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The Municipality Transition Index and its Impact on Higher Education Institutions' Attractiveness in Italy

Alessio Muscillo[1], Angelo Facchini[2], Gabriele Lombardi[3], and Alessandro Rubino[4]

[1]Universitas Mercatorum, Rome
[2]IMT Lucca
[3]University of Florence
[4]University of Bari "Aldo Moro"

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Abstract

This paper investigates the role of the twin transition (green and digital) in attracting students to higher education institutions (HEIs) in Italy. We use a novel composite indicator called Municipality Transition Index (MTI) to measure the twin transition score in each municipality and its potential economic strength and entrepreneurship and innovation potential. We combine the dimensions of the MTI (Digitalization; Energy, resources and climate; Mobility; and Waste) with data from Italian Student Register of Ministry of University (MUR), and data on economic activities at sector level from the Italian National Institute of Statistics (ISTAT) to model and disentangle two different paradigms: traditional measurements of students' flows and universities' attractiveness, and the estimated change when the MTI is accounted for. By segmenting the mobility of the students engaged in HEIs involved in sectors and disciplines relevant for the smart specialization agenda, we can identify the differentiated impact that the twin transition can play in regions experiencing significant deviations (both positive and negative) from long-term trends of students' mobility. The study aims to contribute to the development of Smart Specialisation strategies and the attractiveness of regions and universities alike.

Keywords: Twin transition, Higher education institutions, Municipality Transition Index, Smart specialization, Students' mobility

JEL codes: I23 - Higher Education; Research Institutions; R58 - Regional Development Planning and Policy; Q55 - Environmental Economics: Technological Innovation

1 Introduction

Higher education institutions (HEIs) can contribute to economic development in cities and rural areas by promoting the identification of comparative advantages and diversified industrial bases, and incentivizing the linkage between innovation and entrepreneurship, in line with the EU Smart Specialisation Strategy (Foray et al., 2011).

In Italy, regional and local economies have a differentiated profile in terms of human capital and productive ecosystems, both of which are characterized by regional embeddedness. Progress towards green and digital innovation varies between regions and at the municipal level (Rissola et al., 2018), and these factors play a key role in determining Smart Specialisation strategies and the attractiveness of regions and universities.

Students' mobility is not solely determined by the characteristics of universities, but also by characteristics of the territory in which the HEIs are located (Trippl et al., 2015; Lombardi and Ghellini, 2019). In Italy, there is almost unidirectional migration of students towards wealthier northern regions, with anticipation of the job market being a main driver (Tosi et al., 2019; Van Bouwel and Veugelers, 2013). The readiness for the twin transition (green and digital) constitutes an additional pulling factor for local entrepreneurship and HEIs' attractiveness. However, measures of preparedness for the transition have not been used to explain students' and workers' mobility, despite their importance for the potential future economic strength of a territory.

To address this gap, we use a novel composite indicator – the Municipality Transition Index (MTI) developed in Muscillo et al. (2023) – to measure the twin transition score in each municipality and characterize a territory's current and potential economic strength, entrepreneurship, and innovation potential. We combine the MTI with data from the Italian Student Register of the Ministry of University (MUR) and data on economic activities at the sector level from the Italian National Institute of Statistics (ISTAT) using a multilevel approach.

Our goal is to model and disentangle two paradigms: the traditional measurement of students' flows and universities' attractiveness, and the estimated change when the MTI is accounted for. We aim to identify the differentiated impact that the twin transition can have on regions that experience significant deviation (both positive and negative) from long-term trends of students' mobility.

Furthermore, we measure the impact of the twin transition and smart specialization on students' mobility by segmenting the mobility of students engaged in HEIs involved in sectors and disciplines relevant to the smart specialization agenda (Foray et al., 2012; McKeever et al., 2018), such as water and waste treatment, e-health, advanced diagnostics, biotechnology, bioinformatics, technologies for smart building, energy efficiency, renewable energy, and circular economy (Rissola et al., 2018).

Our study provides insights for policy makers, HEIs, and students on the potential and challenges of the twin transition and smart specialization, and on how they can shape the attractiveness of universities and regions, as well as support the development of the economy and the creation of local employment opportunities (Balland et al., 2017; Malerba and McKelvey, 2020).

