Unveiling Gender Disparities in Kazakhstani Education: A Comprehensive Analysis Using Unified National Testing Results

By

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Abstract

Gender inequality remains a major issue in Kazakhstan's education system. Despite legislation providing equal access to education for both genders, women remain underrepresented in academia and the labor market, particularly in STEM fields. This under-representation limits the potential for growth, innovation and scientific progress. For social justice, economic growth and national development, it is necessary to eliminate the gender gap in education. In Kazakhstan, state scholarships are awarded and university admission is determined by a standardized exam called the Unified National Testing (UNT). A major education reform in 2017 changed the format of the exam and made it optional for high school graduates, which may affect the gender gap in education. This paper aims to measure gender differences in education based on UNT scores and specialization choices between 2015 and 2020. The analysis classifies female and male specializations, estimates gender differences in UNT scores before and after the 2017 policy change, and examines graduates' proportion in the choice of specialization. The study finds that higher UNT scores are associated with a higher probability of being female, and that this gender gap is widening each year. Despite educational reforms, women are still heavily underrepresented in high-paying, male-dominated fields, but there is a shift towards neutral specializations among female graduates. These results show that social expectations and gendered specializations can have a significant impact on educational attainment in Kazakhstan.

Keywords: Gender inequality; Kazakhstani education; Unified National Testing (UNT); Gender disparities; Educational reform; Gendered specializations; Social expectations; Educational outcomes.

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List of Abbreviations

UNT - Unified National Testing

MoSHE - Ministry of Science and Higher Education of the Republic of Kazakhstan

HEI - Higher Education Institution

EHEA - European Higher Education Area

SCES - State Standards of Compulsory Education

STEM - Science, Technology, Engineering, and Mathematics

1 Introduction

In Kazakhstan, as in many other education systems around the world, gender inequality remains a serious problem. Gender inequality can persist and affect the overall quality and outcomes of education, even though Kazakhstan's new laws constitutionally guarantee equal access to education for both genders. Women have historically been underrepresented in Kazakhstan's academic circles and labor market, particularly in STEM. This is one of the fastest growing and highest paid fields, and the lack of diversity is hampering progress (Kredina et al., 20-23). A country's potential for innovation and scientific progress is severely limited by this under-representation. The development of science and technology requires more dynamic and diverse human capital, and this can be achieved by encouraging and supporting women to enter these fields (Cohen-Miller et al., 20-21).

"Education is a powerful driver of human capital, economic growth, social cohesion, cultural transformation, environmental sustainability and peaceful coexistence" (UNESCO, 2019). Eliminating gender disparities in education is not only a matter of achieving social justice; providing equal access to education for both genders has a strategic goal of accelerating social progress and national development. Gender equality in education has a wide range of benefits, including reducing the poverty rate, promoting economic growth and improving the health of the population (Spankulova et al., 2019). It is of great importance to raise and resolve this issue, as it challenges social norms and allows students to correctly assess the skills they need to choose a career based on their own interests, rather than social expectations or gender norms.

In Central Asia, Kazakhstan is a developing country with the highest economic growth rate. Since gaining independence from the Soviet Union in 1991, Kazakhstan has continued to introduce new education policies based on the experience of other developed countries.

Independent external evaluation of the quality of education, based on reliable and comparable data, is one of the most important elements of effective education management (Reshetnikova & Kisikova, 2013, p.169). Since 2004, the Unified National Testing (UNT) has been a standardized exam for university admission and scholarship distribution in the Kazakhstani education system. The UNT helps to ensure that graduates are assessed equally across the country. As a result, the UNT is one of the most important parts of educational assessment in Kazakhstan, where several educational reforms have taken place over the past two decades. One of the most significant and recent was the policy change in 2017, which changed the format of the exam and made it optional to take, providing flexibility for candidates. This policy could have a significant impact on reducing the gender gap, as only those who want to go on to higher education will now take the exam, and the change in format will allow them to focus their preparation on the subjects of their choice.

The aim of this paper is to measure gender differences in education based on UNT results and choice of specialization between 2015 and 2020. The specific objectives are to identify female and male specializations from the dataset, to estimate gender differences in UNT scores in general and before and after the policy change in 2017, and to measure gender differences in the choice of specialization between 2015 and 2020.

This thesis is divided into several chapters. The literature review section provides an overview of gender norms and expectations in Kazakhstan and previous literature on gender inequalities in Kazakhstani education. The background information section provides a brief description of the educational reforms and programmes implemented in Kazakhstan in order to understand the context of the analysis. The methodology section provides detailed information on the dataset used, data preparation and descriptive statistics. It also includes an explanation of how the logit regression prediction models were used in the analysis for the classification of specializations and for the analysis of UNT scores and specializations of choice. The results section presents the classification of specializations and, based on this, the regression results for the analysis of UNT scores and overall trends in specialization choices. The discussion provides an interpretation of the results, possible explanations and limitations of the analysis. Finally, the paper concludes with the main findings on gender inequality in Kazakhstani education.

It was found that there is a gender gap in UNT scores among Kazakhstani graduates, with females often outperforming males. Prediction models showed that from 2015 to 2020, the probability of being female increases with higher UNT scores. This relationship suggests that despite educational reforms, such as the 2017 policy change, gender disparities persist and continue to increase. Furthermore, females continue to be underrepresented in high-paying and prospective male-dominated fields, even though they have started to occupy more neutral specializations. These results show that gendered specializations, probably together with social expectations, still have a significant impact on school performance.

2 Literature Review

2.1 Gender Norms and Expectations in Kazakhstani Society

The cultural, historical, and social context of Kazakhstan has a significant influence on gender norms and expectations within the country. The roles and viewpoints of Kazakhstani males and females regarding different fields of life, including education, are still largely informed by traditional norms and social standards, despite the recent progress and regulations supporting gender equality.

The historical perspective of females' role in Kazakhstani society is presented by Abdikadyrova et al. (2018), which emphasizes the special role of females in relation to other eastern cultures. In traditional Kazakhstani society, females are valued in a number of ways. They are expected to be housewives, active participants in important cultural and social events, and even to be prepared to participate in conflicts when necessary. These historical perspectives contrast with the difficulties that women currently face. While the re-emergence of traditional norms may enhance respect for women in general, it also reinforces outdated beliefs that restrict the opportunities of women in the contemporary world (Abdikadyrova et al., 2018).

In contemporary Kazakhstan, the challenge persists of achieving a balance between traditional beliefs and the demands of gender equality. As evidenced by legislation and official pronouncements, such as President Nursultan Nazarbayev's Kazakhstan 2050 Strategy, which underscores the value of women in society and supports higher female participation in the labor market and social life, the government is engaged in efforts to promote gender equality (Abdikadyrova et al., 2018). However, these progressive methods frequently conflict with deeply entrenched social traditions. Despite legislation guaranteeing equal access to education, gender disparities in the quality and outcomes of education persist. Cultural norms often exert pressure on females to prioritize household obligations over their academic or professional goals (Nam, 2024; Abdikadyrova et al., 2018).

2.2 Previous Studies on Gender Disparities in Kazakhstani Education

The publication of several studies that presented strong evidence of gender disparity in education in Kazakhstan has attracted considerable attention. A comprehensive analysis of gender tendencies in the system of higher education in Kazakhstan is provided by Bisenbaev et al. (2023). The research demonstrated a pronounced feminisation of the higher education sector, with the number of female PhD graduates exceeding that of male PhD graduates since 2012. However, this trend is eclipsed by the phenomenon of "gender inversion," whereby structural issues make it more challenging for women to transition from a PhD to a Doctor of Science (DrS). In order to create a more diverse and inclusive academic environment, the study recommends the reorganization of the system of scientific indicators, with an emphasis on quality evaluations, and the provision of increased support for researchers (Bisenbaev et al., 2023).

CohenMiller et al. (2021) examine the issue of gender parity in the STEM field of higher education in Kazakhstan, which is a male-dominated field. The results indicate that there are significant differences in the recruitment, promotion, and retention of females in STEM fields. They attribute these discrepancies to pervasive prejudices, a dearth of mentors and role models, and also to social pressure on women who are expected to balance their careers with household responsibilities. In order to reduce the gender imbalance in education and employment in the field of STEM, the authors propose goal-oriented methods, such as recruitment tactics, tutoring programmes, and gender bias awareness campaigns (CohenMiller et al., 2021).

The studies presented here demonstrate the intricate interrelationship between gender disparities and educational attainment in Kazakhstan. The studies highlight the ways in which institutional practices, structural barriers, and cultural norms contribute to gender disparities. In order to resolve these issues and guarantee equal opportunities for females in education and beyond, substantial political reforms, cultural changes, and support structures are required. The results presented serve to highlight the importance of continuous research and the implementation of methods aimed at combating deeply rooted gender prejudices and the creation of inclusive learning environments, which facilitate the realization of the potential of the student irrespective of gender.

3 Contextual Background

Since 1991, when Kazakhstan gained independence from the Soviet Union, Kazakhstan has made significant changes to its education system in order to improve the quality of education, make it more accessible and make it more internationally competitive. Thanks to fundamental educational policies such as 'About Education' (1992) and 'About Higher Education' (1993), which set out basic guidelines for higher education institutions (HEIs), the main reforms in higher education focused on the transition from the Soviet-controlled system to a market-oriented system (Hartley et al., 2016).

Since gaining independence, Kazakhstan has worked to decentralize authority and give higher education institutions greater institutional autonomy. As a significant step towards aligning Kazakhstan's higher education with the standards of the European Higher Education Area (EHEA), Kazakhstan joined the Bologna process in 2010. This includes the strengthening of academic mobility, the introduction of a credit-based system and the creation of a three-tier degree system (Kerimkulova & Kuzhabekova, 2017). Despite these initiatives, MoSHE continues to play an important role in enforcing the State Standards of Compulsory Education (SCES), which define curricula, teaching methods and quality standards of provision. However, thanks to the Bologna process, the academic freedom of higher education institutions has increased (Kerimkulova & Kuzhabekova, 2017).

