Networks and Spatial Economics (2019) 19:125–148
https://doi.org/10.1007/s11067-019-09445-w

Socio-Economic Determinants of Student Mobility and Inequality of Access to Higher Education in Italy

Umut Türk[1]

Published online: 12 February 2019

Abstract

This paper introduces a modified version of the Hansen-gravity model as a framework to estimate the accessibility of higher education (HE) institutions in Italy from equal opportunities perspective. The fundamental assumption underlying gravity models is that accessibility decreases with spatial distance from opportunities. The paper extends the gravity equation to include socio-economic factors influencing the access to HE. The findings reveal differences in response to quality and other institutional characteristics by parental background and gender. Finally, decomposition of overall inequality into spatial and aspatial components reveals both the physical and social distance between groups of students seeking higher education opportunities in the country.

Keywords Spatial interaction · Higher education accessibility · Gravity model · Equality of opportunity

1 Introduction

An intuitive way to increase spatial accessibility is to decentralise the service in question. This was the strategy implemented by the Italian authorities in the period 1990-1998. With one of the lowest participation and graduation rates in Europe, the supply of higher education (HE) was expanded drastically. The reforms required larger universities to set up new types of faculties and nine new higher education institutions were established as a result of the decentralisation process (MIUR 1997). However, these reforms took place without any field examination of accessibility or demand (Bratti et al. 2008). More than a decade later, there is no explicit measure of spatial accessibility of the universities in the country.

✉ Umut Türk
umut.turk@agu.edu.tr

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

In a system granting free access to HE for every potential candidate, the foremost aim of policymakers is to guarantee full access to the service irrespective of the location of residence. Previous research has focused on measuring accessibility through an examination of the match between the locational distribution of facilities or services and the locational distribution of residents (Talen and Anselin 1998). In this framework, the spatial distance between the residence of origin and the location where opportunities are located is regarded as an important factor determining the spatial accessibility. The underlying idea is that people from more isolated locations face considerable costs to access to opportunities with costs growing with spatial distance.

Since parents determine the residential location of students prior to HE enrolment, inequalities in access to HE across students' locations of origin should be regarded as unfair. A modern theory of inequality building on equality of opportunity (EOp) arguments suggests that the differences in outcomes due to the factors that are beyond individual responsibility are unfair and should be compensated by the society (Dardanoni et al. 2006). Reducing geographical disparities in access can be seen in fact as a way of *levelling the playing field* (Roemer 1998) and providing equal opportunities to benefit from HE irrespective of the place of origin. The geographical location can be an unfair source of inequality in access on a large scale: a student living in an area where HE services are well-supplied faces smaller costs of transportation, lower opportunity costs in commuting, and no housing costs compared to those who need to commute or move to benefit from HE services. However, focusing only on geography may leave the influence of socio-economic factors in relation to gender, experiences at home, and parental background unexplored. The paper argues the existence of a gradient of economic circumstances of origin on the degree of spatial access to HE. Although distance matters in explaining accessibility, other variables determine differences in costs of movement correlated with distance, which at the same time, influence the distribution of accessibility. This paper tries to single out the contribution of spatial distance and economic circumstances on inequality in access to HE. The paper redefines the problem of disparities in spatial access on the basis of both the physical distance from universities and the socio-economic distance between student groups that generates an additional inequality in access within the same location. The paper studies the variability in access both when focusing on comparisons of people located at different origin points from HE but all sharing the same family background (highlighting the share of inequality due to spatial distribution of HE institutions in the country), and when comparing people located at the same origin points but with differing backgrounds of family origin. The latter indicates the ability of families to cover the costs of displacement and compensate for distance from the location of origin and shows the share of inequality in access due to the socio-economic background of students.

In order to undertake the analysis, the paper sequentially employs a model and an index to measure overall inequality in access, which is then decomposed into its geographical and socio-economic components. First, a spatial interaction model (SIM) is used to disentangle the mobility dynamics of different student groups. Being flexible and straightforward enough these models enable to investigate flows between origins and destinations (Sen and Smith 2012). SIMs likewise model actual flows of commodities, information, emails, phone calls, money, and of people along with any other sort of movements (see Haynes and Fotheringham 1984; Sen and Smith 2012, for reviews). In the present application, student flows between parental residents and universities are defined as interactions between localities. To account for socio-economic factors influencing the access, the observed flows of students are partitioned into subgroups each representing a different *type*. It is a common practice for EOp studies to partition the population according to exogenous factors, which are assumed to be beyond people's control (Checchi and Peragine 2010, see for instance; Ferreira and Gignoux 2011) and resulting subgroups are represented by types (Roemer 1998). For the second step, the parameters that are distinctively calibrated for each type by the SIMs are imported to a Hansen (1959)-like index to measure potential accessibility for 110 Italian provinces (NUTS3 level regions). Finally, the inequality in accessibility among provinces is decomposed as follows: the access score in each province is replaced with its average access score across socio-economic groups hence the only variation is allowed to be due to the geographical distribution of universities. Then the access scores computed for each socio-economic group is replaced with its average access score across provinces hence remaining variation is allowed to be due to socio-economic backgrounds. This operation enables investigating the relative contributions of spatial and aspatial factors in the total inequality in access to HE.

The paper contributes to the literature by extending the classical spatial accessibility analysis to incorporate the socio-economic circumstances of students in a spatial accessibility measure for Italian HE institutions. This practice goes beyond the mere concern of inequalities in outcomes. For the spatial accessibility analysis, this means that the inquiry may shift from "spatial accessibility where?" to "spatial accessibility where and for whom?". It also contributes to the EOp literature by showing how the spatial dimensions of the theory can be incorporated into models that rely solely on geography. Finally, the findings in this paper provide detailed information for policymakers regarding which groups of students to target and specifically in which locations the assistance is needed most for a fair access to HE.

The remainder of the paper is organized as follows: the second section introduces the model, and the accessibility index adopted, the third section sets out the data and variables, the fourth section shows the empirical method for calibration and findings where inequality in access is decomposed into within and between components for different populations of students. The fourth section demonstrates the extent to which the spatial inequality has decreased following the HE expansion efforts initiated in the 90s. Finally, the conclusions and a set of policy implications are given in the fifth section.

2 Theoretical Framework

This section presents the spatial interaction model used to analyse student flows and the potential accessibility index. The link between these two builds on the distance parameter, which is assumed to reflect both physical and social costs in migrating or commuting to destination universities. The distance elasticity is expected to be conditional on the spatial distance from universities and the socio-economic background of students.

2.1 A Spatial Interaction Model of Student Mobility

Spatial interaction models are used to predict the size of spatial flows between origins and destinations in areas of interest. The models have been used mainly for transportation and environmental planning, then developed further for a variety of applications where a movement and/or interaction takes place. Several studies use SIMs for health system planning and allocation of funds (Wilson and Gibberd 1990), prediction of hospital flows (Mayhew et al. 1986), as well as labour studies such as job accessibility, investigation of the daily commute to work (Reggiani et al. 2011) and equity issues in job accessibility given transportation means (Garcia et al. 2018).

