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

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

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**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 key assumption underlying gravity models is that accessibility decreases with spatial distance from opportunities. The paper extends the gravity equation to allow for the inclusion of socio-economic factors influencing the access to HE. The findings reveal differences in response to quality and to 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

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# 1 Introduction

An intuitive way to increase spatial accessibility is to decentralize 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 9 new higher education institutions were established as a result of the decentralization process (MIUR). 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.

In a system granting free access to HE for every potential candidate, the foremost aim of policy makers is to guarantee full accessibility 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 & Anselin, 1998). In this framework, the spatial distance between 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 larger costs to access to opportunities, with costs growing with spatial distance.

Since the residential location of students prior to HE enrolment is detemined by parents, inequalities in access to HE across students' locations of origin should be regarded as unfair. Modern theory of inequality, building on equality of opportunity (EOp) arguments, suggests that the differences in outcomes due to factors that are beyond individual responsibility are unfair and should be compensated by society (Dardanoni et al., 2006). Reducing geographical disparities in accessibility can be seen, in fact, as a way of *leveling 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 accessibility on the large scale: a student living in an urban area where HE services are supplied faces smaller costs of transportation, lower opportunity costs in commuting and no housing costs, compared to students living in the countryside 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 distance elasticity. Although distance matters in explaining accessibility, there are other variables that determine differences in costs of movement, correlated with distance which, at the same time, might influence the distribution of accessibility. This paper tries to single out the contribution of spatial distance and economic circumstances on inequality in accessibility to HE by using a multidisciplinary approach, where the problem of disparities in spatial access is redefined on the basis of both the physical distance from universities and the social distance between student groups that generates an additional inequality in access within the same location. The paper looks at 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, which is taken as a proxy of the ability of families to cover costs of displacement and, if possible, to compensate for distance from the location of origin. The latter shows the share of inequality in access due to the socio-economic background of students.

In an empirical application, 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 migration dynamics of dif-

ferent student groups. Being flexible and simple enough, these models enable the investigation flows between origins and destinations (Sen & Smith, 2012). Actual flows of commodities, information, emails, phone calls, money and of people along with any other sort of movements are likewise applicable to SIMs (see Haynes & Fotheringham, 1984; Sen & Smith, 2012, for reviews). In the present application, student flows from parental residents to universities are defined as interactions between localities and, to account for socio-economic factors in place, the total 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 (see for instance Checchi & Peragine, 2010; Ferreira & Gignoux, 2011) and resulting subgroups are defined as 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 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.

The paper contributes to the literature by extending 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 on 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 highly detailed information for policy makers regarding which groups of students to target and specifically in which locations the assistance is needed most.

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 empirical method for calibration and findings where inequality in access is decomposed into within and between components. Finally the conclusions and possible policy implications are given in the fifth section.

## 2 Theoretical Framework

This section presents the model adopted for student flows and the potential accessibility index. The link between these two builds on the distance parameter assumed to reflect both physical and social costs in migrating or commuting to destination universities. The response to distance is expected to be conditional on 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. They 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. Recently, most applications relate to health system planning, decisions concerning hospital locations, the analysis of interaction between patients and physicians as well as labour studies such as job accessibility and an investigation of the daily commute to work (Mayhew et al., 1986; R. M. Wilson & Gibberd, 1990;

Reggiani et al., 2011).

Particularly with regard to SIMs applied to HE choice, Sa et al. (2004) studied the demand for HE in the Netherlands, given the attractiveness and accessibility of universities. Alm & Winters (2009) correlated the distance from parental residence to state HE institutions with tuition, financial aid and school quality as institution fixed characteristics and found a varying deterrence effect of distance in relation to these characteristics. Cooke & Boyle (2011) included several origin and destination attributes to SIMs, 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 looked at 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 certain regions and to settle down there after graduation. These studies estimate the distance elasticity of university choice given the attributes of origins/destinations and some also include university characteristics. However they do not incorporate the socio-economic profile of students in the analysis. 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 this 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 basic assumption is that a positive interaction between each pair of locations exists [1].