The UNT is a composite exam for secondary school graduation and university admission, first proposed in 2004. The initial exam contained 125 questions covering five subjects (mathematics, Russian, Kazakh, history of Kazakhstan, and a subject of choice) (Zhumabaeva, 2016). By providing equal opportunities for all students to continue their education based on their academic performance, this standardized approach aims to provide fairness and openness in the selection process for university admission and scholarship distribution (Zhumabaeva, 2016).

However, in 2017, there was a change in educational policy that separated secondary school graduation from university admission. In other words, the UNT was only required for those who wanted to pursue higher education and apply for scholarships. The new format also consists of five subjects, but the maximum score is now 140: three compulsory subjects (mathematical literacy, reading literacy and history of Kazakhstan) and two optional subjects that correspond to the desired university specialization. For example, students wishing to apply to medical school will choose biology and chemistry, students wishing to apply to engineering school will choose mathematics and physics, and so on. These changes were made to give students more choice and flexibility for their future (Unified National Testing, n.d.).

4 Methodology

4.1 Data Collection: Unified National Test (UNT) Results

For the analysis, the scholarship distribution dataset based on UNT scores was used. It includes the personal identification number of each applicant, their full name, their UNT scores, whether they have village quotas, the university code to which they were accepted, the code for their specialization, and the name of specialization they will study during their bachelor's degree. The data is publicly available and is published each year by MoSaHE, which is responsible for allocating scholarships to applicants. The dataset from 2015 to 2020 was used to analyze pre- and post-2017 UNT policy change. And because after 2020 the number of times applicants are allowed to take the UNT was changed to 4-5 times a year (previously it was only once a year) so that they can use their highest score to apply for a scholarship, the data from 2020 wasn’t used.

The most significant advantage of utilizing UNT data is that it permits the examination of the initial career decisions made by recent graduates. Previous studies on gender disparities have primarily focused on older working adults, whose career choices are often influenced by the need to balance professional and personal responsibilities. In the context of Kazakhstan's economic situation and family structure, it is common for women to select careers that allow them to manage household duties and childcare alongside their jobs. However, the UNT data reflects the decisions of recent graduates who are typically single and unencumbered by these responsibilities. This provides a more accurate representation of their genuine preferences and interests in specialization, without the immediate constraints of family obligations. It is plausible that, as they begin families, these individuals may transition to more traditionally "female" occupations such as teaching. However, the UNT data reveals their choices when they are relatively free to pursue their aspirations. It is crucial to acknowledge that factors such as misperceptions of skills, social expectations, and family pressure may still exert influence on their decisions.

The figures below show the total number of applicants for state scholarships, the total number of scholarships awarded to applicants and the corresponding percentages over the period 2015 to 2020.

Figure 1 Total number of applicants that applied for scholarship, and the total number of scholarship holders.

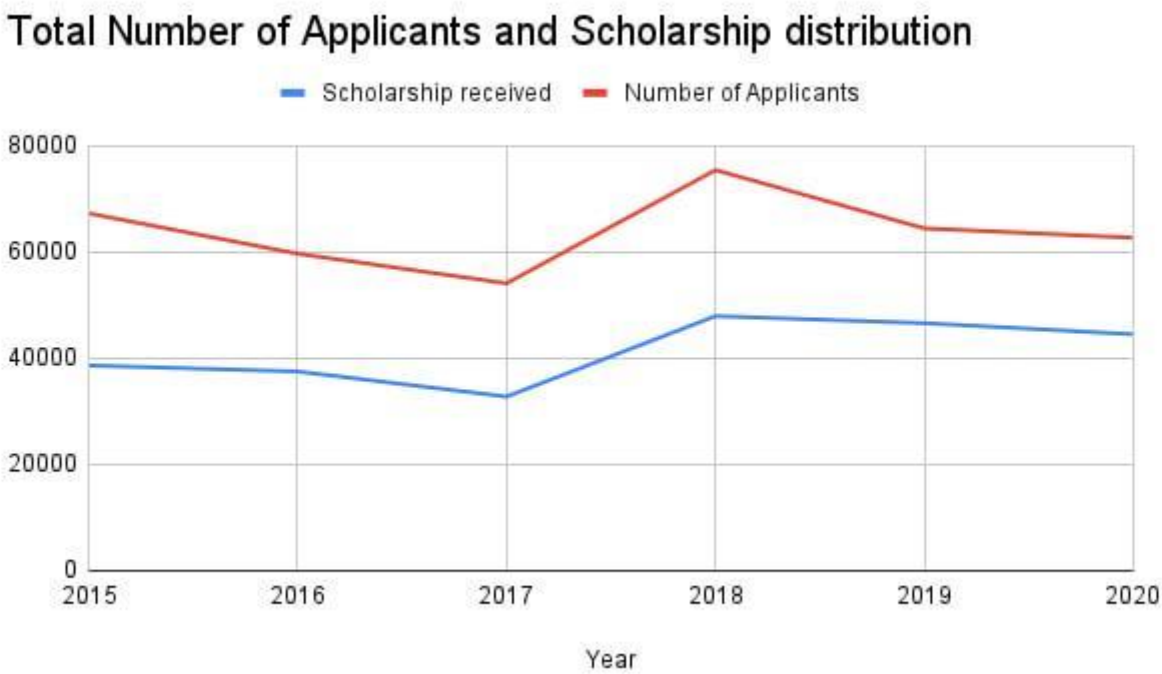
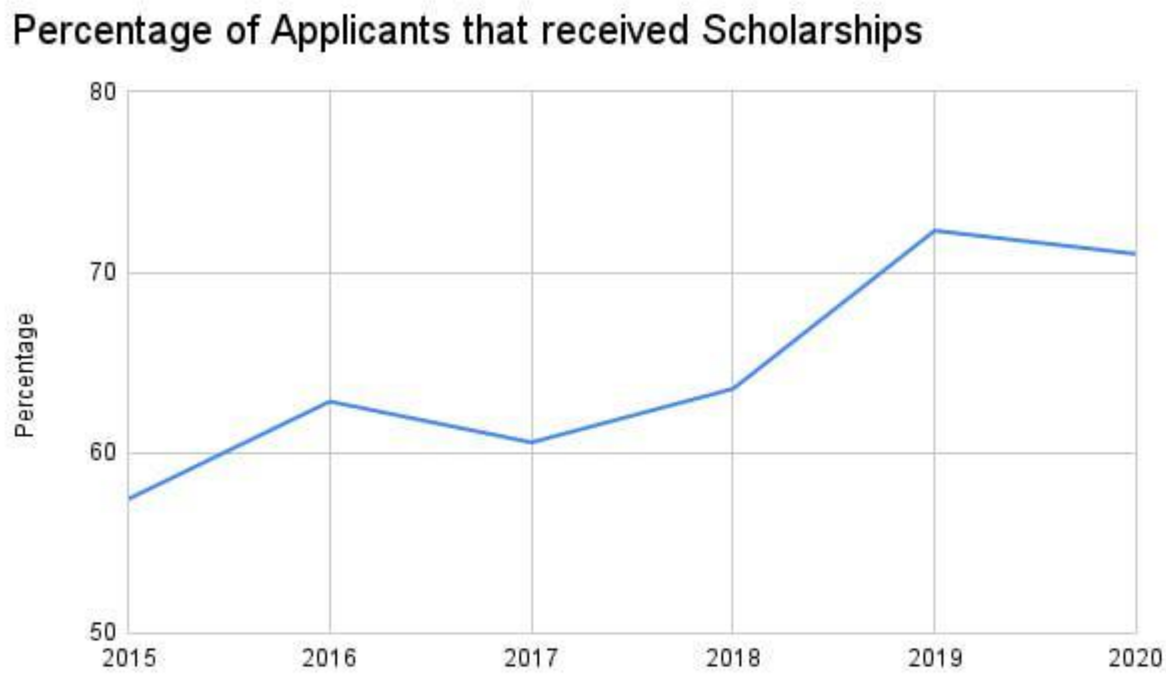


Figure 2 The percentage of applicants that received state scholarships.



The figures show that the total number of scholarships is increasing every year. In 2015, only 57.4% of applicants received a scholarship, but in 2020, 71% of applicants received a state scholarship. Figure 1 shows that as the number of applicants increases, the number of scholarships also increases and vice versa, which means that the number of scholarships is not fixed each year.

UNT results are used in the distribution of government scholarships, and graduates can apply for government-funded scholarships if their UNT score is above the minimum passing score. These scholarships are distributed on the basis of the highest score until all available scholarships are distributed. This guarantees that the highest scoring graduates will receive a state scholarship for their further education. The majority of UNT participants receive the state scholarship, as shown in Figure 2, especially those who apply for in-demand specializations, as the government usually allocates more scholarships for science and technology specializations than for humanities. However, graduates who apply for specializations for which there are fewer scholarships available, or those who obtained lower UNT scores, may not be accepted.

As the datasets include the majority of UNT participants, it can be assumed that the distribution of male and female graduates is representative of the overall applicant pool. Although this assumption cannot be verified due to the lack of data on lower-scoring graduates who did not receive the state scholarship, it is reasonable to assume that the gender distribution in these datasets is not significantly different from the general population of all UNT participants. Thus, these datasets provide a robust basis for analyzing gender differences in educational outcomes.

4.1.1 Data Preparation

In terms of data preparation, the most important variable for the analysis, gender, is missing, so a new variable was created to determine gender based on the name suffix. Since Kazakhstani names have gender-specific surnames and patronymics, it was possible to define the gender of 97% of all applicants from 2015 to 2020 by running the standard function. Then, as the data included both specialization codes and names, they were truncated to standardize the categories for regression analysis. Finally, a one-hot encoding method for categorical variables was used and the UNT scores were normalized based on year. One-hot encoding is a widely accepted method that converts categorical variables such as university and specialization into binary vectors, creating variables for each university and specialization that allow them to be included in the logistic regression (Géron, 2019).

The dataset is divided into two subsets: a training set and a test set. The training set comprises 80% of the data, while the test set comprises 20%. Then, the logit model is trained utilizing the maximum likelihood estimation (MLE) method on the training sample. The efficacy of the model is then assessed through the calculation of precision, recall and F1 scores on both the training and test samples, in order to ascertain the accuracy of the gender prediction.

