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Movers and stayers in STEM enrollment in Italy: who performs better?

Antonella D'Agostino^{1*} , Giulio Ghellini² and Gabriele Lombardi³

*Correspondence:

antonella.

dagostino@uniparthenope.it

¹ Dipartimento di Studi

Aziendali e Quantitativi

(DISAQ), Palazzo Pacanowski,

University of Naples

"Parthenope", Via Generale

Parisi, 13 – IV Piano,

80132 Napoli, Italy

Full list of author information

is available at the end of the

article

Abstract

Recently, the mobility behavior of Italian university students has garnered increasing interest from both social scientists and politicians. The very particular geographical characteristics of the country, together with the recognized persistence of a significant economic gap between the southern and northern regions, drive a large number of students to move from the first macro-region to the latter. As this phenomenon has several economic and social implications for policy-makers—at both central and local levels—it has led to various theories and prejudices. The present article will study the differences between the performance of STEM students who have decided to move from the south to the north and those who have decided to stay close to their hometowns. We devised multilevel modelling techniques to analyze this issue using administrative microdata from the Italian Ministry for Universities and Research (MUR), including eight cohorts of students from AY 2008–2009 to AY 2015–16, who enrolled in STEM fields after earning their high school diploma. One of the main findings is that individuals who moved from the south show lower levels of performance than their stayer counterparts who are enrolled in northern or central universities.

Keywords: Inter-regional student mobility, STEM, Performance, Variance component model

Introduction

Currently, STEM (Science, Technology, Engineering, and Mathematics) studies in higher education (HE) are emphasized worldwide. This prominence is due to the critical role of this field of study for the development, productivity, and growth of modern society. For this reason, it is possible to argue that losing human capital in such a field could be detrimental to a specific area or region (De Philippis, 2017; Rothwell, 2013). In Italy, this is likely happening in the southern regions, which are losing a considerable share of their student population due to higher education studies, seen even more sharply in the STEM field. Southern students have been migrating towards the richer and more innovative regions, which are concentrated in the north and center of the country, with an increasing trend during the last decade (Attanasio & Enea, 2019; Columbu et al., 2021a; D'Agostino et al., 2019a, 2019b).

In this framework, the relationship between internal migration and students' performance in their HE careers is an interesting issue to investigate for at least a couple of reasons.

First, from a social point of view, students who stay home experience less pressure during their studies. Namely, they face fewer 'settling costs' from economic (e.g., no expenses for room and board), psychological (e.g., no need to familiarize themselves with a new place and a completely different lifestyle), and social (e.g., less need to find new friends) points of view. We can also argue that these stressors can negatively influence the HE performance of movers. Therefore, they could be penalized even if they most likely represent the part of the student population with the most remarkable spirit of initiative and enterprise.

Second, from 2014, Italian universities receive economic incentives from the Italian Ministry for Universities and Research (MUR) for providing degrees within the prescribed time (Viesti, 2018); therefore, the prediction of student performance is an essential and challenging issue.

Hence, the following two research questions are central to the present study:

- i) Is the HE performance of movers significantly different from that of stayers in STEM fields?
- ii) Is there any difference in the HE performance between southern vs. northern/central migrant students in STEM fields?

In particular, our analysis adds further knowledge to the existing literature regarding the relationship between mobility and student performance in the Italian setting, such as Enea (2018), who explored the mobility of southerners from their first level to second level university degrees by considering both the time-to-graduation and the final marks for their bachelor's degrees. Moreover, Attanasio et al. (2018) studied Italian university science students' careers during the last decade, and an analysis was carried out by Boscaino et al. (2018), which only referred to Sicilian students.

In addition, it is important to point out that the previously mentioned research objectives aim to investigate whether or not a relationship between first-year university student mobility and academic performance exists. Furthermore, we are concentrating on a bachelor's degree level. In other words, we are referring to students' performance immediately after their transition from high school to higher education. Such a choice requires inspiration and—adapting it to the characteristics of the Italian higher education system—revisits the seminal paper by Hills (1965), who highlights how the transition between different levels of higher education institutions can cause a significant difference in the performance of native and non-native students. In particular, if students who relocate from one country to another seem to suffer a decrease in their own performance immediately after a transition, we aim to examine whether this type of reduction in performance also appears in the case of internal mobility.

Finally, this paper uses a novel and unique data set provided by the MUR, thanks to an agreement between the ministry and several Italian universities.¹ In the empirical analysis, this data set allows us to consider different cohorts, and for each cohort, the several STEM bachelor's degree programs in which first-year students are enrolled. Thus, a multilevel analysis has been implemented, taking into account the effect of both degree programs and cohorts at the time of enrolment.

This article is structured according to the following outline. The section, “[Introduction](#)”, presents the Italian Higher Education system's peculiarities that might affect a student's decision to move. Moreover, literature on university students' academic performance is explored to determine the factors that can foster or depress that performance. The “[Data description](#)” and “[Methods](#)” sections present the data used and the estimation strategy. The section, “[Empirical evidence](#)”, discusses our main findings. The “[Conclusion](#)” presents some final remarks.

Literature review

Academic performance of freshmen students: characteristics and shortcomings

It is essential to consider what is already known about the relationship between students' performance and their mobility choices. Studies highlighting the factors driving students' performance levels in higher education are often conducted through multilevel models.

In these models, both the individual level, which usually explains the most significant part of the variance, and the level of the degree program, which is typically able to explain much less variation, are considered (Tefaw & Derebew, 2014; Van den Berg & Hofman, 2005). However, Beekhoven et al. (2003) highlighted some program characteristics that are helpful in explaining a larger part of the variation. They found that the most effective programs are those with a high share of enrolled women, who are recognized as performing better at university, and those programs requiring a greater number of study hours per week. Beyond individual attitudes, other important factors are the students' socio-economic and family background and the secondary educational institution attended, although these result in differences that are much more evident in lower performing students (Birch & Miller, 2006; Hijaz & Naqvi, 2006; Mwandigha et al., 2018). This last caveat is better clarified by Win and Miller (2005), who points out that the undeniable role of secondary schools is in stimulating academic performance, which has a much greater influence than individual characteristics. At the same time, a good university can generate an ‘immersion effect’ and a ‘reinforcement effect’ so that students in high-achieving school environments may perform better.

