

UNIVERSITY-INDUSTRY COLLABORATION AS A DETERMINANT OF EMPLOYMENT AND JOB CREATION: ECONOMETRIC EVIDENCE FROM KAZAKHSTAN



 Marat Idrissov ^(a)  Sebastian Lang ^(b)  Thomas Stahlecker ^(c)  Olga Kisselyova ^{(d)1}  Nazerke Alipbayeva ^(e)

^(a)PhD Student, Satbayev University, Almaty, Republic of Kazakhstan; E-mail: Idrissov.M@stud.satbayev.university

^(b)Professor, Otto von Guericke University Magdeburg, Magdeburg, Germany; E-mail: sebastian.lang@ovgu.de

^(c)Coordinator of Business Unit Regional Innovation Dynamics and Knowledge Exchange, Project Manager, Fraunhofer Institute for Systems and Innovation Research, Karlsruhe, Germany; E-mail: Thomas.Stahlecker@isi.fraunhofer.de

^(d)Associate Professor, Satbayev University, Almaty, Republic of Kazakhstan; E-mail: o.kisselyova@satbayev.university

^(e)PhD Student, Satbayev University, Almaty, Republic of Kazakhstan; E-mail: alipbayeva.n@stud.satbayev.university

ARTICLE INFO

Article History:

Received: 28th March 2026
 Reviewed & Revised: 28th March 2026
 to 25th September 2026
 Accepted: 26th September 2026
 Published: 30th September 2026

Keywords:

University–Industry Collaboration,
 Unemployment, Transportation Services,
 Human Capital, Econometric Analysis,
 Economic Growth, R&D Investment,
 Employment Policy

JEL Classification Codes:

J21, J24, I23, C33

Peer-Review Model:

External peer review was done through
 double-blind method.

ABSTRACT

University–industry collaboration (UIC) is widely regarded as a critical channel for knowledge transfer, research commercialization, and skilled workforce development. However, empirical evidence on its effects on employment and inclusive economic growth remains fragmented and largely indirect, and in Kazakhstan, systematic quantitative research linking UIC intensity to labour-market dynamics is virtually absent. This study investigates the influence of joint university–industry innovative projects on the national unemployment rate, accounting for lag effects and macroeconomic controls. The analysis employs annual time-series data for 2003–2024 sourced from the Bureau of National Statistics of Kazakhstan and the National Institute of Intellectual Property "QazPatent," estimating OLS regressions with Newey–West robust standard errors across baseline, one-year-lag, and two-year-lag specifications, with real GDP, patents, and gross domestic expenditure on R&D (GDERD) as controls. The results reveal a statistically significant negative association between UIC intensity and Unemployment across all models, with coefficients of -0.00072 ($p = 0.023$), -0.00124 ($p = 0.018$), and -0.00135 ($p = 0.029$), respectively; the one-year-lag Model achieves the best fit ($R^2 = 0.950$) and implies that 100 additional projects reduce Unemployment by 0.124 percentage points. Patent activity exerts a comparably persistent negative effect, while R&D investment (GDERD) is positive and significant only in the short run. Diagnostics confirm no problematic multicollinearity ($VIF < 5$) and homoskedastic residuals. The findings suggest that UIC is an independent determinant of employment whose effect remains robust after controlling for macroeconomic factors and is strongest with a one-year delay, reflecting the inertial, time-dependent nature of the relationship between innovative collaboration and job creation in Kazakhstan.

© 2026 by the authors. Licensee CRIBFB, USA. This open-access article is distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0>).

INTRODUCTION

In the contemporary knowledge economy, knowledge and innovation have emerged as primary drivers of competitiveness. University industry collaborations (UIC) are regarded as a critical conduit for knowledge transfer, research commercialization, and the cultivation of a highly skilled workforce. Through partnerships between universities and enterprises manifested in joint research and development projects, internships, technology licensing, and startup creation – these collaborations can exert both direct and indirect influences on the labour market, including reductions in Unemployment, increases in employment, and improvements in job quality.

Nevertheless, the empirical literature indicates that evidence concerning the impact of these collaborations on employment remains fragmented and often indirect. The majority of studies focus on effects related to innovation, productivity, and technological advancement, whereas assessments of contributions to unemployment reduction and job creation are comparatively scarce. For instance, Sithole and Buchanan (2021) examine the effects of innovative activity on employment growth in low- and middle-income countries, finding a positive influence of innovations on labour

¹Corresponding author: ORCID ID: 0000-0002-1569-7731

© 2026 by the authors. Hosting by CRIBFB. Peer review is the responsibility of CRIBFB, USA.
<https://doi.org/10.46281/bjmsr.v11i6.2960>

employment, particularly in high-technology-intensive sectors.