[1](see A. S. Fotheringham & Webber, 1980; A. Fotheringham & O'Kelly, 1989; Sen & Smith, 2012, for reviews)

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

$T_{ij}$ refers to student flow from their residence $i$ to university $j$

$O_i$ origin dummies for 110 Italian provinces (NUTS3 level regions)

$D_j$ total number of students reaching university $j$

$K_i = [\sum_j D_j^{\alpha} f(d_{ij})]^{-1}$ is the balancing factor ensuring that the marginal total constraint $\sum_j T_{ij} = O_i$ is satisfied. [2]

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

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

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

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

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

[2] 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 constained by destination (not attraction constrained) but to make sure that the number of trips produced by an origin do not exceed the number of residents, the model is constrained from production side. For the formal development see A. G. Wilson (1971)

The common interpretation of $\mu$ 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 $\lambda_l$ is the distance elasticities given the institutional characteristics.

## 2.2 Adopted 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:

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

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 accessibility when $i$ and $j$ are not located in the same province by $\delta_{ij}$.

# 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 (*Inserimento professionale dei laureati*, 2011) including 14,000 male and 17,400 female graduates in 2007 and data from MIUR (Ministry of Education, 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 enrolled. The actual flow of students between the province of residence and the exact addresses of universities is extracted and stacked into a table as a column vector as the variable of interest.

## 3.1 Types

This paper argues that at least three aspatial factors 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 less drop-outs are observed for students with highly educated parents(Checchi & 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 (see Frenette, 2003; Lupi & Ordine, 2009). Finally, even though education is the primary area where women have made substantial gains and now largely out-perform men (DiPrete & Buchmann, 2006), the question whether there are systematic differences in spatial access to education among males and females remains an important one.

Observed flows are partitioned according to three sets of proxies referring to the socio-economic circumstances of students. Each subgroup forms

a type, which cannot be chosen by students. Accordingly, three circumstance variables are employed as shown in 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 the 8 years of compulsory schooling in Italy. "High education" consists of parents with at least a bachelor's degree. In the survey 40.66% of mothers and 39.69% fathers are categorized as basically educated , and 14.56% and 20.06% as highly educated, respectively. Survey data contains information on 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.

## 3.2 Distance

The distance from parental residence to HE institutions strongly influences the likelihood of participation and the HE outcomes of students (see for example Gossman et al., 1967; McHugh & Morgan, 1984; Tinto, 1973; Ordovensky, 1995; Gibbons & Vignoles, 2009; Suhonen, 2014). The costs of commuting or migrating may deter access or may impose a barrier when enrolling at a university. 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% studied in their hometown, 40.64% of students was 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 characterized by strong family ties (Alesina & Giuliano, 2010).

In this 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 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 values are examined against observed flows and the power specification of the distance proved most suitable for the data [3]

## 3.3 University Attractiveness

As far as institutonal attractiveness is concerned, previous studies of SIMs provide mixed findings. Sa et al. (2004) use university rankings as a quality indicator for Dutch students, but the coefficient proves to be negative. Although the authors explain this counterintuitive result as consumption behavior by students in relation to HE (Sa et al., 2004), this is not entirely convincing. 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 two university fixed characteristics in order to account for attractiveness: the share of successful students in the year before our sample's enrolment and the share of limited places provided by each university. In Italy after secondary school, students take a national exam (Esame di Maturità ). The share of students with the highest grades (90-100) from this test in the period 2002-2003 is included in the model (source: MIUR, 2004). Although many programmes are offered on a free-access principle, some require entrance tests, indicating excess demand for these programs. The proportion of limited places to the to-

[3] Also in previous studies the power- decay function has been found to be more suitable for long distance interactions owing to the log-cost perception (A. S. Fotheringham & Webber, 1980; Reggiani et al., 2011).

tal number of places available at University is then used as a quality indicator for the same period (source MIUR, 2004).

### 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 (see Gibbons & Vignoles, 2009, for a similar application to British students).

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

## 4 Empirical Method and Findings

The examination of the model is operated through related statistical log linear models which were developed alongside entropy maximizing models. There are several ways of handling spatial interaction models (see A. G. Wilson, 1971; Yun & Sen, 1994; LeSage & Pace, 2008). This study makes use of the Poisson gravity models, [4] with the same statistical properties, producing identical estimations to entropy maximization models (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, whereas $T_{ij}$ is the expectation of observed flows, treated as a random variable and assumed to have a Poisson distribution

[4](see Flowerdew & Aitkin, 1982; Smith, 1987, for theoretical development)

(Baxter, 1982) [5].