4.1.2 Descriptive Statistics

The table below shows female, male, and total number of graduates that received the scholarship from 2015 to 2020.

Table 1 Female, male, and total number of graduates from 2015 to 2020.

Gender	Count
Female	105772
Male	81262
Total	187034

There are a total of 187,034 graduates who received a state scholarship between 2015 and 2020. As we can see, female scholarship recipients make up 56.6%, while male scholarship recipients make up 43.4%. This difference could be due to several reasons, such as women getting higher scores and therefore receiving more scholarships, or there being more female applicants than male applicants overall, which explains this difference.

Table 2 shows the descriptive statistics for some of the variables. As the variables University and SpecCode have vectors of coefficients, they have not been included in the table below.

Table 2 Descriptive Statistics for some variables.

	mean	*std*	*min*	*25%*	*50%*	*75%*	*max*
gender_male	0.4347	0.4957	0	0	0	1	1
Score	92.2857	21.8936	25	79	92	109	140
before2017	0.2432	0.4290	0	0	0	0	1

Competition_village quota	0.1614	0.3679	0	0	0	0	1

As it can be observed, the descriptive statistics of the variable $Score$ are before normalization and the variables $gender_{male}$, $before2017$, and $Competation_{village\ quota}$ are binary.

4.2 Logistic Regression Analysis

The main questions we are trying to answer are: What is the relationship between UNT scores and the likelihood of a graduate being male or female, and how does the gender distribution vary across different specializations in Kazakhstani higher education? Furthermore, to what extent do these relationships contribute to the gender disparity in Kazakhstani education, and how have they evolved over time, especially in light of the 2017 policy change?

To answer these questions, logistic regression is used, where the dependent variable is gender (1 if male, 0 if female). Using the UNT score, the choice of specialization and other control variables, it is possible to use this method to model the probability of being male. It is possible to determine the gender differences in the choice of specialization and UNT exam performance, which in turn show the relationships between these variables and the probability of being male.

4.2.1 Overview of Logistic Regression and Maximum Likelihood Estimation

Logistic regression is used in this analysis because the dependent variable, $gender_{male}$, is binary, and this logit model helps to solve the issue of sparse data. The logit regression model is employed to predict gender based on a set of control variables. Furthermore, the analysis employs the Maximum Likelihood Estimation (MLE) method to quantify the regression parameters, thereby ensuring optimal alignment with the data, since in our data we have a selection. Given that the sample size for each year is sufficiently large, the asymptotic properties of MLE ensure the reliability and accuracy of parameter estimation.

Before running the logit regression, the best fit of the model is found using 3-fold cross validation based on the F1 score, which is used to evaluate the efficiency of the models. In the analysis, L1 or Lasso regularization was used to prevent overfitting of the model by adding a penalty term. In other words, L1 regularization has the effect of shrinking some coefficients in order to perform feature selection efficiently. The Stochastic Average Gradient Descent algorithm was used for optimisation, as it is efficient for this large dataset and helps to address the limitation of incomplete data.

4.2.2 Predictive Model: Classification of Specializations

As there are more than 200 specializations in total, in order to make the analysis more comprehensive, to see the general trends over the years and to see the effect of the 2017 policy change, the specializations are first classified into female, male and neutral. For this purpose, the dataset is divided into training and test subsets (80% - 20%), in this case using the aggregated data from 2015 to 2020. A further binary variable, before2017, is introduced, with a value of 1 indicating data from 2015 to 2016 and 0 indicating data from 2017 to 2020, to control for the potential effect of the 2017 policy. The effectiveness of the model is then assessed using precision, recall and F1 scores on both the training and test samples, with the aim of determining the model's ability to accurately predict gender.

The logit regression is run to predict gender of an applicant based on control variables:

$$logit(P(gender_{male} = 1)) = \beta_0 + \beta_1 \times Score + \beta_2 \cdot University$$

$$+\beta_3 \cdot SpecCode + \beta_4 \times Competition + \beta_5 \times before2017$$

where $logit(P(gender_{male} = 1))$ is the probability of applicant being a male given predictors, β_0, β_1, β_4, β_5 are coefficients for intercept, UNT score, whether applicant has a village quota, and if the year is before 2017, β_2 and β_3 are vectors of coefficients for the one-hot encoded vectors for University and Specialization.

Then, based on the results, significant coefficients for specializations are found and ranked, and F1 scores are calculated for each specialization. The F1 score is used as a performance measure for classification because of its widespread use and the balance between precision and accuracy it provides, allowing effective classification of specializations (Sokolova & Lapalme, 2009). This is necessary in order to determine the optimal cut-off point for classifying specializations as female, male or neutral.

4.2.3 Predictive Model: General Trends in UNT Results

Using our classification of female, male, and neutral specializations from the previous part, we can group them to conduct further analysis. Then, one-hot encoder is applied for male and female specializations as they are categorical variables.

The following logit regression is then run to predict gender based on the control variables for each year:

$$logit(P(gender_{male} = 1)) = \beta_0 + \beta_1 \times Score + \beta_2 \times Specialization_{male}$$

$$+\beta_3 \times Specialization_{female} + \beta_4 \times Competition$$

where $P(gender_{male} = 1)$ is the probability of applicant being a male given predictors, β_0, β_1, β_2, β_3, and β_4 are coefficients for intercept, UNT score, whether applicant chose male specialization, whether the applicant chose female specialization, and whether the applicant has a village quota, respectively.

The resulting model has the capacity to predict the significance of predictors of gender, as well as the coefficients on the UNT score and specializations. This enables us to conduct the analysis on the overall trend of UNT results, specializations, and to see if there was an effect of 2017 policy shift.

4.2.4 Predictive Model: General Trends in Specialization Choices

Using the results of the previous regressions and their coefficients, it is possible to analyze whether the gender gap in the choice of specialization has decreased or increased over the years. The generalized picture is presented with the categorization of female and male specializations. The analysis was then carried out for each specialization (without classification) for each year, in order to have a closer look at which specializations were most associated with being male or female.

5 Results

5.1 Classification of Specializations

After all the data preparation, training the model, finding the best configurations and running the regressions, the following efficiency measures were obtained for the training and test samples.

Figure 3 Evaluation of the efficiency of the model using precision, recall and F1 scores on both the training and test samples for the aggregated model.

	precision	recall	f1-score	support
0.0	0.81	0.65	0.72	21076
1.0	0.64	0.80	0.71	16167
accuracy			0.72	37243
macro avg	0.72	0.73	0.72	37243
weighted avg	0.73	0.72	0.72	37243

train sample

	precision	recall	f1-score	support
0.0	0.81	0.65	0.72	84193
1.0	0.64	0.80	0.71	64775
accuracy			0.71	148968
macro avg	0.72	0.72	0.71	148968
weighted avg	0.73	0.71	0.71	148968

As you can see, the accuracy and F1 values for the test and training samples are 72% and 71% respectively. This means that our prediction model successfully predicts gender 72% of the time, conditional on the control variables. These metrics show that our logit regression model performs well in predicting gender based on UNT scores, university, specialization, competition type, and if it is before 2017. Now that we have confirmed that our model is valid, we can use the results of the logistic regression to make classifications on gender specializations.

Table 3 Shortened logit regression results for classification of specializations using aggregated data.

	Coefficient	*Standard Error*	*t Stat*	*P-value*	*Lower 2.5%*	*Upper 97.5%*
Score_norm	-0.1490	0.047	-3.190	0.001	-0.241	-0.057
Competition	-0.0454	0.018	-2.513	0.012	-0.081	-0.010
before2017	-0.1761	0.019	-9.465	0.000	-0.213	-0.140
University_158 (Kokshetau University after Myrzakulov)	0.8807	0.290	3.033	0.002	0.312	1.450
University_20 (Academy of Sport and Tourism)	0.8747	0.123	7.124	0.000	0.634	1.115
SpecCode_B002 (preschool education)	-3.9279	0.265	-14.803	0.000	-4.448	-3.408
SpecCode_B065 (transport technologies)	2.6001	0.144	18.096	0.000	2.319	2.882

As we have over 200 variables for specializations and over 100 variables for universities, the table of results shown is abbreviated. However, we can make a generalized interpretation that a negative coefficient means that there is a higher probability of being female. Similarly, a positive coefficient means that there is a higher probability of being male. The magnitude of these probabilities depends on the coefficients. After running the regression, the analysis for classifying specializations as female, male or neutral was carried out.

Figure 4 The plot of F1 scores against the coefficients of the specializations for male specialization cutoff.