Our econometric analysis contributes to the literature on the determinants of student mobility patterns and the potential role of sustainability and the twin transition in attracting students to HEIs. Previous studies have shown that factors such as the quality of education, the availability of scholarships, and the presence of cultural and recreational facilities can influence students' mobility decisions (Türk, 2019; Ciriaci, 2014; Giambona et al., 2017; Columbu et al., 2021). However, the role of sustainability and the twin transition in attracting students has received less attention in the literature.

2 Data and Methods

2.1 Data

We use two main sources of data to investigate the relationship between students' mobility patterns and the sustainability performance of municipalities. The first source of data is students' mobility data from the "national student registry" (*Anagrafe Nazionale Studenti*, or ANS), which provides information on the destination of students enrolled in higher education institutions (HEIs) across different municipalities. The data is obtained from the Italian Student Register of the Ministry of University (MUR), which collects information on students enrolled in HEIs in Italy. The data includes information on the municipality of origin and the municipality of destination for each student, as well as other demographic and academic information.

In Table 1 we report the descriptive statistics about the flows of students by origin and destination municipalities. In other words, if Flow_{ij} is the number of students moving from origin municipality i to destination municipality j, then the total outflow of students from i is $\sum_j \text{Flow}_{ij}$, while the total inflow of students to j is $\sum_i \text{Flow}_{ij}$. In particular, we can see that the number of origin municipalities amount to 7372 which is roughly 93% of the total number of municipalities present in Italy (7903, as of 2021). Whereas the number of destination municipalities are, of course, just 203 because these are the cities that host a university or a HEI.

The second source of data is the Municipality Transition Index (MTI) developed by Muscillo et al. (2023), which combines data from various open-data sources, including the Italian National Institute of Statistics (ISTAT), the European Environment Agency (EEA), and the European Commission, among others. The MTI is based on 18 key performance indicators, and is designed to assign a score to municipalities in four areas: Digitalization (D), Energy, Climate and Resources (ECR), Mobility (M), and Waste (W). The scores in each of these areas are then aggregated using a normalized weighted sum to yield the overall MTI score, that is, for a given municipality:

$$\text{MTI} = 0.2 \times \text{D} + 0.3 \times \text{ECR} + 0.2 \times \text{M} + 0.3 \times \text{W},$$

where the weights of 0.3 are for the factors ECR and W which are considered as directly involved in the green transition whereas those like D and M are considered facilitating factors, that is, more indirect and, hence, each gets a weight of 0.2. It should be noted that the scores for every area, D, ECR, M and W all lie in $[0, 1]$, and so does the MTI, with 1 being the ideal maximum value attainable.

Describing more in depth the MTI goes beyond the scope of this paper, for which we refer to Muscillo et al. (2023) for more details. However, it is important to notice that the MTI distribution appears to be bell-shaped, suggesting that the level of transition towards green and digital economy in Italian municipalities is not evenly distributed. There are also differences in the MTI scores between urban centers and peripheral areas, with major central cities generally scoring higher than smaller, more remote and isolated municipalities. Interestingly, the MTI is not particularly strongly correlated with the wealth of a territory, indicating that the transition towards a sustainable and digital economy may not always be related to the economic prosperity of a region.

These findings suggest that the MTI may be a useful tool for policymakers and researchers seeking to better understand the factors driving the transition towards a sustainable and digital economy and to identify areas where intervention may be needed. By focusing on specific areas such as digitalization, energy, climate and resources, mobility, and waste, the MTI provides a comprehensive view of the challenges and opportunities facing municipalities as they work towards a more sustainable future. The MTI is a valuable instrument for assessing the level of transition towards a sustainable and digital economy in Italian municipalities, providing valuable insights into how different municipalities are performing in adapting to the green and digital transition.

Crucially, the MTI's version that we will use in this paper is the one referring to year 2020, which is also the year of reference for the students' data from our ANS dataset.[1]

In Tables 2 and 3 we report some descriptive statistics about the origin municipalities and destination municipalities, respectively. Comparing these tables it can be observed that the origin municipalities have, on average, fewer inhabitants (7372 versus 98,043) and a lower income per capita compared to the destination cities (17,628 versus 20,837). This is expected since destination cities are usually larger and wealthier cities where we can find universities or high education institutions. As for the MTI, we can see that on average the MTI is lower in origins than in destination (0.5 versus 0.59). Moreover, when considering its 4 sub-dimensions, we can also see that the difference between origins and destinations is highly notable in terms of digitalization (with an average D of 0.51 versus 0.74), in terms of energy, climate and resources (average ECR of 0.37 versus 0.44) and in terms of mobility (0.33 versus 0.47). Finally, by observing the average latitude of the origin and destination cities, it can be noted that the former is higher than the latter (43.30 versus 43.16). It should be noted that this does not necessarily prove the existence of a considerable north-to-south student flow, but only suggests that on average, the cities with outgoing student flows are located further north than those with incoming flows, without taking into account the number of students involved in these movements.

