# Impact of High-Speed Railways on Student Preference among Turkish Provinces: A Gravity Model Approach

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## ABSTRACT

In Türkiye, students are admitted to universities through centralised examinations, which enable them to choose cities outside their residential town. Over the past two decades, Türkiye has expanded higher education by establishing new universities and augmenting the enrollment capacities of existing universities. Therefore, each province has at least one state university, depending on the potential demand for higher education in the corresponding region. The establishment of new universities nationwide has led to an increase in student mobility between provinces.

We employ a gravity model to analyse higher education student mobility among Turkish provinces, positing that both the distance between cities and the potential student population influence student movement between provinces. We utilise the R package *thestat*s, created by Çavuş and Aydın (2022), which is based on the YÖK-ATLAS data from 2018 to 2020. Our findings suggest that the gravity model explains the student flows among the provinces of Türkiye.


**Keywords:** *Gravity models, higher education, panel data analysis*

**JEL Codes**: C23, A22, I21, I23

## 1. INTRODUCTION

Over the past three decades, two pivotal changes have been made in terms of higher education policies implemented in Türkiye. The first wave of university expansion was marked by the establishment of 23 state universities in 1992. The second expansion, which was based on the government campaign for a university in every single city, took place between 2006 and 2008 (Kolat and Göktaş, 2024). By 2008, each province had a state university, which reduced commuting costs for prospective students. These universities are primarily located in the provincial centres. Furthermore, the quotas of existing universities were increased. On the other hand, enrolments have kept pace with these new additional quotas. The increased quotas induced demand for higher education.

In Türkiye, the transition to higher education is facilitated through a centralised YKS (Higher Education Institutions Examination). Those in their final year of secondary education institutions or who have graduated from a secondary education institution can apply for the YKS exam. The exam consists of three sessions: the Basic Proficiency Test (TYT), the Field Proficiency Test (AYT), and the Foreign Language Test (YDT) (OSYM, 2023). Students who succeed in these tests are subject to a centralised placement based on the scores they receive from the tests. Generally, the transition to higher education follows the standard procedure

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mentioned above; however, there may be additional field-specific criteria, such as special aptitude tests and similar assessments, at the university or department level.

According to official data released by the Council of Higher Education (YÖK) for the 2024–2025 academic year, Türkiye's higher education system continues to experience strong demand and high participation rates. Of 1,021,986 available university placements, 987,388 students were successfully enrolled, yielding an overall placement rate of 96.6 per cent.

In state universities, the backbone of Türkiye's higher education infrastructure, 598,709 seats were offered in regular undergraduate programs. Of these, 591,257 were filled, reflecting a high enrolment rate of 98.8 per cent. Vaqif (non-government) universities also demonstrated robust performance, with an overall enrolment rate of 91.14 per cent. Moreover, vocational schools, particularly those offering associate degree programs, achieved full capacity, reporting a 100% enrolment rate.

According to the Council of Higher Education (YÖK), the Turkish higher education ecosystem comprises 208 universities as of the 2024–2025 academic year. This figure encompasses both state and vaqif (non-profit private) institutions, underscoring the nation's strategic emphasis on enhancing the accessibility and regional distribution of tertiary education opportunities. These figures underscore the sustained expansion and appeal of higher education in Türkiye, highlighting the increased capacity of institutions and the growing demand for tertiary education across various regions and disciplines.

The importance of university enrolment in Türkiye lies in its role in driving economic growth (OECD, 2024), enhancing social mobility (YÖK, 2024), fostering innovation (World Bank, 2024), and promoting global competitiveness (European Commission, 2024). With the government's commitment to expanding access to higher education and improving its quality, Türkiye can leverage its young, dynamic population to build a prosperous and stable future. The benefits extend beyond economic development, contributing to social cohesion, democratic engagement, and improved public services.

Distance and space may not matter for competitive departments, such as faculties of law, medicine, and schools of education. The common feature of these programs is that they enable the practice of the profession after graduation. For instance, a person's appointment as a teacher is unaffected by the university from which they graduated. After graduation, an additional test must be taken to be appointed as a teacher.