Some contributions to academic performance are specifically related to the STEM fields. For example, Crisp et al. (2009) demonstrated how, even though these fields are constantly achieving greater importance in public programs stimulating higher education attendance; however, it is still difficult for some categories, such as women and ethnic minorities, to pursue a STEM degree successfully. Public support seems to not play a

¹ Database MOBYSU.IT [Mobilità degli Studi Universitari in Italia], research protocol MUR—Universities of Cagliari, Palermo, Siena, Torino, Sassari, Florence and Naples Federico II, scientific representative Prof. Massimo Attanasio (UNIPA), Data Source ANS-MIUR/CINECA.

role in mitigating this difficulty, but the presence of a robust cultural capital (e.g., parental education) appears to be effective. Although the scientific literature that has been reviewed indicates, in general, lower levels of performance for men, Soler et al. (2019) find lower performance for women in STEM fields, especially in higher education rather than in high school. Specifically, regarding first-year students, several studies provide coherent evidence about the importance of schooling background (Touron, 1987), the importance of being in a stimulating environment (Van Overwalle, 1989), and the effect of individual attributes, such as an ability to manage study activities (Huon et al., 2007) and self-esteem (Schaeper, 2019).

Analyzing the student population in the STEM fields has become particularly important, since a growing interest in these fields worldwide is causing an increasing adoption of strategies for stimulating enrolment. These strategies must be coupled with strategies for ensuring that the new entrants can adapt to the new educational context as quickly as possible.

There is an evident stratification in the types of people who decide to enroll in a STEM degree program, since the best explanatory variable for students' performance in these fields is the level of their father's education (Lopez & Jones, 2017). Packard & Jeffers (2013) have found that there is a significant need to accompany new STEM students through the transition to a higher education system to preserve their performance and motivation levels. On the other hand, a strong effect of the social context in STEM fields, regardless of the institution's facilities, is frequently discussed (Jackson, 2010; Jackson & Lanaan, 2015). In particular, women's performance difficulties in these fields are recognized and attributed to a low socialization environment, a lack of mentors, and the internalization of stereotyped social norms.

Being a mover in the Italian HE system

According to Graziosi (2010), Italy experienced a transition from a small and élitarian group of universities to a large, universal higher education system in recent decades. It is important to note that in Italy, in 1870, there were only 23 universities, while now there are 91, including public, private, and online HE institutions. Moreover, during the twentieth century, the number of students enrolled in Italian universities increased from 27,000 to 1,800,000. Then, in 2015–2016, due to the financial crisis, the numbers dropped to 1,600,000. This situation has been primarily due to the poor investment of the Italian government in higher education, which has been considerably below the OCSE average. Furthermore, the decline in enrolments was also due to the loss of trust by students and their families in the belief that education is able to foster social mobility. As the inequality of opportunity to access university study increases, the Italian higher education system is slowly becoming more classist (Capano et al., 2017). In this system, numerous policy reforms have tried to channel funds towards institutions with better reputations. However, at the same time, these policies are based on a myopic viewpoint, which is ultimately poorly matched to the available data. Currently, Italy is at the bottom of the list of European countries regarding the number of university graduates. In addition, the Italian higher education system reflects the socio-economic framework of a country that is split into two parts. On one hand, the south-central and islands regions tend to lose their high school graduates, namely, their future specialized workforce. On

the other hand, the north absorbs human capital and financial resources that are no longer devoted to a particular macro area of the country (Viesti, 2016). Thus, the specific situation that emerges in Italy is that the migration of students to the northern regions fosters the pauperization of the south in terms of highly specialized human capital. Therefore, it is not possible to investigate the characteristics of Italian students' mobility without referring to the fact that the movement is channeled in a single direction (from south to north), with very little chance of returning and, thereby, enriching the specialized workforce in the areas of origin. This phenomenon exacerbates an issue that has unsuccessfully appeared in Italian policy agendas for decades. D'Antone and Miotti (2016) describe how southern Italy suffers from a lack of economic growth that could absorb its highly specialized workforce. Cersosimo et al. (2016a) have observed how low-income southerners are progressively abandoning enrollment in a university degree program, while the richer southerners refer to emigrate. Undoubtedly, the quantity of educational institutions in the south is the lowest levels within a landscape in which universities base a significant part of their attractiveness on the relationships with their territories and with the external demand that they can deal with. These two elements are have already become quite depleted in southern Italy (Petrosino & Schingaro, 2016).

Mixed evidence has emerged regarding the motivations driving the decision of whether to move or not. According to Cersosimo et al. (2016b), the decision to stay is related to the convenience of remaining in a particular comfort zone, while the desire to move is stimulated by the possibility of finding an educational supply that better suits individual *desiderata*. Only a tiny portion of those who stay make their decision, because they feel that they do not have any other choice. Nevertheless, a survey of Italian students conducted by the RUI Foundation (2015) between 2012 and 2015 highlights the enormous economic costs of moving to another region. From this perspective, although the decision to move does not seem to be a necessity, it is at least perceived as such.

Several studies in different countries have shown the greater importance of territorial characteristics (e.g., job market conditions) in attracting students, compared to other factors (e.g., university attractiveness), which are more closely related to keeping students in their comfort zone (Lörz et al., 2016; Prakhov & Bocharova, 2016). Consequently, Kim (2017) points out that academic capitalism intersects the old hierarchies in local areas (in terms of economic growth or labour market conditions) with new academic stratification (i.e., the reputation of universities).