In particular, with regard to HE choice, Sa et al. (2004) studied the demand for HE in the Netherlands given the attractiveness and accessibility of universities. Alm and Winters (2009) correlated the distance from parental residence to state HE institutions with tuition, financial aid, and school quality as institutional fixed effects and found a varying deterrence effect of distance in relation to destination characteristics. Cooke and Boyle (2011) incorperated SIMs with several origin and destination attributes including the number of high school graduates in origins, employment growth both in origins and destinations, and the relative quality of amenities. Singleton et al. (2012) integrated SIMs with geodemographic analysis and studied both socio-spatial conditions in the neighbourhood and the attractiveness of destinations. For the Italian data, Dotti et al. (2013) investigated the role of universities in attracting successful students to specific regions and their likelihood of settling down after graduation. These studies estimate the distance elasticity of university choice given the attributes of origins/destinations and a few also include university characteristics. However, these contributions do not incorporate the socio-economic profile of students in the analyses. The present paper examines the role of socio-economic characteristics of students in distance elasticity. Furthermore, based on the distance elasticity values, the paper transforms SIMs into an explicit measure of accessibility.

SIMs can incorporate a range of origin and destination constraints and take a number of forms according to the constraint structure. The following formula is a production-constrained form of SIMs that suggests that the interaction between any two units must be directly proportional to the masses of origin and destination and inversely related to the distance between them. The underlying assumption is that a positive interaction between each pair of location exists (Fotheringham and Webber 1980; Fotheringham and O'Kelly 1989; Sen and Smith 2012).

$$T_{ij} = K_i O_i^{\theta} D_j^{\alpha} f(d_{ij}) \quad (1)$$

T_{ij} refers to the student flows from parental residence i to university j
O_i origin dummies for 110 Italian provinces (NUTS3 level regions)
D_j total number of students reaching university j

$[K_i = \left[\sum_j D_j^\alpha f(d_{ij})\right]^{-1}]$ is the balancing factor ensuring that the marginal total constraint $\sum_j T_{ij} = O_i$ is satisfied.[1]

$f(d_{ij}) = d_{ij}^{-\beta}$ is a function of distance, where d_{ij} is the Euclidean distance between city i and university j

For the present application, the model is extended to include several university fixed characteristics and interactions with distance. Finally, the following model is obtained:

$$T_{ij} = K_i O_i^\theta D_j^\alpha SocialCapital_j{}^\gamma L_j{}^\eta \exp(-\beta ln(d_{ij}) + \mu\delta_{ij} + \sum_l \lambda_l ln(d_{ij})U_{jl}) \tag{2}$$

where $SocialCapital_j$ and L_j are two variables accounting for the attractiveness of destinations. Following the previous studies (Lowe and Sen 1996, see for example; Gitlesen and Thorsen 2000; McArthur et al. 2011), a Kronecker delta is added to the model as follows:

$$\delta_{ij} = \begin{cases} 1 & i = j \\ 0 & \text{otherwise} \end{cases}$$

The common interpretation of μ is that it reflects the benefit of residing and studying in the same city or a start-up cost in case i and j are not in the same province. Furthermore, $f(d_{ij})$ interacts with several destination characteristics U_{jl} where l is the number of interaction terms and λ_l is the distance elasticities given the institutional characteristics.

2.2 Adapted Accessibility Index

In this paper, the accessibility concept is interpreted as the potential availability of HE given the spatial distribution of institutions in the country. The roots of the index go back to Hansen (1959) when he first proposed the following gravity model of accessibility:

$$A_i = \sum_{j=1}^{J} S_j d_{ij}^{-\beta}$$

where A_i is a measure of accessibility, S_j is the number of opportunities at the destination and d_{ij} is the distance between an origin and a destination. A similar accessibility index can be constructed as follows:

$$A_i = \sum_{j=1} \frac{C_j d_{ij}^{\hat{\beta}}}{\delta_{ij}} \tag{3}$$

[1] With K_i the model becomes production-constrained. The choice of this model is justified by the fact that most of the programmes are provided in an open-access fashion in Italy. Therefore, theoretically, students are free to choose any destination desired hence the model is not constrained by destination (not attraction constrained) but to make sure that the number of trips produced by an origin does not exceed the number of residents, the model is constrained from the production side. For the formal development see Wilson (1971).

where

$$\delta_{ij} = \begin{cases} exp(\hat{\mu}) & i \neq j \\ 1 & \text{otherwise} \end{cases}$$

$\hat{\mu}$ and $\hat{\beta}$ are the two parameters that channel (2) to (3) and are calibrated beforehand by the production-constrained SIM (2). C_j is the total number of places offered by each institution. Additionally, the index discounts access when i and j are not located in the same province by δ_{ij}.

3 Data and Variables

Table 1 shows the variables used in the analyses carried out in this paper. The data is extracted from a data survey provided by the Italian National Institute of Statistics (ISTAT) (*Inserimento professionale dei laureati*, 2011) including 14,000 male and 17,400 female graduates in 2007 and statistics provided by the Statistics and Study Office of Ministry of Education and Research (MIUR, 2003-2004-2005). The survey data includes the information of student residence in 110 Italian provinces (NUTS3 level regions) before enrolling to a university, and the name of university enroled. The actual flow of students between the province of residence and the exact addresses of universities are extracted and stacked into a table as a column vector as the variable of interest.

3.1 Types

In the EOp literature, types are defined according to a set of circumstances that are typically based on parental background and gender. The principle when partitioning the population into types is that the circumstance variables must satisfy the exogeneity requirement. That is belonging to a particular type should not be the choice of the individual. The consensus is that parental characteristics and gender are two circumstances that satisfy this requirement. Accordingly, the present paper argues that at least three aspatial and exogenous factors (circumstances) are particularly relevant to the study of HE accessibility. Firstly, the role of parental education is a well-explored factor that affects the educational choices and outcomes of students. Specifically, in the Italian context, the educational level of parents is found to be highly influential for the academic attainment of Italian students (Checchi et al. 2003; Bratti et al. 2008). Higher HE participation rates and fewer drop-outs are observed for students with highly educated parents (Checchi and Flabbi 2007; Brunori et al. 2012). Moreover, since commuting or migrating to a place involves a cost, the financial condition of families is another aspatial factor relevant to access (Frenette 2003, see; Lupi and Ordine 2009). Finally, even though education is the primary area where women have made substantial gains and now largely out-perform men (DiPrete and Buchmann 2006), the question whether there are systematic differences in spatial access to education between males and females remains an important one.

Following previous studies, the observed flows are partitioned according to three sets of proxies referring to the socio-economic circumstances of students as shown in

Table 1 Variables in analysis, data from ISTAT and MIUR

Variables	Description
Residence	The province of residence before enroling at a university (ISTAT)
Destination University	The university enroled: a total of 63 state and 14 private universities in 2007 (ISTAT)
Distance	Euclidean distance between the city centroids and University addresses, measured in QGIS based on coordinates.
Sex	14,000 male and 17,400 female students graduated in 2007 (ISTAT)
Parent's Education	The highest degree obtained by parents (ISTAT)
	Two categories: at least one highly educated parent or both basic educated
	basic education is up to high school degree and
	high category at least bachelor' s degree.
Financial Condition	Occupation type of parents (ISTAT)
	Three categories: both-high, one-high, both-low
	High=Managers, Directors, High/Medium Qualification
	Low=Office Workers, Lower-Skilled Workers
$SocialCapital_p$	A composite index of social capital combining
L_j	Proportion of limited places offered by universities to the total places (MIUR)
U_{jl}	Institutional characteristics to be interacted with distance (MIUR)
	U_{j1} 1 if private 0 otherwise
	U_{j2} 1 if polytechnic 0 otherwise
	U_{j3} 1 if south U_{j4} 1 if centre U_{j5} 1 if island 0 otherwise
Types	group1 (both basic educated parents, male , low financial condition)
	group2 (both basic educated parents, female , low financial condition)
	group3 (both basic educated parents, male, medium financial condition)
	group4 (both basic educated parents, female, medium financial condition)
	group5 (both basic educated parents, male, high financial condition)
	group6 (both basic educated parents, female, high financial condition)
	group7 (at least one high educated parent, male, low financial condition)
	group8 (at least one high educated parent, female, low financial condition)
	group9 (at least one high educated parent, male, medium financial condition)
	group10(at least one high educated parent, female, medium financial condition)
	group11(at least one high educated parent, male, high financial condition)
	group12(at least one high educated parent, female, high financial condition)
Types 2	group1 (low educated parents, male)
	group2 (low educated parents, female)
	group3 (parents' education up to high school,male)
	group4 (parents' education up to high school, female)
	group5 (at least one high educated parent, male)
	group6 (at least one high educated parent, male)

