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The Effect of Economic and Social Inequalities on Academic Success in Türkiye: Evidence from the Classical and Bayesian Discrete Choice Models*

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Abstract

The main objective of this study is to determine the effects of economic and social inequalities on academic success and to test whether the cycle of inequality is active through education. This objective is accomplished using classical and Bayesian discrete choice models for the sample obtained from Türkiye. The results reveal that students' economic and social characteristics affect their academic success and that these characteristics are possible sources of inequality in education. According to the findings obtained from models employed in the study, income, private school education, parental education level, region of residence, neediness to work, and the level of happiness with the family were found to have statistically significant effects on student success in getting into the desired university department and university placement ranking. Additionally, the results are compatible with the studies that report that the Bayesian approach yields more stable and appropriate results with smaller standard errors and confidence intervals.

Keywords: economic and social inequality, academic success, discrete choice models, Bayesian econometric approach

JEL Classification: C11, C25, I24, D63

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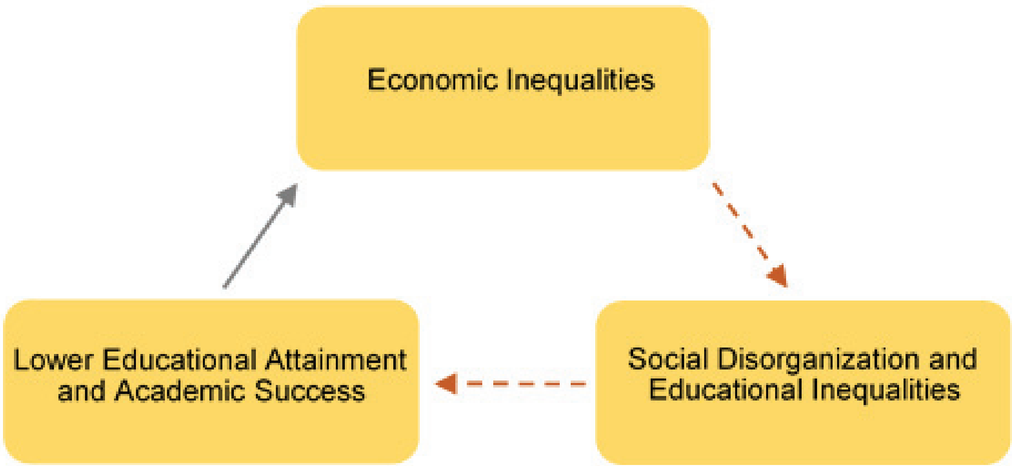
1. Introduction

Inequality is an economic and social problem that occurs in all fields of life for different reasons. Although economic inequality comes to mind first when talking about inequality, inequality is an issue that needs to be addressed in different dimensions and dynamics. Economic inequality is a measurement tool for many other inequalities. Thus, it is a 'showcase' variable. However, it is essential to understand the multidimensional pattern in the background. While economic inequalities are the result of many other inequalities, they can also stand as the cause of these inequalities. This statement holds true for social and many other fields of inequality. In this case, the following question arises: 'Is inequality a vicious circle?'. The answer is not simple. In particular, the cause-and-effect relationship between inequalities in education and other inequalities is a subject of debate that needs to be carefully examined. This relationship pattern is the starting point of this study.

The relationship between education and socioeconomic inequalities is explained by a two-way interaction: causality from education to socioeconomic inequalities and causality from socioeconomic inequalities to education. Theories of educational inequalities used to explain individual income differences are crucial for understanding these relationships. While income inequalities are explained by educational inequalities, educational inequalities are based on inequalities in social, economic, and environmental factors (Sahota, 1978). There are studies with different perspectives trying to explain this pattern. Some studies addressing the relationship between individuals' socioeconomic status and academic success have found evidence supporting this relationship (Sirin, 2005; Hassan and Rasiah, 2011; Gobena, 2018; Pruitt et al., 2019; Liu et al., 2022; Islam and Khan, 2017; Li et al., 2023). On the other hand, in the study by Sulaiman et al. (2020), students stated that the socioeconomic status of their families did not affect their academic success. However, this does not weaken the consensus in the literature on the existence of a relationship between socioeconomic status and academic success. Machebe et al. (2017), confirming that family income affects students' academic success, revealed that parents' participation in their children's school activities compensated for this disadvantage. The socioeconomic profile of a family directly affects the investment in a student's education (better quality school, supporting books, tutors, etc.), creating effects on academic success (Hassan and Rasiah, 2011; Suna et al., 2020). Another mechanism influencing this relationship emerges through the effect of socioeconomic status on students' cognitive and behavioural characteristics. Accordingly, a lower socioeconomic status corresponds to lower academic success and diminished levels of engagement compared to other students, particularly in behavioural and cognitive terms (Tomaszewski et al., 2020; Peng and Kievit, 2020; Lurie et al., 2021). According to Workman (2022), the relationship between income inequality and academic success can be partially explained by the clustering of disadvantaged students in high-poverty schools/districts and the more intensive parenting practices observed among parents with high socio-economic status.

Another dimension of the pattern is the effect of educational inequalities on economic inequalities. Here, the educational inequalities that arise due to individuals' socioeconomic characteristics, not the inequalities that occur based on structural factors, are evaluated. These inequalities are expected to affect individuals' income levels by influencing academic success, the quality of university education, and, ultimately, human capital. In addition, Chevalier et al. (2013) showed that family income and family education level, which are two important components of an individual's socioeconomic status, affect the individual's decision to continue education as well. In his study, Prakhov (2021) reported that an individual's income at work after graduation was positively related to academic success at university entrance and found that family income and school structure had an indirect effect on the individual's income. The impact of an individual's socioeconomic status on education and its quality is evident. At this point, a cycle of inequality comes to the fore. This is because many studies confirm the positive effect of the level and quality of education on the wages earned in working life (Kurt and Gümüş, 2020; Li et al., 2021). Watts (2020) found that academic success, along with some other factors, is important for economic gains and the long-term validity of the effect.

Figure 1: Inequality cycle



Source: authors' processing

The inequality cycle discussed with evidence from the literature is summarised in Figure 1. Hence, it is anticipated that students' socioeconomic status will be reflected in their level of academic success, marked by various social and educational differences. Differences in academic success level will have effects on the individual's post-graduation (short- and long-term) income. Therefore, there is a self-reinforcing cycle in which economic inequalities create economic inequalities through education.