We employ a gravity model to analyse higher education student mobility among Turkish provinces, positing that both the distance between cities and the potential student population influence student movement between provinces. We utilise the R package *thestats*, created by Çavuş and Aydın (2022), which is based on the YÖK-ATLAS data from 2018 to 2020. Having high-speed train lines has a positive impact on both the origin and destination cities. We found that the gravity model explains the student flows among the provinces of Türkiye.

## 1. LITERATURE REVIEW

As the recognition of knowledge as a key driver of regional productivity and economic competitiveness expands, the role of higher education institutions (HEIs) in advancing regional development has emerged as a critical area of academic investigation. A substantial body of literature has developed, exploring the direct connections between universities and the industrial sector. These studies have primarily focused on faculty patenting activity, the growth of university-affiliated entrepreneurial ventures, and strategic partnerships between academic institutions and private-sector organisations. However, it can be argued that the most significant and lasting influence of higher education institutions (HEIs) on local economies resides in their role as producers of skilled human capital, generating successive cohorts of graduates who subsequently enter and contribute to regional labour markets.

Analysing these two interconnected decision points provides valuable insights, as they are likely to be linked. For instance, prospective students may choose their study destination based on the anticipated availability of future employment opportunities. In contrast, cities with limited immediate labour market prospects may focus on establishing themselves as attractive educational centres, thereby enhancing their appeal to students and indirectly to potential employers.

These student choice dynamics have important implications for the design and effectiveness of public policies aimed at retaining or attracting a highly educated workforce. A nuanced understanding of the motivations and constraints underlying student and graduate mobility is, therefore, essential for fostering sustainable regional development and competitiveness in the knowledge economy.

Cummings (1993) identified a comprehensive set of determinants influencing cross-border academic and professional mobility, categorised into push and pull factors. The push factors which drive individuals to seek opportunities abroad include limitations in domestic human capital development, inadequate financial resources, a high degree of reliance on international trade, the lack of or weakness of institutional support structures, insufficient local availability of science and technology programs, economic dependency on global markets, restricted access to timely and accurate information, linguistic marginalization, political instability, and prevailing socio-cultural orientations that discourage local advancement.

Conversely, the pull factors that attract individuals to specific host countries comprise the extent of financial and institutional support provided, levels of international trade integration, immigration openness, structural and systemic alignment with the individual's background, the economic scale of the host country, and its fiscal capacity to sustain incoming talent.

Like other studies on higher education choice, Ordovensky (1995) indicated that proximity to home is a significant factor in the enrolment decision. Students are more likely to enrol in institutions that are geographically closer to where they live, as it reduces living and travel costs. In their study, Kjellström and Regnér (1999) noticed that students are less likely to enrol in universities located further from their hometowns or regions. Additionally, Do (2004) concludes that local colleges have a significant influence on students' decisions regarding where to attend college, primarily due to geographic proximity. Based on income groups, Frenette (2006) shows that students from low-income families, especially those living beyond commuting distances, are less likely to participate in higher education compared to their peers. Spiess and Wrohlich (2010) proved that geographic distance plays a significant role in the decision to attend university. As the distance from the nearest university increases, the likelihood of a student attending a university decreases. Suhonen (2014) posits that geographic distance may exert a negative influence on students' selection of certain fields of study, potentially leading to inefficiencies where students are unable to pursue their preferred academic discipline.

On the other hand, some studies suggest that students' decisions to attend university are influenced by factors beyond distance, including educational opportunities, economic factors (Sa and Franca, 2023), and regional disparities (Fagian and Franklin, 2014). Sa et al. (2004) highlight a tension between the restrictive effects of distance and the attractiveness of universities and their surrounding regions. Carla Sa (2007) reveals that students' university choice behaviour is primarily shaped by the deterrent effect of distance and the impact of rental costs. Sá et al. (2011) demonstrated that geographical proximity and the availability of higher education institutions significantly influenced student choices. The research highlights the multifaceted nature of higher education choices, which are influenced by a combination of demographic, socio-economic, and personal preference factors. Gibbons and Vignoles's (2012) findings suggest that the type and calibre of higher education programs in which students enrol are influenced, to some extent, by the characteristics and quality of nearby institutions.