Table 1: the presence of at least one highly educated parent at home where the alternative is both parents with basic education. Here "basic education" means up to a high school degree. "High education" consists of parents with at least a bachelor's degree. In the survey, 40.66% of mothers and 39.69% fathers are categorised as basically educated, and 14.56% and 20.06% as highly educated, respectively. Survey data contains information about parents' professions. This information is categorized as high and low for both fathers and mothers. Hence three groups are constructed as both-low, both-high and one-high-one-low. The gender of students is included in addition to the parental background. The combination of these three categories resulted in 12 types as shown in Table 1.

The objective of aggregating students under types is to obtain subgroups that are homogenous by family background and gender. Any variation computed among them is judged as unfair since it is attributed to circumstances. Therefore, from a modelling perspective, it comes clear that the way circumstances are constructed may affect the IOp share in the total inequality. For this reason, to control the sensitivity of findings, types are alternatively defined only by parental education and gender variables. Table 1 shows 6 groups generated using gender and parental education under the

Table 2 Summary statistics of movers and immobile students

Types	%Total	%Movers	%Immobile
Group1	12%	49%	51%
Group2	13%	46%	54%
Group3	07%	43%–	57%
Group4	09%	45%	55%
Group5	06%	46%	54%
Group6	06%	47%	53%
Group7	01%	38%	62%
Group8	02%	45%	55%
Group9	08%	42%	58%
Group10	09%	47%	53%
Group11	13%	48%	52%
Group12	14%	47%	53%
Humanities	13%	49%	51%
Economics/Statistics	15%	42%	58%
Social policy	08%	49%	51%
Scientific	08%	43%	57%
Law	10%	43%	57%
Engineering	11%	43%	57%
Architecture	05%	51%	49%
Medicine	28%	48%	52%
Physical education	02%	41%	49%
Dropped[a]	60%	34%	66%

[a] Data of students who dropped out is extracted from *ISTAT Percorsi di studio e di lavoro dei diplomati, 2011*

heading *Types 2*. The variable parental education is considered under three categories: lower education that covers 8 years schooling, middle education at least one parent holding up to a high school degree and higher education is defined for those with at least a bachelor's degree. Finally, to demonstrate how effort or choice can be incorporated in accessibility analysis, three alternative types are constructed; i) by the field of study, ii) by family background, gender and Medicine or Economics/Statistics as the field of study and iii) finally family background, gender and those who dropped out of university (Table 2). For the construction of types with students who dropped out of university education, enrolment survey is used (*ISTAT Percorsi di studio e di lavoro dei diplomati, 2011*).

3.2 Distance

The distance from parental residence to HE institutions is a factor that influences the likelihood of participation and the HE outcomes of students. Ordovensky (1995) shows that distance to institutions influence the academic enrolments in the USA, while four-year college enrolment is less sensitive. In a study on the school leavers and university entrants in England, Gibbons and Vignoles (2009) find that distance strongly influences university choice. Similarly, Suhonen (2014) shows that the likelihood of enroling to a specific field decreases as the required distance of access increases. For Italy, the empirical evidence confirms that geographical proximity strongly influences the choice of university (Pigini et al. 2013). Indeed, in the survey data, 59.28% of students studied in their hometown and 40.64% were motivated by the closeness of the institution and only 9.74% by the prestige of the university. For student mobility, distance does not only represent costs but is also a predictor of how far students are allowed to live away from their families, which is very relevant in Italy as it is a country characterised by strong family ties (Alesina and Giuliano 2010).

In the application, d_{ij} is the Euclidean distance between the centroid of city i and the exact address of university j. In the QGIS environment, the coordinates of city centres are matched with the coordinates of the exact location of universities and the Euclidean distance is calculated for each pair. According to the interest of the investigation and the data behaviour, it is possible to find the exponential form, exponential square root, the log of distance or a relevant combination of these (De Vries et al. 2009). To choose the most relevant form of deterrence function, the predicted flows are examined against observed flows and the power specification of the distance proved most suitable for the data. This choice is in line with previous studies that indicate the power-decay function to be more suitable for long distance interactions owing to the log-cost perception (Fotheringham and Webber 1980; Reggiani et al. 2011).

3.3 University Attractiveness

As far as institutional attractiveness is concerned, previous studies of HE provide mixed findings. Sa et al. (2004) use university rankings as a quality indicator for Dutch HE institutions, but the coefficient is estimated negative. The authors explain this result as consumption behaviour by students in relation to HE (Sa et al. 2004). Similarly, Singleton et al. (2012) employ Times Good University Guide rankings but set an arbitrary power of 0.5 rather than empirical derivation. Dotti et al. (2013) construct an index identifying a province as attractive if inflows exceed outflows, neglecting institutional attractiveness. This paper employs a university fixed-characteristics and a social capital index to account for attractiveness: Many programmes are offered on a free-access principle in Italy, but a few require entrance tests, which indicates excess demand for these programs. The proportion of limited places to the total number of places available at University is used as a quality indicator for the period prior to the year 2007.[2]

Moreover, the city where a university is located may make it more attractive for a potential candidate. There are several criteria for how a city is considered as attractive such as higher job accessibility and employment opportunities, better public services, the degree of recreational and social activities, and human capital. A number of studies find a positive and significant relationship between social capital and attractive features of localities. A higher social capital has been shown to associate with improved efficiency of society (Putnam 2001), reduced crime (Buonanno et al. 2009), resilience and attractive attributes of cities. For example, using a composite index of social capital (Östh et al. 2018) find a significant relationship between social capital and job accessibility, human capital accumulation, and wealth of Swedish municipalities. Their paper uses a resilience definition of social capital, where resilience is defined as the ability of systems to absorb and respond to external shocks Reggiani et al. (2002). As underlined by Modica and Reggiani (2015), both stability and adaptivity define spatial resilience, and such attributes might make a location more preferable to alternatives. Following these contributions, the present paper uses a social capital index as a proxy of the attractiveness of cities. The index is defined and measured by the Community Connectivity Capacity (CCC) index as in Östh et al. (2018), which include variables that communicate resilience related attributes of cities. The index is a composite measure of four variables standardised and aggregated at a province level: i) civic engagement as proxied by voter participation,[3] ii) the share of individuals owning their homes as a measure of metropolitan stability iii) the share of individuals working in non-profit organizations iv) number of museums in each province.[4] For the construction of the variables in ii and iii ISTAT is used.

3.4 Interactions

Finally, several destination characteristics are interacted with distance to see how the willingness to migrate to further destinations varies among different types.

Table 1 shows the interacted institutional characteristics including the following: whether the university at the destination is a private institution, dummies for the south, central and island locations and a dummy with value 1 for polytechnic universities.

[2] source: www.anagrafe.miur.it

[3] source: http://elezionistorico.interno.gov.it

[4] source: http://dati.beniculturali.it/datasets/luoghi-della-cultura

4 Empirical Method and Findings

The examination of the model is operated by related statistical log linear models, which were developed alongside entropy maximizing models. There are several ways of handling spatial interaction models such as entropy maximazing and calibration (Wilson 1971; Yun and Sen 1994), and half-life models (Östh 2011). This study makes use of the Poisson gravity models that have[5] the same statistical properties as entropy maximization models and produce identical estimations (Baxter 1982).