This study aims to investigate the effects of students' socioeconomic characteristics on their academic success in Türkiye. Türkiye, which ranks last among OECD countries in terms of equal income distribution, had a Gini coefficient value of 0.415 in 2023 (OECD, 2023). Therefore, the effect of this high level of inequality, along with some other socioeconomic variables, on academic success is noteworthy. In other words, this study examines whether some inequalities in education support high-income inequality. According to the proposed inequality cycle, income inequality and other social factors cause inequalities in education. A consequence of inequalities in education is lower academic success, wage differences in working life, and income inequality. When it is assumed that the effect of socioeconomic characteristics, which are considered the cause and effect of inequality in Türkiye, on academic success is found to be significant, it can be stated that a part (shown by orange-dashed arrows) of the inequality cycle is active. The effect of academic success on economic inequalities is confirmed by the literature discussed. However, this part of the cycle is not included in the scope of this study. It is envisaged that the conclusions put forward for Türkiye in the study can be used to develop anti-inequality policies for countries with high levels of inequality.

This study tests the relationship between students' socioeconomic characteristics and their academic success in Türkiye. The null hypothesis in the test of the relationship between socioeconomic status and academic success is that the coefficients of the independent variables are equal to zero. Failure to reject the null hypothesis means that socioeconomic inequalities are not transmitted to academic success through education. Accordingly, it suggests that the inequality cycle is not active. The desired situation for more equal living conditions is for the coefficients of the variables in the model to be statistically equal to zero.

2. Data and Methodology

This study explains the variable of academic success with a series of explanatory variables that represent the economic and social situation in Türkiye and are possible sources of inequality. University admission success and exam score ranking in Türkiye, which are perceived as outcomes of the entire pre-university education life, were accepted as academic success criteria. A survey was conducted with 509 newly enrolled students at the university, selected by the convenience sampling method. Opinions of experts in education, preliminary interviews, and researcher expectations were used for determining the independent variables and preparing the survey form. The dependent and independent variables used in the study, categories of variables, and descriptive statistics are presented in Table 1.

Table 1: Variables, categories, and descriptive statistics

Variables			Descriptive statistics	
	Categorical variables			
		Categories of variables	**Freq.**	**Percent**
Dependent variables	**Student's success in getting into the target undergraduate department**	Unsuccessful	248	48.72
		Successful	261	51.28
	Student's undergraduate placement examination ranking	1-10,000	65	12.77
		10,001-20,000	69	13.35
		20,001-50,000	92	18.27
		50,001 or above	283	55.60
Independent variables	**The region of Türkiye where the student resides**	Marmara region	87	17.09
		Central Anatolian region	72	14.15
		Aegean region	83	16.31
		Mediterranean region	63	12.38
		Black Sea region	57	11.20
		Eastern Anatolian region	85	16.70
		Southeastern Anatolian region	62	12.18
	Administrative structure of the student's place of residence	Province	213	41.85
		District	191	37.52
		Village	105	20.63
	Gender	Female	341	66.99
		Male	168	33.01
	The student's parents are both alive.	No	62	12.18
		Yes	447	87.82
	Maternal education level	No formal education	124	24.36
		Primary or middle school	222	43.61
		High school	86	16.90
		Associate or bachelor's degree	54	10.61
		Master's or doctorate degree	23	4.52
	Paternal education level	No formal education	27	5.30
		Primary or middle school	223	43.81
		High school	112	22.00
		Associate or bachelor's degree	111	21.81
		Master's or doctorate degree	36	7.07
	Chronic illness or disability that affects the student's life	No	394	77.41
		Yes	115	22.59
	The student having their own room	No	266	52.26
		Yes	243	47.74
	The student having a personal computer	No	332	65.23
		Yes	177	34.77
	The student having internet access	No	209	41.06
		Yes	300	58.94
	Availability of private courses and lesson support for the student	No support	274	53.83
		Only private courses	171	33.60
		Both private courses and lesson support	64	12.57
	The student having to work to earn a living for themselves and their family	No	355	69.74
		Yes	154	30.26
	The happiness evaluation of the student regarding the time spent with their family	Very unhappy	10	1.96
		Moderately unhappy	49	9.63
		Moderately happy	280	55.01
		Very happy	170	33.40
	Numerical variables			
			Mean	Std. dev.
	Average monthly income of the student's family (TL)		7687.527	10603.01
	Number of siblings of the student		4.212	2.615
	Duration (years) of the student's private school education		1.025	2.939

Note: information about the student's socioeconomic characteristics covers the period during which they reside with their family.
Source: authors' processing

Discrete choice models were used to analyse the effect of differences in students' economic and social characteristics on their academic success. Binary choice models (binary probit-logit) were used to explain student success in getting into the desired university department with independent variables. Student success in the placement examination was divided into four categories, and its relationship with the student's socioeconomic characteristics was analysed using ordered choice models (ordered probit-logit).

Binary choice models are models with a categorical dependent variable in which there are two choice alternatives for the decision units. They try to explain the probability of the decision-making unit choosing alternative 1 in the face of alternatives coded as 1 and 0, such as success or failure, having or not having, and choosing or not choosing (Davidson and MacKinnon, 2003). These models differ according to the characteristics of the cumulative distribution function. A model constructed based on the normal cumulative distribution function is called probit. $P\left(y_i = 1 \middle| x_i\right)$ represents the probability of the dependent variable taking the alternative value of 1. The probit model is written as follows:

$$\Phi\left(x_i'\beta\right) = F\left(x_i'\beta\right) = \int_{-\infty}^{x'\beta} \frac{1}{\sqrt{2\pi}} e^{\frac{-1}{2}Z^2} dZ = P\left(y_i = 1 \middle| x_i\right) \tag{1}$$

where Φ is the normal cumulative distribution function (Greene, 2018). The probit model differs from the logit model in terms of the cumulative distribution function. The logit model with the logistic cumulative distribution function is written as follows (Wooldridge, 2020):

$$\Lambda(x_i'\beta) = \frac{e^{(x_i'\beta)}}{1 + e^{(x_i'\beta)}} = P\left(y_i = 1 \middle| x_i\right) \tag{2}$$

Here Λ represents the logistic cumulative distribution function. Binary choice models explain the probability of the event occurring in a two-alternative situation (the probability of being successful, choosing, having, etc.) as a function of independent variables. On the other hand, in multinomial choice models, the dependent variable has more than two alternatives.