Cullinan et al. (2013) observed in their analysis of Irish data that the likelihood of higher education participation decreased notably for individuals from lower socioeconomic backgrounds as the distance to the institution increased. Moreover, the deterrent effect of distance was found to intensify progressively with greater travel. Cooke and Boyle (2011) supported the gravity model. They proved that several less densely populated states situated near larger, more densely populated ones, particularly in the eastern region of the United States, benefit from positive externalities resulting solely from their geographical proximity.

Although the data are available, few studies have been conducted on the case of Türkiye. Bekaroğlu (2021) can be an example of studies conducted in Türkiye. According to his findings, although distance hurts both genders, its effect and the influence of temporal trends are less pronounced among female students. Gür (2022) reveals the interprovincial and interregional mobility of enrolled students. The province of residence is a significant factor in determining university placement. Regarding mobility, students not only prefer universities within their province of residence but also tend to gravitate toward one of the three major metropolitan cities or to other provinces and metropolitan areas that are geographically closer to them. The findings of Erol et al. (2012) suggest that students' preferences are influenced by both their economic status and their proximity to educational institutions.

## 2. METHODOLOGY

In gravity model applications, especially in the aviation sector, OLS is the most frequently used estimator. Studies typically restrict the sample to cargo flows of at least 1 tonne to avoid issues arising from the log-linear specification. Log-transforming values below one results in adverse or undefined outcomes, which are not suitable for modelling a dependent variable such as cargo volume.

Moreover, even after applying the logarithmic transformation, the error terms from OLS estimations include heteroskedasticity. In addition, imposing a lower bound on the dependent variable introduces sample selection bias, which can potentially distort the consistency of the estimated coefficients (Aydın and Ülengin, 2022).

Given this limitation of the OLS estimator, the PPML method is adopted as a more suitable alternative for estimating gravity model equations.

The gravity model is based on Isaac Newton's gravitational law (Newton,1687) and is formulated as follows:

$$F_{ij} = G\frac{Mi\,Mj}{d_{ij}^2} \tag{3.1}$$

In Equation (3.1), F denotes the gravitational force between objects i and j; M represents their respective masses; $d_{ij}$ indicates the distance between them; and G is the gravitational constant. When panel data includes all observational units, the fixed effects model is typically utilised to address unit-specific heterogeneity. However, time-invariant regressors such as geographic distance and dummy variables are omitted due to their collinearity with the fixed effects after applying the within transformation. (Gül and Tatoğlu, 2019)

The Poisson Pseudo Maximum Likelihood (PPML) estimator, introduced by Silva and Tenreyro (2006), is the primary technique among various estimation methods designed to address the limitations of the OLS model, due to its consistency in the presence of heteroskedasticity and its suitability for datasets with a high frequency of zero outcomes. Hence, the PPML estimation method has become a preferred approach in empirical gravity model analysis, primarily due to its robustness to heteroscedastic errors and its capacity to accommodate zero-valued trade observations (Arvis and Shepherd, 2013; Iwasaki and Saganuma, 2013).

This study covers 81 provinces in Türkiye from 2018 to 2020. The dataset by Çavuş and Aydın (2023) enables the study of these three specific years. The dataset encompasses all universities, their faculties, and the programs offered within Türkiye's provinces.

When determining the optimal locations for new sites, a critical factor to consider is the selection behaviour of students regarding their choice of educational facilities, namely, university campuses. This dimension has been extensively examined within the framework of spatial models, where consumer choice theories hold a central role. Such models are fundamentally inspired by the adaptation of Newton’s law of gravitation to economic contexts. The resulting "gravity model" and its numerous variations have since been widely applied across various disciplines, including regional science, transportation planning, marketing, and facility location analysis.