Table 1: Descriptive statistics of total outflow from origin municipalities and of total inflow to destination municipalities

	total outflow from origin	total inflow to destination
count	7372.0	203.0
mean	41.4	1502.3
std	253.4	4045.2
min	1.0	5.0
25%	5.0	50.0
50%	12.0	153.0
75%	33.0	933.5
max	17368.0	32729.0

2.2 Econometric analysis

We estimate a gravity model to investigate the relationship between the sustainability performance of municipalities and students' mobility patterns. The gravity model is a well-established framework that models the flow of people, goods, or ideas between two locations as a function of the distance between the locations and the characteristics of the locations (Anderson, 2011). This approach is

[1] It should be noted that, in principle, the MTI may be available for different years, but, by construction, it is not readily usable in a time-series fashion because comparison between different years is not possible, due to different sets of the sub-indicators used to compute it. This, in turn, is due to the fact that over time, KPIs as well as policies, are updated and may lose salience or importance.

Table 2: Descriptive statistics of variables for origin municipalities

	origins							
	Pop	IncomePC	MTI	D	ECR	M	W	latitude
count	7372.0	7372.0	7372.0	7372.0	7372.0	7372.0	7372.0	7372.0
mean	7945.33	17628.68	0.5	0.51	0.37	0.33	0.72	43.30
std	43119.66	3770.88	0.09	0.18	0.16	0.21	0.16	2.60
min	41.0	8620.15	0.14	0.0	0.0	0.0	0.0	35.59
25%	1165.75	14656.86	0.44	0.42	0.26	0.17	0.67	41.08
50%	2636.5	17787.5	0.5	0.42	0.36	0.3	0.76	44.39
75%	6646.0	20288.69	0.56	0.67	0.46	0.48	0.83	45.53
max	2761632.0	45645.12	0.76	0.97	0.99	1.0	0.99	47.05

Table 3: Descriptive statistics of variables for destination municipalities

	destinations							
	Pop	IncomePC	MTI	D	ECR	M	W	latitude
count	203.0	203.0	203.0	203.0	203.0	203.0	203.0	203.0
mean	98043.08	20837.18	0.59	0.74	0.44	0.47	0.7	43.16
std	238781.78	3140.95	0.07	0.1	0.15	0.18	0.09	2.49
min	1376.0	13134.17	0.34	0.26	0.1	0.07	0.33	36.91
25%	21374.0	18709.51	0.55	0.73	0.34	0.36	0.66	41.16
50%	47040.0	20827.15	0.59	0.78	0.43	0.49	0.71	43.81
75%	91601.5	22760.43	0.63	0.81	0.55	0.6	0.76	45.41
max	2761632.0	32382.16	0.73	0.85	0.88	0.9	0.93	46.79

particularly preferable in our setting because the intensity of the flow of students between two cities heavily depends on the size of these cities, that is, their mass in terms of population.

The dependent variable in our econometric analysis is the flow of students from an origin municipality i to a destination municipality j, denoted by Flow_{ij}. The independent variables include the population and income per capita of the origin and destination municipalities, represented by Pop_i, Pop_j, IncomePC_i, and IncomePC_j, respectively. Additionally, the distance between the municipalities is included as an independent variable, denoted by Dist_{ij}.