In a nutshell, Italian students are highly selective in their choice of the educational curricula offered by the universities to which they apply (Cattaneo et al., 2018; Columbu et al., 2021b). At the same time, they are also conditioned by migration chains (Genova et al., 2019), and by the anticipated conditions of the job market (Giambona et al., 2017). In the Italian system—with its outstanding gap between north and south—this translates into a race for 'better' universities in the northern regions, driven by a system of funding allocations that exacerbates the division between the two main macro areas of the country and the consequent unidirectional migration flows (Cattaneo et al., 2017b; Viesti, 2018). This situation reshapes the social norms previously used by students to identify the institution of choice, further fostering the previously described migration flows (Cattaneo et al., 2017a).

In this final perspective, the work of Ragozini et al. (2016) is fascinating, which identifies four channels through which migration choices are motivated: (i) forced migrations, in search of a specific degree program that is not available nearby; (ii) geographical proximity migrations, moving outside the region of residence but toward the nearest university; (iii) anticipatory migrations, toward territories offering more significant opportunities than those of residence; (iv) migrations toward those universities which are considered to be the most prestigious. Especially the last two motivations are those which, in the end, generate the phenomenon that emerges as a well-recognized, unique directional migration flow from the south to the north (Attanasio & Priulla, 2020).

Finally, relationships between performance and mobility in Italy can be summarized. Students' performance does not depend on socio-demographic features but rather on motivations and inclinations. However, non-resident students show lower performance than residents, and males do not perform as well as females. The final grades attained in high school exert a positive effect on performance for both 'good' and 'average' students. Yet, lyceum students from the south who migrate to the north generally perform slightly better than lyceum stayers (both southerners and northerners) (Adelfio & Boscaino, 2016; Adelfio et al., 2014). The differences in performance between STEM movers and stayers in an environment of almost unidirectional migration flows from the south to the north of Italy can be read through various lenses. On one hand, there may be consequences due to the well-known north–south gap in students' mathematical performance, as indicated by the Italian PISA achievement tests (Bratti et al., 2007). Conversely, this evidence weakens the widespread conviction that less attractive universities adopt softer grading policies (Lombardi & Ghellini, 2019).

Data description

As mentioned in the Introduction, this study is based on micro-data provided by MUR through an agreement between the ministry and several Italian universities. In particular, for the empirical analysis, the database was restricted to 406,587 first-year students enrolled in STEM bachelor's degree programs (excluding online programs) across eight cohorts, from academic years 2008–2009 through 2015–2016.

To categorize degree programs into a STEM field, the primary reference is Andersson and Olsson (1999). In a manual they formalized the CEDEFOP and EUROSTAT classification for vocational education and training, which the European Commission then adopted in 2015. Accordingly, the STEM fields of study can be classified in the following three categories (Code² for each degree classification included between brackets):

1. Natural sciences, mathematics and statistics (L-13, L-2, L-27, L-29, L-30, L-32, L-34, L-35, L-41);
2. Information and Communication Technologies (L-8, L-3, L-43);
3. Engineering, manufacturing and construction (LM-4 CU, L-7, L-9, L-17).

It is important to note that, unlike the European Commission's guidelines, this study includes architecture, mainly due to the presence of some degree programs, such as

² The full list is available at <http://www.miur.it/UserFiles/2600.pdf>.

Architecture and Engineering, which are challenging to categorize univocally. Furthermore, according to the guidelines, all the degree programs related to health studies have been excluded from the sample.

According to our research objective, we selected only the first year of the students' careers from their enrollment.

The underlying structure of our sample is quite complex, because the data contain multiple academic cohorts of first-year students and, in each cohort, there are several degree programs. This evidence leads to a three-level hierarchical data structure with 406,587 freshmen (level 1) nested within 5571 program-cohorts (level 2), further nested within 1166 degree programs (level 3). It is important to stress that the "cohort" refers to the eight cohorts between the academic years 2008–2009 and 2015–2016, whereas the "program-cohorts" refer to the 5571 groups, or program-by-cohort combinations of students, which are formed by crossing 1,166 degree programs with the eight cohorts.

The dependent variable of our study is the academic performance of each student, measured by the credits earned during the first year of enrolment. Indeed, as regulated by Ministerial Decree 509/1999 by MUR,³ academic credits are used by Italian universities to estimate the workload required to graduate.

In particular, for the econometric analysis, we use a normal score transformation (Conover, 1999). The normal score transformation is designed to transform data so that it closely resembles a standard, normal distribution. This transformation has also been used by Leckie (2013) for studying student performance in the UK. Let N be the total number of students in the data set. The steps in this transformation are as follows: (i) the N students are ranked by their original scores and (ii) the standard normal score y_i for the i th ranked student in the data is calculated as

$$y_i = \Phi^{-1} \left[\frac{i - 0.5}{N} \right], \quad (1)$$

where Φ^{-1} denotes the inverse of the standard normal cumulative distribution function and i represents the position of the students once they are ordered by their original scores. In Fig. 1, we plot the c.d.f. of the credits earned during the first year of enrolment before and after the normal score transformation.

The advantage of this simple transformation is that it preserves order, and students with the same number of credits will also receive the same standard, normal score. Moreover, with this transformation, the effects of covariates can be interpreted in terms of standard deviation units of the response. Last but not least, this transformation makes the choice of econometric models based on a normal distribution assumption reasonable.