According to the gravity model, as the physical distance between the student's home and the university increases, the probability of enrolment decreases. This finding directly supports the gravity model's assumption that distance is a key factor in reducing interaction between two locations (Newton,1687; Ravenstein, 1885). The distance variable, one of the classical variables in the gravity model, can cause numerous problems during empirical applications. The literature debates how distance should be measured. However, in these models, the great circle method typically measures the geographical distance, which represents trade costs (Kızıltan and Şahin, 2020). Nonetheless, this research studies the gravity model within a country. Therefore, we use transportation distance in km.

Kaya et al. (2023) predicted 2023 air cargo transportation data using three different approaches, including the gravity model. The first one is the Poisson pseudo maximum-likelihood estimator, the second one is the ordinary least squares estimator, and the third one is similar to the OLS estimator, but the dependent variable with zero value has been changed by adding a small amount to the observations and included in the analysis (PPML, OLS and OLS*). When the findings are compared, it is observed that the PPML estimator is the most successful among the others; however, the prediction performances of the models may vary for some cities.

Aydın and Ülengin (2022) initially estimate the gravity model using both PPML and OLS techniques based on cross-sectional air cargo data between city pairs. The coefficient on the distance variable is positive and statistically significant, indicating that longer domestic routes in Türkiye are associated with higher volumes of air cargo.

Hwang and Shiao (2011) argue that distance and population variables may capture unobserved unit-specific effects in the gravity model. To account for potential time variation, year dummies are included and estimated using both PPML and OLS. While OLS results indicate no significant temporal effects, PPML estimates reveal a statistically significant increase in cargo volumes in 2020 relative to 2012.

In this study, the total student mobility between the two provinces was calculated, including students enrolled in both state universities and foundation universities located in those provinces. Regarding the period covered by the data set, a threshold score calculation is applied to the university entrance exam. Students who score below the threshold cannot make university preferences. Therefore, students with an average level of success may prefer to enrol in any university without considering distance. Additionally, prestigious universities located in a particular province attract students from every province in Türkiye. Similarly, when considering the cost of living, individual preferences come to the forefront in cases where the cost of obtaining a bachelor's degree at a public university in a different province is similar to that of obtaining a bachelor's degree at a private university in the same province. Considering all this, there is no clear expectation regarding the sign of the coefficient for the distance variable. In this context, the study can be expanded in later stages by adding living costs.

The gravity model, which is generally used for modelling international foreign trade, is a good example of an unnested multidimensional panel data analysis method. This study employs the gravity model approach to model students' preferences when making their university choices. Table 1 shows the variables, their explanations, and the dimensions of analysis.

$$FLOW_{ij} = \beta_0 * \frac{(\mathrm{CITY_i})^{\beta_1} (\mathrm{CITY_j})^{\beta_2} (\mathrm{YHT})^{\beta_4}}{\mathrm{DISTANCE_{ij}}^{\beta_3}} \tag{3.2}$$

Equation (3.2) represents the simple form of the gravity model. Detailed explanations for FLOWij, CITYi, CITYj, and DISTANCEij are provided under the definitions of these variables.

| Variables | Explanation | Dimensions | Representation |
|---|---|---|---|
| LCITY1 | Total number of students from city i enrolled in a university in Türkiye | City i | $\mu_i$ |
| LCITY2 | Total number of students from city j enrolled in university in Türkiye | City j | $\gamma_j$ |
| LDISTANCE | Total distance between city i and j in km. | | |
| YHT | Dummy variable: High-speed train line between city i and j | | YHT |
| LFLOW | Total student flow from city i to city j | | |
| YEAR | Time | t | $\lambda_t$ |

**Table 3.1** Variable Definitions

Here, LCITY1, LCITY2, LDISTANCE, and LFLOW represent the total number of students in the residence city, the total number of students in the destination city, the total distance, and the total student flow between the two cities, respectively, in natural logarithmic form. YHT represents the high-speed train line dummy variable. If a high-speed train line exists between two cities, it is assigned a value of "1" during the study period, and "0" otherwise.