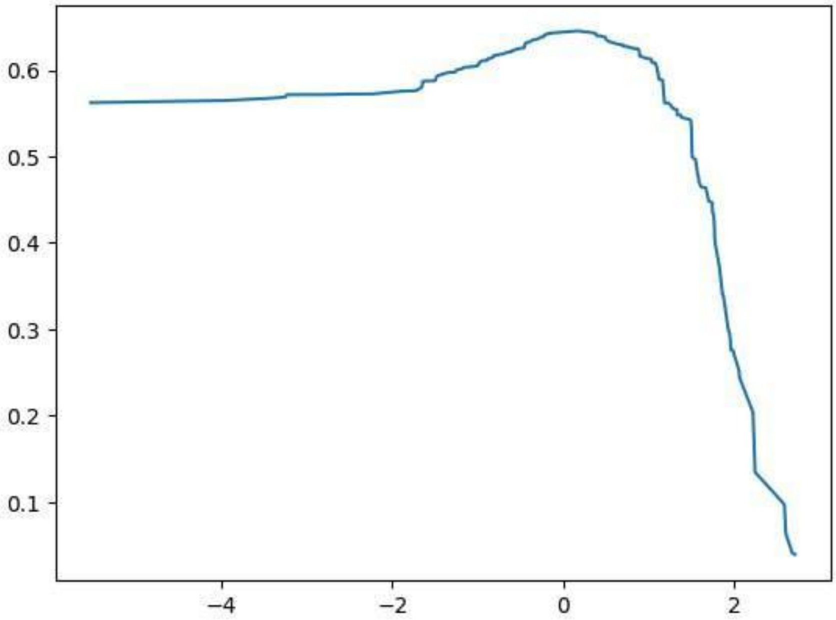
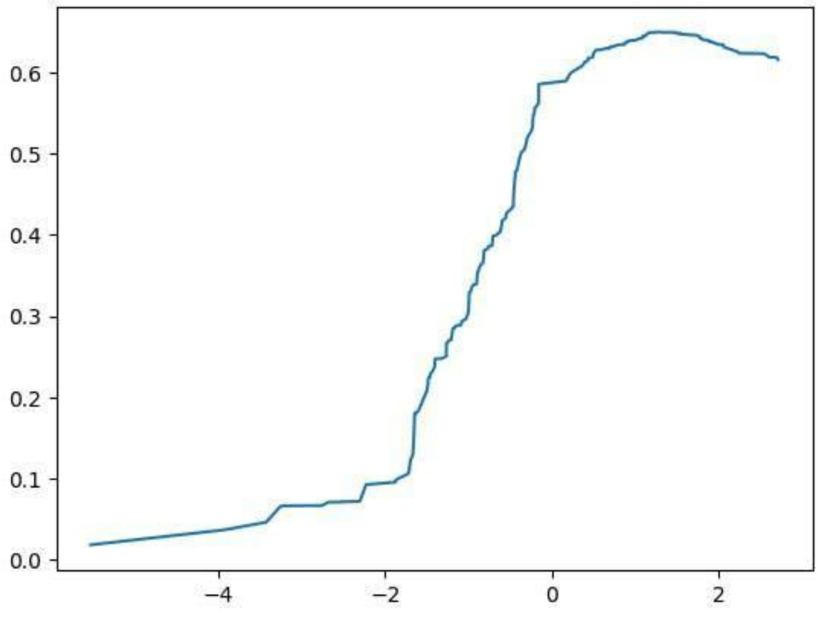


Figure 5 The plot of F1 scores against the coefficients of the specializations for female specialization cutoff.

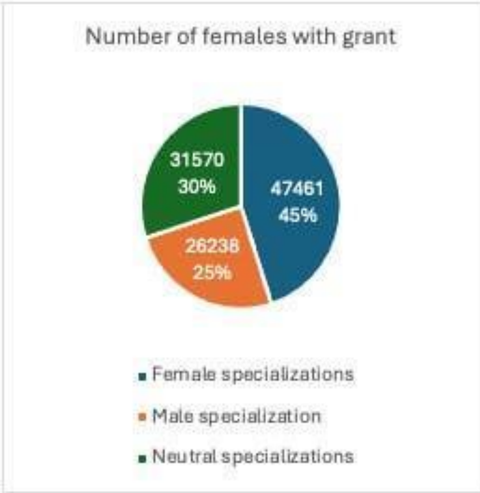


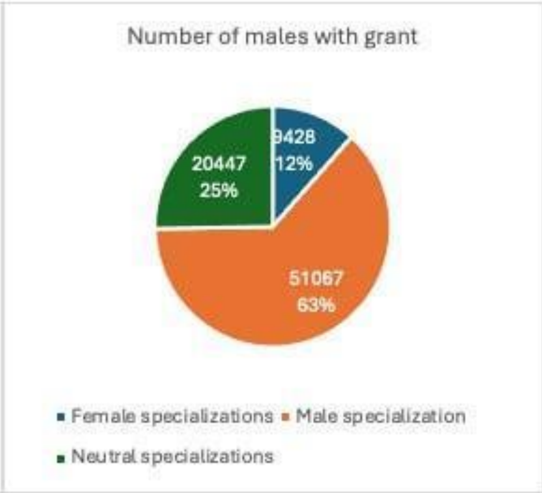
In the figures above, each point represents the specialization, where its x-value is the coefficient and its y-value the corresponding F1 value. On the basis of the figures, we can consider as male specializations those with a coefficient of 0.169 and higher, since the highest

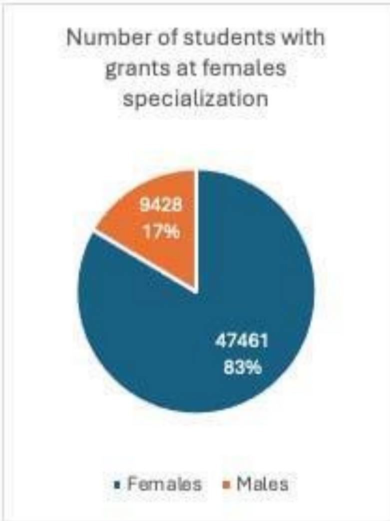
F1 value is when the coefficient is 0.169. Similarly, the female specializations are those that have coefficients lower than 0, as the highest F1 score is when coefficient is 1.304, but the female coefficient should be negative, so we will consider as female specialization those that have coefficient lower than 0. Also, each specialization should be statistically significant to be grouped as male or female specialization. The remaining specializations are grouped as neutral.

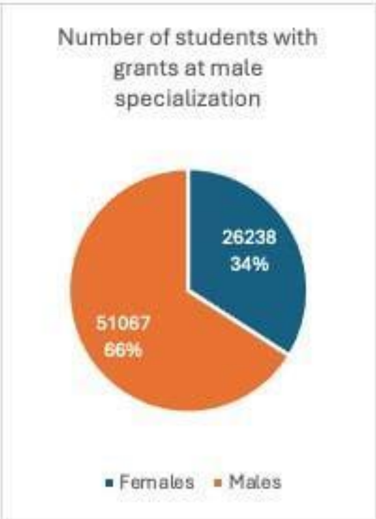
From our analysis, a total of 294 unique specialization choices were observed among Kazakhstani graduates between 2015 and 2020. Of these, 98 specializations were grouped as female, 107 specializations as male, and 89 specializations as neutral.

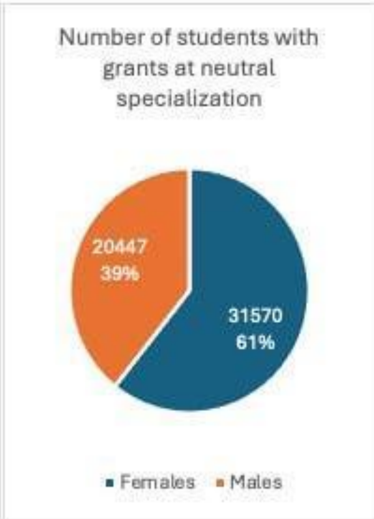
Figure 6 Composition of male and female students choosing female, male, and neutral specializations.











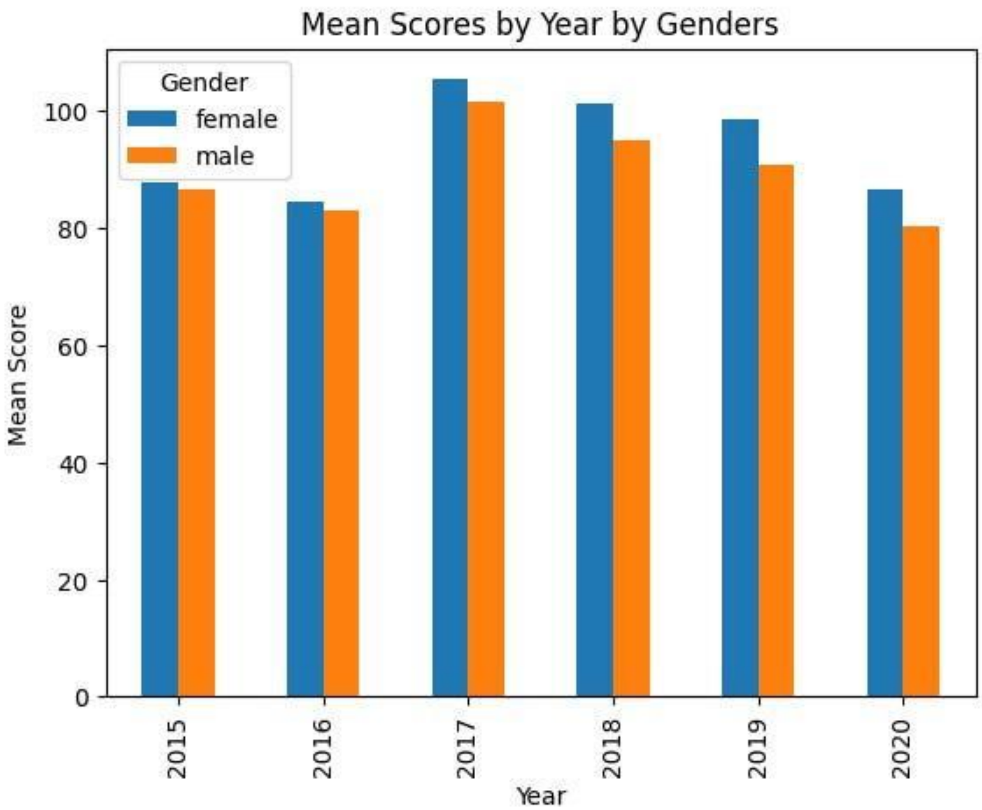
The pie charts above illustrate the correspondence between our classification of gendered specializations and the data. They show the distribution of graduates with state scholarships across different types of specialization (female, male or neutral) and also the gender distribution within these specializations. From the first two graphs showing the number of women and men with scholarships, it can be seen that among female graduates 45% are female, 30% are in neutral and 25% are in male specializations, while among male graduates 63% are in male, 25% in neutral and 12% in female specializations. Similarly, the graphs showing the number of graduates in each specialization category show that in female specializations 83% are female and 17% are male, in male specializations 66% are male and 34% are female, while in neutral specializations 61% are female and 39% are male.

These graphs show clear gender trends in the choice of specialization among Kazakhstani scholarship holders. More male graduates apply for male fields of study, while more female graduates apply for female fields of study. Although the gender distribution is more even in neutral specializations, there are still more women. These graphs show that our analytical classification of female and male specializations is consistent with the data and can be used for further analysis.