Another variable representing the variable of academic success in this study is the categorical form of the student's undergraduate placement examination ranking. Based on the ordered nature of the dependent variable alternatives, ordered choice models were used. Ordered choice models are models in which a continuously changing utility index is censored and included as a dependent variable through a categorisation process that indicates rankings. Ordered probit and ordered logit models are applicable when the observed categories represent the intervals of a latent variable—the utility index—that is linear in unknown parameters and in cases that exhibit a normal or logistic cumulative distribution function for the probability of choice.

In a probit model with a standard normal distribution of the random error term, when the unobserved utility index y^* is censored by the alternative choice J with a threshold value of $J = 1$, the choice alternatives and threshold values can be represented as follows (for $J = 3$):

$$\begin{aligned} &y^* \leq \mu_1 && \Rightarrow y = 0 \\ &\mu_1 < y^* \leq \mu_2 && \Rightarrow y = 1 \\ &\mu_2 < y^* && \Rightarrow y = 2 \end{aligned} \tag{3}$$

Here, μ_{J-1} , which are the unknown coefficients to be estimated with β parameters, indicate order and are greater than zero ($0 < \mu_1 < \mu_2$) (Çelik, 2016). It is assumed that the error term ε has a standard normal distribution with a mean of 0 and a variance of 1. In this case, the probabilities for the alternatives are obtained with help of Equation (4).

$$\begin{aligned} &P\left(y^* \leq \mu_1\right) = P\left(y = 0 | x\right) = \Phi\left(\mu_1 - x'\beta\right) \\ &P\left(\mu_1 < y^* \leq \mu_2\right) = P\left(y = 1 | x\right) = \Phi\left(\mu_2 - x'\beta\right) - \Phi\left(\mu_1 - x'\beta\right) \\ &P\left(\mu_2 < y^*\right) = P\left(y = 2 | x\right) = 1 - \Phi\left(\mu_2 - x'\beta\right) \end{aligned} \tag{4}$$

In examining the choice probabilities among ordered alternatives, the ordered logit model will be preferred over the ordered probit model, as the errors show a logistic distribution. The ordered logit model, which produces similar results to the ordered probit model in practice, is also known as the proportional odds model because it provides constant odds ratios in regression experiments, narrowed by the assumptions it requires (Williams, 2016). Following the terminology in Equation 3, the probabilities for the alternatives in the ordered logit model are written as follows (Kiren Gürler, 2021):

$$\begin{aligned} &P\left(y^* \leq \mu_1\right) = P\left(y = 0 | x\right) = \Lambda\left(\mu_1 - x'\beta\right) = \frac{1}{\left[1 + e^{(x'\beta - \mu_1)}\right]} \\ &P\left(\mu_1 < y^* \leq \mu_2\right) = P\left(y = 1 | x\right) = \Lambda\left(\mu_2 - x'\beta\right) - \Lambda\left(\mu_1 - x'\beta\right) \\ &\qquad = \frac{1}{\left[1 + e^{(x'\beta - \mu_2)}\right]} - \frac{1}{\left[1 + e^{(x'\beta - \mu_1)}\right]} \\ &P\left(\mu_2 < y^*\right) = P\left(y = 2 | x\right) = 1 - \Lambda\left(\mu_2 - x'\beta\right) = 1 - \frac{1}{\left[1 + e^{(x'\beta - \mu_2)}\right]} \end{aligned} \tag{5}$$

In the estimation process of these models, the maximum likelihood estimation (MLE) method which meets the assumed requirements is commonly used, and it constitutes the classical approach in the estimation of discrete choice models. The MLE method aims to obtain parameter estimates that maximise the probability of observing sample data (Kennedy, 2008). The probability density function of the variable based on the set of coefficients θ is shown as $f\left(y | \theta\right)$, where y is the random variable. While the logarithmic form of the likelihood function is written as:

$$\ln L\left(\theta|y\right)=\sum_{i=1}^{n}\ln f\left(y_i|\theta\right) \tag{6}$$

MLE deals with which θ value maximises the probability of choosing the sample at hand.

The alternative to the classical approach in discrete choice models is the Bayesian approach. The most important sources of difference in terms of results between the classical econometric approach and the Bayesian econometric approach, in which researchers can draw conclusions by using a priori information together with existing data, are a priori information and sample size. Despite the concerns that not paying sufficient attention to the selection of a priori information will deviate the estimation results from scientific objectivity (Berger, 2006; Moyé, 2008), it can be stated that the Bayesian approach is a good alternative to the classical approach, especially for small samples, even in cases where a priori information is not used. Several studies using different models, sample sizes, and prior distributions have found that the Bayesian econometric approach yields more appropriate results with smaller confidence intervals and lower standard errors (Acquah, 2013; Chiaka and Adam, 2019; David et al., 2007; Lynch, 2005; Mahanta et al., 2015). Çağlayan Akay and Sedefoğlu (2017), Petrone et al. (2014), and Zellner and Rossi (1984) revealed that the Bayesian econometric approach gave successful results in small samples. Galindo-Garre et al. (2004) demonstrated that point estimates and confidence intervals obtained with the Bayesian approach were better than those obtained with the MLE method, regardless of the prior distribution. Considering the advantages of the Bayesian approach and the learned, accepted, and wide usage area of the classical approach, the calibrated Bayes compromise was proposed through the selection of the strengths of the classical and Bayesian approaches (Little, 2006).

The Bayesian approach works on the principle of obtaining the posterior probability distribution for the parameters. This can be summarised as follows:

$$\text{posterior probability} \propto \textit{likelihood function} \times \textit{prior probability} \tag{7}$$

The point expressed by Equation (7) is that the product of the prior probability distribution and the likelihood function is proportional to the posterior probability (Gelman et al., 2014; Greene, 2018; Koop, 2003). This can be written using econometric terminology as follows:

$$p\left(\theta|y\right)\propto L\left(\theta|y\right)\pi\left(\theta\right) \tag{8}$$

where the prior distribution of θ is $\pi\left(\theta\right)$, the likelihood function for θ is $L(\theta|y)$, and the posterior distribution of θ is $p(\theta|y)$. The Bayesian estimator is expressed as the average of the posterior densities of the coefficients. Estimation is generally obtained by integration, approximate integral calculation with numerical techniques, or Monte Carlo methods (Greene, 2018). In the Bayesian econometric approach, the principle of creating a Markov chain is used in the process of obtaining the posterior distribution through iterative Monte Carlo simulation (Sorensen and Gianola, 2002). In Bayesian econometric modelling, the two main Markov chain Monte Carlo (MCMC) methods employed are the Gibbs sampling algorithm when conditional prior distributions have a standard form, and the Metropolis-Hastings algorithm when conditional prior distributions lack a standard form. For brevity and considering the scope of the study, the details of these methods are not elaborated here.