The model is calibrated by the generalized linear model (GLM) package in R [6], where flows follow a Poisson distribution with a logarithmic link between variables. The estimations are carried out separately for 12 subgroups. Finally, the Poisson regression is:

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

where $k = 1, 2, 3, ...., 12$ represents types, $S_j$ the share of successful students and $L_j$ the share of limited places at $j$, 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 therefore equivalent to the production-constrained model of the entropy-maximizing system.

Table 2 and Table 3 show the results of the first set of regressions where the model has been applied to 10 groups. Groups 5 and 6 are not taken into consideration due to the lower number of observations. As expected, distance has a very strong significantly negative effect, indicating a deterrence impact for each group. For 1 meter decrease in the distance the expectation number of student flows increases by factors varying form 1.499 to 1.709. 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 favourable 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, $\delta$ 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 $\mu$ captures the fact that these students usually live in big cities where large universities are located and hence they do not need to migrate. On the other hand, groups 1 to 4 it may

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

[6] (see Dennett, 2012, for details)

reflect the actual startup costs where these students decide to migrate. As far as the attractiveness of universities is concerned, $S_j$ (the share of successful students at university) is significant and positively affects flows only for students who have at least one highly educated parent. Other students seem to be unaffected by institutional quality. The effect is observed for $L_j$ (the share of limited places offered by universities) again for socially advantaged groups. Among students with disadvantaged parental backgrounds, only female students (groups 2 and 4) are attracted to these limited positions. This is probably due to the fact that female students are interested in faculties such as medicine and nursing, requiring entrance tests. Hence, for students with a poor parental background, what seems to matter is obtaining a degree irrespective of the prestige of the University (Triventi & Trivellato, 2009).

The remaining results allow for interactions between institutional characteristics and distance. Private universites at destination increase the tendency of travelling longer distances for all groups. It is an expected result since for any type deciding to enrol a private university, distance must be becoming irrelevant. Looking at the significance levels, polytechnics do not seem to induce students to travel far except for groups 2 and 7. In contrast to Dotti et al. (2013), 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 1 and 3. These two types comprise male students with poor family backgrounds who may prefer Universities in the south due to the lower cost of living. Finally universities located in Sicily and Sardinia fail to attract students from all backgrounds.

Table 2-Table 3 [About Here]

After obtaining the parameter values from (5), accessibility scores are calculated through Equation 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 $k = 1, 2, 3, ...., 12$. As it for the production constrained SIM, $d_{ij}$ is constructed from city centroids to the exact addresses of universities (to the largest campuses),so there is no zero distance, 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 accessibility to the 77 total number of universities located in 101 different provinces. Maps 1-2 illustrate the access scores of 10 groups, where darker blue indicates a higher score.

Figure 1-2 [About Here]

The first thing to note from the figures is that if a student belongs to a socially advantaged group, then their access is relatively higher where ever they live, except very far south in the country. Similarly 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 where the type comprising 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 101% from group 2 to group 12 whereas parental background does not seem to affect male student access to HE as much as female students. From the least to the highest, access increases 10% on average. Moreover a degree of gender discrimination in access is observed 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 [7]. As shown in Table 4, the resulting inequality is a sum of within and between inequalities.

[7] Mean Logarithmic Deviation is a path-independent decomposable inequality measure (Foster & 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 $\mu_X$ is mean.

The first row of Table 4 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 0.01776 and represents the contribution of socio-economic factors to total inequality (5% of total inequality). Whereas in the second row the variation within provinces is eliminated by substituting each province's accessibility score with its arithmetic mean, in this approach the inequality between provinces is computed as 0.34637 and the contribution of socio-economic factors to total inequality is measures at 7%.