In the econometric model, we control for several covariates, with the definitions reported in Table 1. The main covariate of interest is the variable that identifies the origin–destination movement of each student, hereafter called the 'mobility indicator'. It is noted that we collapsed stayers from north and central regions together with movers from north and central regions, since the main object of this study

³ Available at http://www.miur.it/0006Menu/_C/0012Docume/0098Normat/2088Regola.htm

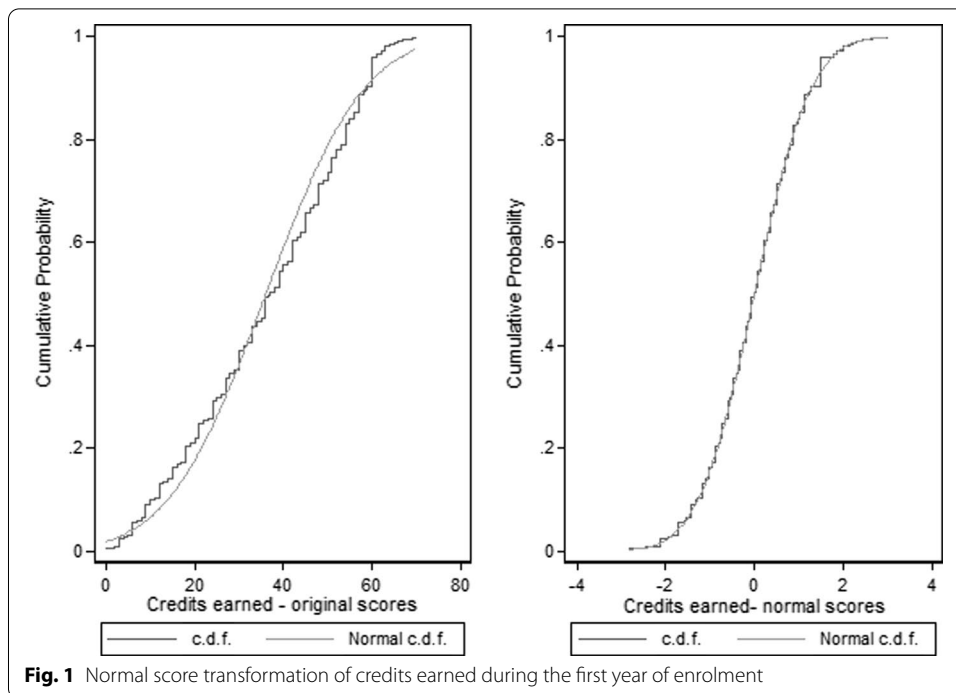


Table 1 Description of variables

Variable	Description
Female	= 1 for female; = 0 for male
HSgrade	= 1 if grade \geq of 75th percentile of the HS grade distribution; = 0 otherwise
Classic Lyceum (%)	= 1 if Classic Lyceum; = 0 otherwise
Scientific Lyceum (%)	= 1 if Scientific Lyceum; = 0 otherwise
Other HS (%)	= 1 if other HS; = 0 otherwise
Late	= 1 if a student obtained his or her secondary education degree later than the year after the end of high school; = 0 otherwise
Change	= 1 if a student changes his or her degree program during the first year of attendance; = 0 otherwise
Stayers from south	= 1 stayers in southern regions; = 0 otherwise
Movers from south	= 1 movers from southern regions; = 0 otherwise
Stayers from N/C	= 1 stayers in the north and central regions; = 0 otherwise
Movers from N/C	= 1 movers from northern/central regions; = 0 otherwise

concerns the effect of mobility from the south to the north. Accordingly, we used stayers and movers from northern and central regions as control categories in the econometric model.

Table 2 shows the main characteristics of our study sample, by cohorts, for the individual covariates described in Table 1. The average values of the dependent variable, expressed in the original score for the sake of simplicity, show a slightly increasing trend over academic years, especially after 2014. The trend for the other variables looks stable across academic years.

Table 2 Descriptive statistics of variables across academic years

	All	2008/2009	2009/2010	2010/2011	2011/2012	2012/2013	2013/2014	2014/2015	2015/2016
Credits Earned (mean)	36.11	35.12	34.91	35.30	35.93	36.30	35.49	37.43	38.08
(SD)	(17.35)	(17.49)	(17.56)	(17.37)	(17.46)	(17.21)	(16.95)	(17.21)	(17.30)
Female (%)	38.90	41.00	40.80	39.70	39.30	38.60	38.30	37.10	36.80
HS Grade (%)	27.50	33.70	27.10	26.30	27.00	25.00	26.70	27.00	27.60
Classic Lyceum (%)	9.90	10.30	10.60	10.40	10.40	10.20	9.70	9.40	8.70
Scientific Lyceum (%)	61.90	59.70	60.40	62.30	63.50	63.40	60.90	61.80	62.90
Other HS (%)	28.10	30.00	29.10	27.20	26.20	26.40	29.40	28.80	28.40
Late (%)	4.90	3.90	4.20	4.00	5.10	4.60	5.50	5.60	6.10
Change (%)	3.20	1.10	2.50	2.90	3.60	3.90	4.10	3.60	4.00
N	406,587	48,317	50,633	52,321	52,213	51,603	44,671	51,821	55,008
Stayers from south (%) ^a	78.17	82.5	79.70	77.60	76.40	76.30	79.5	76.40	76.60
Movers from south (%) ^a	21.83	17.50	20.30	22.40	23.60	23.70	20.5	23.60	23.40
N (only southern students)	152,730	20,249	19,859	19,506	18,522	18,651	17,416	18,601	19,926

^a In this table we include only the percentages that refer to the student mobility from southern regions, because it is the main focus of our study

Methods

Any hierarchical data structure, namely, data with several nested levels, creates a dependence between observations belonging to the same cluster. Ignoring this dependence in econometric models used for data analysis can cause the underestimation of the standard errors of regression coefficients. And, consequently, the overstatement of statistical significance (Goldstein, 2011). Multilevel models solve this issue, because they enable scholars to conduct regression analysis for hierarchical data.

The importance of relying on such a technique in educational studies has been widely addressed, because it allows to appropriately model data that occur within multiple hierarchies, such as students within a particular classroom within a specific school (Bock, 2014; Grilli & Rampichini, 2009; O'Connell & McCoach, 2008). The underlying idea is that each level should be a potential source of unexplained variability (Snijders & Bosker, 2012).