In this study addressing the effects of social and economic factors on academic success in Türkiye using binary and ordered choice models, the models were estimated separately using the classical and Bayesian econometric approaches. Thus, it was aimed to eliminate the effect of sample size on model estimation results. In the process of estimating the models with the Bayesian econometric approach, an information-free normal distribution was preferred to avoid criticism of subjectivity. The models were estimated using the Gibbs sampling algorithm and the Metropolis-Hastings algorithm for optimal results. The aim is to select the most appropriate model where convergence is achieved. Based on such selection, the most appropriate model estimation results are presented here.

3. Results

The findings obtained by estimating the binary probit model using the classical and Bayesian approaches are presented in Table 2. It was observed that the findings did not show any substantial difference in terms of the sign, magnitude, confidence intervals, and statistical significance of the coefficients. In both approaches, living in the Eastern Anatolian region, maternal education level of an associate or bachelor's degree, health status, family income, private school education, and deeming the time spent with family as moderately happy or very happy were found to have significant effects on student success in getting into the desired university department. However, this similarity is not true for the logit model. The results obtained from the classical and Bayesian estimations of the binary logit model are presented in Table 3. The Bayesian estimation of the logit model has important differences from the classical approach. The most striking of these is the difference regarding the significance of the coefficients. It was determined that the credible intervals obtained with the Bayesian approach differed significantly from those obtained with the classical approach, and accordingly, some variables reported as significant with the classical approach were statistically insignificant. Considering the sign of the coefficient related to the maternal education level of an associate or bachelor's degree, which was reported as statistically insignificant, unlike in the classical approach, it can be stated that the sign of the variable in question does not match economic expectations.

Table 2: Binary probit model classical and Bayesian estimation results

Variable		Classical approach				Bayesian approach				
		Coeff.	Std. error	Confidence interval		Mean	Std. dev.	MC-error	Credible interval	
Region	Central Anatolian	−0.0067	0.2259	−0.4494	0.4360	0.0002	0.2312	0.0040	−0.4496	0.4556
	Aegean	−0.1049	0.2233	−0.5426	0.3328	−0.1067	0.2249	0.0039	−0.5488	0.3373
	Mediterranean	−0.0233	0.2344	−0.4828	0.4360	−0.0203	0.2362	0.0039	−0.4826	0.4412
	Black Sea	−0.1449	0.2388	−0.6130	0.3230	−0.1463	0.2436	0.0040	−0.6262	0.3356
	Eastern Anatolian	−0.5705	0.2240	−1.0096	−0.1314	−0.5937	0.2280	0.0038	−1.0437	−0.1526
	Southeastern Anatolian	−0.2448	0.2390	−0.7134	0.2237	−0.2526	0.2393	0.0038	−0.7223	0.2125
Place of residence	District	−0.0044	0.1453	−0.2892	0.2804	−0.0055	0.1457	0.0025	−0.2893	0.2810
	Village	−0.1916	0.1807	−0.5458	0.1625	−0.1987	0.1836	0.0029	−0.5611	0.1580
Gender: Male		0.2464	0.1488	−0.0453	0.5381	0.2491	0.1488	0.0025	−0.0442	0.5396
Number of siblings		0.0011	0.0315	−0.0607	0.0629	0.0019	0.0319	0.0005	−0.0598	0.0660
Student’s parents are both alive.: Yes		−0.0494	0.1970	−0.4355	0.3367	−0.0469	0.2002	0.0032	−0.4315	0.3528
Maternal education level	Primary or middle school	−0.1080	0.1858	−0.4722	0.2561	−0.1133	0.1858	0.0029	−0.4712	0.2503
	High school	−0.3545	0.2653	−0.8745	0.1655	−0.3705	0.2669	0.0044	−0.8873	0.1548
	Associate or bachelor’s degree	−0.8342	0.3573	−1.5346	−0.1337	−0.8745	0.3576	0.0060	−1.5760	−0.1711
	Master’s or doctorate degree	0.3478	0.5992	−0.8265	1.5223	0.4583	0.6133	0.0191	−0.6602	1.7456
Paternal education level	Primary or middle school	0.1349	0.2901	−0.4338	0.7037	0.1476	0.2958	0.0045	−0.4284	0.7391
	High school	0.1116	0.3132	−0.5022	0.7254	0.1242	0.3152	0.0047	−0.4932	0.7445
	Associate or bachelor’s degree	0.0930	0.3572	−0.6072	0.7932	0.0963	0.3597	0.0057	−0.5950	0.8066
	Master’s or doctorate degree	0.4120	0.4617	−0.4928	1.3169	0.4453	0.4650	0.0084	−0.4440	1.3566
Chronic illness or disability: Yes		0.3988	0.1617	0.0818	0.7159	0.4110	0.1588	0.0027	0.1009	0.7205
Income		0.000030	0.000012	5.71e-06	0.000056	0.000033	0.000012	4.2e-07	9.56e-06	0.00005
Student’s own room: Yes		0.1794	0.1496	−0.1139	0.4727	0.1782	0.1509	0.0024	−0.1099	0.4777
Student’s personal computer: Yes		−0.0055	0.1647	−0.3284	0.3173	−0.0043	0.1652	0.0026	−0.3273	0.3153
Student’s internet access: Yes		0.2100	0.1519	−0.0877	0.5078	0.2090	0.1535	0.0023	−0.0861	0.5128
Student’s private school education		0.1183	0.0377	0.0444	0.1923	0.1276	0.0389	0.0010	0.0532	0.2046
Private courses and lesson support	Only private courses	−0.1784	0.1440	−0.4607	0.1039	−0.1912	0.1428	0.0023	−0.4694	0.0904
	Both private courses and lesson support	−0.0966	0.2456	−0.5780	0.3847	−0.1055	0.2450	0.0041	−0.5774	0.3669
Working in a job: Yes		−0.0854	0.1537	−0.3867	0.2159	−0.0900	0.1531	0.0023	−0.3911	0.2100
Happiness with family	Moderately unhappy	0.6940	0.6836	−0.5459	2.0339	0.8965	0.7369	0.0207	−0.4117	2.4844
	Moderately happy	1.4359	0.6603	0.1416	2.7301	1.6621	0.7130	0.0207	0.4182	3.2211
	Very happy	1.5442	0.6654	0.2400	2.8485	1.7785	0.7167	0.0205	0.5316	3.3434
Constant		−1.6269	0.7891	−3.1737	−0.0802	−1.8709	0.8424	0.0215	−3.6371	−0.3236
Model fit statistics		LR statistic		119.91		Acceptance rate			1	
		Log-likelihood		−286.361		Average efficiency			0.315	
		Probability		0.000		Log-marginal likelihood			−468.395	
		AIC		636.722		DIC			636.664	