5.2 Gender Disparities in UNT Performance

The bar chart illustrates the mean scores achieved by each gender in each year of the sample.

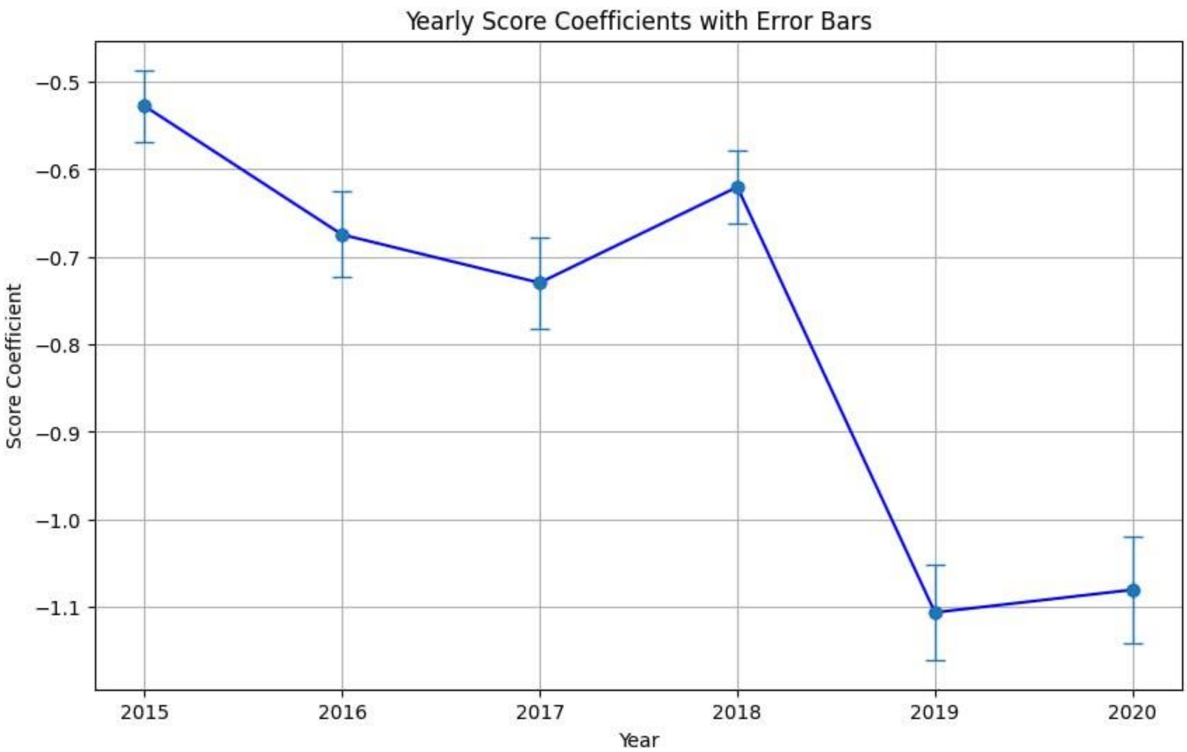
Figure 7 Mean UNT scores by each gender from 2015 to 2020.



Although these averages are not entirely accurate, as data on lower-scoring UNT participants is missing every year, who did not receive scholarships, the goal of this analysis is to examine the differences in scores between genders, which were assumed to be consistent. As can be observed, the mean scores for both genders are demonstrably lower in 2015 and 2016 than in the subsequent years. This is to be expected, given that the format of the UNT was changed in 2017 to allow a maximum of 140 points (previously, the maximum score was 125). It is also evident that, on average, women received higher UNT scores than men in all years of the sample. Although there are yearly fluctuations in the mean UNT scores, the magnitude of the differences between the genders remains consistent.

By running logit regression, the change in the log-odd coefficient on the UNT score over the period from 2015 to 2020 is illustrated in the following figure.

Figure 8 Log-odd coefficients of Score predictor with error bars from 2015 to 2020.



In a logit regression, the coefficient indicates the change in the log odds of the dependent variable. It is crucial to emphasize that all the log-odds coefficients of UNT scores are statistically and economically significant for all years. The complete set of regression results can be found in the Appendix. Consequently, for the year 2015, a one-unit increase in the UNT score is associated with a decrease in the log-odds of an applicant being male by -0.5275, ceteris paribus. In other words, in 2015, for each unit increase in the UNT score, the odds of the applicant being male decreased by 41%, as the $odds\ ratio = exp(-0.5275) = 0.590$. Similarly, all other log-odds coefficients can be defined.

We can see the general trend that all log-odds coefficients are negative over the 5-year period, meaning that higher UNT scores are associated with a higher probability of being a female graduate. The trend remains consistent and the coefficient becomes more negative each year, meaning that the gender gap in UNT scores is increasing.

To determine the impact of the 2017 policy change, a logit regression was run on the aggregate data with an interaction term for UNT score and pre-2017 period.

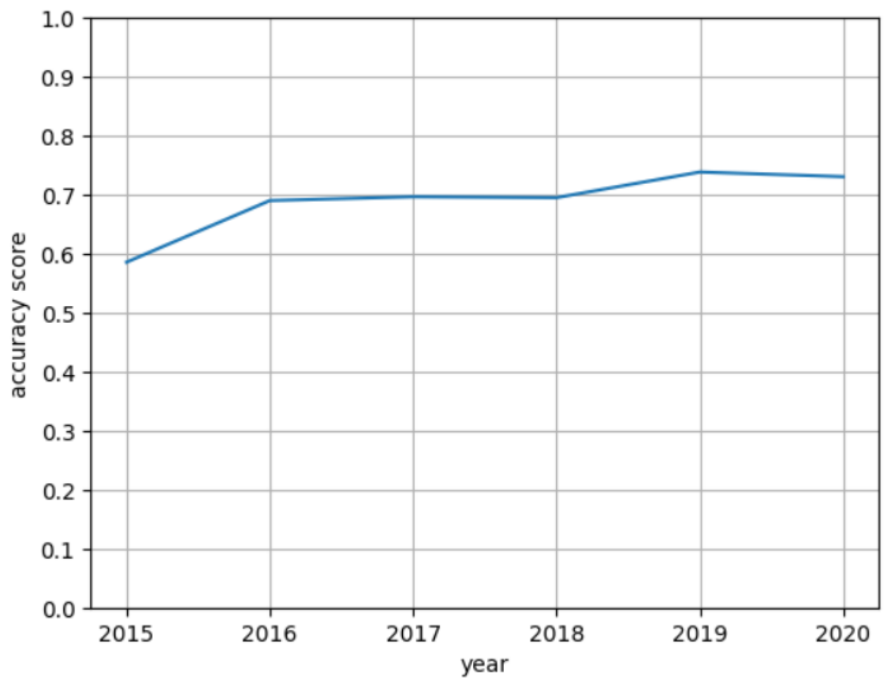
Table 4 The logit regression for aggregated data with an interaction term.

	Coefficient	*Standard Error*	*t Stat*	*P-value*	*Lower 2.5%*	*Upper 97.5%*
Score_norm	-0.8726	0.022	-40.300	0.000	-0.915	-0.830
before2017	0.4661	0.105	4.452	0.000	0.261	0.671
male_specialization	1.0295	0.013	79.279	0.000	1.004	1.055
female_specialization	-1.1543	0.016	-72.090	0.000	-1.186	-1.123
general_competition	0.2315	0.015	15.501	0.000	0.202	0.261
Score_norm*before2017	-0.3455	0.123	-2.800	0.005	-0.587	-0.104

This logit regression on aggregated data supports the previous findings that higher UNT scores generally increase the probability that the graduate is female, as the coefficient for UNT score is still negative (-0.8726). The gender gap has increased after 2017, as shown by the statistically significant coefficient of an interaction term (-0.3455), with the effect of higher UNT scores favoring female graduates becoming more pronounced. These results suggest that the 2017 policy change, which changed the format of the UNT and made it optional, had a significant impact on the problem of gender inequality in Kazakhstani education. Specifically, it exacerbated the previous trend of higher UNT scores increasing the likelihood of the applicant being female, thus widening the gender gap.

The accuracy scores were measured for each year and the results are presented in the figure below.

Figure 9 Accuracy scores of logit regressions from 2015 to 2020.

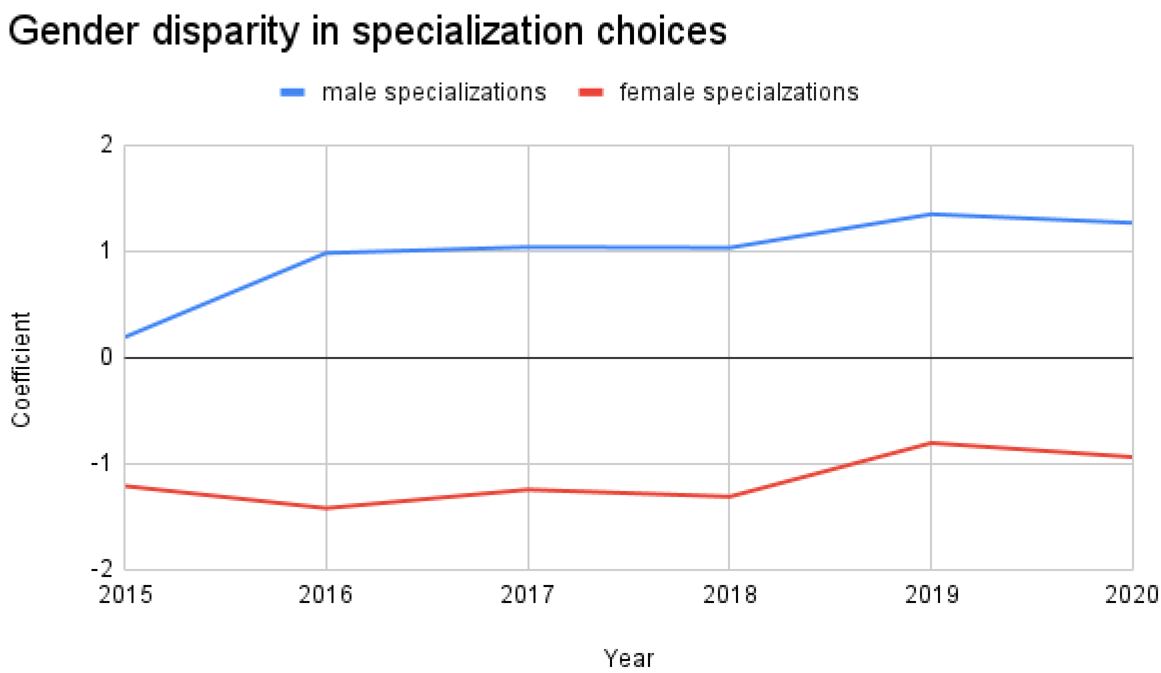


It can be seen that the predictive quality of our model is less than 60% in 2015, as measured by the accuracy score, but then it continues to increase and by 2020 it has an accuracy score of over 70%. This means that the gender gap in specializations and UNT scores was less significant in 2015 and started to increase each year.