| Variables | Obs | Mean | Std Dev. | Min. | Max. |
|---|---|---|---|---|---|
| FLOW | 9,720 | 81.14 | 233.27 | 0 | 4551 |
| CITY1 | 9,720 | 5,022.34 | 8,853.64 | 337 | 86,795 |
| CITY2 | 9,720 | 6,265.84 | 10,619.29 | 337 | 86,795 |
| DISTANCE | 9,720 | 761.27 | 395.65 | 29 | 2,059 |
| YHT | 9,720 | 0.005 | .0701 | 0 | 1 |

**Table 3.2** Descriptive Statistics

The dataset is summarised using the descriptive statistics of the variables presented in Table 3.2. The lower mean and standard deviation values pertain to the YHT variables. Furthermore, the maximum values of the variables differ significantly from each other. As shown in the table, all variables have been included in the model in logarithmic form due to the high differentiation among the variables.

| Null Hypothesis | LR Statistic | P Value |
|---|---|---|
| $H_0 = \mu_i = \gamma_j = \lambda_t = 0$ | 6652.21 | 0.000 |
| $H_0 = \mu_i = 0$ | 3459.87 | 0.000 |
| $H_0 = \gamma_j = 0$ | 1888.76 | 0.000 |
| $H_0 = \lambda_t = 0$ | 612.16 | 0.000 |

**Table 3.3** Likelihood Ratio Test Results

Within the scope of the study, the presence of unit effect was tested by using the LR test. The results displayed in Table 3.3 indicate that the null hypothesis of the LR test was rejected in testing the joint significance of each unit effect, meaning that at least one unit effect is significant under the alternative hypothesis. Each effect was investigated separately to see which unit effect is significant under the alternative hypothesis. When the LR test results are evaluated for each unit effect — specifically, resident city, destination city, and time unit effects — all are statistically significant. A three-dimensional three-effect model specification is preferred, as all unit effects are significant based on the LR test results.

Equation (3.3) displays the three dimensional and three effect panel data specification.

$$\mathrm{LFLOW}_{\mathrm{ijt}} = \alpha + \beta_1\ \mathrm{LCITY1}_{\mathrm{it}} + \beta_2\ \mathrm{LCITY2}_{\mathrm{jt}} + \beta_3\ \mathrm{LDISTANCE}_{\mathrm{ij}} + \beta_4\ \mathrm{YHT}_{\mathrm{ijt}} + \mu i + \gamma j + \lambda t + \mathrm{u}_{\mathrm{ijt}} \quad (3.3)$$

$i=1,.....,N, j=1,...M, t=1,....T$

$\mathrm{LFLOW}_{\mathrm{ijt}}$ represents the logged values of total student flow between $\mathrm{city}_{\mathrm{i}}$ and $\mathrm{city}_{\mathrm{j}}$ at time t, $\mathrm{LCITY1}_{\mathrm{it}}$ represents the total number of students from $city_i$ enrolled university in time t, $\mathrm{LCITY2}_{\mathrm{jt}}$ represent the total number of students from $city_j$ enrolled university in time t, $\mathrm{LDISTANCE}_{\mathrm{ij}}$ represent the distance between $city_i$ and $city_j$ in km, $\mathrm{YHT}_{\mathrm{ijt}}$ represent the highspeed train line between $city_i$ and $city_j$ in time t.

There are two distinct methods for estimating the equation. One is a fixed-effects estimator, and the other is a random-effects estimator. Since the main independent variables are unit or time-invariant variables in unnested multidimensional panel data models, generalised least squares estimation cannot be performed under the assumption of random effects (Tatoğlu Yerdelen, 2024, p. 396). The within-group estimator and the least squares dummy variable estimator are used under the assumption of fixed effects. In contrast, the maximum likelihood estimator is used under the assumption of random effects. Additionally, it is worth noting that although the loss of degrees of freedom is not significant due to the considerable sample size, the coefficients of the dummy variables become unstable as N and T increase. The Hausman test generally determines the selection of an estimator. Due to the inability to calculate the difference between the variances of the estimators, the Hausman test does not yield results. The robust Hausman test, however, is not yet available for these models.