In terms of studying students' performance, it is crucial to consider two potential sources of clustering in our data. As explained in Section "Data description", data contain multiple academic cohorts of first-year students, and we can think that degree programs potentially have different effects in different academic cohorts. To this extent, first-year students from the same program-cohorts appear more similar than first-year students

from different program-cohorts. Therefore, the data structure has three levels: freshmen (level1) nested within program-cohorts (level 2) nested within degree programs (level 3). For this reason, three-level multilevel regression models have been used to explore such data. In particular, in this article, we focus on multilevel linear regression models for continuous responses (outcomes or dependent variables). We specify a variance component model by following Leckie's (2013) approach.

The response variable for all of our analyses is the standard normal score, obtained by transforming the credits earned during the first year of enrolment using Eq. 1. This transformation generates model residuals at each level in the hierarchy, reflecting the normality assumption of the error components produced by the specified variance component model.

Accordingly, the three-level variance component model can be summarized as follows:

$$y_{ijk} = \alpha_0 + \sum_{g=1}^3 \gamma_g z_{ijk} + \sum_{t=2009}^{2015} \alpha_t year_t + \sum_{h=1}^H \beta_h x_{ijkh} + \sum_{l=1}^L \eta_l AS_{jkl} + v_k + u_{jk} + e_{ijk} \tag{2}$$

where y_{ijk} is the standardized score observed for the i th student ($i = 1, \dots, n_{jk}$) enrolled in the j th program-cohort ($j = 1, \dots, J_k$ denotes the program-cohort combination for each program k) within program k ($k = 1, \dots, K$ indicates the number of degree programs in the data).

α_0 is the mean response across all programs, v_k is the random effect of program k , u_{jk} is the random effect of program-cohort j within program k , and e_{ijk} is the residual error term. The random effects and residual errors are assumed to be independent and normally distributed with zero means and constant variances σ_v^2 , σ_u^2 , and σ_e^2 respectively.

The vectors γ_g , α_t and β_h are the unknown parameters to be estimated. They refer to the three dummies z_g , $g = 1, \dots, 3$ summarizing the effect of the mobility indicator (stayers from the northern and central regions is the baseline), the seven cohort dummies $year_t$ (the baseline is 2008–2009), and the H control variables (x) that summarize individual characteristics, respectively. Moreover, η_l is the unknown vector of parameters that refer to the L dummies AS_l , $l = 1, \dots, L$ indicating different areas of study (AS) (L09—Industrial Engineering, as the baseline).

We used two approaches to interpret the relative magnitude of the variance components in our estimates. The variance partition coefficients (VPCs) were used, which report the response variance's proportion lying at each level of the model hierarchy. Therefore, we computed the program-level VPC as the ratio of the program variance to the total variance (i.e., $VPC_v = \sigma_v^2 / (\sigma_v^2 + \sigma_u^2 + \sigma_e^2)$) and the program-cohort-level VPC as the ratio of the program-cohort variance to the total variance (i.e., $VPC_u = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2 + \sigma_e^2)$).

We also used the intra-class correlation coefficients (ICCs) that measure the expected degree of similarity (or homogeneity) between responses within a given cluster (e.g., degree programs). Therefore, we computed the program-cohort ICC (i.e., $(\sigma_v^2 + \sigma_u^2) / (\sigma_v^2 + \sigma_u^2 + \sigma_e^2)$) that measures the correlation between two students who attend the same program-cohort (and, therefore, the same program). In addition, we computed the program ICC (i.e., $\sigma_v^2 / (\sigma_v^2 + \sigma_u^2 + \sigma_e^2)$), which measures the correlation between two students who are enrolled in different program-cohorts but who attend the same program.

Table 3 Variance component model and OLS estimates

	Model I (a)	Model I (b)	Model I ©	Model II (a)	Model II (b)	Model III (a)	Model III (b)	OLS
Constant	-0.0694*** (0.122)	-0.0321*** (0.00591)	-0.0762*** (0.0125)	-0.0176 (0.0135)	-0.0386** (0.0135)	-0.1010*** (0.0267)	-0.1744*** (0.0275)	-0.0990*** (0.0053)
2009/2010							0.0396*** (0.0131)	0.0413*** (0.0058)
2010/2011							0.0497*** (0.0136)	0.0594*** (0.0057)
2011/2012							0.0672*** (0.0137)	0.0893*** (0.0057)
2012/2013							0.1011*** (0.0139)	0.1219*** (0.0058)
2013/2014							0.1248*** (0.0138)	0.0968*** (0.0060)
2014/2015							0.1709*** (0.0138)	0.1805*** (0.0058)
2015/2016							0.2097*** (0.0138)	0.2209*** (0.0057)
Female				0.00277 (0.00311)	0.0587*** (0.0036)	0.0583*** (0.00357)	0.0580*** (0.0036)	0.0538*** (0.0038)
HS Grade				0.662*** (0.00311)	0.7430*** (0.0040)	0.743*** (0.0040)	0.7440*** (0.0040)	0.7379*** (0.0043)
Female#HSGrade				-	-0.1920*** (0.0060)	-0.193*** (0.0060)	-0.1923*** (0.0060)	-0.1837*** (0.0065)
Classic Lyceum				-0.197*** (0.00462)	-0.1970*** (0.0046)	-0.1970*** (0.0046)	-0.1972*** (0.0046)	-0.2283*** (0.0049)
Other HS				-0.3771*** (0.00321)	-0.3780*** (0.0032)	-0.3780*** (0.0032)	-0.3780*** (0.0032)	-0.3792*** (0.0034)
Late				-0.1541*** (0.00631)	-0.1520*** (0.0063)	-0.1520*** (0.0063)	-0.1541*** (0.0063)	-0.1383 (0.0067)
Program Change				-0.2921*** (0.00961)	-0.2930*** (0.0096)	-0.2930*** (0.0096)	-0.2945*** (0.0096)	-0.1803*** (0.0081)
Stayers from South				-0.1712*** (0.0168)	-0.1680*** (0.0168)	-0.1830*** (0.0161)	-0.1842*** (0.0160)	-0.3182*** (0.0033)
Movers from South				-0.1942*** (0.00525)	-0.1920*** (0.0052)	-0.1920*** (0.0052)	-0.1924*** (0.005)	-0.2534*** (0.0054)
Movers from N/C				0.0168 (0.00943)	0.0161 (0.0094)	0.0135 (0.0094)	0.0121 (0.0094)	-0.0006 (0.0092)
Degree classification	No	No	No	No	No	Yes	Yes	Yes
Random components								
var (Programs)	0.150*** (0.0075)	-	0.171*** (0.0077)	0.142*** (0.0072)	0.114*** (0.0073)	0.114*** (0.0061)	0.111*** (0.0058)	-
var (Programs_Cohorts)	0.039*** (0.0012)	0.175*** (0.0036)	-	0.039*** (0.0011)	0.039*** (0.0012)	0.040*** (0.0012)	0.036*** (0.0011)	-
var (Residual)	0.803*** (0.018)	0.803*** (0.0036)	0.803*** (0.0018)	0.696*** (0.0015)	0.695*** (0.0016)	0.695*** (0.0016)	0.695*** (0.0015)	-
- LogL	537,632	539,552	542,208	508,876	508,369	508,273	508,084	
AIC	1,075,273	1,079,111	1,084,423	1,017,779	1,016,767	1,016,605	1,016,240	-
N	406,587	406,587	406,587	406,587	406,587	406,587	406,587	406,587