For the sake of a better understanding of the computed inequality, take 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 151 km to the nearest city, Foggia (social distance). Moreover, in order for her to have similar access to a female student with better family origin (group12) living in Napoli, she has to travel 460 km to the nearest city (social+physical distance). Therefore, the findings indicate that despite the expansion of HE supply in the country, access to HE is strongly unequal due to the spatial distribution of opportunities with additional disparity due to socio-economic factors at the locations of origin.

Table 4 [About Here]

## 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 background of students. Using a spatial interaction model, the flows of students to universities are defined as interactions between provinces in Italy. The results demonstrate that poor family back-

ground students are impervious to university-quality effects and university quality becomes relevant only for students with better family backgrounds. The model allowed for interactions between institutional characteristics and distance to see how elasticity with respect to spatial distance varies given the heterogeneity of the universities. The results indicates that private universities attract students and increase their willingness to travel longer distances. Universities located in the central region attract more students than in the south and the location in Sicily or Sardinia deters flows.

As far as distance is concerned, the values of these parameters are highly significant and negative in sign, indicating a deterrence effect for each group of students. In line with previous studies, $\delta$ was significant at the 0.01 level for all groups and positive in sign, capturing the benefit of residing and studying in the same city. For the second step computed deterrence functions and $\delta$s were imported into a Hansen-like accessibility index and accessibility scores of 110 Italian provinces to 77 Italian universities were computed. The results show that socio-economic background matters especially for female student mobility. Finally, the share of aspatial factors in inequality of access between types proved to be 5% with the first approach and 7% when computed with the second approach.

This 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 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 adopted. Firstly, an effective policy may target the types with lower potential accessibility to assist them though 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.

## References


Alesina, A., & Giuliano, P. (2010). The power of the family. *Journal of Economic growth*, *15*(2), 93–125.

Alm, J., & Winters, J. V. (2009). Distance and intrastate college student migration. *Economics of Education Review*, *28*(6), 728–738.

Baxter, M. (1982). Similarities in methods of estimating spatial interaction models. *Geographical Analysis*, *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. *Economics of Education Review*, *31*(5), 764–777.

Checchi, D., & Flabbi, L. (2007). Intergenerational mobility and schooling decisions in germany and italy: the impact of secondary school tracks.

Checchi, D., et al. (2003). The italian educational system: family background and social stratification. In *Isae conference on monitoring italy.*

Checchi, D., & Peragine, V. (2010). Inequality of opportunity in italy. *The Journal of Economic Inequality*, *8*(4), 429–450.

Cooke, T. J., & Boyle, P. (2011). The migration of high school graduates to college. *Educational Evaluation and Policy Analysis*, *33*(2), 202–213.

Dardanoni, V., Fields, G. S., Roemer, J. E., & Puerta, M. L. S. (2006). How demanding should equality of opportunity be, and how much have we achieved? *Mobility and inequality: Frontiers of research from sociology and economics*, 59–82.

de Barros, R. P. (2009). *Measuring inequality of opportunities in latin america and the caribbean.* World Bank Publications.

Dennett, A. (2012). *Estimating flows between geographical locations:get me started inspatial interaction modelling* (Tech. Rep.). Citeseer.

De Vries, J. J., Nijkamp, P., & Rietveld, P. (2009). Exponential or power distance-decay for commuting? an alternative specification. *Environment and Planning A*, *41*(2), 461–480.

DiPrete, T. A., & 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, N. F., Fratesi, U., Lenzi, C., & Percoco, M. (2013). Local labour markets and the interregional mobility of italian university students. *Spatial Economic Analysis*, *8*(4), 443–468.

Ferreira, F. H., & Gignoux, J. (2011). The measurement of inequality of opportunity: Theory and an application to latin america. *Review of Income and Wealth*, *57*(4), 622–657.

Flowerdew, R., & Aitkin, M. (1982). A method of fitting the gravity model based on the poisson distribution*. *Journal of regional science*, *22*(2), 191–202.

Foster, J. E., & Shneyerov, A. A. (2000). Path independent inequality measures. *Journal of Economic Theory*, *91*(2), 199–222.

Fotheringham, A., & O'Kelly, M. E. (1989). *Spatial interaction models: formulations and applications* (Vol. 5). Kluwer Academic Pub.

Fotheringham, A. S., & Webber, M. J. (1980). Spatial structure and the parameters of spatial interaction models. *Geographical Analysis*, *12*(1), 33–46.

