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Original Article

PREDICTING THE GROWTH TREND OF DEMAND FOR DISTANCE EDUCATION IN IRAN: A CASE STUDY OF PAYAME NOOR UNIVERSITY

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ABSTRACT

Awareness of the strategic role of higher education has led many countries to pursue long-term goals. The aim of this study is to identify the factors affecting the growth trend of the student in higher education by 2029. The statistical population of the whole is Payame Noor University. The method of this research is documentary-analytical. First, the factors influencing the demand for higher education, especially in open and distance education, were examined and analyzed using a regression model. Research data evaluated using the ordinary least squares regression method. The results show that economic factors have the most critical impact on increasing the demand for distance education. The forecast results show that the growth trend of the student population until 2029, between the two groups of men and women, is equally slightly decreasing.

Keywords: Higher education demand, Distance learning, Payame Noor University, Predicting the growth trend.

INTRODUCTION

Recognition of the strategic importance of higher education has led many countries to pursue long-term goals. One of the goals of higher education is to increase the number of registrants.

Demand for higher education means that the total number of students who apply for higher education in a country each year is affected by micro and macro factors. People delay entering the job market by deciding to continue their education after high school. To increase the percentage of graduates in the target community, individual and societal priorities should facilitate long-term investment in higher education with the benefits of short-term early employment, and adequate resources should be available to support these priorities (Oliviera *et al*., 2015).

Private demand for higher education has been examined in many studies to understand better the decision-making process for choosing to enter university (Flanery and O'Donoghue, 2013).

Examining student decision-making patterns informs the strategic planning and policy-making of higher education institutions. Numerous factors affect the demand for higher education in specialized texts, the most important of which classify into four categories: Individual/cognitive, social/family, economic/occupational, and structural/organizational variables. According to the human capital model, if the rate of return to higher education justifies the students "decision to pursue higher education, ideally, it should be based on students" perceptions of the cost/benefit of higher education (Menon *et al*, 2016).

Experimental economics research on the factors affecting access to education after high school emphasizes the impact of socio-economic conditions on the family. These works often emphasize that household income and social-economic status of parents have a significant impact on the likelihood of attending higher education (Castro *et al*., 2016).

The family's demand for higher education has two reasons: One is to raise education and social prestige, and the second is to acquire more skills and use them in the labor market. Higher education is not only prepared for consumer, but also has an investment nature, known for its neoclassical and human capital dimensions, respectively. According to human capital theory, the demand for education depends on the cost/benefit of higher education in the long run. Higher education enrollees are looking to earn more in the future than they do now (Ghavidel and Jahani, 2015).

The research background on the factors influencing the entry into higher education is very diverse. Menon *et al*. (2016) and Farajollahi *et al*. (2018) have stated that economic variables are the determining factor in choosing to continue higher education. According to Castro *et al*. (2016), household income is half the gap in access to university between rich and low-income families. The other half of the difference is parents' education, family background, and cognitive skills. Ghavidel *et al*. (2015) stated that forecast results in the structural method show the greater effectiveness of economic growth indicators. Most forecasts show a decrease in registrants by 2025, especially for men in Iran. Hartog and Serrano (2007) stated that permanent income is the most essential factor in entering higher education. According to Vieira and Vieira (2014) and Oliveira *et al*. (2015), economic conditions are less relevant than policy orientations. Therefore, the continuation or increase of higher education participation depends more on the choice of policies than on economic conditions. The only economic factor in the model is unemployment, which, unlike previous research, has hurt aggregate demand. According to Christofides *et al*. (2008), Flannery and Udonu (2009) further drive economic demand and reduced labor market opportunities in demand for higher education. Vieira and Vieira (2014), in their forecasts until 2030, have stated that the relatively slight and expected decrease in the number of registrants in the coming years will be due to continued population decline and the indirect impact of the economic crisis.

The nature and features of open and distance learning have changed with the advent of online networking technologies in the 1990s and their application in educational processes. As an educational model, online learning has embraced by learners and higher education institutions. It has become part of the mainstream because of the increased ingenuity of educational content, and the ability to reduce time and space barriers between learners, educators, and learning resources. Virtual learning is the provision of education in a digital tool that tends to support and enhance learning, which is based on a simultaneous and asynchronous communication network to build and shape knowledge. Research indicates that preparedness and strategy development are critical to the success of online learning activities (Firat and Bozkurt, 2020). The lack of proper training for faculty members is one of the biggest obstacles for educators participating in distance learning activities (Lee and Busch, 2005).