The Poisson gravity model takes the following form:

$$E(N_{ij}) = T_{ij} = O_i^{\theta} D_j^{\alpha} f(d_{ij}) \tag{4}$$

where N_{ij} indicates observed flows, T_{ij} is the expectation of observed flows treated as a random variable and assumed to have a Poisson distribution (Baxter 1982).[6]

The model is calibrated by the generalized linear model (GLM) package in R,[7] where flows follow a Poisson distribution with a logarithmic link between the variables. The estimations are carried out separately for 12 subgroups. Finally, the Poisson regression is as follows:

$$\begin{aligned} T_{ijk} &= \exp[constant + O_i + \alpha D_{jk} + \mu \delta_{ij} + \beta ln(d_{ij}) \\ &\quad + \gamma SocialCapital_p + \eta L_j + \sum_l \lambda_l ln(d_{ij}) U_{jl}] \end{aligned} \tag{5}$$

where $k = 1, 2, 3, ..., 12$ represents types, $SocialCapital_p$ social capital at the province where destination university is located and L_j the share of limited places at the university j, and U_{jl} a set of interactions on distance. This regression produces an exponential value of factor for origin i and is proportionally equivalent to the product $K_i O_i$, and is hence equivalent to the production-constrained model of the entropy-maximizing system.

Tables 3 and 4 show the results of the first set of regressions, where the model is used for 10 groups. Groups 7 and 8 are not taken into consideration due to lower number of observations. As expected, distance has a very strong negative effect, indicating a deterrence impact for each group. For 1 km decrease in the distance, the expected number of student flows increases by factors varying from 1.499 to 1.709 (one to two students). The impact is higher for female students than for male students except for those with at least one highly educated parent. As a student's family background becomes more favorable in terms of the proxies specified above, the difference between male and female shrinks and ultimately female students feel less deterred. As in previous studies, δ is significant at the 0.01 level for all groups and positive in sign, capturing the benefit of residing and studying in the same city. Similar values are observed for different types but with different motivations. For socially advantaged groups the parameter μ captures the fact that these students usually live in big cities where large universities are located and hence they do not need to migrate.

[5] see Flowerdew and Aitkin (1982) and Smith (1987) for theoretical development.

[6] The probability mass function of flows is given by $Pr(T_{ij}) = \frac{\exp^{-N_{ij}} N_{ij}^{T} ij}{T_{ij}!}$.

[7] see Dennett (2012) for details.

Table 3 Results of poisson regression first 5 groups

Groups	(1)	(2)	(3)	(4)	(5)
Variables	Basic-Male-Lower Class	Basic-Female-Lower Class	Basic-Male-Middle Class	Basic-Female-Middle Class	Basic-Male-High Class
SocialCapital	0.094***	0.072***	0.068***	0.059***	0.059**
	(0.006)	(0.013)	(0.007)	(0.016)	(0.019)
L_j	0.067	0.245**	0.095	0.627***	−0.013
	(0.044)	(0.086)	(0.049)	(0.066)	(0.124)
$\hat{\mu}$	0.357***	0.388***	0.323***	0.271***	0.277***
	(+0.017)	(0.036)	(0.021)	(0.030)	(0.053)
Distance	−1.557***	−1.718***	−1.503***	−1.529***	−1.556***
	(0.018)	(0.038)	(0.020)	(0.030)	(0.050)
Institutional interactions					
x Private Univ.	0.589***	0.542***	0.601***	0.578***	0.413***
	(0.024)	(0.020)	(0.027)	(0.031)	(0.059)
x Polytechnic	0.152***	0.450	0.089	0.054	0.089
	(0.043)	(0.023)	(0.035)	(0.052)	(0.082)
x South	0.356***	0.397***	0.512***	0.392***	0.504***
	(0.026)	(0.054)	(0.027)	(0.043)	(0.074)
x Center	0.437***	0.637***	0.477***	0.465***	0.417***
	(0.026)	(0.058)	(0.029)	(0.076)	(0.071)
x Island	−0.221***	−0.167	−0.097	−0.303***	0.074
	(0.155)	(0.111)	(0.057)	(0.173)	(0.136)
(Intercept)	7.732***	7.09***	7.639***	7.086***	6.325***
	(0.086)	(0.176)	(0.099)	(0.138)	(0.239)
Observations	2,424	2,424	2,424	2,424	2,424
R2	0.83	0.84	0.86	0.84	0.85

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each column includes a student group (type) based on parental education, student's gender and, the financial condition of parents, respectively

On the other hand, groups 1 to 4 it may reflect the actual startup costs of spatial mobility. As far as the attractiveness of universities is concerned, L_j (the share of limited places offered by universities) is significant and positively affects flows only for female students or male students who have at least one highly educated parent. Among the students with disadvantaged parental backgrounds, only female students (groups 2 and 4) are attracted to these limited positions. This is probably because female students are interested in faculties such as medicine and nursing requiring entrance tests. Hence, for male students with a poor parental background, what seems to matter is obtaining a degree irrespective of the prestige of the university (Triventi

Table 4 Results of poisson regression last 5 groups

Groups	(6)	(9)	(10)	(11)	(12)
Variables	Basic-Female-High Class	$\geq$ 1high-Male-Middle Class	$\geq$ 1high-Female-Middle Class	$\geq$ 1high-Male-Higher Class	$\geq$ 1high-Female-Higher Class
SocialCapital	0.087***	0.029***	0.088***	0.051***	0.065***
	(0.017)	(0.024)	(0.012)	(0.010)	(0.021)
L_j	0.419***	0.217	0.506***	0.354***	0.338***
	(0.107)	(0.169)	(0.077)	(0.072)	(0.014)
$\hat{\mu}$	0.332***	0.319***	0.332***	0.332***	0.288***
	(0.032)	(0.065)	(0.033)	(0.031)	(0.063)
Distance	–1.555***	–1.460***	–1.486***	–1.451***	–1.423***
	(0.046)	(0.064)	(0.032)	(0.030)	(0.059)
Institutional Interactions					
x Private Univ.	0.455***	0.370***	0.513***	0.565***	0.626***
	(0.054)	(0.082)	(0.040)	(0.035)	(0.072)
x Polytechnic	0.089	0.253**	-0.028	0.187***	0.216
	(0.103)	(0.092)	(0.071)	(0.046)	(0.072)
x South	0.309***	0.168	0.255***	0.287***	0.128
	(0.071)	(0.109)	(0.049)	(0.047)	(0.103)
x Center	0.316***	0.196**	0.342***	0.305***	0.325***
	(0.066)	(0.095)	(0.046)	(0.041)	(0.072)
x Island	–0.152	–0.689***	–0.289**	–0.314***	–0.122
	(0.120)	(0.204)	(0.101)	(0.086)	(0.158)
(Intercept)	6.109***	5.342***	6.460***	6.840***	5.526***
	(0.219)	(0.295)	(0.151)	(0.140)	(0.276)
Observations	2,424	2,424	2,424	2,424	2,424
R2	0.81	0.86	0.84	0.84	0.87

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each column includes a student group (type) based on parental education, student's gender, and the financial condition of parents, respectively

and Trivellato 2009). On the other hand, all types of students show a statistically significant and positive response to the social capital level of cities, where destination universities are located. This means that irrespective to the socio-economic background, students consider such attractive characteristics of destination cities as human capital accumulation, employment opportunities, and social activities that are proxied by the social capital index in the model.