Standard Deviations between brackets. Significance levels as follows: *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$

Empirical findings

We fit several variance component models, and both the Likelihood ratio (LR) tests and the Akaike's (1973) information criterion (AIC) were used to compare the different models and for the selection of the final model (Whittaker & Furlow, 2009). Results are presented in Table 3, where the simple OLS regression is included also. The first model is the null model (Model I (a), Table 3), which does not contain any covariates. It only

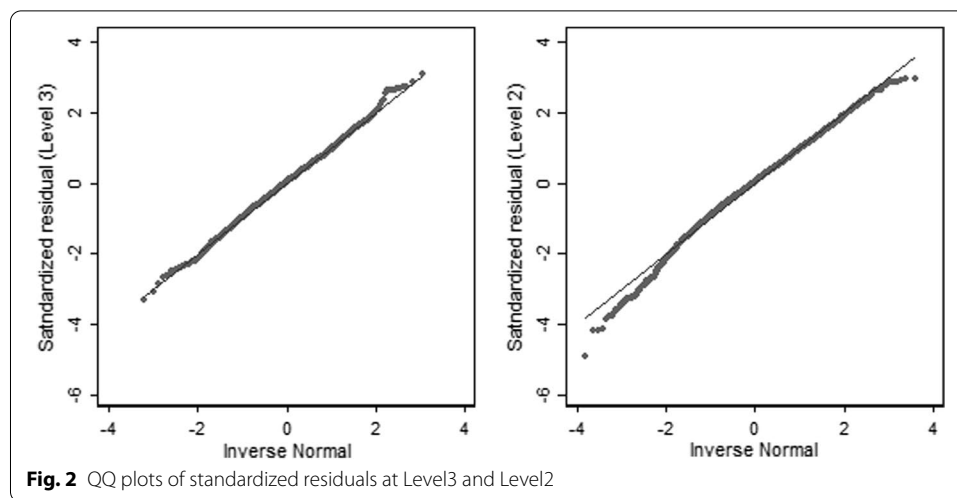


Table 4 VPC and ICC statistics for the three-level variance components model (null-model) for students' performance

Level	VPC	ICC
Program	0.15	0.15
Program-cohort	0.4	0.19
Student	0.81	

decomposes the total response variable variation into separate level-specific variance components. Considering the null model, the intercept—which measures the overall mean of the standardized, average number of credits earned by students (adjusted for the average provided in each degree program)—is statistically significant at the 1% level. The LR test showed that this three-level model is preferred over its single-level counterpart ($X^2 = 73828.69, p < 0.0001$). The normal assumption of random effects was judged by the standardized residuals' quantile–quantile (Q.) plots (see Fig. 2). The results indicate that very few observations deviated from the 45-degree line, suggesting that the residuals at both Level3 (Program) and Level2 (Program-cohort) are approximately, normally distributed.

The LR test also showed that this three-level model is preferred over Model I (b), which is a simpler, two-level, students-within-program model ($X_1^2 = 9152.26, p < 0.0001$). Moreover, it is also preferred over Model I (c), which is a two-level students-within-program-cohorts model ($X_1^2 = 3839.99, p < 0.0001$).⁴ Therefore, we can conclude that students from the same program are significantly more alike than students from different programs. Similarly, students enrolled in the same program-cohort are significantly more homogeneous than students enrolled in different program-cohorts.

⁴ Snijders and Bosker (2012) discussed the technical issue that arises when using these LR tests in this framework because the null joint hypothesis is on the boundary of the parameter space. Indeed, we reject the null hypothesis even more strongly than we initially thought. Nevertheless, it is of more concern that when we do not just reject the null hypothesis based on the reported level, as in this situation, it is very likely that we should, in fact, reject the null hypothesis based on the actual level.

In summary, a three-level multilevel approach is favored over a single-level approach (simple OLS) and it is also preferred over carrying out either of the potential two-level analyses of these data. In Table 4, VPCs and ICCs are reported for the null model. Turning our attention to the VPC statistics, it is possible to observe that 15% of the variation in student performance lies between programs, 4% lies within programs between program-cohorts, and 81% lies within program-cohorts between students.