Payame Noor University (PNU), one of the largest open and distance universities in Iran, plays a crucial role in this process. Many students enter this university every year. Knowing what factors increase or decrease the growth of the student population in this university is very important for strategic planners, which will discuss below. Therefore, the purpose of this study is to identify the factors affecting the demand for higher education, especially distance education, and forecast for the coming years until 2029.

RESEARCH METHOD

The method of this research is documentary-analytical. The statistical population includes all centers and units of Payame Noor University, which is about 500 centers and units in 31 provinces. The data of the available years have used chronologically. In this paper in order to analyze the data, the ordinary least squares regression model is used. To obtain the variables, first a list of factors affecting the demand in higher education using the Delphi method and according to the background and dialogue with experts. After conducting studies and re-interviewing with experts, finally gave effective variables were collected. The dependent variable in this study is the number of male and female enrollees in the undergraduate course at Payame Noor University from 2001 to 2014 annually. The independent variable includes 31 variables that have studied as factors affecting the demand for higher education. Since the use of erratic time series in conventional econometric methods may lead to false regression, it is necessary first to ensure the reliability of the time series used in estimating the model's parameters study before making any estimates. One standard method for this purpose is the generalized Dickey-Fuller test. In this test, the statistics for the generalized Dickey-Fuller test compared with the critical quantity in the McKinnon's table. If the absolute value of T is computationally greater than the absolute value of McKinion's statistics, the null hypothesis rejected, which implies that the time series is stable.

The desired variables and data have collected during a long process. MICRO FIT and MIPLE software used for data analysis. Four regression models have been used in this study to estimate the data, which are:

LN(femail/mail)=C+LBT+LYK+LU+DLNT+DLCPI+DLYF+DLN2+DLBA

That:
LNfemail/mail: Number of female and male enrollees in undergraduate courses at PNU. C: intercept. LBT: General budget. LYK: Average earnings of production workers. LU: The unemployment rate for teens 15–24 years. DLNT: The total population of the country. DLCPI: Consumer price index. DLYF: Earning a master's degree. DLN2: Workforce graduated from secondary school. DLBA: Higher education funding.

LN(femail/mail)=C+DLSE+LSEE+DLCT+LGDP+LGNP+DLNEE+LYA+DLYD

That:
DLSE: The share of total employment in the industrial sector. LSEE: The share of employees with higher education to all employees. DLCT: Scholarships and student loans. LGDP: GDP. LGNP: Gross national product. DLNEE: Active population (total workforce). LYA: The average annual household income. DLYD: Diploma income.

LNfemail(mail)=C+LB1+LS3+LCA+LYL+LNE+DLN3

That:
LB1: Urban household dimension. LS3: Population of elementary school students. LCA: Average cost of the whole household. LYL: Bachelor's degree income. LNE: Number of employees in industrial workshops. DLN3: The population of university graduates in the workforce.

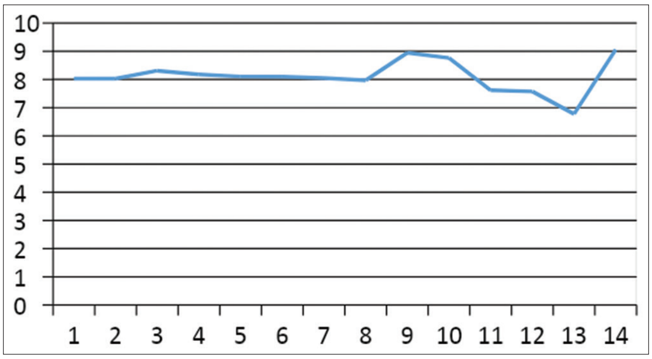

Fig. 1: Graph predicts the growth trend of women in distance education

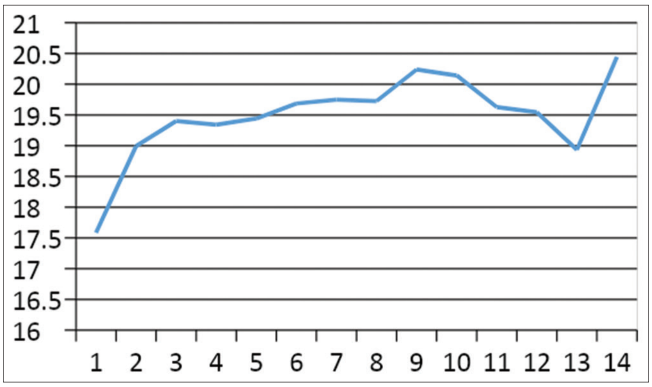

Fig. 2: Predicting growth trend of male student population in distance education

LNfemail(mail)=C+LB2+DLS2+LS1+LSK+DLSA+DLSAE+DLN1+LYE+LSF

That:
LB2: Rural household dimension. DLS2: Number of middle school students. LS1: Number of high school students. LSK: Agricultural tuition. DLSA: Tuition for basic sciences. DLSAE: Tuition in the humanities. DLN1: Population studying or graduating from the workforce. LYE: National income. LSF: Technical and engineering tuition.

