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Impact of Energy Factors and Digitalization Advancement on Employment: Evidence from Mining, Industry and Electricity Labor Markets

Saule Kaliyeva, Rakhila Rakhmetova, Ainura Maxyutova, Ryszhan Kabylkairatkyzy*, Ilyas Sadykov

Institute of Economics of the Science Committee of the Ministry of Science and Higher Education, Almaty, Kazakhstan.
*Email: riszhan_1993@mail.ru

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ABSTRACT

The research aims to assess the impact of energy and digitalization factors on employment in labor markets associated with energy sources. For this purpose, linear and nonlinear autoregressive distributed lag (ARDL & NARDL) models were applied. The following indicators were gathered for this purpose from official domestic and international statistics sources for the years 1998-2023: Internet users, fixed phone subscriptions, mobile cellular subscriptions, and ICT service exports - explanatory variables, Kazakhstan's crude oil production, average yearly price of Brent crude oil, US dollars per barrel, and CO_2 emissions per person (tons). The manufacturing sector, mining and quarrying, and electricity, gas, steam, and air conditioning were the three labor market segments that were examined. According to the study's findings, employment in these three industries is positively impacted by energy-related variables, but negatively by digitalization variables. This suggests that new job opportunities have been made possible by digitization. The study's findings also indicate that employment in these industries is somewhat reliant on the supply of oil and its global price. The export of raw materials continues to be the main focus of Kazakhstan's economy; thus, some policy implications are given in conclusion section. This study adds some empirical value to existing literature on energy labor markets.

Keywords: Energy, Employment, Digitalization, CO_2 Emissions, Oil Production, Oil Price
JEL Classifications: P18, P28, Q43M

1. INTRODUCTION

The most significant sectors of any nation's economy are those of industry and energy, and even minor adjustments can have a significant impact on the course of the economy (Pacana and Siwiec, 2019). Over the past century, technological advancements, automation, and the use of renewable energy sources have caused structural shifts in employment in industry, particularly the energy and oil and gas sectors (Mayen Huerta et al., 2024; Adjei et al., 2024; Razzaq and Malik, 2025). Employment in renewable energy is going upward globally (Chirkova and Berezhnoy, 2022). In these fields, the distribution of resources for worker skill enhancement, research and development, and ICT utilization significantly affects labor supply and demand. (IEA, 2023). The largest growth was observed in the clean energy sector, which added 1.5 million new jobs in 2023, accounting for 10% of total economic job growth in leading clean energy technology markets. Efficient technologies and electrification will also help to move closer to the Net Zero Emissions by 2050 Scenario. The way that employment difficulties are handled varies by city and sector (Chulanova et al., 2024). Employment as a whole is the most important economic indicator and many macroeconomic factors have influence on it (Asaleye et al., 2022). Labor potential is influenced by factors such as human capital, lever of professional training (Salkynbayeva et al., 2024), knowledge of technology, automation, initial qualifications of workers and their advancement path of it (Makiev et al., 2024).

Conditions for enhancing the quality attributes of labor resources lead to the creation of the labor market (Chulanova, 2019). This is a very complex sector, so labor resource development must be considered at the national level. When planning employment in the energy and industrial sectors at the regional level, the spread of accepted software standards and innovative technologies, programs aimed at increasing production efficiency played an important role. Employment generation in the energy sector of the economy is associated with the development of new technologies or the implementation of projects to expand existing energy systems. This is due to the availability of labor-intensive technologies and digitalization, which enable the attainment of a certain production target with significant additional employment (Zare and Lazarova-Molnar, 2024). Deep synergy of digitalization and greening have also spatial effects on employment (Graadal, 2023; Li et al., 2024).

Thus, the article consists of following parts: Introduction, Literature review, Methodology and Conclusion.

2. LITERATURE REVIEW

Industry digitization and how emerging digital technologies are altering the structure of employment (Idayanti and Siswanto, 2022; Reznikova and Tsygankova, 2024). Oil and gas sector are prone to technology changes too (Abdalla, 2023). Energy sector is developing hand in hand with economic development, environmental needs, and technological progress (Ram et al., 2020). Technological progress can be the salvation of both labor and capital (Kennedy, 1964), but technical progress cannot be neutral; it tends towards a certain factor of production with a lower price (Flatau, 2022). Wang et al. (2020) analyzed the influence of Internet technology on employment at the industry level in China. The results of the study show that the progress of Internet technologies in one industry will contribute to the progress of Internet technologies in related industries and they contribute to employment in industry. Chopra et al. (2024) emphasize that the joint and close partnership of academia with industry on the innovation strategy of the enterprise, and its technological success is very important in understanding the development of employment. Industry 4.0 unites green employment, corporate social responsibility and technological progress (Ekimova, 2025) and some researchers link the boom in employment in the renewable energy sectors with Industry 4.0 (Rutkowska and Sulich, 2020; Ghannouchi, 2023; Kilinç and Güven, 2024). Jung and Kim (2023) analyzed the impact industry 4.0 technologies on the employment of entire industries, and came to conclusion that it increased employment in the whole industry, including financial and insurance sectors. Applying ARDL and NARDL methods, Sankaran et al. (2024) revealed that gross capital formation and technology spillover have positive impact on employment, meaning шnvestments in the extractive industry and the penetration of foreign technology have a rather favorable effect on the labor market in these sectors. Having analyzed 28 China's manufacturing industries Wang et al. (2024) concluded that the shift toward technological progress has a positive impact on total manufacturing employment and a significant positive impact on unskilled labor, while not having a significant impact on skilled labor employment. Having analyzed the oil and gas sector of Russia in the context of digitalization, Kazanin (2020) came to the conclusion that implementation of digital technologies in exploration and production, processing and transportation will promote the efficiency of this sector. Such implementations will bring structural changes in demand and supply side of skilled and unskilled labor force. Chaudhuri et al. (2024) analyzed effect of energy transition on India's employment, and concluded that as dominant source of fuel in power generation in coal sector they have higher employment rate. In this case, power of solar energy and wind energy can help shift labor force to renewable energy sector. Although Simas and Pacca's (2014) study shows the main contribution of wind energy to job creation is during the construction phase and, despite the small number of jobs created in operations and maintenance compared to new installed capacity, meaning employment dynamics as not stable as wished to be.