## 3. FINDINGS

Following the selection of the panel data model to be employed in the analysis, estimations were performed, and the results of both estimators are shown in Table 4.1.

| | **2018** | | **2019** | | **2020** | |
|---|---|---|---|---|---|---|
| | **OLS** | **PPML** | **OLS** | **PPML** | **OLS** | **PPML** |
| DISTANCE | -0.948*** | -0.911*** | -0.955*** | -0.891*** | -0.959*** | -0.911*** |
| | (0.019) | (0.014) | (0.020) | (0.016) | (0.019) | (0.015) |
| CITY1 | 0.735*** | 0.813*** | 0.713*** | 0.774*** | 0.712*** | 0.762*** |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.012) | (0.010) |
| CITY2 | 0.788*** | 0.856*** | 0.742*** | 0.822*** | 0.764*** | 0.825*** |
| | (0.013) | (0.011) | (0.014) | (0.012) | (0.013) | (0.010) |
| YHT | 0.354** | 0.097** | 0.528*** | 0.203*** | 0.492** | 0.092* |
| | (0.175) | (0.043) | (0.159) | (0.047) | (0.200) | (0.054) |
| INTERCEPT | -3.116*** | -4.403*** | -2.085*** | -3.401*** | -2.383*** | -3.401*** |
| | (0.190) | (0.155) | (0.199) | (0.173) | (0.191) | (0.154) |
| N | 3,240 | 3,240 | 3,240 | 3,240 | 3,240 | 3,240 |
| $R^2$ | 0.772 | 0.8441 | 0.734 | 0.8125 | 0.755 | 0.8309 |

*Note: *, **, and *** represent significance at 10%, 5%, and 1%, respectively. Standard errors are presented in parentheses. $R^2$ represent the Pseudo $R^2$ for PPML regression.*

**Table 4.1** Cross-Sectional Results of OLS and PPML Estimations

The most significant difference between OLS and PPML is that zero observations in the dependent variable are treated as zero in the PPML approach, whereas in OLS, zero observations of the dependent variable are included in the model in logarithmic form and treated as 1. According to the OLS and PPML estimation results of the model, all variables are statistically significant in all years, and only the coefficients of distance and the constant term have a negative sign. When evaluated year by year, it is observed that the coefficient of the YHT variable increased by approximately 1.5 times from 2018 to 2019, while a slight decrease was observed in 2020, according to the OLS estimator. There is no significant differentiation between resident city and destination city variables from year to year, according to both estimators. There is a slight decrease in distance coefficients from year to year, as indicated by the OLS estimator. Generally, it can be said that the results of all estimations for all years are very close to each other, except for YHT, according to each estimation approach.

| | **OLS** | **PPML** | **OLS** | **PPML** |
|---|---|---|---|---|
| DISTANCE | -1.015*** | -0.900*** | -1.015*** | -0.903*** |
| | (0.012) | 0.009 | (0.012) | (0.008) |
| CITY1 | 0.799*** | 0.765 *** | 0.823*** | 0.781*** |
| | (0.008) | (0.006) | (0.008) | (0.005) |
| CITY2 | 0.752*** | 0.818*** | 0.773*** | 0.833*** |
| | (0.007) | (0.006) | (0.007) | (0.006) |
| YHT | 0.388*** | 0.185*** | 0.308*** | 0.143*** |
| | (0.110) | (0.029) | (0.105) | (0.027) |
| 2019 | | | 0.485*** | 0.465*** |
| | | | (0.018) | 0.017 |
| 2020 | | | 0.310*** | 0.259*** |
| | | | (0.018) | (0.016) |
| INTERCEPT | -2.732*** | -3.464*** | -3.361*** | -3.957 |
| N | 9,720 | 9,720 | 9,720 | 9,720 |
| $R^2$ | 0.723 | 0.8146 | 0.740 | 0.8285 |

*Note:* *, **, and *** represent significance at 10%, 5%, and 1%, respectively. Standard errors are presented in parentheses. $R^2$ represent the Pseudo $R^2$ for PPML regression.
**Table 4.2** Panel Data Results of the OLS and PPML Estimations

Typically, the Hausman test does not yield results in the model selection process because it fails to satisfy the test's asymptotic properties. Therefore, we report both OLS and PPML estimator results for the panel. Two regression results, including the high-speed dummy variable and year effect, are reported in Table 4.2.