Source: authors’ own calculations

Table 3: Binary logit model classical and Bayesian estimation results

Variable		Classical approach				Bayesian approach				
		Coeff.	Std. error	Confidence interval		Mean	Std. dev.	MC-error	Credible interval	
Region	**Central Anatolian**	−0.0145	0.3737	−0.7470	0.7180	0.0236	0.1274	0.0028	−0.2207	0.3030
	Aegean	−0.1707	0.3687	−0.8936	0.5520	0.0070	0.1219	0.0019	−0.2477	0.2606
	Mediterranean	−0.0283	0.3825	−0.7781	0.7214	−0.0134	0.1182	0.0049	−0.2664	0.2204
	Black Sea	−0.2501	0.3912	−1.0170	0.5167	−0.0236	0.1256	0.0016	−0.3034	0.2236
	Eastern Anatolian	−0.9243	0.3729	−1.6552	−0.1934	−0.1574	0.1587	0.0104	−0.5320	0.0683
	Southeastern Anatolian	−0.3722	0.3931	−1.1427	0.3983	−0.0164	0.1261	0.0030	−0.2862	0.2355
Place of residence	**District**	−0.0048	0.2384	−0.4721	0.4624	0.0231	0.1116	0.0018	−0.1982	0.2626
	Village	−0.2951	0.2962	−0.8757	0.2854	−0.0832	0.1283	0.0038	−0.3848	0.1331
Gender: Male		0.3984	0.2482	−0.0879	0.8849	0.0688	0.1252	0.0051	−0.1389	0.3647
Number of siblings		0.0040	0.0520	−0.0979	0.1061	−0.0598	0.0329	0.0013	−0.1210	0.0108
Student's parents are both alive.: Yes		−0.0618	0.3259	−0.7007	0.5769	−0.0440	0.1213	0.0027	−0.3198	0.1902
Maternal education level	**Primary or middle school**	−0.1835	0.3068	−0.7848	0.4178	−0.0134	0.1091	0.0015	−0.2424	0.2125
	High school	−0.5864	0.4409	−1.4507	0.2778	−0.0637	0.1295	0.0043	−0.3692	0.1613
	Associate or bachelor's degree	−1.4151	0.5990	−2.5892	−0.2409	−0.0895	0.1668	0.0072	−0.4776	0.1497
	Master's or doctorate degree	0.5189	1.0564	−1.5515	2.5894	0.0381	0.1430	0.0028	−0.2280	0.3679
Paternal education level	**Primary or middle school**	0.2821	0.4924	−0.6831	1.2473	−0.0150	0.1127	0.0020	−0.2466	0.2119
	High school	0.2391	0.5302	−0.8000	1.2782	−0.0395	0.1197	0.0021	−0.3015	0.1868
	Associate or bachelor's degree	0.2119	0.6043	−0.9726	1.3964	−0.0529	0.1291	0.0030	−0.3535	0.1767
	Master's or doctorate degree	0.7425	0.7902	−0.8064	2.2914	0.0060	0.1507	0.0093	−0.2909	0.3015
Chronic illness or disability: Yes		0.6562	0.2680	0.1309	1.1816	0.0885	0.1364	0.0054	−0.1272	0.4193
Income		0.000058	0.000027	4.87e-06	0.000111	0.000060	0.000019	4.1e-07	0.00002	0.00010
Student's own room: Yes		0.3032	0.2449	−0.1768	0.7834	0.0627	0.1196	0.0039	−0.1470	0.3399
Student's personal computer: Yes		−0.0366	0.2721	−0.5700	0.4967	0.0099	0.1178	0.0017	−0.2337	0.2590
Student's internet access: Yes		0.3379	0.2499	−0.1520	0.8279	0.0837	0.1255	0.0047	−0.1211	0.3779
Student's private school education		0.1999	0.0685	0.0656	0.3342	0.1267	0.0579	0.0025	0.0285	0.2542
Private courses and lesson support	**Only private courses**	−0.2871	0.2364	−0.7504	0.1762	−0.0699	0.1185	0.0050	−0.3399	0.1383
	Both private courses and lesson support	−0.1715	0.4048	−0.9649	0.6219	−0.0004	0.1209	0.0040	−0.2575	0.2469
Working in a job: Yes		−0.1357	0.2536	−0.6329	0.3614	−0.0714	0.1177	0.0055	−0.3335	0.1395
Happiness with family	**Moderately unhappy**	1.1369	1.2098	−1.2342	3.5080	−0.1550	0.1698	0.0082	−0.5640	0.0772
	Moderately happy	2.3918	1.1682	0.1021	4.6814	0.0235	0.1445	0.0056	−0.2017	0.3036
	Very happy	2.5521	1.1741	0.2509	4.8534	0.0993	0.1658	0.0079	−0.1207	0.4330
Constant		−2.8176	1.3758	−5.5141	−0.1210	−0.1196	0.1846	0.0105	−0.5187	0.1163
Model fit statistics		LR statistic		119.22		Acceptance rate			0.592	
		Log-likelihood		−286.706		Average efficiency			0.1071	
		Probability		0.000		Log-marginal likelihood			−297.295	
		AIC		772.280		DIC			632.513	

Source: authors' own calculations

According to the findings obtained from the binary choice models, the positive effect of family income and the number of years in private school education on success in getting into the desired university department was confirmed by all alternative models. On the other hand, in the case that was rejected by the Bayesian logit model and confirmed by the other three alternative models, the variables of living in the Eastern Anatolian region and maternal education level of an associate or bachelor's degree were found to have statistically significant negative effects on academic success, while chronic illness or disability, income, the number of years in private school education, and deeming the time spent with family as moderately happy or very happy were determined to have statistically significant positive effects on academic success. Given the coefficients of the variables, it is clear that maternal education level and health status have signs that are not consistent with expectations. The rejection of these variables, which do not match expectations, by the Bayesian logit model suggests that this model is more sensitive in decision processes. However, further evidence is needed on this subject. Thus, based on the evaluation of the variables on which the models generally agree in terms of coefficients, signs, and significance and that align with economic criteria, it can be stated that student success in getting into the desired university department is affected by income, private school education, happy time spent with the family, and the region where the student resides.