5.3 Overall Trends in Specialization Choices

In order to analyze the trends of the gender gap in the choice of specialization over the years the coefficients on male and female specializations are used from the previous regressions.

Figure 10 The coefficients on male and female specializations from prediction models over the years.

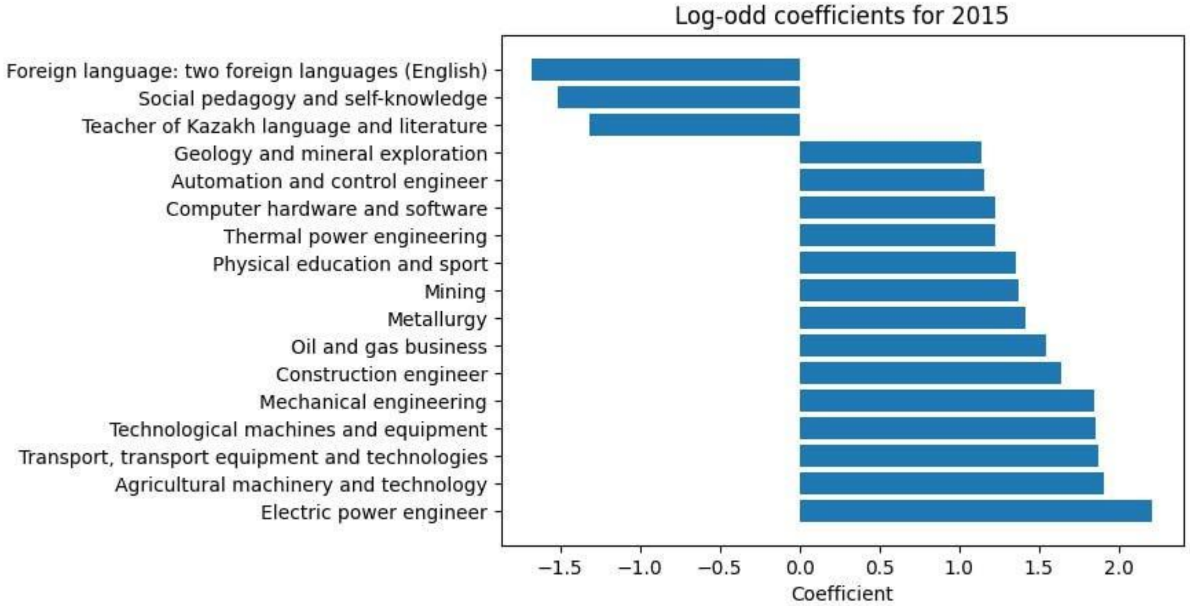


As can be seen from the graph above, the coefficients on male specializations are consistently positive, while the coefficients on female specializations are consistently negative from 2015 to 2020. As all these coefficients are statistically and economically significant, this means that there are persistent gender disparities in the choice of specialization, with male specializations being strongly associated with being male and vice versa.

However, if we analyze the magnitude of these coefficients, we can see that the coefficient for male specializations increases from 0.1884 in 2015 to 1.2660 in 2020. This means that, over the years, the probability of being male increases significantly if a male specialization is chosen, so that male specializations become more male-dominated. In contrast, the coefficient on female specializations increases in the later years of the analysis (decreasing in absolute terms), implying that female specializations become less female-dominated from 2019 onwards.

To analyze trends in the choice of each specialization between the genders (unclassified), we extract the log-odd coefficients of the statistically and economically significant predictors of specialization for each year. The following figures are complementary to our results, in case we want to see the exact composition of the specializations that were most popular among men and women from 2015 to 2020.

Figure 11 Log-odd coefficients of most significant specialization predictors for 2015.



The figure illustrates that some specializations exhibit strong negative log-odd coefficients, while others display strong positive ones. For instance, the log-odd coefficient of the "Foreign language: two foreign languages (English)" specialization is approximately -1.7. The negative sign indicates that selecting this specialization reduces the log-odds of the graduate being male. Given that the odds ratio is equal to the exponential of -1.7, graduates who select the "Foreign language: two foreign languages (English)" specialization are approximately 81.7% less likely to be male. This is a highly significant result, indicating that the vast majority of graduates who select this specialization are likely to be female. A similar observation can be made in the case of the "Electric power engineer" specialization, where the log-odd coefficient is approximately 2.3. This results in an odds ratio of exp(2.3) = 9.974. This indicates that graduates who select this specialization are approximately 9.9974 times more likely to be male. Consequently, an overall positive log-odd indicates a high probability that the graduate selecting this specific specialization is male, whereas a negative log-odd signifies a high probability that the graduate selecting this specific specialization is female.

The 2015 data indicates that the probability of a graduate being female is highest if they have selected one of the following specializations: 'Foreign language: two foreign languages (English)', 'Social pedagogy and self-awareness' or 'Teacher of Kazakh language and literature'. Conversely, the graduate is most likely to be male if he/she has chosen "Geology and mineral exploration", "Automation and control engineer", "Computer hardware and software", "Thermal power engineering", "Physical education and sports", "Mining", "Metallurgy", "Oil and gas industry", "Construction engineer", "Mechanical engineering", "Technological machinery and equipment", "Transport, transport equipment and technologies", "Agricultural machinery and technologies", "Electrical engineer". It is noteworthy that the log odds demonstrate the continued existence of "gendered specializations" and the persistence of a significant gender disparity in educational opportunities in Kazakhstan.

Similarly, the results can be interpreted in the context of subsequent years.

Figure 12 Log-odd coefficients of most significant specialization predictors for 2016.

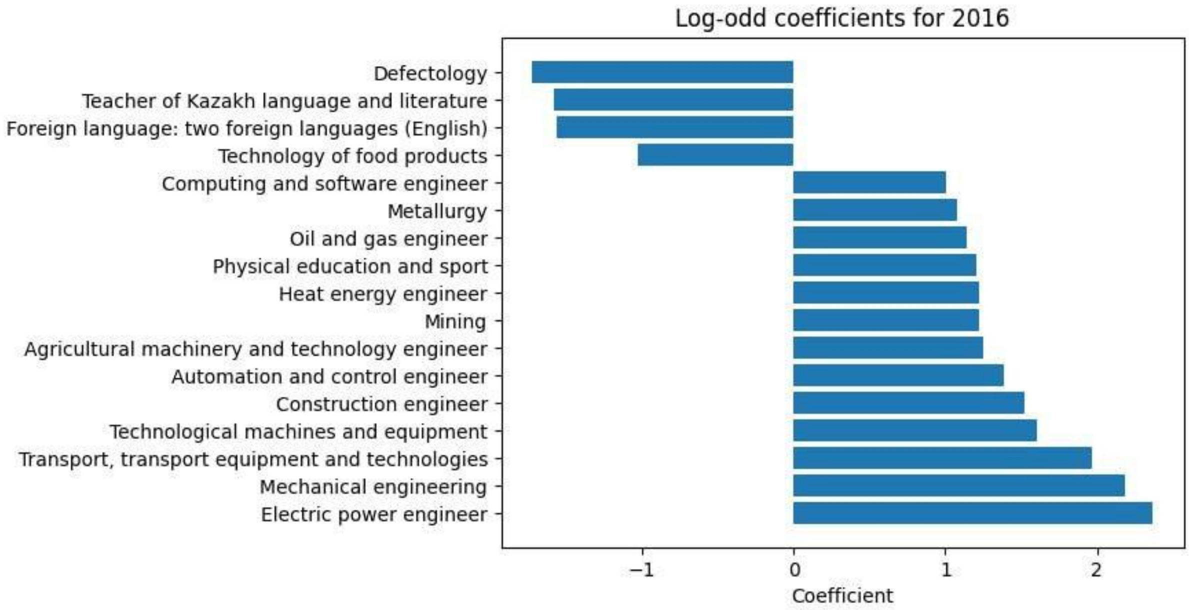


Figure 13 Log-odd coefficients of most significant specialization predictors for 2017.