The usual gravity model equation for this type of analysis is as follows:

$$\text{Flow}_{ij} = \beta_0 \ \text{Pop}_i^{\beta_1} \ \text{Pop}_j^{\beta_2} \ \text{IncomePC}_i^{\beta_3} \ \text{IncomePC}_j^{\beta_4} \ \text{Dist}_{ij}^{-\beta_5} \ \varepsilon_{ij},$$

for all origin city i and destination city j, where $\beta_0, \beta_1, \ldots, \beta_5$ are the estimated coefficients and ε_{ij} represents the error term. This equation can be rewritten in logarithms

$$\begin{aligned} \log\left(\text{Flow}_{ij}\right) = &\log\left(\beta_0\right) + \beta_1 \log\left(\text{Pop}_i\right) + \beta_2 \log\left(\text{Pop}_j\right) + \beta_3 \log(\text{IncomePC}_i) + \beta_4 \log(\text{IncomePC}_j) \\ &- \beta_5 \log(\text{Dist}_{ij}) + \log(\varepsilon_{ij}), \end{aligned}$$

for every pair of origin-destination municipalities i, j.[2] In this framework, the MTI is meant to capture the municipality's performance in terms of urbanization and modernization, and it is used

[2] To simplify and enhance readability, from now on we will omit the constant and the coefficients β in the

as an indicator of the municipality's potential to attract students. To do so, we modify the above equation by adding the municipality transition index of the destination municipality, represented by MTI_j, as an independent variable:

$$\begin{aligned} \log\left(\mathrm{Flow}_{ij}\right) = & \log\left(\mathrm{Pop}_i\right) + \log\left(\mathrm{Pop}_j\right) + \log(\mathrm{IncomePC}_i) + \log(\mathrm{IncomePC}_j) \\ & - \log(\mathrm{Dist}_{ij}) + \mathrm{MTI_j} + \log(\varepsilon_{ij}), \end{aligned} \tag{1}$$

which is the actual equation that we estimate.

To estimate the gravity model presented here, we can use a panel data approach with fixed effects, random effects, and Poisson Pseudo-Maximum Likelihood (PPML) models. These three models are estimated while accounting for the panel structure of the data[3] and controlling for unobserved heterogeneity at the origin level. The fixed effects ordinary least square (OLS) model controls for time-invariant unobserved heterogeneity, while the random effects OLS model additionally allows for unobserved heterogeneity that varies over time. The PPML model is appropriate when the dependent variable is a count variable, such as the flow of students between municipalities in this case. Thus, the flow of students is a count variable because it takes on discrete non-negative integer values and represents the number of students moving between municipalities. The models are estimated with robust standard errors clustered at the origin level to account for potential serial correlation and heteroscedasticity in the error term.

The coefficient estimates, standard errors, and p-values for each independent variable in the fixed effects, random effects, and PPML models are reported in Table 4. The number of observations (47,484) corresponds to the number of origin-destination pairs, while the number of clusters (or of groups) is the number of origin municipalities (7,372). The results indicate that the population and income per capita of the origin and destination municipalities, as well as the distance between them, have significant effects on the flow of students. Specifically, from the analysis of the first two columns of the table (fixed and random effects OLS) we can see that a one percent increase in the population of the origin and destination municipalities is linked to an increase in the flow of students by 0.33% and 0.23%, respectively. The effect of the income per capita of the origin municipality is negative and significant, with a 1% increase being linked to a -1.16% decrease in the flow of students. On the contrary, the effect of the income per capita of the destination municipality is positively significant, with a 1% increase corresponding to an increase in the flow of students of 0.86% or 0.33%, depending on the model used. As for the distance between origin and destination municipalities, a one percent increase in distance between them always significantly decreases the flow of students, by -0.77% or by -0.59% depending on the model used. As shown by the corresponding p-values in Table 4 (in parentheses, third rows for each independent variable), all these results are statistically significant at 1%.

Lastly, regarding the MTI of the destination municipality, we can see that it has a positive and significant effect on the flow of students, with a higher MTI indicating a higher level of green and digital transition in the destination municipality. Specifically, since MTI ranges from 0 to 1, an increase in the MTI of the destination by 0.1 (10 units) increases the flow of students by 0.055 or 0.059 (i.e., 5.5 or 5.9 percentage points) in the fixed-effects and random-effects models, respectively. This suggests that students are more likely to move to destination municipalities with a higher level of MTI.

regression equations. So that a regression equation will simply be written as: $\log\left(\mathrm{Flow}_{ij}\right) = \log\left(\mathrm{Pop}_i\right) + \log\left(\mathrm{Pop}_j\right) + \log(\mathrm{IncomePC}_i) + \log(\mathrm{IncomePC}_j) - \log(\mathrm{Dist}_{ij}) + \log(\varepsilon_{ij})$.