RESULTS

In this section, we first examine the factors affecting the growth of the student population among men and women. Then identify the most critical factors that affect the increase or decrease in demand for distance education, which identified in the following tables.

Results of the findings in the women's section.

As shown in the tables above, diploma income (Table 1) has had the most significant impact on increasing women's access to higher education. Moreover, the urban household dimension (Table 2) has had the most significant impact on reducing the population of women entering higher education. Economic factors, followed by labor market factors, have had the most significant impact on women's access to distance education.

MEN'S RESULTS

The results of the men's section tables show that, like the results of the women's section, diploma income (Table 3) has had the most significant on increasing women's enrollment in distance education. Then, the urban household has had the most significant impact on reducing women's access to distance education. As in the women's section, in the men's section, the results show that economic and labor market factors have had the most significant impact on increasing or decreasing distance education (Tables 4-8).

Table 1: Ordinary least squares estimation (model 2-femail)

Regressor	Coefficient	SE	T-ratio	Probability
DLSE	−0.019	0.535	−0.035	0.973
LSEE	−0.017	0.026	−0.664	0.543
DLCT	−0.170	0.063	−2.696	0.054
LGDP	−0.084	1.118	−0.075	0.944
LGNP	0.189	1.080	0.175	0.869
DLNEE	0.235	0.544	0.432	0.687
LYA	−0.336	0.124	−2.699	0.054
DLYD	0.118	0.018	6.389	0.003

Observation: 14, *R*-Squared: 0.994, *R*-Bar-Squared: 0.98, *F*: 77.58, DW: 2.504.
SE: Standard error

Table 2: Ordinary least squares estimation (model 3-femail)

Regressor	Coefficient	SE	T-ratio	Probability
LB1	−0.760	0.131	−5.780	0.002
LS3	−0.849	0.196	−4.328	0.008
LCA	0.053	0.155	0.341	0.747
LYL	−0.326	0.130	−2.494	0.055
LNE	0.004	0.017	0.283	0.788
DLN3	0.010	0.020	0.547	0.608

Observation: 14, *R*-squared: 0.992, *R*-bar-squared: 0.982, *F*: 95.70, DW: 1.506.
SE: Standard error

Table 3: Ordinary least squares estimation (model 2-mail)

Regressor	Coefficient	SE	T-ratio	Probability
DLSE	0.161	0.600	0.269	0.801
LSEE	−0.023	0.030	−0.766	0.486
DLCT	−0.190	0.071	−2.676	0.055
LGDP	0.432	1.252	0.345	0.747
LGNP	−0.377	1.209	−0.312	0.770
DLNEE	0.221	0.609	0.363	0.734
LYA	−0.242	0.139	−1.737	0.157
DLYD	0.115	0.020	5.591	0.005

Observation: 14, *R*-squared: 0.992, *R*-bar-squared: 0.975, *F*: 58.29 , DW: 2.405.
SE: Standard error

Table 4: Ordinary least squares estimation (model 1-femail)

Regressor	Coefficient	SE	T-ratio	Probability
LBT	0.134	0.013	0.998	0.392
LYK	−0.055	0.025	−2.204	0.115
LU	−0.564	0.240	−2.342	0.101
DLNT	0.118	0.026	4.519	0.020
DLCPI	0.037	0.165	0.227	0.835
DLYF	−0.026	0.049	−0.534	0.630
DLN2	0.024	0.041	0.600	0.590
DLBA	0.024	0.091	0.270	0.804

Observation: 14, *R*-squared: 0.993, R-bar-squared: 0.972, *F*: 48.249, DW: 2.131.
SE: Standard error

Table 5: Ordinary least squares estimation (model 4-femail)

Regressor	Coefficient	SE	T-ratio	Probability
LB2	−1.302	1.256	−1.036	0.409
DLS2	1.842	2.110	0.873	0.475
LS1	−0.468	0.923	−0.506	0.663
LSK	−0.228	0.382	−0.597	0.611
DLSA	1.552	1.993	0.778	0.518
DLSAE	−0.277	0.364	−0.760	0.527
DLN1	−0.294	1.046	−0.281	0.805
LYE	0.004	0.133	0.030	0.978
LSF	0.109	0.215	0.507	0.662