The number 7 goal of sustainable development goals is access to affordable and clean energy (UN DESA, 2024). In order for governments to prepare for the necessary labor force size, it is imperative to anticipate the labor force as many nations attempt to rapidly increase their renewable capacity (Langdon et al., 2025). Also, renewable energy sources and technology advancement can diminish reliance on conventional energy sources and mitigate environmental harm (Udemba et al., 2023; Oteng et al., 2024; Okeke, 2025). In a world transition towards a low-carbon economy, the employment implications of renewable energy growth are of paramount importance. Hlongwane et al. (2025) investigated impact of solar, hydro, wind, nuclear, and other renewables on employment in emerging BRICS. Their research demonstrated that to leverage their job creation potential and promote sustainable economic growth, nations should prioritize investments in hydropower, solar power, and wind power. According to Nasirov et al. (2021) and Li et al. (2022), compared to fossil fuels, solar, wind, and bioenergy create more jobs per unit of energy produced. Alfalih and Bel (2021) demonstrated in their study that employment in the oil and gas industry is not always positively impacted by foreign direct investment. Foreign direct investment's negative impact may exceed its positive impact. Vilema-Escudero et al. (2024) investigated the relationship between energy intensity and employment in 13 Latin American countries. Their panel data regression model indicated a negative relationship between energy intensity and employment. Their research shows that governments need to adopt comprehensive policies that promote energy efficiency and quality employment. Elom et al. (2024) used panel rigorous regression models to examine the causal association between carbon emissions, employment, education, and the use of renewable energy in Africa. They came to the conclusion that employment, renewable energy, and education investments are beneficial for reducing carbon emissions in Africa following discovering bidirectional correlation between the measures.

3. METHODS

Considering the findings of the Literature review in the preceding part, authors examine the correlation between the

Republic of Kazakhstan's digitalization indicators and labor market indicators from 1998 to 2023, specifically: Individuals using the Internet, Fixed telephone subscriptions, Mobile cellular subscriptions, ICT service exports, also Cude oil production (Mln t) Kazakhstan, Average annual Brent crude oil price, U.S. dollars per barrel, Per capita CO□ emissions (tons) variables are taken.

The employed population variables in the manufacturing industry (EPMI), mining and quarrying (EPMQ), and electricity, gas, steam, and air conditioning (EPEGSAC) sectors were selected as labor market indicators, and the regression equations (1-3) that corresponded to these variables were taken into consideration:

$$EPMQ = f\,(COP, ABCOP, IUIP, FTS, CO2E, MCS, ICT) \qquad (1)$$

where all of their definitions and measurements are given in the Table 1.

Next, *EPMI and EPEGSAC* are assessed by following regression model:

$$EPMI = f\,(COP, ABCOP, IUIP, FTS, CO2E, MCS, ICT) \qquad (2)$$

$$EPEGSAC = f\,(COP, ABCOP, IUIP, FTS, CO2E, MCS, ICT) \quad (3)$$

With the exception of EPMQ, all of the variables under investigation were determined to be stationary at the level of I (0) or initial differences I (1) during the study, according to the findings of the ADF test (Table 2). Additionally, EPMQ is not stationary unless there is a first discrepancy between the trend and the intercept. As a result, the ARDL methodology is applied, the order of variable integration is taken into account to assess the ARDL model's suitability for the study, and a special test is used to select a maximum of two lags for the ARDL1 and ARDL2 models and lag 1 for the NARDL3 model (Table 3).

First difference was used to estimate linear ARDL models, and both short- and long-term evaluations of the correlation between variables were carried out. First difference was used to estimate linear ARDL1 and ARDL2 models based on the Granger causality test results (Table 4). Long- and short-term assessments of the relationship between variables were performed in the case of 1st difference with Intercept. Only when there was a first difference without an interceptor trend were the IUIP and FTS models computed using NARDL3 models.

The findings of the boundaries test, which looks for long-term associations, are shown in Table 5. The process ascertains whether cointegration exists between the chosen variables in the lagged distributed autoregressive linear (ARDL) model. Three primary models were built. The ARDL process ascertains whether cointegration exists between the chosen variables in these distributed lag linear autoregressive models. The ARDL model structure 1-3 is represented by equations 4-6, respectively, and the limits test verifies long-term relationships.

Thus, the ARDL1 structure of model 1 is expressed in a linear form 3:

$$\begin{aligned} EPMQ_{\ddot{u}\ddot{u}\ddot{u}} == {} & \beta_0 + \sum_{k=1}^{l}\beta_1\ EPMI_{-} + \sum_{k=0}^{m}\beta_2\ COP_{-} + \\ & \sum_{k=0}^{n}\beta_{3k} ABCOP_{t-k} + + \sum_{k=0}^{p}\beta_{4k} IUIP_{t-k} + \\ & \sum_{k=0}^{q}\beta_{5k} FTS_{t-k} + \sum_{k=0}^{r}\beta_{6k} CO2E_{t-k} + \sum_{k=0}^{s}\beta_{7k} MCS_{t-k} + \\ & \sum_{k=0}^{v}\beta_{8k}\ \ddot{u}\ddot{u}\ddot{u}\ddot{u}\ddot{u}\ddot{u}\ddot{u}_{t-k} + \gamma_1 \quad {}_{t-i} + \gamma_2 \quad {}_{t-i} + \gamma_3 \quad {}_{t-i} + \\ & \gamma_4 FTS_{t-i} + \gamma_5 CO2E_{t-i} + \gamma_6 MCS_{t-i} + \gamma_7 ICT_{t-i} + \varepsilon_t \end{aligned} \qquad (4)$$

where, operator Δ represents the differencing operation.