Findings from the classical and Bayesian estimations of ordered probit and logit models are presented in Table 4 and Table 5. According to the findings obtained from the ordered choice models, the classical approach determined that the variables of living in the Aegean and Mediterranean regions and family income positively affected success in university placement. The expression "positively affected" is intentionally chosen here. This is because in order not to cause any numerical confusion in the study, undergraduate placement ranking was categorised according to the numerical values of the success ranking. In other words, it should be taken into account that the student in a higher value category has a higher numerical value of success ranking (while the undergraduate placement ranking is in the range of 0–10,000 for the 0^{th} category, the 1^{st} category represents the placement ranking between 10,001 and 20,000). The category with a higher numerical value means lower academic success. As a result of the estimations made with the Bayesian approach, it was determined that living in the Aegean and Mediterranean regions, maternal education level of an associate or bachelor's degree, maternal education level of a master's or doctorate degree, paternal education level of an associate or bachelor's degree, family income, private school education, and being moderately happy and very happy with the family increased student success level in undergraduate placement rankings. On the other hand, living in the Southeastern Anatolian region, maternal education level of primary or middle school, having to work to earn a living for oneself and family, and being moderately unhappy during the time spent with family were detected to have negative effects on success ranking. The findings suggest that in Türkiye, economic and social characteristics are influential on individuals' undergraduate placement ranking, which is considered an outcome of the entire educational life, and success in getting into the desired department.

Table 4: Ordered probit model classical and Bayesian estimation results

Variable		Classical approach				Bayesian approach				
		Coeff.	Std. error	Confidence interval		Mean	Std. dev.	MC-error	Credible interval	
Region	Central Anatolian	−0.2231	0.2017	−0.6185	0.1721	−0.0554	0.1471	0.0017	−0.3479	0.2313
	Aegean	−0.4123	0.1975	−0.7995	−0.0250	−0.1955	0.1526	0.0087	−0.4980	0.0961
	Mediterranean	−0.4461	0.2168	−0.8711	−0.0210	−0.1751	0.1545	0.0021	−0.4812	0.1260
	Black Sea	−0.1992	0.2133	−0.6174	0.2190	−0.0120	0.1572	0.0051	−0.3273	0.2928
	Eastern Anatolian	−0.1425	0.1978	−0.5302	0.2451	0.0539	0.1436	0.0015	−0.2290	0.3341
	Southeastern Anatolian	0.3581	0.2374	−0.1071	0.8234	0.3632	0.1733	0.0028	0.0315	0.7088
Place of residence	District	−0.0547	0.1303	−0.3102	0.2006	−0.0077	0.1117	0.0019	−0.2266	0.2134
	Village	−0.1792	0.1709	−0.5143	0.1558	−0.0866	0.1408	0.0020	−0.3674	0.1859
Gender: Male		−0.0059	0.1327	−0.2660	0.2541	0.0425	0.1159	0.0020	−0.1826	0.2777
Number of siblings		0.0022	0.0285	−0.0537	0.0581	0.0519	0.0240	0.0005	0.0048	0.0993
Student’s parents are both alive.: Yes		−0.0230	0.1864	−0.3884	0.3422	0.1498	0.1436	0.0052	−0.1352	0.4271
Maternal education level	Primary or middle school	0.2268	0.1735	−0.1132	0.5669	0.2841	0.1228	0.0025	0.0461	0.5282
	High school	0.1744	0.2455	−0.3067	0.6556	0.2293	0.1533	0.0028	−0.0650	0.5396
	Associate or bachelor’s degree	0.0748	0.3204	−0.5531	0.7028	0.0951	0.1847	0.0043	−0.2607	0.4653
	Master’s or doctorate degree	−0.7079	0.3948	−1.4817	0.0658	−0.3083	0.2141	0.0046	−0.7429	0.0964
Paternal education level	Primary or middle school	−0.0692	0.2814	−0.6208	0.4823	0.2566	0.1465	0.0035	−0.0295	0.5442
	High school	−0.1863	0.3034	−0.7810	0.4083	0.1453	0.1562	0.0048	−0.1543	0.4535
	Associate or bachelor’s degree	−0.3918	0.3351	−1.0486	0.2650	−0.0016	0.1599	0.0030	−0.3145	0.3146
	Master’s or doctorate degree	−0.4941	0.4045	−1.2871	0.2987	−0.0726	0.1967	0.0035	−0.4629	0.3112
Chronic illness or disability situation: Yes		0.0557	0.1432	−0.2249	0.3364	0.0608	0.1231	0.0024	−0.1785	0.3005
Income		−0.000042	0.00001	−0.00006	−0.00001	−0.000041	0.00001	3.3e−07	−0.000064	−0.000019
Student’s own room: Yes		−0.1278	0.1348	−0.3920	0.1364	−0.0433	0.1178	0.0019	−0.2735	0.1871
Student’s personal computer: Yes		−0.0169	0.1457	−0.3025	0.2687	−0.0249	0.1244	0.0017	−0.2666	0.2194
Student’s internet access: Yes		0.0502	0.1456	−0.2352	0.3356	0.0877	0.1236	0.0014	−0.1547	0.3300
Student’s private school education		−0.0349	0.0243	−0.0826	0.0127	−0.0332	0.0234	0.0004	−0.0793	0.0124
Private courses and lesson support	Only private courses	0.0577	0.1325	−0.2020	0.3176	0.0412	0.1140	0.0036	−0.1798	0.2651
	Both private courses and lesson support	0.1489	0.2120	−0.2665	0.5644	0.0856	0.1496	0.0076	−0.2065	0.3738
Working in a job: Yes		0.1665	0.1450	−0.1176	0.4507	0.2552	0.1209	0.0012	0.0196	0.4934
Happiness with family	Moderately unhappy	0.1270	0.5163	−0.8849	1.1390	0.4798	0.2125	0.0183	0.0518	0.9115
	Moderately happy	−0.5837	0.4731	−1.5112	0.3436	0.0565	0.1576	0.0146	−0.2410	0.3667
	Very happy	−0.6782	0.4786	−1.6163	0.2598	−0.0597	0.1700	0.0103	−0.3956	0.2724
Model fit statistics		LR statistic		184.19		Acceptance rate			0.606	
		Log-likelihood		−485.707		Average efficiency			0.059	
		Probability		0.000		Log-marginal likelihood			−548.702	
		AIC		1039.414		DIC			1035.565	