Frenette, M. (2003). Access to college and university: Does distance matter. ottawa. *Statistics Canada, Catalogue*(11F0019MIE2003201).

Gibbons, S., & Vignoles, A. (2009). Access, choice and participation in higher education.

Gitlesen, J. P., & Thorsen, I. (2000). A competing destinations approach to modeling commuting flows: a theoretical interpretation and an empirical application of the model. *Environment and Planning A*, *32*(11), 2057–2074.

Gossman, C. S., et al. (1967). Migration of college and university students in the united states.

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of planners*, *25*(2), 73–76.

Haynes, K. E., & Fotheringham, A. S. (1984). *Gravity and spatial interaction models* (Vol. 2). Sage publications Beverly Hills.

LeSage, J. P., & Pace, R. K. (2008). Spatial econometric modeling of origin-destination flows*. *Journal of Regional Science*, *48*(5), 941–967.

Lowe, J. M., & Sen, A. (1996). Gravity model applications in health planning: Analysis of an urban hospital market*. *Journal of Regional Science*, *36*(3), 437–461.

Lupi, C., & Ordine, P. (2009). Family income and students'mobility. *Giornale degli Economisti e Annali di Economia*, 1–23.

Mayhew, L., Gibberd, R., & Hall, H. (1986). Predicting patient flows and hospital case-mix. *Environment and Planning A*, *18*(5), 619–638.

McArthur, D. P., Kleppe, G., Thorsen, I., & Ubøe, J. (2011). The spatial transferability of parameters in a gravity model of commuting flows. *Journal of Transport Geography*, *19*(4), 596–605.

McHugh, R., & Morgan, J. N. (1984). The determinants of interstate student migration: A place-to-place analysis. *Economics of Education Review*, *3*(4), 269–278.

Ordovensky, J. F. (1995). Effects of institutional attributes on enrollment choice: Implications for postsecondary vocational education. *Economics of Education Review*, *14*(4), 335–350.

Pigini, C., Staffolani, S., et al. (2013). *Enrollment costs, university quality and higher education choices in italy* (Tech. Rep.). University Library of Munich, Germany.

Reggiani, A., Bucci, P., & Russo, G. (2011). Accessibility and network structures in the german commuting. *Networks and Spatial Economics*, *11*(4), 621–641.

Roemer, J. E. (1998). *Theories of distributive justice*. Harvard University Press.

Sa, C., Florax, R. J., & Rietveld, P. (2004). Determinants of the regional demand for higher education in the netherlands: A gravity model approach. *Regional Studies*, *38*(4), 375–392.

Sen, A., & Smith, T. (2012). *Gravity models of spatial interaction behavior*. Springer Science & Business Media.

Singleton, A. D., Wilson, A., & OBrien, O. (2012). Geodemographics and spatial interaction: an integrated model for higher education. *Journal of Geographical Systems*, *14*(2), 223–241.

Smith, T. E. (1987). Poisson gravity models of spatial flows*. *Journal of Regional Science*, *27*(3), 315–340.

Suhonen, T. (2014). Field-of-study choice in higher education: Does distance matter? *Spatial Economic Analysis*, *9*(4), 355–375.

Talen, E., & Anselin, L. (1998). Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. *Environment and Planning a*, *30*(4), 595–613.

Tinto, V. (1973). College proximity and rates of college attendance. *American Educational Research Journal*, *10*(4), 277–293.

Triventi, M., & Trivellato, P. (2009). Participation, performance and inequality in italian higher education in the 20th century. *Higher Education*, *57*(6), 681–702.

Wilson, A. G. (1971). A family of spatial interaction models, and associated developments. *Environment and Planning A*, *3*(1), 1–32.

Wilson, R. M., & Gibberd, R. (1990). Allocating resources between health care regions: Catchment populations and allocating for equity. *European Journal of Operational Research*, *49*(3), 333–347.

Yun, S., & Sen, A. (1994). Computation of maximum likelihood estimates of gravity model parameters*. *Journal of Regional Science*, *34*(2), 199–216.