The estimation of ARDL2 is as follows:

$$\begin{aligned} EPMI_t = {} & \beta_0 + \sum_{k=1}^{l}\beta_{1k}\ EPMI_{t-k} + \sum_{k=0}^{m}\beta_{2k} COP_{t-k} + \sum_{k=0}^{n}\beta_{3k} ABCOP_{t-k} + \\ & + \sum_{k=0}^{p}\beta_{4k} IUIP_{t-k} + \sum_{k=0}^{q}\beta_{5k} FTS_{t-k} + \sum_{k=0}^{r}\beta_{6k} CO2E_{t-k} + \\ & \sum_{k=0}^{s}\beta_{7k} MCS_{t-k} + \sum_{k=0}^{v}\beta_{8k} ICT_{t-k} + \gamma_1 COP_{t-i} + \gamma_2 ABCOP_{t-i} + \\ & \gamma_3 IUIP_{t-i} + \gamma_4 FTS_{t-i} + \gamma_5 CO2E_{t-i} + \gamma_6 MCS_{t-i} + \gamma_7 ICT_{t-i} + \varepsilon_t \end{aligned} \qquad (5)$$

The following logarithmic equation represents NARDL3:

Table 1: Model variables and sources

Variables	Definitions	Sources
EPMQ	Mining and quarrying	Bureau of National statistics of the Republic of Kazakhstan
EPMI	Manufacturing industry	Bureau of National statistics of the Republic of Kazakhstan
EPEGSAC	Electricity, gas, steam and air conditioning	Bureau of National statistics of the Republic of Kazakhstan
COP	Cude oil production (Mln t) Kazakhstan	Trading Economics
ABCOP	Average annual Brent crude oil price, U.S. dollars per barrel	Statista
IUIP	Individuals using the internet (% of population)	World bank
FTS	Fixed telephone subscriptions (per 100 people)	World bank
CO_2E	Per capita CO_2 emissions (tons)	World bank
MCS	Mobile cellular subscriptions (per 100 people)	World bank
ICT	ICT service exports (BoP, current US$)	World bank

Source: Authors

Table 2: ADF unit root tests

Variables	Intercept			Trend and intercept			None		
	Level	First diff.	Order of integration	Level	First diff.	Order of integration	Level	First diff.	Order of integration
EPMQ	−0.392 (0.896)	−3.140** (0.037)	I (1)	−2.756 (0.225)	−3.144 (0.119)	>I (1)	0.793 (0.878)	−3.133*** (0.003)	I (1)
EPMI	−0.154 (0.933)	−4.25*** (0.003)	I (1)	−2.761 (0.223)	−4.231** (0.014)	I (1)	1.557 (0.967)	−3.997*** (0.0003)	I (1)
EPEGSAC	−3.019** (0.050)	−8.142* (0.000)	I (0)	−4.178** (0.016)	−7.962** (0.000)	I (0)	−3.306** (0.002)	−8.325** (0.00)	I (0)
COP	−3.08*** (0.041)	−3.39*** (0.022)	I (0)	−2.115 (0.510)	−4.70*** (0.006)	I (1)	2.787 (0.998)	−1.617* (0.098)	I (1)
ABCOP	−2.032 (0.272)	−4.491** (0.002)	I (1)	−2.037 (0.554)	−4.46*** (0.009)	I (1)	−1.195 (0.606)	−4.514*** (0.000)	I (1)
IUIP	−0.475 (0.879)	−2.642* (0.099)	I (1)	−2.805 (0.210)	−2.492 (0.328)	>I (1)	−0.054 (0.655)	−1.448 (0.134)	>I (1)
FTS	−1.851 (0.348)	−1.243** (0.038)	I (1)	−1.009 (0.924)	−2.521 (0.316)	>I (1)	−0.699 (0.403)	−1.301 (0.173)	>I (1)
CO2E	−1.691 (0.423)	−5.01*** (0.000)	I (1)	−0.579 (0.972)	−6.69*** (0.000)	I (1)	0.474** (0.810)	−4.844*** (0.000)	I (0)
MCS	−1.842 (0.352)	−2.023* (0.076)	I (1)	−1.453 (0.817)	−2.327 (0.405)	>I (1)	0.474 (0.541)	−1.900* (0.056)	I (1)
ICT	−0.402 (0.894)	−1.040** (0.021)	I (1)	−0.725 (0.999)	−5.159** (0.002)	I (1)	0.340 (0.776)	−4.655** (0.000)	I (1)

*, **, ***denote statistically significant at the 10%, 5% and 1% levels, respectively
P-value is inside brackets

$$\begin{aligned}\Delta LOG\ EPEGSAC_t &= \beta_0 + \sum_{k=1}^{l}\beta_{1k}\ LOG\ EPEGSAC_{t-k}\ + \\ &\sum_{k=0}^{m}\beta_{2k}LOG(COP_{t-k}) + \sum_{k=0}^{n}\beta_{3k}LOG(ABCOP_{t-k}) + \\ &\sum_{k=0}^{p}\beta_{4k}LOG(CO2E_{t-k}) + \sum_{k=0}^{q}\beta_{5k}LOG(MCS_{t-k}) \\ &+ + \sum_{k=0}^{r}\beta_{6k}LOG(ICT_{t-k}) + \gamma_1 LOG(COP_{t-i}) + \\ &\gamma_2 LOG(ABCOP_{t-i}) + \gamma_1 COP_{t-i} + \gamma_2 ABCOP_{t-i} + \\ &\gamma_3 LOG(CO2E_{t-i}) + \gamma_4 LOG(MCS_{t-i}) + \\ &\gamma_5 LOG(ICT_{t-i}) + \varepsilon_t \end{aligned} \tag{6}$$

4. DATA AND FINDINGS

4.1. Data

This study looks at how Kazakhstan's three segments of labor market are affected by seven energy and digitalization parameters. The World Data Bank and Bureau of National statistics of the Republic of Kazakhstan, Trading Economics, Statista official websites provided the data used in the study, which spans the years 1998-2023. Internet users, fixed phone subscriptions, mobile cellular subscriptions, and ICT service exports of Kazakhstan, Kazakhstan's crude oil production (Mln t), average yearly price of Brent crude oil, US dollars per barrel, and CO_2 emissions per person (tons) are the explanatory variables in this study.