[3] It contains observations of the same variables (origin) for multiple destinations, where each destination represents a different unit. Although there is only one time period, the data still exhibits a panel-like structure.

All these results seem to be confirmed also with the analysis of the estimates provided by the PPML model, with the only exception being the sign of the coefficient of the income per capita of the destination municipality. While this is contrasting with the sign of the estimated coefficients of the OLS models, it is worth mentioning that the PPML model estimated here does not take into account fixed effects. A more in-depth analysis is left to future research. Overall, then, these effects are consistent across all three models, suggesting that these results are robust, although the magnitude of the effects varies slightly.

Table 4: Regression results for equation 1. The dependent variable is the logarithm of the flow of students, $\log(\text{Flow}_{ij})$

Independent variable	**Fixed Effects OLS**	**Random Effects OLS**	**PPML Model**
$\log(\text{Pop}_{\text{orig}})$	(omitted)	0.33	0.65
		(0.01)	(0.02)
		(0.000)	(0.000)
$\log(\text{Pop}_{\text{dest}})$	0.23	0.23	0.56
	(0.00)	(0.00)	(0.01)
	(0.000)	(0.000)	(0.000)
$\log(\text{IncomePC}_{\text{orig}})$	(omitted)	-1.16	-1.70
		(0.03)	(0.08)
		(0.000)	(0.000)
$\log(\text{IncomePC}_{\text{dest}})$	0.86	0.33	-0.41
	(0.05)	(0.04)	(0.13)
	(0.000)	(0.000)	(0.001)
$\log(\text{Dist}_{\text{orig}-\text{dest}})$	-0.77	-0.59	-1.07
	(0.01)	(0.01)	(0.02)
	(0.000)	(0.000)	(0.000)
Destination MTI	0.55	0.59	2.64
	(0.08)	(0.07)	(0.26)
	(0.000)	(0.000)	(0.000)
Constant	-7.48	5.51	12.38
	(0.42)	(0.32)	(0.90)
	(0.000)	(0.000)	(0.000)
	R^2 within = 0.38	R^2 within = 0.38	R^2 = 0.46
	R^2 between = 0.03	R^2 between = 0.37	
	R^2 overall = 0.18	R^2 between = 0.34	
number of observations (origin-destination) = 47484			
number of groups (origins) = 7372			
observations per group: min = 1, average = 6.4, max = 83			

Legend: for every independent variable, the first row is the estimated coefficient β, the second row the standard error, and the third row the corresponding p-value. Standard errors are adjusted for 7372 clusters (origins).

Let us further expand the analysis with a slightly modified specification of the regression equation:

firstly, we add the MTI of the origin municipality while, secondly, we also add the difference in latitude between destination and origin city, denoted by $\Delta\text{Lat}_{ij} = \text{Lat}_j - \text{Lat}_i$, which can be useful to capture a decades-long trend of migration from South to North in Italy. In other words, we estimate the following equation:

$$\begin{aligned}\log(\text{Flow}_{ij}) = &\log(\text{Pop}_i) + \log\left(\text{Pop}_j\right) + \log(\text{IncomePC}_i) + \log(\text{IncomePC}_j) \\ &- \log(\text{Dist}_{ij}) + \text{MTI}_\text{i} + \text{MTI}_\text{j} + \Delta\text{Lat}_{ij} + \log(\varepsilon_{ij}).\end{aligned} \tag{2}$$

Obviously, the MTI of the origin will be omitted in the fixed effects OLS model, just like the other origin-invariant variables. The results of the estimation of this model can be seen in Table 5 and are in line with those shown in Table 4. The only additions that are worth mentioning are that, firstly, the MTI of the origin seems to have a positive and significant effect on the flow of students and, secondly, the difference in latitude between destination and origin municipality is positively significant (at least in the random effect model and in the PPML model) which suggests a prevalence of students' movements from South to North.