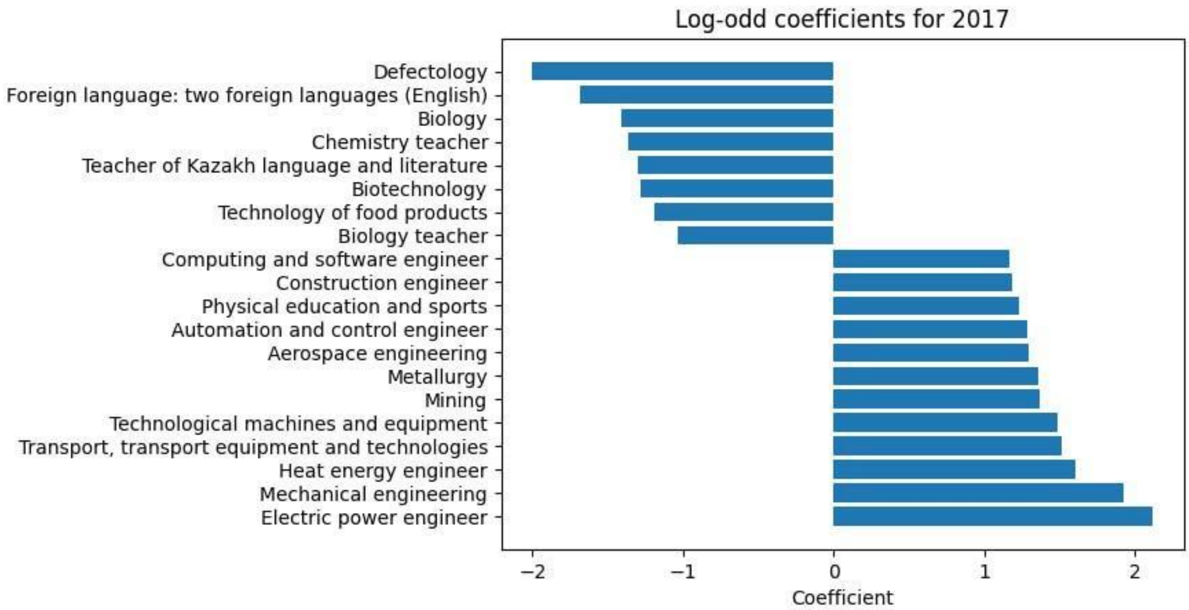


Figure 14 Log-odd coefficients of most significant specialization predictors for 2018.

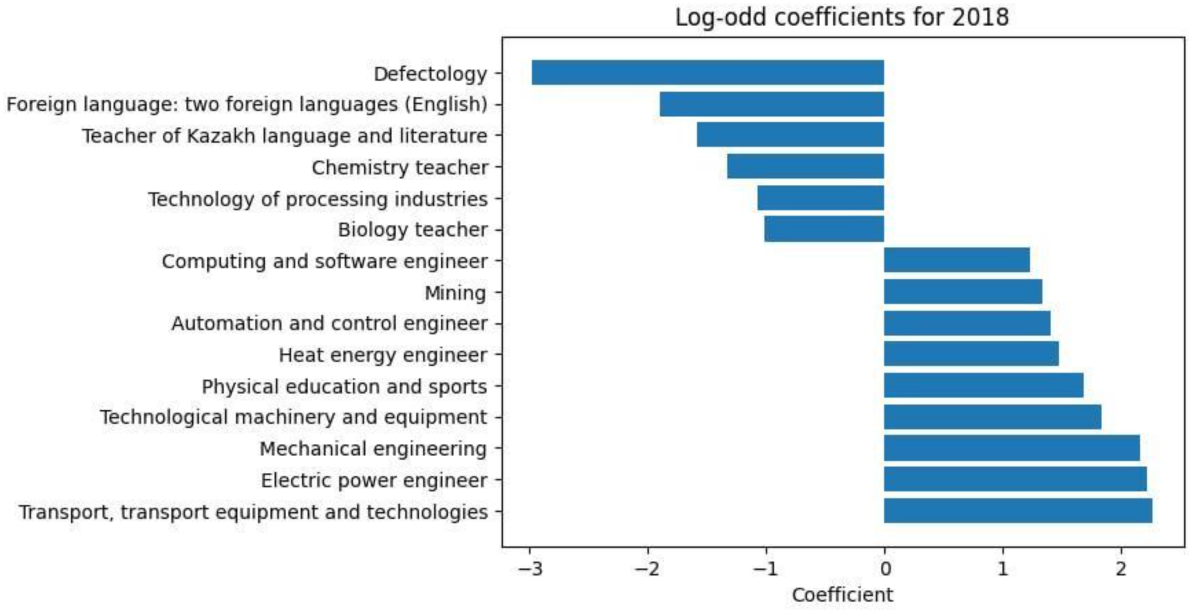


Figure 15 Log-odd coefficients of most significant specialization predictors for 2019.

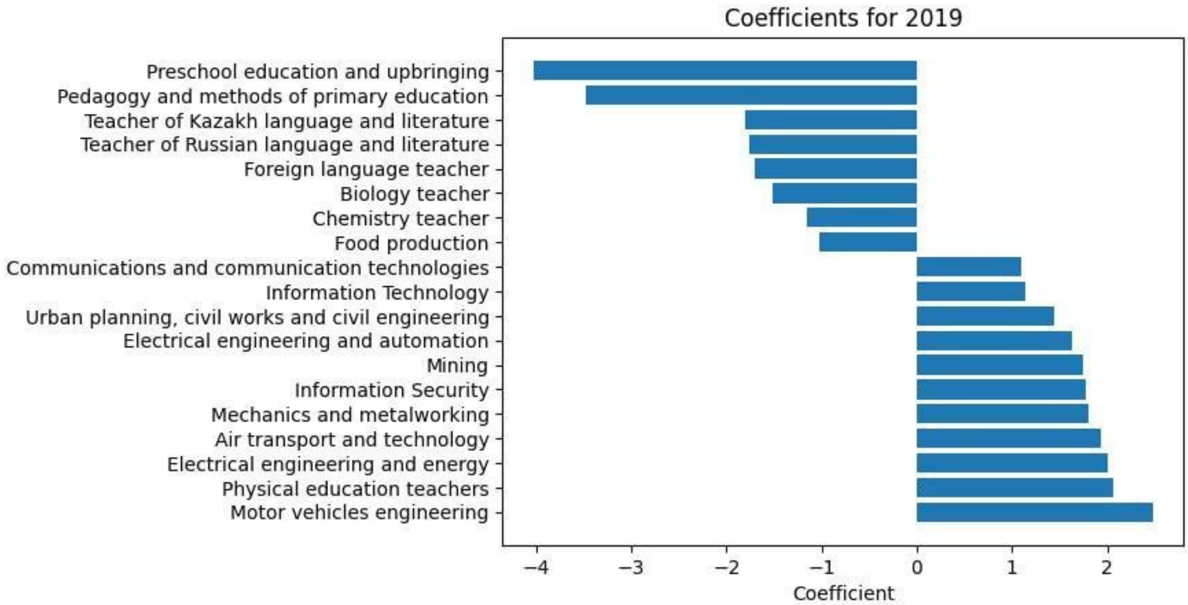
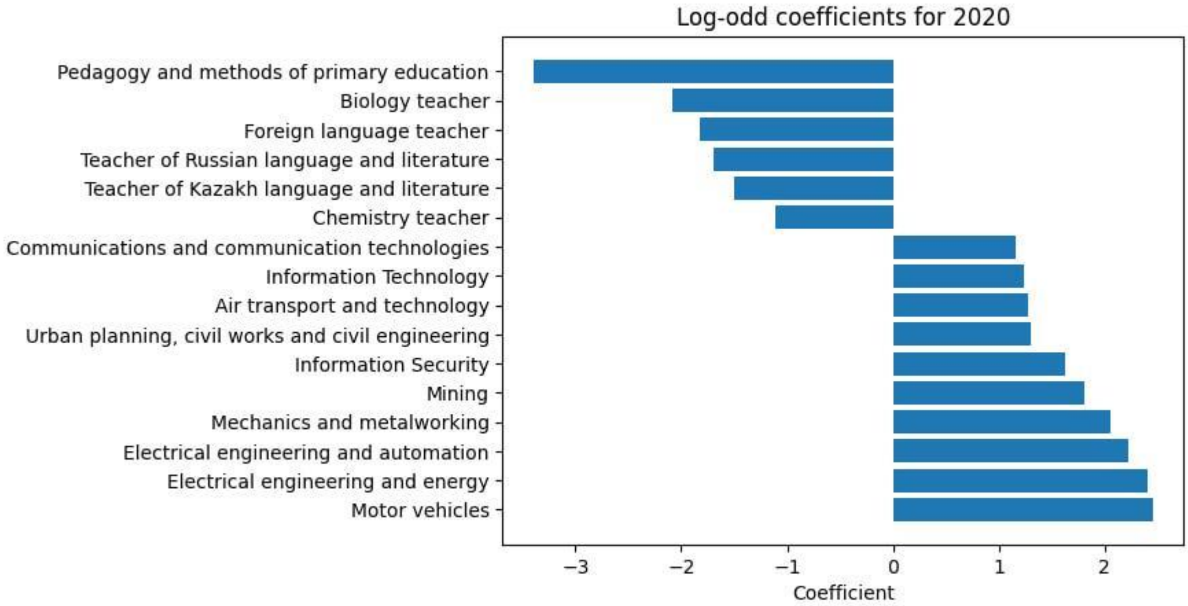


Figure 16 Log-odd coefficients of most significant specialization predictors for 2020.



The bar charts displaying the significant log-odd coefficients of specializations from 2015 to 2020 demonstrate clear gender disparities in specialization choices among fresh graduates in Kazakhstan. Over the course of these years, the probability of an applicant selecting traditionally "female" occupations, such as teaching or preschool education, is significantly higher if the applicant is female. Conversely, the probability of an applicant selecting "male" occupations, particularly in STEM fields, is considerably higher if the applicant is male. This trend persists even after the policy changes introduced in 2017, indicating that gender-specific career choices among graduates are enduring.

6 Discussion

6.1 Interpretation of Findings

6.1.1 Differences in UNT scores

Based on the results, there is a significant gender gap in UNT scores among Kazakhstani graduates. On average, female graduates tend to have higher UNT scores than their male counterparts. Our prediction model shows the same results: the higher the UNT score, the more likely the gender is to be female. The trend is continuous, with the gender gap widening each year. The policy change in 2017 contributed to this widening of the gender gap in UNT scores. The only exception is 2018, where the gender gap in UNT scores decreased compared to the previous year, but still remained negative. This phenomenon is most likely also due to the policy change in 2017. In 2018, as the format of the UNT changed significantly, not only making it optional, both genders did not have enough time to adapt to the new format of the exam, which is why the gender gap decreased.