The definitions and measurements of all indicators are given in Table 1 below:

The dynamic change of all indicators presented in the table in the period 1998-2023 is depicted in the following graph:

From the analysis of the graph presented in Graph 1, it is clear that the variables under study are suitable for analysis. The graph shows clear, consistent, and stable time patterns, indicating that changes in the variables are suitable for further study.

4.2. Descriptive Statistics

The hypothesis was tested in this study using the ARDL model and descriptive statistics. Several facets of the data set can be understood by descriptive statistics. For every variable utilized in our model, the descriptive statistics findings shown in Table 6 include aggregated averages like mean and median, as well as measures of dispersion and variation like minimum and maximum standard deviation, skewness, and Jarque-Bera statistic.

According to descriptive statistics, the average values of the employment indicators in the labor market segments of Mining and quarrying (EPMQ), Manufacturing industry (EPMI), Electricity, gas, steam and air conditioning (EPEGSAC) are 234.37, 537.91 and 194.92, and the median values are 223.05, 542.61 and 148.94, respectively, and the standard deviations are 40.13, 44.01 and 239.94, which indicates relatively stable values. All P > 0.05,

Table 3: Selection order criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
ARDL1 EPMQ						
0	−92.90511	NA	354.0495	8.687401	9.032986	8.774314
1	−81.53629	14.82889*	145.2087*	7.785765*	8.180719*	7.885094*
ARDL2 EPMI						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	−113.9530	NA	1420.803	10.07941	10.42301	10.17057
1	−88.47327	33.97292*	186.4276	8.039439*	8.432124*	8.143619*
NARDL3 EPEGSAC						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	61.64849	NA	2.48e-11	−4.554041	−4.210442	−4.462884
1	250.5834	251.9132	2.58e-16	−16.21528	−13.46649	−15.48602
2	355.0161	78.32459*	9.59e-18*	−20.83468*	−15.68069*	−19.46732*

Table 4: Noncausality tests in the sense of Granger for the vector autoregressive (1) (1998-2023)

Direction of causality	F-statistic	Prob.
EPMQ		
COP does not granger cause EPMQ	2.037307	0.3611
ABCOP does not granger cause EPMQ	2.969954	0.2265
IUIP does not granger cause EPMQ	40.45639	0.1000
FTS does not granger cause EPMQ	2.268679	0.3216
CO_2E does not granger cause EPMQ	2.863491	0.2389
MCS does not granger cause EPMQ	4.437656	0.1087
ICT does not granger cause EPMQ	1.644694	0.4394
EPMI		
COP does not granger cause EPMI	1.219239	0.5436
ABCOP does not granger cause EPMI	0.824608	0.6621
IUIP does not granger cause EPMI	0.596882	0.7420
FTS does not granger cause EPMI	0.230638	0.8911
CO_2E does not granger cause EPMI	0.417400	0.8116
MCS does not granger cause EPMI	0.727422	0.6951
ICT does not granger cause EPMI	0.591015	0.7442
EPEGSAC		
COP does not granger cause EPEGSAC	2.009157	0.3662
ABCOP does not granger cause EPEGSAC	0.722217	0.6969
IUIP does not granger cause EPEGSAC	0.392390	0.8219
FTS does not granger cause EPEGSAC	3.743491	0.1539
CO_2E does not granger cause EPEGSAC	3.369935	0.1855
MCS does not granger cause EPEGSAC	1.271978	0.5294
ICT does not granger cause EPEGSAC	4.804133	0.1105

The study revealed a causal relationship from all variables to EPMQ, EPMI, EPEGSAC

indicating that the series are uniformly distributed. The Jarque-Bera statistics values are 3.51, 1.22, and 573.82, respectively, and the probabilities of association are 0.17, 0.54, and 0.11, respectively. Additionally, all indicators' standard deviations are higher than 0.10. Table 2 shows that the time series' skewness coefficient is >0, indicating that the EPMQ, EPEGSAC, ABCOP, IUIP, FTS, MCS, and ICT indicators have a right skewness. The distribution is near normal, with no extreme kurtosis, according to the kurtosis value for each indicator.

4.3. Unit Root Test

The levels or differences of time series variables were tested for stationarity using Augmented Dickey-Fuller (ADF) unit root tests. It is crucial to ascertain whether series are stationary before looking at their long-term interactions. While certain variables are ideally stationary at the first difference I(1) level, others can be employed at the I(0) level. The majority of the study series are not stationary at the level, according to the ADF results, as indicated in Table 2.

Table 5: Results of cointegration test

Model	F-statistics	Critical bounds	Decision
ARDL1 ARDL (1, 0, 0, 1, 0, 0, 0, 1)	4.541900	2.83-3.91	Cointegration
ARDL2 ARDL (1, 1, 1, 0, 0, 1, 1)		2.83-3.91	Cointegration
NARDL3 NARDL (1, 2, 1, 2, 2, 2)	8.853405	2.87-4.05	Cointegration

Critical bounds are reported at 1% (***) and 10% (**) level of significance

In the first discrepancy between the trend and the intercept, only the EPMQ is non-stationary. Therefore, the ARDL cointegration approach is the most effective strategy to estimate or evaluate the long-term relationship between the study variables in this situation if EPMQ is not utilized.