The remaining results allow for interactions between institutional characteristics and distance. Private universities at destination increase the tendency of travelling longer distances for all groups. It is an expected result, since for any type deciding to enrol at a private university, the distance must be becoming irrelevant. Looking at the significance levels, polytechnics do not seem to induce students to travel far except for groups 1, 5 and 9 which are distinctively male students. Interacting distance with macro-regions, where universities are located, shows that the central region attracts more students than the south for all students except types 3 and 5. These two types comprise male students with poor family backgrounds who may prefer universities in the south due to lower costs of living. Finally, universities located in Sicily and Sardinia fail to attract students from all backgrounds.

After obtaining the parameter values from (5), accessibility scores are calculated by Eq. 3 for each group with their respective impedance functions as follows:

$$A_{ik} = \sum_{j=1} \frac{C_j d_{ij}^{\hat{\beta}_k}}{\delta_{ijk}} \tag{6}$$

where $k = 1, 2, 3, ..., 12$, C_f is the total number of places available at university j and as in (5) d_{ij} is the distance between city centroids and the exact addresses of universities (to the largest campuses); hence zero distance does not occur, which in return accounts for the self-potential (local demand) of universities within provinces. The measured scores indicate potential access in terms of the places offered to students. Higher scores indicate better access to a total of 77 universities located in 101 different provinces. Figure 1 illustrates the access scores of 10 groups, where darker grey indicates a higher score.

The first thing to note from the figures is that if a student belongs to a socially advantaged group, the access is relatively higher in each location, except very far south in the country. Whilst, for socially disadvantaged groups, even if they live in a big city where large universities are located, access remains low, particularly in the south. The lowest access is observed for group 2 including female students with lower-class parents with a basic education. The types constructed for this paper seem particularly relevant for female students. Access increases on average 70% from group 2 to group 12, whereas for male students from the worse backgrounds to the best, access increases 25% on average. Moreover, a degree of variation in access is observed between male and female students in the first 4 groups but lessens as parental education and financial condition improve.

Decomposition of Access Inequality To disentangle the relative contributions of spatial and aspatial factors to inequality, a decomposable inequality index is used.[8] As shown in Table 5 (Model 1), the resulting inequality is a sum of within and between inequalities. The first row of Table 5 shows the inequality decomposition where the variation within types of students is suppressed by substituting each type's accessibility score with its arithmetic mean. By this method, the inequality between the types of students is computed as 0.05607 and represents the contribution of socio-economic factors to total inequality (9% of total inequality). Whereas in the second row, the

[8]Mean Logarithmic Deviation is a path-independent decomposable inequality measure (Foster and Shneyerov 2000). It is defined as: $MLD(X) = \frac{1}{N}\sum_1^N \ln \frac{\mu_x}{x_i}$ where X is a distribution, N population size and μ_X is mean.

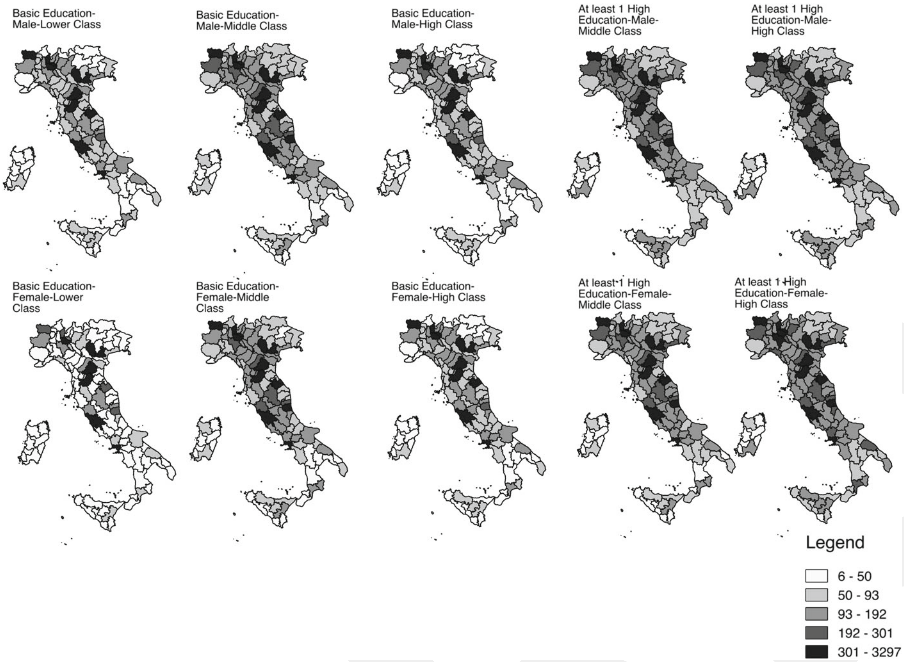

Fig. 1 Accessibility Maps of 10 types based on parental education, gender, and financial condition of parents

variation within provinces is eliminated by substituting each province's accessibility score with its arithmetic mean. By this approach, the inequality between provinces is computed as 0.61672 and the contribution of socio-economic factors to total inequality measures at 4%. The relative contributions to the total inequality of space and socio-economic factors vary according to the approach chosen. The reason is that the first approach emphasises the inequalities between socio-economic groups, hence aspatial reasons. Meanwhile, the second approach focuses on differences in access due to parental locations, hence spatial reasons. Therefore, it is policymakers' responsibility to choose which approach to adapt based on the instruments available at hand. Interestingly, Checchi and Peragine (2005) compute IOp in education as 7.2% in South and 5.3% in Northern Italy based on the PISA survey. Their findings are comparable with the computations of this paper. Although the former uses a different outcome and measurement methods, similar circumstances seem to cause similar variation in opportunities.

To demonstrate the computed inequality, consider a female student with a poor family background (group 2) living in Matera, in order for her to have as much access as a male student with the same family origin (group 1) living in the same city, she has to travel 147 km to the nearest city, Lecce (social distance). Moreover, in order for her to have similar access to a female student with a better family origin (group12) living in Naples, she has to travel 365 km to the nearest city Rome (social+physical distance).

Table 5 Decomposition of inequality in access, the field of study (MLD measures)

		Spatial inequality	Inequality due to socioeconomic background	Total inequality
Model 1	Inequality in access to HE (First Approach)	0.58585 (91%)	0.05607 (9%)	0.64192 (100%)
	Inequality in access to HE (Second Approach)	0.61672 (96%)	0.02520 (4%)	0.64192 (100%)
	Inequality in access to HE Prior to Reforms (First Approach)	0.70392 (92%)	0.05898 (8%)	0.7629 (1005)
Mode2	Inequality in access to HE (First Approach)	0.57575 (92%)	0.04749 (8%)	0.62324 (100%)
	Inequality in access to HE (Second Approach)	0.60173 (96.5%)	0.02151 (3.5%)	0.62324 (100%)
Model 3	Field of study	0.52098 (48%)	0.47386 (52%)	0.99484 (100%)
	Parental Education-Gender-Medicine	0.37750 (88%)	0.05328 (12%)	0.43078 (100%)
	Parental Education-Gender-Economics/Statistics	0.23983 (55%)	0.19687 (45%)	0.4367 (100%)
	Parental Educaiton-Gender-Dropped Out	0.12962 (50.5%)	0.12737 (49.5%)	0.25699 (100%)

Table shows the decomposition of inequality in access for corresponding models as indicated in the first column. Percentage contribution to total inequality in parenthesis

4.1 Spatial Inequality Pre-Reform Period

The survey used in the present paper is repeated every four years. However, in the previous years, the geographical information of parental residence and the name of the university enroled are not provided. For this reason, in order to study whether spatial inequality has decreased as a result of the reforms implemented since the year 1990, additional analyses were carried out with the assumption that distance elasticities competed by (5) are valid also for the other waves. The third row of Table 5 shows the inequality decomposition assuming that students show similar mobility behaviours over time whilst with a fewer set of available universities[9] from parental residences. Since the differences between types are retained, the aspatial share of inequality remains the same while the spatial inequality shows a decline from 0.70392 to 0.58585 (MLD measures) 17% following the expansion process from the 90s to 2007. The map displayed in Fig. 2 shows the increase in spatial accessibility of HE for each province based on the difference between the access scores computed in 1990 and 2007. Darker grey indicates the degree of increase. When accessibility is increased in a location it spills over nearby locations. The impact of the reforms mainly concentrates in the centre and expands towards south and Sicily. Meanwhile, Sardinia has not benefited from the reforms.