Table 5: Regression results for equation 2. The dependent variable is the logarithm of the flow of students, $\log(\text{Flow}_{ij})$

Independent variable	**Fixed Effects OLS**	**Random Effects OLS**	**PPML Model**
$\log(\text{Pop}_{\text{orig}})$	(omitted)	0.30	0.63
		0.01	0.02
		0.000	0.000
$\log(\text{Pop}_{\text{dest}})$	0.23	0.25	0.59
	0.00	0.00	0.01
	0.000	0.000	0.000
$\log(\text{IncomePC}_{\text{orig}})$	(omitted)	-0.92	-1.44
		0.03	0.09
		0.000	0.000
$\log(\text{IncomePC}_{\text{dest}})$	0.84	0.02	-0.74
	0.06	0.04	0.14
	0.000	0.644	0.000
$\log(\text{Dist}_{\text{orig}-\text{dest}})$	-0.77	-0.64	-1.13
	0.01	0.01	0.02
	0.000	0.000	0.000
ΔLatitude	0.00	0.06	0.11
	0.00	0.00	0.01
	0.447	0.000	0.000
Origin MTI	(omitted)	0.30	0.47
		0.06	0.20
		0.000	0.019
Destination MTI	0.54	0.42	2.38
	0.08	0.07	0.25
	0.000	0.000	0.000
Constant	-7.26	6.30	13.14
	0.51	0.32	0.94
	0.000	0.000	0.000

Legend: for every independent variable, the first row is the estimated coefficient β, the second row the standard error, and the third row the corresponding p-value. Standard errors are adjusted for 7372 clusters (origins).

2.3 Unpacking the effect of the four MTI's dimensions

Let us know replicate the previous analysis while unpacking the MTI in its 4 dimensions: digitalization (D); energy, climate and resources (ECR); sustainable mobility (M) and waste management (W). In terms of notation, we denote with D_i, ECR_i, M_i and W_i the corresponding scores that in the 4 above-mentioned dimensions of municipality i. By doing this, we can try to assess whether some specific dimensions contribute relatively more to the potential attractiveness of a municipality. Here we present some preliminary results, leaving a more in-depth analysis to future research.

We then consider the following specification, where we include the scores for both origin cities i

and destination cities j:

$$\begin{aligned}\log\left(\text{Flow}_{ij}\right) = \; & \log\left(\text{Pop}_i\right) + \log\left(\text{Pop}_j\right) + \log(\text{IncomePC}_i) + \log(\text{IncomePC}_j) - \log(\text{Dist}_{ij}) \\ & + \mathrm{D_i} + \mathrm{ECR_i} + \mathrm{M_i} + \mathrm{W_i} \\ & + \mathrm{D_j} + \mathrm{ECR_j} + \mathrm{M_j} + \mathrm{W_j} + \Delta\text{Lat}_{ij} + \log(\varepsilon_{ij}).\end{aligned} \tag{3}$$

The results are reported in Table 6 and show that the estimated coefficients for the variables regarding population, income per capita and distance remain practically unchanged, in terms of magnitude, sign and stastical significance. On the contrary, the analysis of the 4 coefficients corresponding to the MTI's areas, the situation seems more complex. From the point of view of the origin municipality, D and ECR have a positively significant effect on students' mobility, whereas W has a negative effect. On the other hand, from the point of view of the destination municipality, all coefficients are statistically significant but the effect of D and W is negative while that of ECR and M is positive.

Table 6: Regression results for equation 3. The dependent variable is the logarithm of the flow of students, $\log(\text{Flow}_{ij})$

Independent variable	**Fixed Effects OLS**	**Random Effects OLS**	**PPML Model**
$\log(\text{Pop}_{\text{orig}})$	(omitted)	0.31	0.64
		0.01	0.02
		0.000	0.000
$\log(\text{Pop}_{\text{dest}})$	0.24	0.24	0.53
	0.00	0.00	0.02
	0.000	0.000	0.000
$\log(\text{IncomePC}_{\text{orig}})$	(omitted)	-1.11	-1.65
		0.03	0.09
		0.000	0.000
$\log(\text{IncomePC}_{\text{dest}})$	0.63	0.24	-0.34
	0.05	0.04	0.14
	0.000	0.000	0.013
$\log(\text{Dist}_{\text{orig}-\text{dest}})$	-0.79	-0.62	-1.11
	0.01	0.01	0.02
	0.000	0.000	0.000
D_{orig}	(omitted)	0.10	0.21
		0.03	0.09
		0.002	0.028
ECR_{orig}	(omitted)	0.31	0.27
		0.04	0.09
		0.000	0.003
M_{orig}	(omitted)	-0.02	-0.08
		0.03	0.07
		0.443	0.248
W_{orig}	(omitted)	-0.21	-0.28
		0.03	0.08
		0.000	0.000
D_{dest}	-1.49	-1.33	-2.36
	0.06	0.05	0.20
	0.000	0.000	0.000
ECR_{dest}	0.34	0.35	0.83
	0.03	0.03	0.09
	0.000	0.000	0.000
M_{dest}	0.69	0.50	1.38
	0.04	0.03	0.11
	0.000	0.000	0.000
W_{dest}	-0.74	-0.77	-1.57
	0.07	0.06	0.21
	0.000	0.000	0.000
Constant	-3.78	7.46	15.30
	0.42	0.40	1.15
	0.000	0.000	0.000