Since 2019, the gender gap has only increased and continues to increase. This does not necessarily mean that women are more career-oriented, so they try to get good results in the UNT in order to be accepted in the specialization of their choice. One of the explanations could be that there are indeed more men than women who do not prepare seriously for an exam or even decide not to take the UNT every year. It may be that men want to start working as soon as possible, for example by starting their own business, so that they can start earning real money sooner. They may also be less concerned about the specialization in which they are accepted, as they can easily change their field later and are generally not socially criticized for such decisions. Women, on the other hand, strive for higher education so that in the future they can work in stable jobs with good social packages, such as teaching or nursing, to combine with their marriage, household duties and easily get paid maternity leave for 3 years.

Another possible explanation can be that women are expected by their families to perform well at school. Culturally, Kazakhstani families tend to compete with each other based on their children's performance. Because social expectations are much higher for females than for males in Kazakhstan, and because females are brought up to be obedient and people-pleasing, they tend to be more disciplined and focused on getting good grades, which does not necessarily mean better quality learning or acquiring a better education. In most cases, they focus too much on grades rather than on learning itself, so that they can gain the approval of their families, or at least not disappoint them.

Another interpretation of women obtaining higher UNT scores could be that they choose easier' subjects for the UNT. However, the choice of subjects and the analysis of UNT scores show that differences in the difficulty of UNT subjects are not the main reason for the gender gap. Men who choose STEM fields and women who choose to be chemistry, biology, physics, computer science or mathematics teachers, these specializations require the same set of subjects for the UNT (such as mathematics and physics, mathematics and computer science, chemistry and biology, etc.). There is no division of mathematics for science and general mathematics in the UNT exam. Thus, the higher UNT scores of female graduates are a measure of higher overall academic excellence rather than an easier choice of subjects.

6.1.2 Differences in Specialization of Choice

The results also show significant gender differences in the specialization of choices. Male specializations become more male-dominated over the years, but surprisingly female specializations become less female-dominated in recent years. These results suggest that women are most likely to enter more neutral specializations, but that male-dominated specializations remain and become more male-dominated. There is strong evidence that the gender gap in the choice of specialization among Kazakhstani graduates is persistent.

The main explanation can be due to social norms and expectations. Since there is no data on perceived norms etc., it is not possible to check it. But in general, there is a clear conventional division between male and female activities, not only in the choice of specialization. From childhood, girls are encouraged to take dance or gymnastics classes and discouraged from taking 'male' martial arts classes. In the home, young girls are expected to cook and do all the cleaning, while boys are taught to fix minor problems in home technology, etc. The same can be for the classification of the specialization of choice. It's not that women want to go into STEM, for example, it's that society shames them. In most cases, women may have this real belief that they shouldn't go into some fields and that it's better if they go into others like others do.

This interpretation also can also be applied to male graduates. In many cases they are even more ashamed of entering a culturally accepted 'female' field than women who enter traditionally 'male' fields. This is probably why the coefficients for male specializations are getting higher every year, while some women manage to go into a neutral field.

Looking at a popular Kazakhstani job searching website, hh.com, we can see that there are significant differences in the average salaries associated with male- and female-dominated fields. For example, the average salary for local IT specialists starts at USD 1000 per month, while the average salary for teachers is USD 500 per month. This large difference in salaries, which favors male-dominated fields, may influence graduates' choice of specialization. However, social norms may discourage women from entering this field, further exacerbating the gender gap.

Despite the fact that each year the government increases the number of scholarships for STEM specializations, recognising the importance of this rapidly developing sector, and that the government launches and supports gender equality programmes, these deeply rooted social norms and beliefs may have a significant impact on graduates and their choice of specialization. Female graduates continue to choose mainly female specializations, although there are some improvements, but not significant ones.

6.2 Limitations

The main limitation of our data is that it introduces selection. We only have data on those graduates who received the government grant. Even though we have the majority of all graduates, and we assume that they represent the total pool of all graduates for that year, the results on the choice of specialization may be, if not completely, at least partially different. Therefore, we do not have data on students who did not receive a grant.

We also have no data on those graduates who deliberately chose not to go to UNT. This is partly good, as in most cases they are outliers with better financial positions who can afford to study abroad, and therefore they would contaminate our results on the general Kazakhstani population. But there are some universities in Kazakhstan, not many, that don't require the UNT score for admission and offer their own internal scholarships. So some graduates may decide not to take the UNT and apply for state scholarships, which also introduces selection.

Another limitation is that the specializations do not necessarily represent the graduates' choice of specialization. It is true that the field of choice is correct, as graduates choose the electives for the UNT, but for some graduates the specialization in which they were accepted is not the one they originally wanted. For example, due to the high competition for some specializations, their lower UNT score or the limited number of state scholarships available for a particular specialization, some students were accepted for the specialization 'Nursing' when their first choice was 'General Medicine', which is a big difference.

7 Conclusion

In conclusion, the analysis showed strong empirical results supporting gender differences in education both in UNT scores and in the choice of specialization among Kazakhstani graduates. The predictive model was used for this purpose. The results show that, on average, higher UNT scores increase the probability that the gender is female in all years, but when it comes to the choice of specialization, the choice of low-paying specializations without career advancement increases the likelihood of gender being female. Although there is some improvement in the sense that women are starting to choose neutral specializations, this is not yet substantial. This shows that social expectations and gendered professions still may play an important role in Kazakhstani education in the 21st century. Female graduates inherently can underestimate their abilities and potential, so they tend to choose 'safe' occupations, even though, as the analysis shows, they do not perform as well as men, but even better. The same is true for male graduates, who are stuck in male specializations and severely under-represented in female specializations. It can be concluded that although the 2017 policy change was intended to give students more flexibility and freedom, in practice it has not had a significant impact on reducing the gender gap in education, but only worsened it.

Appendices

Appendix 1 The logit regression results for 2020

Logit Regression Results

Dep. Variable:	is_male	**No. Observations:**	30316
Model:	Logit	**Df Residuals:**	30312
Method:	MLE	**Df Model:**	3
Date:	Fri, 24 May 2024	**Pseudo R-squ.:**	0.1732
Time:	21:39:29	**Log-Likelihood:**	-17015.
converged:	True	**LL-Null:**	-20579.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Score_norm	-1.0803	0.061	-17.728	0.000	-1.200	-0.961
male_specialization	1.2660	0.034	36.956	0.000	1.199	1.333
female_specialization	-0.9366	0.039	-23.994	0.000	-1.013	-0.860
general_competition	0.0029	0.036	0.081	0.935	-0.067	0.073

Appendix 2 The logit regression results for 2019

Logit Regression Results

Dep. Variable:	is_male	**No. Observations:**	31275
Model:	Logit	**Df Residuals:**	31271
Method:	MLE	**Df Model:**	3
Date:	Fri, 24 May 2024	**Pseudo R-squ.:**	0.1742
Time:	21:39:27	**Log-Likelihood:**	-17744.
converged:	True	**LL-Null:**	-21488.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Score_norm	-1.1062	0.054	-20.316	0.000	-1.213	-0.999
male_specialization	1.3479	0.035	38.841	0.000	1.280	1.416
female_specialization	-0.8040	0.040	-20.241	0.000	-0.882	-0.726
general_competition	0.1297	0.033	3.874	0.000	0.064	0.195

Appendix 3 The logit regression results for 2018

Logit Regression Results

Dep. Variable:	is_male	**No. Observations:**	30795
Model:	Logit	**Df Residuals:**	30791
Method:	MLE	**Df Model:**	3
Date:	Fri, 24 May 2024	**Pseudo R-squ.:**	0.1456
Time:	21:39:26	**Log-Likelihood:**	-18146.
converged:	True	**LL-Null:**	-21239.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
Score_norm	-0.6192	0.041	-15.273	0.000	-0.699	-0.540
male_specialization	1.0321	0.027	38.262	0.000	0.979	1.085
female_specialization	-1.3098	0.034	-38.386	0.000	-1.377	-1.243
general_competition	0.1810	0.032	5.629	0.000	0.118	0.244

Appendix 4 The logit regression results for 2017

Logit Regression Results

Dep. Variable:	is_male	**No. Observations:**	20349
Model:	Logit	**Df Residuals:**	20345
Method:	MLE	**Df Model:**	3
Date:	Fri, 24 May 2024	**Pseudo R-squ.:**	0.1374
Time:	21:39:24	**Log-Likelihood:**	-12022.
converged:	True	**LL-Null:**	-13938.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	std err	z	P>|z|	[0.025	0.975]
Score_norm	-0.7285	0.052	-13.974	0.000	-0.831	-0.626
male_specialization	1.0378	0.033	31.431	0.000	0.973	1.103
female_specialization	-1.2438	0.044	-28.361	0.000	-1.330	-1.158
general_competition	0.1463	0.041	3.585	0.000	0.066	0.226

Appendix 5 The logit regression results for 2016

Logit Regression Results

Dep. Variable:	is_male	**No. Observations:**	20454
Model:	Logit	**Df Residuals:**	20450
Method:	MLE	**Df Model:**	3
Date:	Fri, 24 May 2024	**Pseudo R-squ.:**	0.1328
Time:	21:39:22	**Log-Likelihood:**	-12100.
converged:	True	**LL-Null:**	-13953.
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Score_norm	-0.6411	0.049	-13.030	0.000	-0.737	-0.545
male_specialization	0.9818	0.033	29.595	0.000	0.917	1.047
female_specialization	-1.4186	0.049	-28.735	0.000	-1.515	-1.322
general_competition	0.0281	0.043	0.659	0.510	-0.055	0.112

Appendix 6 The logit regression results for 2015

Logit Regression Results

Dep. Variable:	is_male	**No. Observations:**	15777
Model:	Logit	**Df Residuals:**	15773
Method:	MLE	**Df Model:**	3
Date:	Fri, 24 May 2024	**Pseudo R-squ.:**	0.01952
Time:	21:39:12	**Log-Likelihood:**	-10516.
converged:	True	**LL-Null:**	-10725.
Covariance Type:	nonrobust	**LLR p-value:**	2.017e-90

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Score_norm	-0.5275	0.041	-12.960	0.000	-0.607	-0.448
male_specialization	0.1884	0.062	3.053	0.002	0.067	0.309
female_specialization	-1.2092	0.074	-16.375	0.000	-1.354	-1.064
general_competition	0.2491	0.040	6.157	0.000	0.170	0.328

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