Observation: 14, *R*-squared: 0.988, *R*-bar-squared: 0.930, *F*: 17.053, DW: 1.448.
SE: Standard error

Table 6: Ordinary least squares estimation (model 1-mail)

Regressor	Coefficient	SE	T-ratio	Probability
LBT	0.021	0.014	1.466	0.239
LYK	−0.032	0.027	−1.172	0.326
LU	−0.291	0.265	−1.100	0.351
DLNT	0.094	0.028	3.283	0.046
DLCPI	−0.064	0.182	−0.355	0.746
DLYF	0.008	0.054	0.164	0.880
DLN2	0.028	0.045	0.638	0.568
DLBA	−0.048	0.100	−0.484	0.662

Observation: 14, *R*-squared: 0.991, *R*-bar-squared: 0.964, *F*: 36.93, DW: 2.143.
SE: Standard error

Table 7: Ordinary least squares estimation (model 3-mail)

Regressor	Coefficient	SE	T-ratio	Probability
LB1	−0.507	0.147	−3.433	0.019
LS3	−0.690	0.220	−3.129	0.026
LCA	−0.033	0.175	−0.191	0.855
LYL	−0.417	0.147	−2.834	0.036
LNE	−0.021	0.019	−1.066	0.335
DLN3	0.027	0.022	1.239	0.270

Observation: 14, *R*-squared: 0.989, *R*-bar-squared: 0.975, *F*: 70.20, DW: 1.620.
SE: Standard error

Table 8: Ordinary least squares estimation (model 4-mail)

Regressor	Coefficient	SE	T-ratio	Probability
LB2	−0.476	0.949	−0.501	0.666
DLS2	1.098	1.595	0.688	0.562
LS1	0.095	0.698	0.136	0.904
LSK	−0.714	0.288	−2.473	0.132
DLSA	0.649	1.506	0.430	0.709
DLSAE	−0.156	0.275	−0.567	0.628
DLN1	0.011	0.790	0.014	0.990
LYE	0.603	0.100	5.979	0.027
LSF	0.445	0.162	2.734	0.112

Observation: 14, *R*-squared: 0.997, *R*-bar-squared: 0.984, *F*: 74.97, DW: 2.201.
SE: Standard error

Predicting the growth trend of the student population among men and women.

By analyzing the changes in the independent variables and considering these changes for the future, and then placing them in the regression lines, the prediction for the rate of changes in the number of students in the future has used. Students' fluctuations and changes take into account in the forecast. The graph shows that the overall result is declining by 2029, and it predicted that the number of male and female students will decrease (Figs. 1 and 2).

DISCUSSION AND CONCLUSION

The results of the present study show that a large number of Iranian students are looking for e-learning. The idea of gaining more knowledge and gaining better job opportunities in the future through virtual and distance education has increased their interest in continuing their education in this type of higher education. Economic factors and the labor market have been statistically very significant in the regression model and have a positive effect on students' attitudes to pursue higher education. These results show that Iranian students are concerned about their future careers and the high unemployment rate in the workforce in recent years.

Therefore, planning for educational policy should depend on the needs of the labor market and the demands of the labor force, and also, career guidance should provide for young people in policy-making to reduce the unemployment rate of university graduates.

In this study, the ordinary least squares model for distance education in Iran evaluated, using data from the total number of male and female registrants from 2001 to 2014. The purpose of this study was to identify the influential factors of registration and provide demand forecasts by 2029.

As the results show, economic and labor market factors have had a significant impact on the growth of enrollment in distance education in Iran. They are consistent with the results of research by Menon *et al*. (2016), Custer *et al*. (2016), Ghavidel *et al*. (2015), Hartog and Serrano (2007), Christofides *et al*. (2008), and Farajollahi *et al*. (2018).

It should be noted that the results of this study are not consistent with the results of Vieira and Viera (2014) and Oliveira *et al*. (2015).

In the forecast section, the growth trend of the student population among men and women has shown that by 2029, the number of enrollees will decrease slightly. The results of this section are consistent with the results of Ghavidel and Jahani (2015) and Viera and Viera (2014). Of course, Ghavidel *et al*. have noted that there will be a decrease in registrants, especially among men. Vieira and Viera have indicated that the number of registrants will decrease due to population decline and the economic crisis.

Therefore, in distance education, among the effective factors in the growth process of students, designing appropriate electronic content, expanding bandwidth, and providing appropriate speed on the internet are what educational planners, engineers, and educational design technicians should pay enough attention to. Due to health crises and lack of access to some geographical areas and their great distance from educational centers, there is a need for significant planning in this area.

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