The unit root results support the primary hypotheses, which call for the ARDL model test to verify the existence of long-term correlations between the labor market indicators from 1998 to 2023 and the Republic of Kazakhstan's energy and digitalization indicators as reported in the study.

4.4. Granger Causality Test

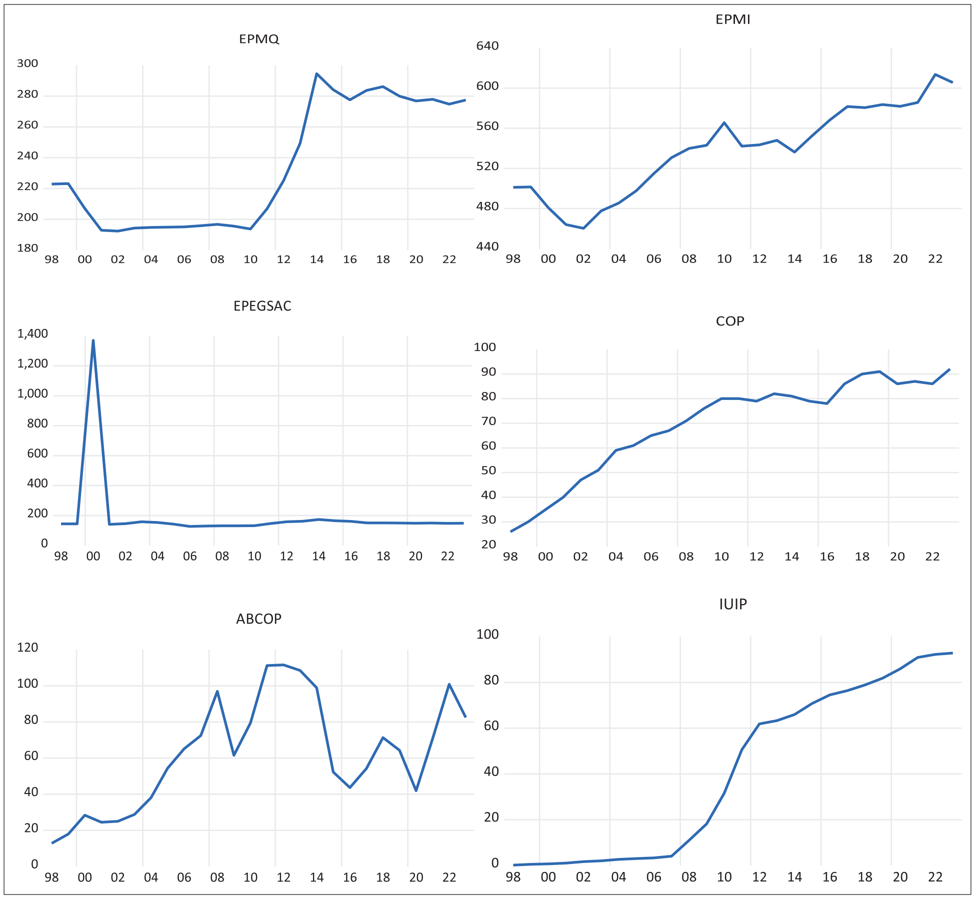
The Granger test, which examines the null hypothesis that changes in the dependent variable are not causal (noncausality), is used to examine the causal relationship between the seven energy and digitalization variables and the labor market indicators.

To increase the accuracy of the stability test, this study also used pair-to-pair Granger causation to determine the causality between variables as shown in Table 4.

4.5. Co-Integration Test

The long-term relationship between the variables under consideration and EPMQ, EPMI, and EPEGSAC during the 1998-2023 period with the Republic of Kazakhstan's labor market indicators and digitalization and energy indicators is examined in this study using the ARDL boundary testing procedure. Before the co-integration test can be performed, it is important to determine the criteria for the length of the lag. The delay length criterion is determined based on LR, FPE, AIC, SC and HQ. Table 3 shows the results of the selected lag. As shown in Table 3, the chosen

Graph 1: Evolution of all variables for Kazakhstan (1998-2023)



Source: Authors

Table 6: Values of descriptive statistics of the displayed series

Values	EPMQ	EPMI	EPEGSAC	COP	ABCOP	IUIP	FTS	CO_2E	MCS	ICT
Mean	234.37	537.91	194.92	69.42	62.23	41.00	18.02	12.94	92.28	1.38E+08
Median	223.05	542.61	148.94	78.50	62.91	41.10	16.95	13.60	121.84	1.10E+08
Maximum	294.58	613.65	1370.00	92.00	111.63	92.88	25.20	16.20	176.79	7.32E+08
Minimum	192.37	460.31	127.16	26.00	12.80	0.13	11.30	7.70	0.19	34864810
Standard deviation	40.13	44.01	239.94	19.89	30.38	37.25	4.76	2.30	63.07	1.47E+08
Skewness	0.26	−0.17	4.78	−0.89	0.12	0.09	0.17	−0.77	−0.39	3.078596
Kurtosis	1.28	1.99	23.93	2.55	1.91	1.26	1.64	2.63	1.57	12.16276
Jarque-Bera	3.51	1.22	573.82	3.62	1.35	3.31	2.14	2.71	2.86	132.0227
Probability	0.17	0.54	0.11	0.16	0.51	0.19	0.34	0.26	0.24	0.000000
Sum	6093.64	13985.7	5067.88	1805.00	1618.04	1066.12	468.50	336.40	2399.28	3.58E+09
Sum Sq. Dev.	40267.3	48429.4	1439273	9888.35	23073.1	34691.4	566.72	132.56	99439.11	5.44E+17
Obs	26	26	26	26	26	26	26	26	26	26

length of the lags is 2 for NARDL3 because it has more stars and was used throughout the study. Furthermore, one lag was chosen for the ARDL1 and ARDL2 models.