According to the OLS model, all variables are statistically significant, and their coefficient signs are consistent with the expected direction. Although the gravity model theoretically yields negative signs for distance, it is worth noting that, in terms of the data used, distance is a time-invariant variable, and we do not have any specific expectations for distance coefficients. The estimation findings indicate that overall student mobility between cities i and j increases by roughly 0.79% and 0.75%, respectively, for every 1% increase in the total number of students placed in universities from cities i and j, while holding the effects of other variables constant. Additionally, a 1% increase in the presence of the YHT train line between cities i and j will lead to a 0.38% increase in total student mobility between city i and j. Besides that, a greater increase in coefficients is observed in 2019 compared to 2018, and a further increase is observed in 2020 compared to 2019.

PPML estimator results show that all independent variables are statistically significant, and their coefficient signs are consistent with expectations. According to the estimation results, while the effects of other variables are held constant, a 1% increase in the number of students placed in universities from city i results in approximately a 0.76% increase in total student mobility between cities i and j. A 1% increase in the distance between city i and city j approximately reduces the total student mobility between the two cities by 0.90%. In comparison, each 1% increase in the existence of a high-speed train line between city i and city j increases the total student mobility between cities i and j by around 0.18%. Therefore, the YHT dummy variable supports the notion that one of the most important factors for students in the context of choosing a university in another city is the existence of a high-speed train line.

## 4. CONCLUSION

This study investigates student mobility between 81 cities in Turkey for the period of 2018-2020 by using a gravity model approach, considering the distance between two cities, the total number of students enrolled in universities from each city, and the presence of high-speed train alternatives in terms of transportation options between the two cities. The findings have shown that the coefficients of all variables are statistically significant. It is observed that the existence of a high-speed train line between two cities is one of the most influential variables in the university preference process of individuals.

Individual differences are a significant factor influencing university and program preferences. Each person has different personal expectations and preferences, which are influenced by various factors, including the environment in which they live, the education they have received, their financial resources, and their future aspirations. In this case, the study can be expanded to include variables related to individual differences. This study could be expanded to include more personalised variables, such as economic conditions or the ranking of university entrance exams.

## REFERENCES

Arvis, J. F. and B. Shepherd (2013). The Poisson quasi-maximum likelihood estimator: A solution to the “adding up” problem in gravity models. *Applied Economics Letters*, 20(6), 515-519.

Aydın, U. and B. Ülengin (2022). Analysing air cargo flows of Turkish domestic routes: A comparative analysis of gravity models. *Journal of Air Transport Management*, 102, 102217.

Bekaroğlu, C. (2021). Impact of Distance on State University Enrolments: A Panel Data Analysis. *Yönetim Bilimleri Dergisi*, 19(40), 450-488.

Çavuş, M. and O.Aydın (2023). thestats: An Open-Data R Package for Exploring Turkish Higher Education Statistics. Yuksekogretim Dergisi, 13(1), 1–7.

Çavuş, M., and O.Aydın. (2022). thestats: R Package for Exploring Turkish Higher Education Statistics (p. 0.1.0) [Dataset].

Cooke, T. J., and P. Boyle (2011). The Migration of High School Graduates to College. *Educational Evaluation and Policy Analysis*, *33*(2), 202–213.

Council of Higher Education (YÖK). (2024). Türkiye Yükseköğretim Raporu 2024. Ankara: YÖK Publications.

Cullinan, J., D. Flannery, S. Walsh and S. Mc Coy (2013). Distance effects, social class and the decision to participate in higher education in Ireland, *Economic and Social Review*, 44, 19–51.