4.2 Alternative Models

This section considers alternative aggregations of students based on parental education, the field of study, and dropping out behaviour. First, to examine the sensitivity of the findings in line with previous studies, the student population is aggregated based on parental education and gender as follows: students of parents holding up to middle school, those with one of the parents holding a high school or vocational degree, and at least one highly educated parent (at least university degree). A total of 6 groups are generated by combining these three categories with gender. The model is estimated as in (5) with the same set of controls as presented in section 3 and accessibility is competed by the equation (6). Table 5 contains the decomposition results of inequality in access when only parental education and gender are considered (Model 2). The results are very similar to the previous model (see regression output in Appendix). The model captures slightly lower total inequality and a lower share of inequality due to socio-economic backgrounds.

The assumption underlying the models 1 and 2 is that two sets of circumstances drive the accessibility of HE: parental residence prior to enrolment hence the distance to university and socio-economic/demographic backgrounds. Therefore, the models are specified without an effort or choice dimension. The sixth row of Table 5 shows the inequality decomposition of models where the field of study is incorporated as effort. First, the students are aggregated only by their *choice* regarding the field of study where the only circumstance variable is the distance from universities.

[9]There were 60 universities and fewer places and sites available to students source:La localizzazione geografica degli atenei statali e non statali in Italia dal 1980 al 2000, 2001.

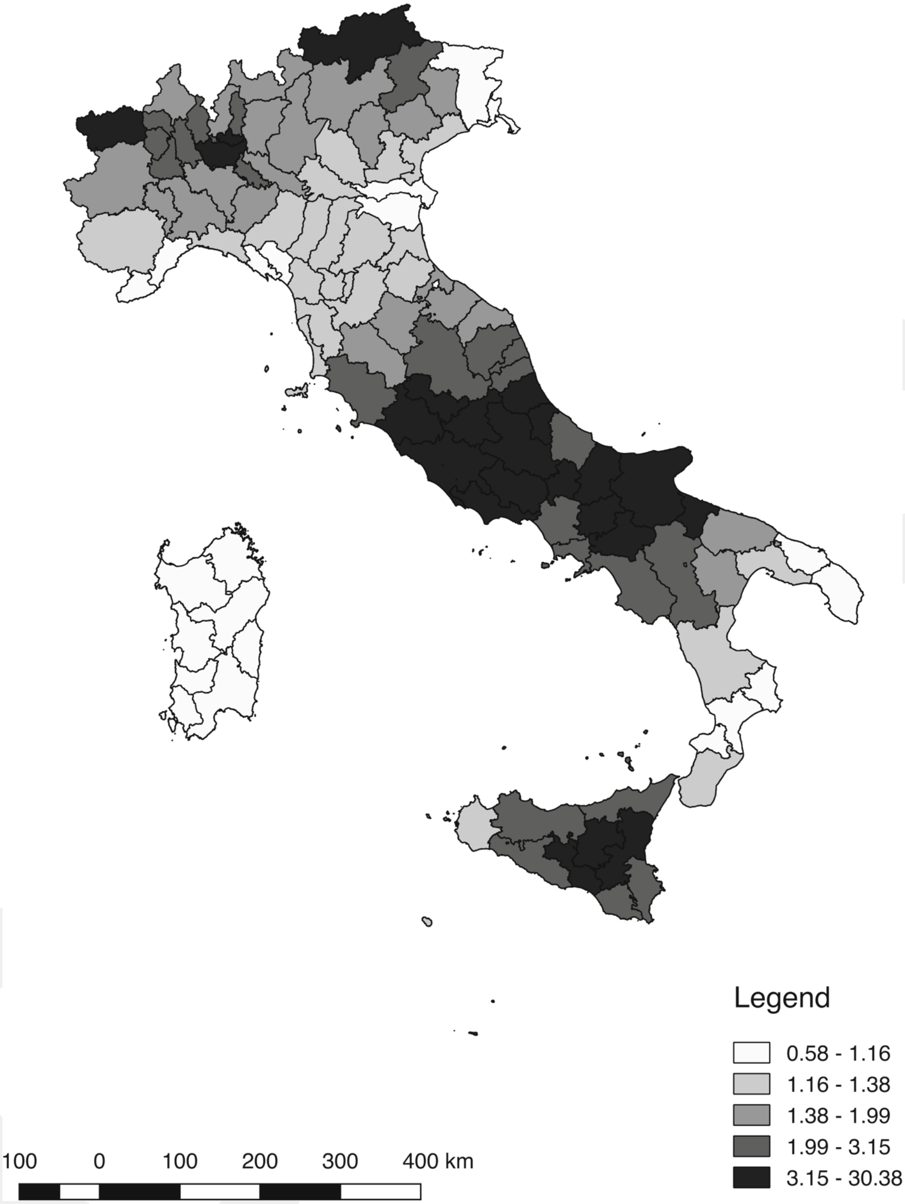

Fig. 2 Increase in Spatial Accessibility of HE from 1990 to 2007

The results indicate that 52% of inequality in access is a result of choosing a specific field and the spatial distribution of universities is responsible for 48% of inequality. The interpretation is that after deciding which field to pursue some students attend the universities closest to home while others are more mobile. In this setting, the unevenness in access or mobility/immobility pattern is relatively less related to the spatial distribution of universities. From equal opportunities perspective, the choice of field clearly indicates *effort* rather than a *circumstance*. However, inherited circumstances may play a role in the degree of access after the field of study has been chosen. This can be seen in Table 5 (Model 3), where students are aggregated by parental education and gender as in the Model 2, but observations are restricted to the students those who studied Medicine or Economics/Statistics, the two degrees that highly represented in the data survey (Table 2). The seventh row illustrates the decomposition of inequality in access for medical students given their socio-economic background. The results indicate that 88% of inequality is due to the spatial distribution of universities providing Medical degrees and 12% is the contribution of socio-economic/demographic characteristics. As for the Economics/Statistics students the decomposition results are 55% and 45%, respectively. For Medicine, the results are similar to the models where choice is not taken into consideration. The reason is that there are relatively few universities offering Medical degrees and for this reason, spatial distribution of universities generates higher inequality. Meanwhile, the contribution of aspatial circumstances to the total inequality is higher for Economics/Statistics students since almost every faculty offers these degrees and students with poor family backgrounds have lower access (and mobility) even though spatially there is a large bundle of alternatives available from parental residences. As a final consideration, Model 2 is run for students those who dropped out of university education. With this aggregation half of the variation in access is computed to be due to space and the other half due to family background and gender. Although the share of aspatial reasons to inequality increase, a lower overall inequality is computed. The reason is that this population of students show a higher sensitivity to distance and a majority of them remain in parental residences (Table 2). Therefore, they are characterised by a higher immobility and the lower variation in access is related to the similar immobility patterns irrespective of the distance from universities. The model captures a lower willingness to migrate by poorer family backgrounds.