4.6. Results of Long- and Short Run Relationship

The first difference of the ADF test was used in the study to estimate the linear models ARDL1, ARDL2, and NARDL3. The findings of the long-term and short-term analyses of the relationship between the variables are shown in Table 7.

The derived F-statistics (4.541900, 6.860608, and 8.853405) are more than the upper bound of 3.91 and 4.05 and are statistically significant at the 1-10% significance levels, according to the findings of the cointegration F-test for these models (Table 5). According to the findings, there is a long-term relationship between the variables that were chosen and they are cointegrated in the case of Kazakhstan.

Researchers can assess the long- and short-term effects of changes in the explanatory factors on the dependent variable because the ARDL model was evaluated using first differences. We can move on to the following phase, which entails estimating the long-run and short-run coefficients, since the chosen variables are cointegrated over the long term. The coefficients exhibit elasticities due to the logarithmic nature of NARDL3.

Table 7: Results of ARDL and NARDL estimation (1998-2023)

Variable	Model 1- results of ARDL1 estimationΔEPMQ	Model 2- results of ARDL2 estimationΔEPMI	Model 3- results of NARDL3 estimationΔEPEGSAC	
	Coefficient (t-Stat)	Coefficient (t-Stat.)	Variable	Coefficient (t-Stat.)
Short run				
EPMQ(−1)*	−0.198* (−2.060)		LOG (EPEGSAC(−1))*	−1.105*** (−9.583)
EPMI(−1)*		−0.3340* (−2.116)	LOG (COP(−1))	0.1433 (0.154)
COP**	−0.2569(−0.576)		LOG (ABCOP(−1))	0.7975*** (5.604)
ABCOP**	0.4602** (2.799)		LOG (CO2E(−1))	2.6245** (3.137)
IUIP**		−1.2150** (−2.810)	LOG (MCS(−1))	−1.068*** (−5.272)
CO2E**		−0.3605 (−0.100)	LOG (ICT(−1))	0.4528** (2.969)
COP(−1)		1.0780** (1.934)	ΔLOG (COP)	−1.0348(−1.177)
ABCOP(−1)		−1.1874*** (−3.517)	ΔLOG (COP(−1))	−1.4845(−1.598)
MCS(−1)		0.8932** (2.752)	ΔLOG (ABCOP)	0.4258** (3.110)
ICT(−1)		1.22E-08 (0.206)	ΔLOG (CO2E)	1.6972* (2.289)
IUIP(−1)	0.8186** (2.234)		ΔLOG (CO2E(−1))	−2.1225** (−3.766)
FTS**	3.4923** (2.333)		ΔLOG (MCS)	−0.8791** (−3.342)
CO2E**	−1.2101(−0.367)		ΔLOG (MCS(−1))	−0.5225** (−2.995)
MCS**	−0.4185* (−1.855)		ΔLOG (ICT)	−0.0098(−0.058)
ICT(−1)	2.98E-08 (0.733)		ΔLOG (ICT(−1))	−0.6474* (−2.642)
Δ(COP)		−0.438114(−0.482)		
Δ(ABCOP)		−0.4015** (−2.107)		
Δ(IUIP)	−0.9813(−1.515)			
Δ(MCS)		0.3591 (1.150)		
Δ(ICT)	−9.37E-08(−1.625)	2.64E-07*** (3.92)		
Long run				
COP	−1.2973(−0.595)	3.2273* (1.938)	LOG (COP)	0.1297 (0.154)
ABCOP	2.3241 (1.684)	−3.5548** (−2.177)	LOG (ABCOP)	0.7216*** (5.052)
IUIP	4.1340*** (3.281)	−3.6375* (−1.836)	LOG (CO2E)	2.3751** (2.734)
FTS	17.6354** (2.14)	−1.0793(−0.102)	LOG (MCS)	−0.9665*** (−5.023)
CO2E	−6.111(−0.336)	2.6740* (2.153)	LOG (ICT)	0.4098*** (3.362)
MCS	−2.113** (−2.598)	3.66E-08 (0.215)		
ICT	1.51E-07 (0.712)	3.2273* (1.938)		
Diagnostic	F-statistics (P-value)	F-statistics (P-value)	F-statistics (P-value)	
Serial correlation	1.959443 (0.1833)	0.960283 (0.4437)	0.497552 (0.6311)	
Heteroskedasticity	1.625282 (0.1971)	0.443725 (0.9123)	0.354341 (0.9603)	
Jarque-Bera	2.746273 (0.2533)	0.818151 (0.6643)	1.336726 (0.5125)	