As thoroughly shown in the previously mentioned literature, most of the variation in students' academic performance lies at the student level, and the present analysis confirms this result. It is clear that, besides the presence of the undeniable role of programs in conditioning students' performance, the latter still relies substantially on the students' characteristics. The ICC statistics indicate that students enrolled in the same program-cohort perform slightly more similarly than students enrolled in adjacent program-cohorts. Indeed, the program-ICC statistic (i.e., the correlation between two students from the same program but different program-cohorts) is equal to 0.15, and the program-cohort ICC statistic (i.e., the correlation between two students from the same program and the same program-cohort) is equal to 0.19.

A further correlation of interest in this framework is the correlation between two program-cohorts within the same program (i.e., $\sigma_v^2/(\sigma_v^2 + \sigma_u^2)$), because it estimates the stability of program performance over time. This correlation is estimated to be equal to 0.79; thus, program performance seems to be relatively stable over time.

Model II (a) includes only the individual predictor variables described in Section "Data description". The LR test ($X_{10}^2 = 58,526.22$, p value < 0.0001) and AIC confirm that the additional individual predictors improve the model's fit. Model II (b) adds an interaction effect between gender and HS grade. The LR test ($X_1^2 = 1014.88$, p value < 0.0001) and AIC confirm that Model II (b) is preferred to Model II (a). Model III also includes degree classes. Both LR test ($X_{15}^2 = 191.53$, p value < 0.0001) and AIC confirm that Model III is still preferred to Model II (b). Finally, in Model III (b), the cohort binary indicators are included to allow that the mean score varies across cohorts (the 2008/2009 cohort is the reference category). Both LR test ($X_7^2 = 378.51$, p value < 0.0001) and AIC confirm that Model III (b) has to be preferred to Model III (a). By comparing the estimates of component of variance between the final model (Model III (b)) and the null model (Model I (a)), we can infer that 15% (i.e., $(\text{total variance}_{\text{full model}} - \text{total variance}_{\text{null model}}) / (\text{total variance}_{\text{null model}})$) of the variation in students' performance is explained by covariates.

Therefore, the final model (Model III (b)) represents an improvement over the null model, and the independent variables help shed light on the determinants of first-year students' performance. The intercept α_0 is estimated to be -0.1744 and gives the predicted normalized score for a student with the characteristic at the baseline level.

It is also interesting to recalculate the correlation between two cohorts within the same program. As we explained before, it provides an estimate of the stability of the programs' performances over time. This correlation is now 0.76, which is lower than that estimated above (i.e., 0.79). Thus, the programs' adjusted performance is less stable than their unadjusted performance. In other words, even if the difference is not great, these results would suggest that the stability of the programs' performance over time is partially driven by the stability of their intake differences over time. This

evidence means that programs that attract high-achieving students in a particular year will tend to attract high-achieving students similarly in the subsequent year.

Some interesting conclusions on the main issue of the paper can be drawn by looking at the fixed part of the model.

With stayer students from the northern and central regions of Italy as the baseline, the first evidence is that movers from the same region do not present any significant statistical difference from the baseline. This result aligns with the evidence obtained from the literature, since most northerners do not move very long distances, remaining in a cultural and socio-economic environment that is much more comfortable compared to the migrating colleagues from the south. However, movers from southern Italy are predicted to make 0.192 standard deviations less progress than stayers in the north/central regions. This outcome is surprising in light of the prior statement that the best students exhibit outstanding entrepreneurship to move as soon as possible toward better environments.

Consequently, the first year of study for students who have moved from the south seems to be generally characterized by the lowest performance in terms of credits earned within the entire sample. It is important to note that the dependent variable, the number of credits obtained by each student, cannot be considered a good proxy for the evaluation of each student. Still, it is a much better approximation for the number of exams successfully passed during the academic year. In other words, nothing can be said about who the best students are in terms of scores, but only in terms of the progress made in their academic curricula.

Concerning comparing stayers from the south and those from the north and center of Italy, the first is predicted to make 0.184 standard deviations less progress than the latter. On one hand, this result can foster prejudice toward the remaining students, depicting them as less capable and resourceful, unable to leave their comfort zone, and with less social and economic pressure to rapidly obtain their degrees. In summary, this evidence conflicts with the commonplace belief that some southern universities may offer facilitated study paths.

Considering the fixed effect of the cohorts, some further considerations can be made. Table 2 includes dummy variables for each available year from 2009–2010 to 2015–2016, keeping 2008–2009 as the baseline. The estimated coefficients are all positively significant at the 1% level, and their size is constantly increasing year by year, in particular, starting from the 2012–2013 cohort. This result should not be surprising, considering that it coincides with the Italian reforms that tied the provision of funding for universities to the number of students they enrolled under the condition of timely graduation. Consequently, there is observed evidence that all universities progressively started relaxing their grading policies, increasing the overall performance of Italian students over time.

The effect of the other covariates introduced in the model shows coherent results with both the results given in prior sections as well as the main findings in the literature. In particular, there is a slightly positive effect for woman on the number of credits earned when the interaction effect with HS grade is included in the model. This estimated interaction effect is negative. Thus, the model seems to somehow capture the more significant difficulties that women generally experience in STEM fields across several studies.

The role of high school background also matters. As expected, students who performed better during their secondary school studies maintain higher performance at the beginning of their university studies as well.

Another reliable result regards the effect of the type of high school attended. The baseline is the lyceum specializing in scientific fields, since it emerges as the one providing the best education background for enrolling in a STEM degree program. Therefore, the lyceum specializing in humanities, and other types of high schools (i.e., other lyceums, technical and vocational schools), have a negatively significant coefficient. If it is not surprising that the scientific lyceum is the one that provides the best preparation for performing well in a STEM degree program, then it is relevant that the coefficient for a classical studies lyceum is almost half that for other high schools. This result demonstrates well-known facts. The first is that lyceums still emerge as the schools that provide better preparation for higher education studies.