Table 1: Variables in analysis, data from ISTAT and MIUR

| Variables | Description |
|---|---|
| Residence | Province of residence before enrollment (ISTAT) |
| Destination University | Enrolled University 63 state and 14 private universities(ISTAT) |
| Distance | Euclidean distance between 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, both basic educated |
| | "basic education" covers high school degree |
| | 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 Worker, Lower-skilled workers |
| $S_j$ | Share of students who achieved highest scores (90-100) |
| | from compulsory test before HE enrollment in the period 2002-2003 (MIUR) |
| $L_j$ | 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 center $U_{j5}$ 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) |

Table 2: Results of Poisson Regression First 5 Groups

| Groups | (1) | (2) | (3) | (4) | (7) |
|---|---|---|---|---|---|
| Variables | Basic-Male-Lower Class | Basic-Female-Lower Class | Basic-Male-Middle Class | Basic-Female-Middle Class | $\geq$ 1high-Male-Lower Class |
| $S_j$ | 0.455 | 0.697 | 0.556 | -0.087 | 1.502*** |
| | (0.421) | (0.373) | (0.595) | (0.504) | (0.396) |
| $L_j$ | 0.158 | 0.303*** | 0.214 | 0.277* | 0.140 |
| | (0.098) | (0.086) | (0.133) | (0.119) | (0.123) |
| $\hat{\mu}$ | 0.249*** | 0.293*** | 0.261*** | 0.300*** | 0.307*** |
| | (0.389) | ( 0.032) | (0.056) | (0.045) | (0.036) |
| Distance | -1.535*** | -1.709*** | -1.530*** | -1.574*** | -1.625*** |
| | (0.047) | ( 0.045) | (0.069) | (0.060) | (0.046) |
| Institutional Interactions | | | | | |
| x Private Univ. | 0.726*** | 0.608*** | 0.509*** | 0.599*** | 0.631*** |
| | (0.070) | ( 0.058) | (0.093) | (0.067) | (0.057) |
| x Polytechnic | 0.003 | 0.240 | 0.105 | 0.276* | 0.134* |
| | (0.072) | (0.088) | (0.105) | (0.105) | (0.022) |
| x South | 0.561*** | 0.359*** | 0.549*** | 0.386*** | 432*** |
| | (0.062) | (0.059) | (0.090) | (0.076) | (0.065) |
| x Center | 0.527*** | 0.545*** | 0.418*** | 0.495*** | 0.467*** |
| | (0.060) | (0.058) | (0.088) | (0.078) | (0.058) |
| x Island | -0.206*** | -0.039 | -0.130 | -0.375* | -0.283* |
| | (0.155) | (0.122) | (0.201) | (0.173) | (0.162) |
| (Intercept) | 6.528*** | 7.258*** | 5.442*** | 6.304*** | 6.790*** |
| | (0.227) | (0.202) | (0.392) | (0.291) | (0.221) |
| Observations | 1,572 | 1,572 | 1,572 | 1,572 | 1,572 |
| R2 | 0.88 | 0.89 | 0.87 | 0.86 | 0.86 |