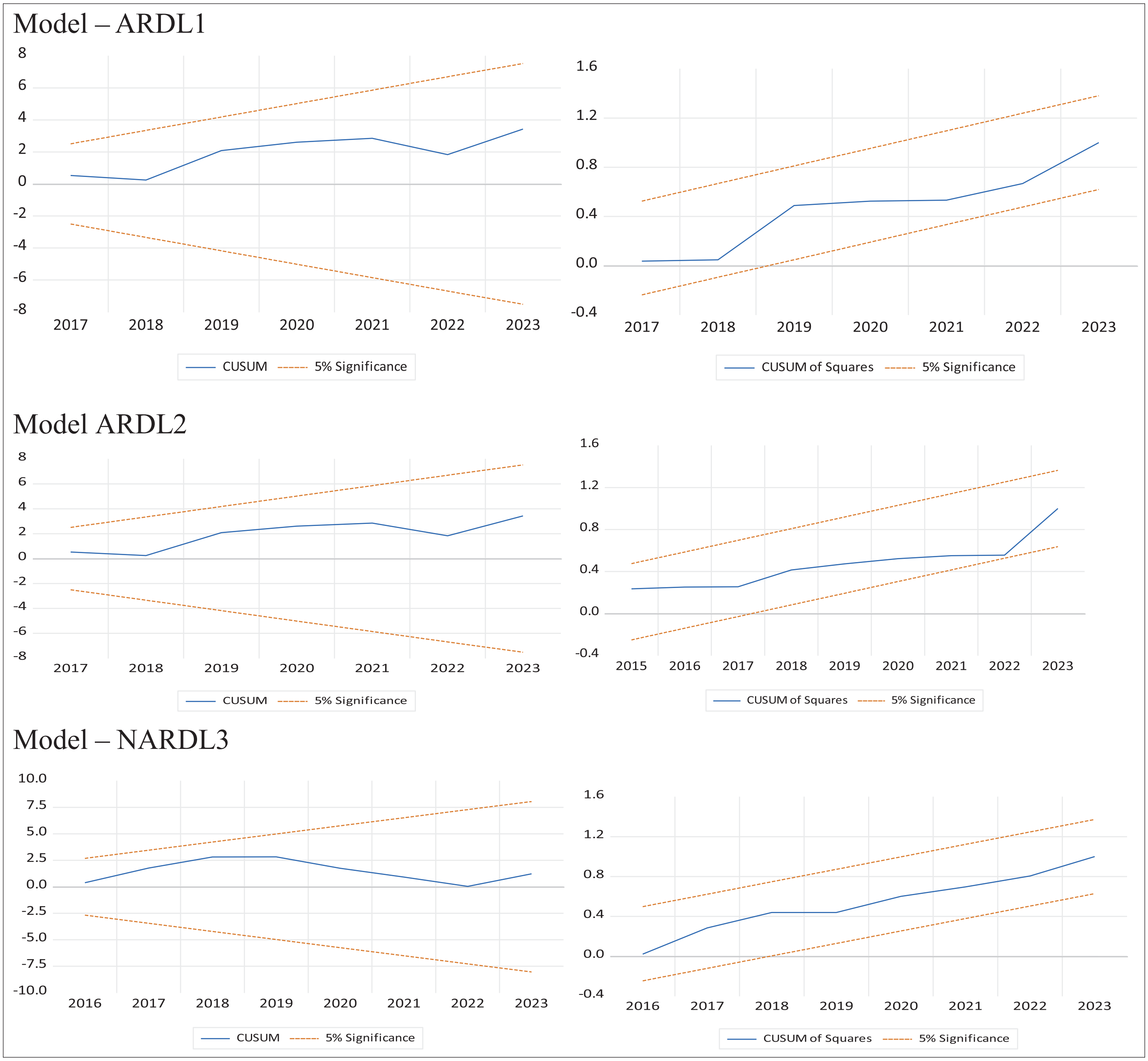
Coefficients are statistically significant at ***1%, **5%, *10% level of significance.
Compiled by the authors

The results of Model 1 - ARDL1 ARDL(1, 0, 0, 1, 0, 0, 0, 1) (Equation 4) showed that in the long run Individuals using the Internet (4.1340) Fixed telephone subscriptions (17.6354) have a positive effect, and Mobile cellular subscriptions (−2.113) have a negative effect on the employed population Mining and quarrying (EPMQ). In the short run, the employed population Mining and quarrying (EPMQ) is positively and significantly affected by Average annual Brent crude oil price, U.S. dollars per barrel (0.4602), Fixed telephone subscriptions (3.4923) and the lagged variable IUIP(−1) (0.8186). An increase in Mobile cellular subscriptions significantly reduces Δ EPMQ (−0.4185).

According to the results of Model 2 - ARDL2 ARDL(1, 1, 1, 0, 0, 1, 1) (Equation 5), it is clear that in the long run, an increase in the level of ABCOP, IUIP will lead to a decrease in EPMI growth (coefficients are −3.5548 and −3.6375, respectively). And an increase in the indicators COP (3.2273), CO2E (2.6740) and ICT (3.2273) in the long run increases EPMI growth. In the short run, the difference in ABCOP (−0.4015) has a negative and significant effect on the growth of the employed population of Mining and quarrying industry, and the difference in Δ (ICT) has a positive effect (2.64E-07). An increase in the lagged variables Cude oil production (1.0780) and Mobile cellular subscriptions (0.8932) significantly increases growth. Individuals using the Internet and the lagged variable ABCOP(−1) have a negative impact on the growth of EPMI, with coefficients of −1.2150 and −1.1874, respectively. An increase in the lagged variable of employed population Mining and quarrying significantly reduces the current EPMI (−0.3340).

Model 3 estimation – logarithmic nonlinear NARDL3 NARDL(1, 2, 1, 2, 2, 2) model (Equation 6) also confirmed that MCS growth by 1% reduces employment growth Electricity, gas, steam and air conditioning by 0.9665%. And ABCOP, CO2E, ICT have a positive effect on EPEGSAC. The corresponding elasticity coefficients are 0.7216, 2.3751 and 0.4098. And in the short term, an increase in the lagged variables ICT(−1) (−0.6474), MCS(−1)) (−0.5225) and CO2E(−1) (−2.1225) significantly reduces EPEGSAC growth, and COP(−1), on the contrary, increases it. In this period, the difference between the ABCOP variable (0.4258) and CO2E (1.6972) has a positive and significant effect on EPEGSAC. An increase in the Lagged variables ABCOP(−1), CO2E(−1), ICT(−1)) by 1% will lead to an increase in EPEGSAC of 0.7975, 2.6245 and 0.4528%, respectively. MCS(−1) in the short term reduces the growth of EPEGSAC (−1.068). An increase in the lagged variable EPEGSAC reduces the current Renewable EPEGSAC (−1.105).

Graph 2: CUSUM and CUSUM squares tests



Source: Authors

The results of Model 1 - ARDL1 ARDL(1, 0, 0, 1, 0, 0, 0, 1) (Equation 4) showed that in the long run Individuals using the Internet (4.1340) Fixed telephone subscriptions (17.6354) have a positive effect, and Mobile cellular subscriptions (-2.113) have a negative effect on the employed population Mining and quarrying (EPMQ). In the short run, the employed population Mining and quarrying (EPMQ) is positively and significantly affected by Average annual Brent crude oil price, U.S. dollars per barrel (0.4602), Fixed telephone subscriptions (3.4923) and the lagged variable IUIP(-1) (0.8186). An increase in Mobile cellular subscriptions significantly reduces Δ EPMQ (-0.4185).