Source: authors’ own calculations

Table 5: Ordered logit model classical and Bayesian estimation results

Variable		Classical approach				Bayesian approach				
		Coeff.	Std. error	Confidence interval		Mean	Std. dev.	MC-error	Credible interval	
Region	Central Anatolian	−0.3454	0.3456	−1.0229	0.3320	−0.1902	0.11087	0.00137	−0.4080	0.0255
	Aegean	−0.6682	0.3365	−1.3277	−0.0087	−0.6860	0.06839	0.00138	−0.8204	−0.5517
	Mediterranean	−0.7658	0.3680	−1.4872	−0.0445	−0.4464	0.12126	0.00197	−0.6856	−0.2096
	Black Sea	−0.3323	0.3697	−1.0569	0.3922	−0.2665	0.18740	0.00160	−0.6348	0.0960
	Eastern Anatolian	−0.2348	0.3441	−0.9092	0.4396	0.0523	0.16321	0.00770	−0.2618	0.3761
	Southeastern Anatolian	0.6523	0.4213	−0.1735	1.4782	0.5996	0.22178	0.00230	0.1636	1.0324
Place of residence	District	−0.1611	0.2236	−0.5995	0.2773	−0.1192	0.13094	0.00100	−0.3778	0.1389
	Village	−0.4186	0.2954	−0.9977	0.1603	−0.4004	0.10836	0.00072	−0.6132	0.1886
Gender: Male		0.0153	0.2287	−0.4331	0.4637	−0.0803	0.17254	0.00485	−0.4168	0.2596
Number of siblings		−0.0084	0.0467	−0.1000	0.0830	0.0039	0.02023	0.00089	−0.0353	0.0438
Student's parents are both alive.: Yes		0.0611	0.3125	−0.5514	0.6737	0.1243	0.17612	0.00198	−0.2205	0.4660
Maternal education level	Primary or middle school	0.3198	0.2961	−0.2604	0.9002	0.3949	0.09849	0.00125	0.2012	0.5883
	High school	0.2058	0.4063	−0.5906	1.0022	0.2853	0.15275	0.00155	−0.0122	0.5856
	Associate or bachelor's degree	0.0502	0.5315	−0.9914	1.0919	−0.3127	0.14465	0.00337	−0.5957	−0.0279
	Master's or doctorate degree	−1.18120	0.6605	−2.4758	0.1134	−1.2002	0.27782	0.00237	−1.7536	−0.6596
Paternal education level	Primary or middle school	0.0123	0.4932	−0.9543	0.9790	0.1004	0.09623	0.00066	−0.0880	0.2900
	High school	−0.1981	0.5294	−1.2358	0.8394	−0.1458	0.15108	0.00246	−0.4431	0.1495
	Associate or bachelor's degree	−0.5544	0.5778	−1.6870	0.5782	−0.4505	0.12282	0.00765	−0.6947	−0.2118
	Master's or doctorate degree	−0.6743	0.7050	−2.0561	0.7074	−0.6005	0.31814	0.00579	−1.2246	0.0317
Chronic illness or disability situation: Yes		0.0504	0.2409	−0.4216	0.5226	0.1731	0.15992	0.00175	−0.1372	0.4874
Income		−0.000078	0.00002	−0.000120	−0.000033	−0.000059	7.68e−06	1.9e−07	−0.000075	−0.000044
Student's own room: Yes		−0.2304	0.2312	−0.6837	0.2227	−0.2476	0.13870	0.00397	−0.5203	0.0246
Student's personal computer: Yes		−0.0635	0.2517	−0.5570	0.4299	0.0006	0.12971	0.00110	−0.2529	0.2565
Student's internet access: Yes		0.0669	0.2494	−0.4220	0.5558	0.0687	0.08841	0.00117	−0.1044	0.2418
Student's private school education		−0.0522	0.0415	−0.1336	0.0291	−0.0577	0.02794	0.00032	−0.1133	−0.0031
Private courses and lesson support	Only private courses	0.1531	0.2274	−0.2926	0.5989	0.1036	0.12476	0.00221	−0.1432	0.3462
	Both private courses and lesson support	0.3532	0.3664	−0.3649	1.0714	0.3232	0.16508	0.00106	−0.0011	0.6460
Working in a job: Yes		0.3115	0.2477	−0.1739	0.7971	0.2885	0.12356	0.00057	0.0470	0.5329
Happiness with family	Moderately unhappy	0.0882	0.9487	−1.7712	1.9478	−0.0241	0.16077	0.00125	−0.3369	0.2927
	Moderately happy	−1.0322	0.8757	−2.7487	0.6841	−0.9483	0.10391	0.00092	−1.1510	−0.7416
	Very happy	−1.1981	0.8824	−2.9278	0.5314	−1.2236	0.07011	0.00086	−1.3605	−1.0854
Model fit statistics		LR statistic		183.63		Acceptance rate			0.565	
		Log-likelihood		−485.984		Average efficiency			0.2278	
		Probability		0.000		Log-marginal likelihood			−732.971	
		AIC		1039.968		DIC			999.482	

Source: authors' own calculations

Some socioeconomic characteristics were found to influence academic success, suggesting that the differences in these characteristics affect the success outcomes. This can be presented as evidence of the existence of economic and social inequalities in education. The point that needs to be emphasised here is that the effect of economic and social characteristics on academic success will emerge as economic and social inequalities in education.

Some differences were observed in the findings from the classical and Bayesian estimations of the ordered choice models. In addition to small differences in coefficient magnitudes, there are differences in confidence intervals in favour of the Bayesian approach. The Bayesian approach offers lower error levels and narrower credible intervals than the classical approach. Despite this, some variables reported as statistically insignificant with the classical approach were found to be significant with the Bayesian econometric approach. This provides evidence that the more sensitive Bayesian econometric approach is an important alternative for absolute discrete choice models.