The chief difference between the results shown in Table 5 prevails from the distinctive ways in which circumstances and effort are treated and related notions of “compensation” and “responsibility”. The compensation principle suggests that if inequalities arise as a result of differences in circumstances than they should be compensated whereas the responsibility principle considers inequalities acceptable when differences in outcomes arise as a result of uneven effort (Fleurbaey 2008). The two principles require different measurement approaches. The responsibility principle adapts an ex-ante perspective, where the objective is to eliminate inequalities among groups with identical circumstances, whereas the approach in the compensation principle is ex-post aiming to eliminate inequalities between individuals who exerted the same level of effort but subject to different circumstances (Fleurbaey and Peragine 2013). The Models 1 and 2 are constructed in a reduced form (Ferreira and Gignoux 2011) based on only two sets of circumstances: spatial distribution of universities, and family backgrounds and gender. Accordingly, in Model 1 and 2, inequality decompositions are based on the accessibility of HE computed for a potential candidate who is to choose a university and a field, given the spatial distribution of universities from parental residences and socio-economic background. Therefore, measurements are ex-ante to any choice, and for this reason, the share of responsibility in the total inequality is higher for the spatial distribution of universities. On the other hand, in Model 3 the field of study is included in the model hence the computations are ex-post to choices. As a result, spatial inequality lessens and a part of responsibility in the total inequality shifts to aspatial reasons. In the first-row of the results derived from Model 3, students are subject to a greater share of aspatial inequality because they choose to pursue a certain degree. In the seventh and eighth rows of Table 5 students are assumed to have exerted the same level of effort by choosing to study Medicine or Economics/Statistics but have different socio-economic backgrounds and gender. In this setting, the responsibility or effort is defined as the choice of field. For instance, medical students have passed an entrance test in order to study Medicine. Therefore, assuming that they have exerted similar levels of effort is not far from reality. Interpretation is that despite the even effort, they have different access to universities due to differential circumstances. Similarly, in the last row students are assumed to have exercised the same level of effort (or lack of effort) by dropping out of university. The model does not study the reasons for dropping out but these students clearly show similar behaviors of mobility prior to the decision to drop out of university.

5 Conclusions

This paper provides empirical evidence for the dynamics of student mobility in Italy and measures inequality in access to HE institutions with particular attention to the socio-economic backgrounds of students. In line with previous studies of EOp, the student population is aggregated into types of individual groups. The types draw on circumstance variables including parental education and occupation type, and gender. The reason for choosing these variables is that there is a broad consensus in the literature that parental attributes and gender cannot be chosen by students, which is the principle requirement when studying inequality of opportunities. In the present paper, the flows of different types of students to destination universities are defined as interactions between provinces in Italy by a spatial interaction model. The results demonstrate that the male students with poor family backgrounds are impervious to university-quality effects and university quality becomes relevant only for students with better family backgrounds. Meanwhile, social capital accumulation of the destination city has proved to attract students from all backgrounds. The model introduces interactions between institutional characteristics and distance to see how elasticity with respect to spatial distance varies given the heterogeneity of the universities. The results illustrate that private universities attract students and increase their willingness to travel longer distances. The universities located in the central region attract more students than in the south, and the universities in Sicily or Sardinia deter flows.

As far as distance is concerned, the coefficients are highly significant and negative in sign, indicating a deterrence effect for each group of students. In line with previous studies, δ is significant at the 0.01 level for all groups and positive in sign, capturing the benefit of residing and studying in the same city. In the second step, computed deterrence functions and δs are imported into a Hansen-like accessibility index, and accessibility scores of 110 Italian provinces to 77 Italian universities are computed. The results show that socio-economic background matters, especially for female student mobility. The spatial access to HE increases on average 70% as the circumstances of female students become better. The share of aspatial factors in inequality of access between types proves to be 9% with the first approach and 4% when computed with the second approach. Moreover, assuming that distance factors remain constant over time, 17% decrease in spatial inequality is observed as a result of the reforms initiated in the 90s. The paper has demonstrated the differences between the ex-ante and ex-post approaches to the measurement and interpretation of IOp by incorporating the field of choice in alternative models. From ex-ante to ex-post the responsibility in total inequality shifts from spatial reasons to aspatial circumstances. A higher deviation is observed especially for students who choose to study Economics and Statistics, whose parental background strongly determines the degree of mobility. Finally, the population of students who dropped out of university shows similar patterns of immobility.

The present paper contributes to the accessibility literature by a multidisciplinary approach providing a spatial accessibility measure for Italian HE institutions with particular attention to socio-economic sources of inequality. It also contributes to EOp literature by showing how spatial dimensions of EOp could be incorporated into models that rely solely on spatial elements. Furthermore, the investigation of 10 types provides a clear ranking. In other words, through this application, this study empirically shows which socio-economic group is better off and by how much. Finally, this study is the first attempt to define the parental location, clearly an exogenous factor for students, as a circumstance.

The findings provide highly detailed information for policy implications. In order to increase accessibility three policy strategies can be adapted. Firstly, an effective policy may target the types with lower potential accessibility to assist them through loans, scholarships, and grants. Secondly, the geographical locations where accessibility is lower can be identified, and accessibility can be increased by the reduction of geographic barriers for cities such as Nuoro, Brindisi, Ragusa, and Belluno where new universities and/or places may be set up. Finally, a combination of these two can be used. For instance, the empirical evidence in this paper shows that female students with disadvantaged family backgrounds located in southern Italy would benefit the most from HE funding. More precisely the identification of inequality resulting from gender and geography can be extracted from the findings as follows: for a female student living in the south with low-income parents both with a basic education, on average the potential accessibility is 146.15% lower than a male student living in the North with better family origin. These examples can be extended to determine a variety of policy strategies.

Appendix

Table 6 Results of poisson regression model 2

Groups Variables	(1) Lower Education-Male	(2) Lower Education-Female	(3) High School Degree-Male	(4) High School Degree-Female	(5) Higher Education-Male	(6) Higher Education-Female
Social capital	0.073***	0.102***	0.067***	0.084***	0.048***	0.060***
	(0.009)	(0.008)	(0.007)	(0.006)	(0.010)	(0.009)
L_j	−0.041	0.446***	0.273***	0.526***	0.355***	0.539***
	(0.062)	(0.055)	(0.047)	(0.042)	(0.067)	(0.063)
$\hat{\mu}$	0.360***	0.381***	0.336***	0.342***	0.331***	0.297***
	(0.027)	(0.022)	(0.020)	(0.018)	(0.029)	(0.0289)
Distance	−1.580***	−1.610***	−1.464***	−1.523***	−1.452***	−1.430***
	(0.025)	(0.023)	(0.021)	(0.018)	(0.029)	(0.028)
Institutional interactions						
x Private Univ.	0.603***	0.563***	0.502***	0.534***	0.537***	0.574***
	(0.025)	(0.032)	(0.026)	(0.022)	(0.032)	(0.029)
x Polytechnic	0.0.029	0.153**	0.103*	0.092	0.186***	0.009
	(0.029)	(0.058)	(0.033)	(0.039)	(0.043)	(0.056)
x South	0.544***	0.381***	0.470***	0.237***	0.287***	0.394***
	(0.034)	(0.032)	(0.031)	(0.028)	(0.045)	(0.037)
x Center	0.482***	0.427***	0.413***	0.345***	0.289***	0.433***
	(0.034)	(0.033)	(0.029)	(0.026)	(0.039)	(0.041)
x Island	−0.112	−0.240***	−0.124*	−0.263***	−0.319***	−0.306***
	(0.048)	(0.061)	(0.062)	(0.054)	(0.081)	(0.077)
(Intercept)	7.084***	7.380***	7.995***	7.705***	6.99***	7.243***
	(0.124)	(0.106)	(0.099)	(0.086)	(0.134)	(0.129)
Observations	2,448	2,448	2,448	2,448	2,448	2,448
R2	0.84	0.84	0.85	0.85	0.84	0.86