According to the results of Model 2 - ARDL2 ARDL(1, 1, 1, 0, 0, 1, 1) (equation 5), it is clear that in the long run, an increase in the level of ABCOP, IUIP will lead to a decrease in EPMI growth (coefficients are -3.5548 and -3.6375, respectively). And an increase in the indicators COP (3.2273), CO2E (2.6740) and ICT (3.2273) in the long run increases EPMI growth. In the short run, the difference in ABCOP (-0.4015) has a negative and significant effect on the growth of the employed population of Mining and quarrying industry, and the difference in Δ (ICT) has a positive effect (2.64E-07). An increase in the lagged variables Cude oil production (1.0780) and Mobile cellular subscriptions (0.8932) significantly increases growth. Individuals using the Internet and the lagged variable ABCOP(-1) have a negative impact on the growth of EPMI, with coefficients of -1.2150 and -1.1874, respectively. An increase in the lagged variable of employed population Mining and quarrying significantly reduces the current EPMI (-0.3340).

Model 3 estimation – logarithmic nonlinear NARDL3 NARDL(1, 2, 1, 2, 2, 2) model (equation 6) also confirmed that MCS growth by 1% reduces employment growth Electricity, gas, steam and air conditioning by 0.9665%. And ABCOP, CO2E, ICT have a positive effect on EPEGSAC. The corresponding elasticity coefficients are 0.7216, 2.3751 and 0.4098. And in the short term, an increase in the lagged variables ICT(-1) (--0.6474), MCS(-1)) (-0.5225) and CO2E(-1) (-2.1225) significantly reduces EPEGSAC growth, and COP(-1), on the contrary, increases it. In this period, the difference between the ABCOP variable (0.4258) and CO2E (1.6972) has a positive and significant effect on EPEGSAC. An increase in the Lagged variables ABCOP(-1), CO2E(-1), ICT(-1)) by 1% will lead to an increase in EPEGSAC of 0.7975, 2.6245 and 0.4528%, respectively. MCS(-1) in the short term reduces the growth of EPEGSAC (-1.068). An increase in the lagged variable EPEGSAC reduces the current Renewable EPEGSAC (-1.105).

To ensure the stability of the linear ARDL1-NARDL3 models, diagnostic tests were performed (Table 7). These include tests for serial correlation, normality, and heteroscedasticity. For all models, the null hypothesis of no serial correlation, homoscedasticity and normality cannot be rejected. This indicates that the model is free of serial correlation and heteroscedasticity. Table 7 presents the results of the diagnostic tests. For the ARDL1 model, the LM statistics is 1.959443, the P = 0.1833. As a result, we accept the null hypothesis in this analysis and conclude that there is no serial correlation in the model. Heteroscedasticity tests showed that the F-statistic is 0.821607 and the P = 0.1971, both values exceeding the 0.05% significance level, indicating that the model is homoscedastic. The model accepts the null hypothesis of the normality test and concludes that the residuals are normally distributed, as evidenced by an F-statistic of 2.746273 and a P = 0.2533, all values at the 5% significance level. Finally, all diagnostic tests for serial correlation with Langrange multiplier, Jarque-Bera normality test and heteroscedasticity test are successful, indicating the robustness of the ARDL1 model. The robustness of the ARDL2 and ARDL3 model is also explained accordingly.

4.7. Stability Tests

The CUSUM and CUSUM Squares tests are used to test whether the estimated models' coefficients remain constant over time, which is an indicator of model stability.

The results of the stability test of CUSUM and CUSUMSQ are shown in Graph 2. At the 5% level of significance tests, the significance of not exceeding the critical thresholds indicates that the model is stable. This test is also used to study the long-term dynamics of regression.

5. CONCLUSION

The aim of the research was to investigate the impact of energy variables and digitalization variables on employment in labor markets related to energy sources. For this purpose, the authors obtained the following indicators from global and domestic official statistical sources for the period 1998-2023: Internet users, fixed phone subscriptions, mobile cellular subscriptions, and ICT service exports - explanatory variables, Kazakhstan's crude oil production, average yearly price of Brent crude oil, US dollars per barrel, and CO_2 emissions per person (tons). Following labor markets were studied: Mining and quarrying, Manufacturing industry and Electricity, gas, steam and air conditioning. Applied ARDL models NARDL results are as follows:

In the long run, the variables Individuals using the Internet and Fixed telephone subscriptions have a positive effect on employment in the Mining and quarrying labor market, while the variable Mobile cellular subscriptions has a negative effect. In the short run, the variables Average annual Brent crude oil price, U.S. dollars per barrel, Fixed telephone subscriptions have a positive and significant effect on employment in the Mining and quarrying labor market. In the long run, increases in the Oil price and Individuals using the Internet slow down the growth of employment in the Manufacturing industry. In the long run, increases in Crude oil production, CO_2 emissions per capita and ICT service exports lead to an increase in employment in the Manufacturing industry. In the short term, Individuals using the Internet and lag variable of Oil price negatively affect the growth of Manufacturing industry employment. In the long term, the growth of mobile cellular subscriptions negatively affects the growth of manufacturing industry employment, while Oil price, CO_2 emissions and ICT service exports positively affect the growth of manufacturing industry employment. And the growth of the lag variables of the latter indicators also affects the growth of manufacturing industry employment in the short term. While technological change may reduce costs in manufacturing sectors, it may also pose a threat to labor supply. In this regard, it is necessary to comprehensively implement training and skill development tasks in order to provide employment to the population whose livelihoods depend on heavy industrial work.

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