The Bayesian econometric approach defines a posterior distribution function for the parameter instead of considering the parameter as a variable with a probability distribution and making a point estimate. Although the posterior distribution function contains all the summary information desired to be obtained regarding the parameter, it is not suitable for presenting the results of econometric research. Reporting point or range estimates is preferred. Using the mean of the posterior distribution as an estimator is an acceptable approach (Erdogan and Uludag, 2014; Greene, 2018; Kennedy, 2008). In evaluating the estimation results, the posterior distribution means were considered as point estimates of the parameters. Accordingly, the posterior distribution means and standard deviations of the distribution were reported. Monte Carlo standard errors (MCSE) were reported among the findings as a statistical indicator completely different from standard deviation. MCSE values can be used as a measure of the accuracy of posterior estimates. However, small MCSEs are not definitive proof that the true posterior distribution has been reached. Monte Carlo standard error values provide evidence of the accuracy of the simulation. The standard deviation of the mean of the posterior distribution, which can be expressed as a function of the sample size in the data set, describes the uncertainty in the parameter, while the Monte Carlo standard error as a result of the simulation describes the uncertainty in the parameter estimate and is expressed as a function of the number of iterations in the simulation. A Monte Carlo standard error that is less than 5% of the standard deviation can be considered evidence that convergence has been achieved as a result of the simulation (Hosmer et al., 2013). The acceptance rate among the reported findings is the acceptance rate of the parameters generated in the MCMC chain. It can be expressed as the ratio of the number of unique parameter values generated to the total number of parameters in the MCMC chain.

The acceptance rate takes a value between 0 and 1. Accepting the recommended parameter value each time (i.e., the ratio converges to 1) indicates that the chain takes small steps each time, making convergence to a stationary distribution difficult. On the other hand, an acceptance rate approaching zero suggests that the chain is stuck on a few values and may require hundreds of iterations for a jump. Different algorithms have distinct recommended acceptance rate values. In the Gibbs sampling algorithm, every draw is accepted, resulting in an acceptance rate value of 1. While various ranges are suggested for the Metropolis-Hastings algorithm, acceptance rate values between 15% and 85% are considered appropriate (Gelman et al., 2014; Lynch, 2005). The average efficiency represents the efficient sample size and can be expressed as a measure of the independence of sampling from the posterior distribution. The efficient sample size takes a value between 0 and 1. If the efficiency for the parameters is above 10%, the algorithm can be considered good; however, if the efficiency is below 1%, it raises concerns about convergence (Sanchez, 2018). One of the criteria used in Bayesian model selection and comparison is the deviance information criterion (DIC). Introduced by Spiegelhalter et al. (2002), DIC can stand as a good Bayesian alternative to AIC and BIC. DIC is a measure related to the deviation in the mean of the posterior distribution of the parameter. In the constructed models, a smaller DIC value indicates a more suitable model.

In the study, the estimation results of the choice models obtained with the classical and Bayesian approaches were evaluated based on the above summary information about the Bayesian approach and the established knowledge of the readers about the classical approach. Based on all these, it can be stated that the models are statistically suitable. With the Bayesian approach, convergence in the estimation processes has been achieved, and appropriate results have been presented.

4. Conclusion

This study aimed to determine the effects of economic and social variables which can be expressed as sources of inequality in education in Türkiye, on academic success. The effect of an individual's socioeconomic status on academic success through some differentiations in the educational process has been confirmed by various studies (Sirin, 2005; Hassan and Rasiah, 2011; Gobena, 2018; Pruitt et al., 2019; Liu et al., 2022; Islam and Khan, 2017; Li et al., 2023). When this finding is evaluated together with the findings from studies revealing that academic success will cause income differences in working life (Kurt and Gümüş, 2020; Li et al., 2021; Prakhov, 2021), a suspicion arises that a cycle of inequality is operating. This is because the socioeconomic status of the individual will affect academic success through the differences it will create in education. Differences in academic success will have an impact on earnings in working life and will be the most important determinant of the socioeconomic characteristics of the individual. To provide insight into whether this cycle is active in Türkiye, the study associated academic success with socioeconomic factors, which are deemed sources of inequality in education. Binary and ordered choice models were used in the analysis of the relationship in question. The models were estimated separately with the classical and Bayesian estimation methods.

The findings obtained from the classical and Bayesian econometric approaches in the study are consistent with Acquah, 2013; Chiaka and Adam, 2019; David et al., 2007; Lynch, 2005; Mahanta et al., 2015, who report that the Bayesian approach yields more stable and appropriate results with smaller standard errors and confidence intervals. Thus, the use of both estimation methods in the study suggests that the results are supported by stronger evidence. With the different models employed in the study, income, private school education, parental education level, region of residence, having to work, and the level of happiness with the family were found to have statistically significant effects on student success in getting into the desired university department and university placement ranking. In this regard, it can be stated that students' economic and social characteristics affect their academic success and that these characteristics are possible sources of inequality in education. Hence, the study concludes that in Türkiye, inequalities in education exist due to economic, regional, and, to a lesser extent, social factors. The findings obtained in the study are similar to those of Sirin (2005), Hassan and Rasiah (2011), Gobena (2018), Pruitt et al. (2019), Liu et al. (2022), and Islam and Khan (2017).

The study results emphasise the need to develop educational policies to reduce the transitivity of socioeconomic characteristics, as a source of inequality in education in Türkiye, to academic success. The distinguishing effect of private school education on academic success reveals the need to review educational standards in public schools. Regulating classroom capacities, redesigning the student, family, and school relationship, and utilising qualified educators are some policy suggestions that may favor public schools. Student's academic success differs depending on the parental education level and happiness level with the family. We recommend providing more guidance and counselling services for disadvantaged students. The effect of family income level, another source of inequality, on student academic success has been confirmed. Income level affects academic success through nutrition, housing, access to paid educational resources, social activities, and many other ways. Here, two alternatives can be mentioned for policymakers. The first is to reduce the pass-through of income to academic success. The second is to provide direct income support to students in low-income groups. We recommend that the direct income support policy, which is expected to yield positive results in the short term, should be supported by educational policies that will reduce the pass-through of income to academic success. More research is needed on possible policy recommendations reducing the income-to-education pass-through.

The study's limitations are that the sample consists of only university-level students, and the scope is only Türkiye. This affects the results for comparisons between different policy recommendations. In addition, the findings may differ for students from different education levels (for students from other age groups). Comparative analyses to be made for different countries and repetition of the study with success criteria to be selected for different education levels are put forward as research suggestions for future studies. The limitations in terms of sample size were tried to be eliminated with the Bayesian method, which produces more successful estimation results in relatively small samples. Additionally, some other variables that may affect the inequality cycle can be included in the model. The possible effects of tuition or investment in education on success can be discussed around the concept of the cycle of inequality.

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