Standard errors in parentheses

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

Education of Parents-Gender of Student-Financial Condition of Parents

# Table 3: Results of Poisson Regression Last 5 Groups

| Groups | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|
| Variables | ≥1high-Lower Class | ≥1high-Male-Middle Class | ≥ 1high-Female-Middle Class | ≥ 1high-Male-Higher Class | ≥1high-Female-Higher Class |
| $S_j$ | 1.745*** | 2.291*** | 1.444*** | 2.006*** | 1.947*** |
| | (0.337) | (0.313) | (0.287) | (0.293) | (0.260) |
| $L_j$ | 0.384*** | 0.184*** | 0.187*** | 0.112** | 0.348*** |
| | (0.065) | (0.073) | (0.072) | (0.082) | (0.081) |
| $\hat{\mu}$ | 0.337*** | 0.287*** | 0.281*** | 0.305*** | 0.273*** |
| | (0.032) | ( 0.032) | (0.029) | (0.029) | (0.027) |
| Distance | -1.581*** | -1.551*** | -1.532*** | -1.522*** | -1.499*** |
| | (0.041) | ( 0.040) | (0.034) | ( 0.035) | (0.032) |
| Institutional Interactions | | | | | |
| x Private Univ. | 0.590*** | 0.490*** | 0.481*** | 0.549*** | 0.573*** |
| | (0.045) | ( 0.043) | (0.038) | (0.037) | (0.033) |
| x Polytechnic | -0.538 | 0.070 | 0.706 | 0.072 | 0.042 |
| | (0.078) | (0.051) | (0.061) | (0.047) | (0.054) |
| x South | 0.123* | 0.436*** | 0.198*** | 0.320*** | 0.255*** |
| | (0.636) | (0.609) | (0.054) | (0.054) | (0.049) |
| x Center | 0.399*** | 0.499*** | 0.418*** | 0.384*** | 0.407*** |
| | (0.053) | (0.516) | (0.045) | (0.045) | ( 0.040) |
| x Island | -0.150 | 0.816 | -0.252* | -0.490*** | -0.331** |
| | (0.125) | (0.130) | (0.111) | (0.118) | (0.103) |
| (Intercept) | 6.654*** | 7.113*** | 7.084*** | 6.851*** | 6.939*** |
| | (0.194) | (0.187) | (0.172) | (0.170) | (0.155) |
| Observations | 1,572 | 1,572 | 1,572 | 1,572 | 1,572 |
| R2 | 0.85 | 0.87 | 0.89 | 0.86 | 0.88 |

Standard errors in parentheses

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

Education of Parents-Gender of Student-Financial Condition of Parents

Table 4: Decomposition of Inequality In Access (MLD measures)

| | Spatial Inequality | Inequality due to socioeconomic background | Total Inequality |
|---|---|---|---|
| Inequality in Access to HE (First Approach) | 0.35444 | 0.01776 | 0.37220 |
| Inequality in Access to HE (Second Approach) | 0.34637 | 0.02583 | 0.37220 |
| Percentage Contribution (First Approach) | %95 | %5 | %100 |
| Percentage Contribution (Second Approach) | %93 | %7 | %100 |