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each column includes a student group (type) based on parental education and student's gender, respectively

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

Alesina A, Giuliano P (2010) The power of the family. J Econ Growth 15(2):93–125

Alm J, Winters JV (2009) Distance and intrastate college student migration. Econ Educ Rev 28(6):728–738
Baxter M (1982) Similarities in methods of estimating spatial interaction models. Geogr Anal 14(3):267–272
Bratti M, Checchi D, De Blasio G (2008) Does the expansion of higher education increase the equality of educational opportunities? Evidence from Italy. Labour 22(s1):53–88
Brunori P, Peragine V, Serlenga L (2012) Fairness in education: the italian university before and after the reform. Econ Educ Rev 31(5):764–777
Buonanno P, Montolio D, Vanin P (2009) Does social capital reduce crime? J Law Econ 52(1):145–170
Checchi D, Flabbi L (2007) Intergenerational mobility and schooling decisions in germany and Italy: the impact of secondary school tracks
Checchi D, Peragine V (2005) Regional disparities and inequality of opportunity: the case of Italy
Checchi D, Peragine V (2010) Inequality of opportunity in Italy. J Econ Inequal 8(4):429–450
Checchi D et al (2003) The italian educational system: family background and social stratification. In: ISAE conference on monitoring Italy
Cooke TJ, Boyle P (2011) The migration of high school graduates to college. Educ Evavl Policy Anal 33(2):202–213
Dardanoni V, Fields GS, Roemer JE, Puerta MLS (2006) How demanding should equality of opportunity be, and how much have we achieved? Mobility and inequality: frontiers of research from sociology and economics pp 59–82
De Vries JJ, Nijkamp P, Rietveld P (2009) Exponential or power distance-decay for commuting? An alternative specification. Environ Plan A 41(2):461–480
Dennett A (2012) Estimating flows between geographical locations:'get me started in'spatial interaction modelling. Tech. rep., Citeseer
DiPrete TA, Buchmann C (2006) Gender-specific trends in the value of education and the emerging gender gap in college completion. Demography 43(1):1–24
Dotti NF, Fratesi U, Lenzi C, Percoco M (2013) Local labour markets and the interregional mobility of italian university students. Spat Econ Anal 8(4):443–468
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
Fleurbaey M (2008) Fairness, Responsibility, and Welfare. Oxford University Press, Oxford
Fleurbaey M, Peragine V (2013) Ex ante versus ex post equality of opportunity. Economica 80(317):118–130
Flowerdew R, Aitkin M (1982) A method of fitting the gravity model based on the poisson distribution. J Reg Sci 22(2):191–202
Foster JE, Shneyerov AA (2000) Path independent inequality measures. J Econ Theory 91(2):199–222
Fotheringham A, O'Kelly ME (1989) Spatial Interaction Models: Formulations and Applications, vol 5. Kluwer Academic Pub., Dordrecht
Fotheringham AS, Webber MJ (1980) Spatial structure and the parameters of spatial interaction models. Geogr Anal 12(1):33–46
Frenette M (2003) Access to college and university: does distance matter? Statistics Canada, Catalogue (11F0019MIE2003201)
Garcia CSHF, Macário MdRMR, Menezes EDdAG, Loureiro CFG (2018) Strategic assessment of lisbon's accessibility and mobility problems from an equity perspective. Networks and Spatial Economics pp 1–25
Gibbons S, Vignoles A (2009) Access, choice and participation in higher education
Gitlesen JP, Thorsen I (2000) A competing destinations approach to modeling commuting flows: a theoretical interpretation and an empirical application of the model. Environ Plan A 32(11):2057–2074
Hansen WG (1959) How accessibility shapes land use. J Am Inst Plann 25(2):73–76
Haynes KE, Fotheringham AS (1984) Gravity and Spatial Interaction Models, vol 2. Sage Publications, Beverly Hills
Lowe JM, Sen A (1996) Gravity model applications in health planning: analysis of an urban hospital market. J Reg Sci 36(3):437–461
Lupi C, Ordine P (2009) Family income and students' mobility. Giornale degli Economisti e Annali di Economia pp 1–23
Mayhew L, Gibberd R, Hall H (1986) Predicting patient flows and hospital case-mix. Environ Plan A 18(5):619–638

McArthur DP, Kleppe G, Thorsen I (2011) The spatial transferability of parameters in a gravity model of commuting flows. J Transp Geogr 19(4):596–605
MIUR (1997) Verifica dei piani di sviluppo dell'universita 1986-90 e 1991-93, doc. 4/97. Ministero dell'Istruzione, dell'Universita e della Ricerca
Modica M, Reggiani A (2015) Spatial economic resilience: overview and perspectives. Networks and Spatial Economics 15(2):211–233
Ordovensky JF (1995) Effects of institutional attributes on enrollment choice: implications for postsecondary vocational education. Econ Educ Rev 14(4):335–350
Östh J (2011) Introducing a method for the computation of doubly constrained accessibility models in larger datasets. Networks and Spatial Economics 11(4):581–620
Östh J, Dolciotti M, Reggiani A, Nijkamp P (2018) Social capital, resilience and accessibility in urban systems: a study on sweden. Networks and Spatial Economics 18(2):313–336
Pigini C, Staffolani S et al (2013) Enrollment Costs, University Quality and Higher Education Choices in Italy. Tech. rep., University Library of Munich, Germany
Putnam R (2001) Social capital: measurement and consequences. Can J Policy Res 2(1):41–51
Reggiani A, De Graaff T, Nijkamp P (2002) Resilience: an evolutionary approach to spatial economic systems. Networks and Spatial Economics 2(2):211–229
Reggiani A, Bucci P, Russo G (2011) Accessibility and network structures in the german commuting. Networks and Spatial Economics 11(4):621–641
Roemer JE (1998) Theories of Distributive Justice. Harvard University Press, Cambridge
Sa C, Florax RJ, Rietveld P (2004) Determinants of the regional demand for higher education in the netherlands: a gravity model approach. Reg Stud 38(4):375–392
Sen A, Smith T (2012) Gravity Models of Spatial Interaction Behavior. Springer Science & Business Media, Berlin
Singleton AD, Wilson A, O'Brien O (2012) Geodemographics and spatial interaction: an integrated model for higher education. J Geogr Syst 14(2):223–241
Smith TE (1987) Poisson gravity models of spatial flows. J Reg Sci 27(3):315–340
Suhonen T (2014) Field-of-study choice in higher education: does distance matter? Spat Econ Anal 9(4):355–375
Talen E, Anselin L (1998) Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. Environ Plan A 30(4):595–613
Triventi M, Trivellato P (2009) Participation, performance and inequality in italian higher education in the 20th century. High Educ 57(6):681–702
Wilson AG (1971) A family of spatial interaction models, and associated developments. Environ Plan A 3(1):1–32
Wilson RM, Gibberd R (1990) Allocating resources between health care regions: catchment populations and allocating for equity. Eur J Oper Res 49(3):333–347
Yun S, Sen A (1994) Computation of maximum likelihood estimates of gravity model parameters. J Reg Sci 34(2):199–216