Conversely, this result provides the only indirect evidence of the possible effect of the socio-economic background. Indeed, high school emerges as a strong source of stratification in the Italian secondary education system, in which the socio-economic background of students from lyceums is generally higher than those attending technical and vocational schools. The last result is observed for those covariates indicating whether students have achieved their secondary education degree late, and if they changed degree programs during their first year of university. In particular, first-year students who enroll in higher education late exhibit a significantly lower performance during their first year. This result is probably reliable, since this variable mainly incorporates those students who failed one or more years during high school, with the possibility that some of them were enrolled later for different (unobservable) events such as a gap year or the impossibility of attending a university immediately due to force majeure (e.g., medical or economic reasons).

Moreover, students who change their degree program during their first year of study present a highly negative significant effect on their performance. This result should not be surprising. Changing degree programs during the first year of university study introduces in the student's experience two major transitions within a short time. The first is the transition from secondary to tertiary education systems. The second is changing degree programs. It can involve (i) a change in the field of study at the same institution (and/or city), (ii) a change of institution (and/or city) in the same field of study, or (iii) a change of both institutions (and/or city) and field of study. Consequently, experiencing a decrease in academic achievements after such a tangled route should be regarded as a physiological issue.

This model also included the fixed effect of the STEM degree classification undertaken. Nonetheless, this covariate is a control variable. For this reason, we do not present estimated coefficients.

Conclusions

This paper analyzes the relationship between student internal mobility and first-year performance by focusing on first-year STEM students within eight different cohorts from 2008–2009 to 2015–2016. The main results of this paper seem to support the hypothesis that—at least in the short term—mobility might curb students' performance.

Nevertheless, our results suggest that only the STEM students that migrate from southern to northern/central universities do not seem to perform as well as their counterparts who enroll in northern/central universities as residents of a north/central region. These findings confirm the evidence stressed in the related literature, that is, that non-resident students do not perform as well as residents. From this point of view, it is possible that first-year students who have moved from a distant region could experience a temporary drop in their academic performance due to the difficulties and pressures encountered during this transition.

Students who enroll in a STEM degree program are expected to be highly talented in mathematics. At the same time, they are likely to be highly motivated, since they have decided to traverse the traditional south-to-north path. However, in this complicated framework, these students suffer much more than their colleagues due to a transition that involves a new institution and a very different location. Indeed, movers from the north do not exhibit significant differences from their stayer colleagues. This evidence is probably due to the well-recognized fact that they move across much shorter average distances, remaining closer to their comfort zones and in local job markets, which are healthy enough to allow them to be more relaxed about a university's reputation.

Moreover, stayers in the south appear to be the students who demonstrate the lowest levels of performance. Indeed, they earn fewer credits during their first year of study than stayers in the north/center, and the estimated coefficient also suggests that they exhibit lower levels of performance than their mover counterparts. These results can be interpreted from at least two perspectives. On one hand, what was observed could be one of the consequences of the well-known north–south gap in students' mathematical performance, which the PISA tests have confirmed for Italian students' achievement. On the other hand, this evidence weakens the widespread, commonplace belief that the less attractive universities adopt softer grading policies.

Further studies are needed to examine in detail what are the particular stressors that moving students from southern regions face and what type of resources universities could provide to help them. Nevertheless, some interesting policy suggestions can be inferred from various best-practice examples from other countries. For instance, universities could establish compulsory learning communities that require the participation of all first-year transfer students from southern regions. Perhaps, students with solid study skills could assist their peers in these communities by sharing their best practices, and by forming study groups.

Furthermore, interconnections should be empowered among the institutions involved in the transition, namely, high schools and universities. As a consequence, university departments would have a clearer idea of the number of transfer students that they may be dealing with, which would allow an adequate preparation of student support systems, at least from a logistic point of view. For instance, it would be beneficial to provide facilities and accommodation for students at more sustainable costs for families with lower economic backgrounds. This policy would guarantee more significant equality of opportunity, which would hopefully translate into reduced psychological shortcomings and more positive outcomes on performance at the beginning of a student's study path. In this perspective, Italian universities could draw on the experience of other contexts to improve their residential housing policies, making student housing more comfortable.

This policy would increase a transfer student's chances to produce higher levels of academic performance than their counterparts who are residents in private homes. Simple measures of this kind may reduce the gap in performance between stayer and mover first-year students, thus improving social equity between the two groups. These initiatives may also assist universities to increase the average overall performance of their students.

Last but not least, as stated in the recent National Plan for Recovery and Resilience, 82 billion euros have been allocated to southern Italy. The policy-makers seem to be headed in the direction of reducing the divergence between the two areas of the country. Since we strongly believe that the internal student migration is not merely a matter of stresses and shocks, but it is also an educational experience at both a personal and a social level, therefore, moving forward in this direction could, in the long run, develop a new framework in which transfers will no longer be unidirectional.

Finally, these findings point to another interesting and challenging direction for further research. By following the same group of students during their second academic year, future studies might provide helpful insights into whether movers from southern regions persist in their academic underperformance or recover to a level of performance that is more similar to their colleagues in northern/central Italy.

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Authors' contributions

Conception of the work: AD, GL and GG; data analysis: AD and GL; interpretation of data: AD, GL and GG; draft of the work: AD and GL; substantial revision: GG. All authors read and approved the final manuscript.

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Declarations

Competing interests

The authors declare that they have no competing interests.

Author details

¹Dipartimento di Studi Aziendali e Quantitativi (DISAQ), Palazzo Pacanowski, University of Naples "Parthenope", Via Generale Parisi, 13 – IV Piano, 80132 Napoli, Italy. ²Dipartimento di Economia Politica e Statistica (DEPS), University of Siena, Piazza S. Francesco, 7-8, 53100 Siena, Italy. ³Area Organizzazione e Sistemi Informativi (AOSI), Rettorato, University of Siena, via Banchi di Sotto 55, 53100 Siena, Italy.

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