts matter? Moving away from the dichotomous understanding of neighborhood effects. Annu Rev Sociol 40:559–579

Singh A (2012) Inequality of opportunity in earnings and consumption expenditure: the case of Indian men. Rev Income Wealth 58(1):79–106

Snijders T, Bosker R (1999) Multilevel analysis: an introduction to basic and applied multilevel analysis. Sage, Thousand Oaks

Türk U (2019) Socio-economic determinants of student mobility and inequality of access to higher education in Italy. Netw Spat Econ 43(1):1–24

Urban S (2009) Is the neighbourhood effect an economic or an immigrant issue? A study of the importance of the childhood neighbourhood for future integration into the labour market. Urban Stud 46(3):583–603

Van Ham M, Manley D, Bailey N, Simpson L, Maclennan D (2012) Neighbourhood effects research: new perspectives. In: Neighbourhood effects research: new perspectives, Springer, pp 1–21

Van Ham M, Hedman L, Manley D, Coulter R, Östh J (2014) Intergenerational transmission of neighbourhood poverty: an analysis of neighbourhood histories of individuals. Trans Inst Br Geogr 39(3):402–417

Van der Klaauw B, Van Ours JC (2003) From welfare to work: Does the neighborhood matter? J Public Econ 87(5):957–985

Vartanian TP (1999) Adolescent neighborhood effects on labor market and economic outcomes. Soc Serv Rev 73(2):142–167