Cummings, W. K. (1993). “Global trends in oversea study.” In C. D. Goodwin (ed.), International

Ege, A. A. (2020). Analyzing the incidence and causes of field of study mismatch in Turkey: evidence from TURKSTAT labor force surveys. A Thesis Submitted to The Graduate School of Social Sciences of Middle East Technical University by Ahmet Alper Ege)

Erol A., H. Yergin and M Mercan (2012). Üniversite öğrencilerinin üniversite tercihlerinin belirleyicileri: Hakkâri örneği. *Sosyal ve Beşeri Bilimler Dergisi*, 4(2), 1-10.

European Commission. (2024). Higher Education and Skills Strategy for Turkey. Brussels: European Commission.

Faggian, A. and R.S. Franklin (2014). Human capital redistribution in the USA: the migration of the college-bound, *Spatial Economic Analysis*, 9, 376–395.

Frenette, M. (2006). Too far to go on? Distance to school and university participation, *Education Economics*, 14, 31–58.

Gibbons, S. and A. Vignoles (2012). Geography, Choice and Participation in Higher Education in England, *Regional Science and Urban Economics,* 42, 98–113.

Gül, H. And F. Yerdelen Tatoğlu (2019). Turizm Talebinin Panel Çekim Modeli Çerçevesinde Analizi. *Turizm Akademik Dergisi*, 6(1), 49-60.

Gür, Bekir S. (2022). Transition to Higher Education: Student Mobility Between Regions and Cities, Journal of University Research, August 2022, 5(2), 130-139.

Hwang, C.C. and G. C. Shiao (2011). Analyzing air cargo flows of international routes: An empirical study of Taiwan Taoyuan International Airport. *Journal of Transport Geography* 19 (4), 738–744.

Iwasaki, I. and K. Suganuma (2013). "A Gravity Model of Russian Trade: The Role of Foreign Direct Investment and Socio-Cultural Similarity," RRC Working Paper Series 40, Russian Research Center, Institute of Economic Research, Hitotsubashi University.

Kızıltan, A., and H. Şahin (2020). A literature review on the main problems encountered in applying the gravity model and empirical solution strategies. *Dumlupınar Üniversitesi Sosyal Bilimler Dergisi,* (64), 175-190.

Kjellström, C. and H. Regnér (1999). The effects of geographical distance on the decision to enrol in university education, *Scandinavian Journal of Educational Research*, 43, 335–348.

Kolat Ş. D. and D. Göktaş (2024). “Effect of 1992 University Expansion on Regional Innovation Ecosystems” Innovation Ecosystem: Definitions, Actors and Applications, Konya: Çizgi Yayınevi

Newton, I. (1687). Philosophiae Naturalis Principia Mathematica. London: Streater.

OECD (2024). Education at a Glance 2024: OECD Indicators. Paris: OECD Publishing.

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

ÖSYM (2023) Yükseköğretim Kurumları Sınavı (YKS) Kılavuzu. https://dokuman.osym.gov.tr/pdfdokuman/2023/YKS/kilavuz_30032023.pdf

Ravenstein, E. George (1885). The Laws of Migration, By John Corbett, in Spatially Integrated Social Science.

Sá, C., R. J. G. M Florax, and P. Rietveld (2004). Determinants of the regional demand for higher education in the Netherlands: a gravity model approach, *Regional Studies*, 38, 375–392.

Sá, Carla; F. Raymond;and P. Rietveld (2007). "Living-arrangement and university decisions of Dutch young adults". http://hdl.handle.net/1822/6824

Sá, C., D. A. Tavares, E. Justino and A. Amaral (2011). Higher education (related) choices in Portugal: joint decisions on institution type and leaving home. *Studies in Higher Education*, 36, 689–703.

Sá Carla, and M. T. A. França (2023). Factors associated with the mobility of college students in Brazil: an analysis using a gravity model, *Higher Education,* 85, 203–223.

Silva, J. S., and S.Tenreyro (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4), 641–658.

Spiess, C. K. and K. Wrohlich (2010). Does distance determine who attends a university in Germany*? Economics of Education Review*, 29, 470–479.

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

Tatoğlu Yerdelen, F. (2024). Panel Data Econometrics. Türkiye, İstanbul: BETA Publishing

World Bank. (2024). Turkey’s Innovation and Knowledge Economy Review. Washington, DC: World Bank Group.