Legend: for every independent variable, the first row is the estimated coefficient β, the second row the standard error, and the third row the corresponding p-value. Standard errors are adjusted for 7372 clusters (origins).

3 Discussion

The results shown in the previous section on the one hand confirm some unsurprising and perhaps mechanical effects, such as the fact that the flows of students are more substantial between larger cities than between small centers, and that distance between origin and destination discourages students' migration. On the other hand, there are some interesting aspects worth exploring. First of all, we think that it is important to take into account that the decision of university students to migrate may be heavily influenced by the anticipation of potential future job opportunities that may arise not only as a result of their studies but also as a result of their physical presence in a specific city. Based on this assumption, the first interesting aspect to evaluate is derived from the analysis of the per-capita income of the cities. When this is seen from the point of view of the city of origin, it can be said that while per-capita income can be considered as a proxy for a city's wealth and, therefore, the availability of means for students to easily migrate to other cities for study reasons, on the other hand, a relatively wealthy city may offer work and lifestyle opportunities and therefore discourage departure or migration to other cities.

From the destination city's perspective, while high per-capita income may be linked to an active socio-economic environment, which is more attractive to students as future workers, it may also be a signal of a high cost of living. Therefore, a trade-off may arise between a short-term higher cost of living that students may have to bear during their years of study and potential better long-term future job and life prospects. This is also already confirmed in the literature (Lombardi and Ghellini, 2019) and can be behind the opposite signs of the estimated coefficients in the OLS models and PPML model which correspond to income per capita of the destination municipality observed in Table 4.

Just like the effect of cities' wealth (in this framework proxied by income per capita) on students' mobility seems complex and multifaceted, this also happens for the level of present and future preparedness of cities to the green and digital transition (here proxied by the MTI). Indeed, the role of the destination's MTI always constitutes a significant pulling factor for the flow of students (Tables 4 and 5) and this is interpretable by saying that cities with a higher MTI are not only more (socio)economically active in the present, and can be expected to be so in the future, but this also makes them more welcoming and attractive to students as well as potential future workers. However, when $\mathrm{MTI}_{\mathrm{dest}}$ is decomposed into its 4 dimensions (Table 6), then this effect is less clear, with a particularly surprising result being the negative coefficients obtained by $\mathrm{D}_{\mathrm{dest}}$. Regarding the MTI of the origin municipality, while it seems to play a less substantial role as a pushing factor for students' mobility, it remains more coherent when decomposed into its 4 dimensions.

Overall, the results suggest that even when controlling for crucial factors such as cities wealth, population, distance and Italian south-to-north migration trend, students are more likely to move to destination municipalities with higher economic and social development and that they move from and are attracted to municipalities with a higher level of attention to the green and digital transition. These effects are consistent across all three models, although the magnitude of the effects varies slightly and some signs still require a deeper understanding.

4 Conclusion and future research

In this paper we investigate the potential impact of the twin transition and sustainability on students' mobility patterns in Italy. Building on previous research, we have used a gravity model and applied it to a novel municipality-level composite indicator, the MTI, which captures the level of attention to the twin transition. Our analysis provides a more nuanced understanding of the factors that influence students' mobility decisions and can inform the development of Smart Specialization strategies and the attractiveness of regions and universities.

By estimating the gravity model, we have identified the factors that may influence students' mobility patterns and the potential impact of sustainability and the twin transition in attracting students to HEIs in Italy. Overall, our findings suggest that municipalities with a higher MTI are more attractive to students and have a greater potential for economic strength and entrepreneurship and innovation. These insights can help policymakers and education institutions to design and implement effective strategies for improving the attractiveness of regions and universities, and for promoting sustainable and inclusive economic growth.

Future research will be dedicated to improve the econometric analysis to unpack the effect of the MTI along its four main components.

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