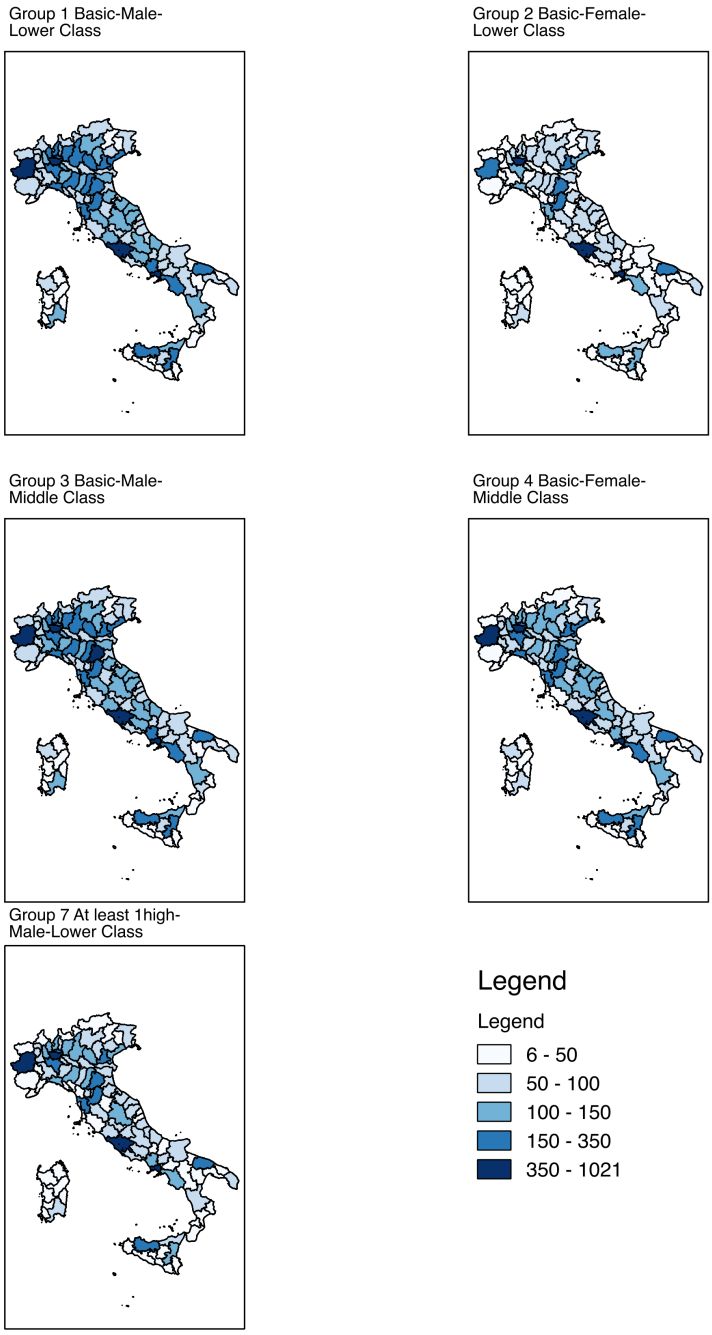


Figure 1: First 5 Groups

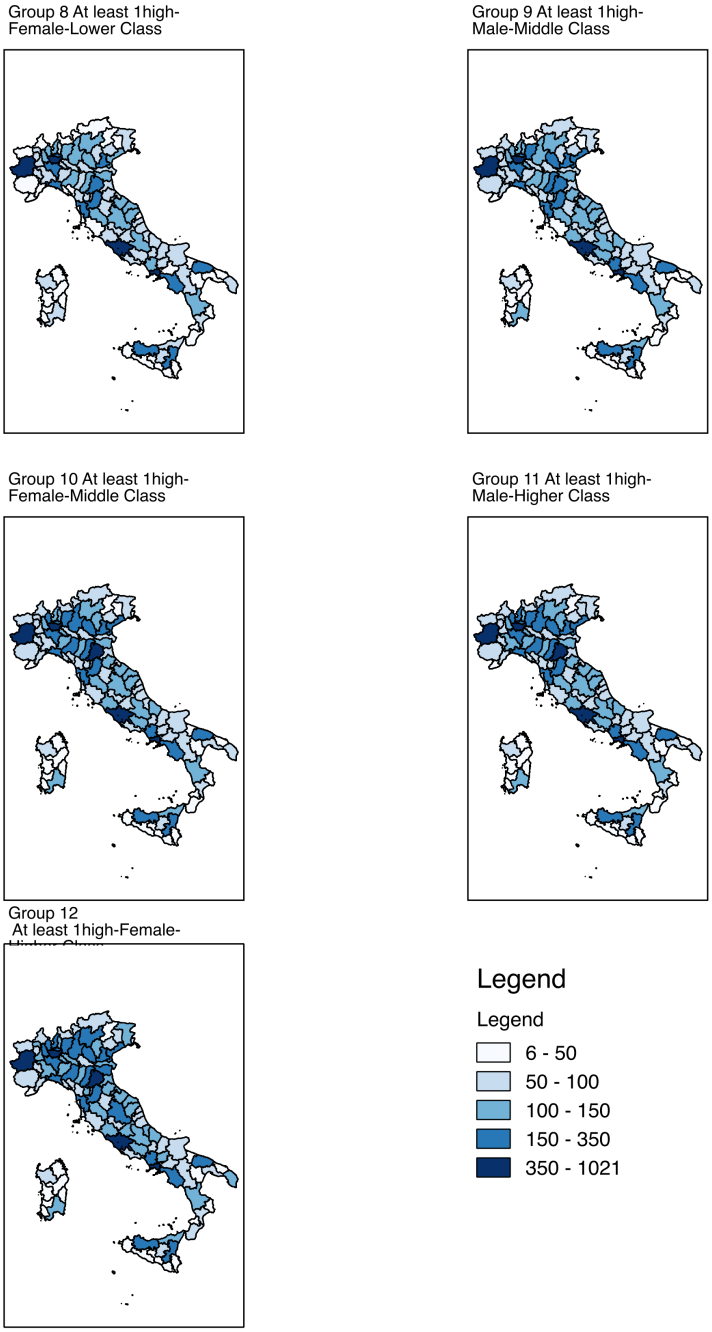


Figure 2: Last 5 Groups