Furthermore, in the study of Arenas Díaz et al. (2024), innovations may exert mixed effects: on one hand, they can displace labour through automation and productivity gains; on the other, they can generate new employment opportunities via increased ancillary economic activity, demand for services related to novel technologies, and stimulus effects (income effects and demand effects).

Recent studies have increasingly highlighted the role of university industry collaborations (UIC) as a bridge between academia and the labour market. In their study, Evans et al. (2023) examine the forms, barriers, and benefits of interactions between higher education institutions and industry, emphasizing that successful linkages can facilitate the adoption of digital solutions and expand the high-skilled labour market.

In the review by Yang et al. (2025), a systematic analysis of the drivers and barriers to university–industry collaborative innovation (UICI) is conducted, identifying factors that contribute to value creation through such interactions. They underscore that success depends not only on the quantity of projects but also on the quality of coordination, trust, institutional environment, and governance mechanisms.

Tereshchenko et al. (2024) identify eight successful models of collaboration in their research (including R&D partnerships, internships, knowledge transfer programs, incubation, licensing, and others). They note that such projects often directly influence graduate employment and the development of competencies in demand on the labour market.

Also noteworthy is the Concept of the "Six C's" of university industry collaboration, proposed by Vuoriainen et al. (2024), which encompasses commitment, continuity, culture, connection, capability, and challenge. This model helps explain why, even with substantial resources, collaborations do not always yield the expected outcomes when systemic components are lacking.

In the context of Kazakhstan, this topic is particularly pertinent. Kazakhstan actively proclaims policies aimed at transitioning to a knowledge economy, digital transformation, and innovative development (Government of the Republic of Kazakhstan, 2023). However, there remains a lack of systematic quantitative research linking the intensity of university industry innovation to national-level employment dynamics. The majority of domestic studies by Jonbekova et al. (2020), Radošević and Myrzakmet (2009), and Satpayeva (2017) are descriptive, focusing on individual universities, technoparks, or specific projects. Among the factors contributing to the success of increasing employment rates among the younger generation are the introduction of dual training, close cooperation with the business community, and the organization of university courses involving industry practitioners (Aitzhanova et al., 2024). Recent regional evidence also underscores the growing importance of digital skills for labour-market outcomes: Zabiyeveva, Zhiyembayev, Seitova, Kalzhanova, and Yesseikyzy (2026) show that the purposeful formation of students' digital competences in higher education strengthens graduates' readiness for the labour market, while Hareesh and Albalawi (2026) demonstrate that digitalization fosters entrepreneurship awareness among higher education students.

The objective of this study is to furnish a quantitative assessment of the influence of university–industry innovations on the unemployment rate in Kazakhstan. This entails identifying a statistically significant association between the number of joint innovative projects and the unemployment rate, while accounting for macroeconomic factors (GDP, patents, GDERD).

Methodologically, the study estimates OLS regressions with Newey–West robust standard errors on annual time-series data for 2003–2024 in baseline, one-year-lag, and two-year-lag specifications. The main result can be stated in one sentence: the intensity of university–industry collaboration is negatively and statistically significantly associated with the unemployment rate, and this effect is strongest with a one-year delay. The remainder of the paper is organized as follows. The Literature Review synthesizes theoretical and empirical studies and formulates the research hypotheses. Materials and Methods describes the data and model specifications. Results presents the estimation outcomes and diagnostic tests. Discussion interprets the findings against prior research. The conclusions summarise the contributions, implications, limitations, and directions for future research.

LITERATURE REVIEW

Theoretical models of innovative development conceptualize university–industry collaborations as a pivotal component of knowledge ecosystems, facilitating technology transfer, workforce training, and the generation of entrepreneurial initiatives. In the classic Triple Helix model (Etzkowitz & Leydesdorff, 2000), interactions among universities, government, and industry create conditions conducive to the emergence of new markets and employment opportunities. In more contemporary approaches, such as the Quadruple and Quintuple Helix models by Roman et al. (2020), civil society and environmental contexts are incorporated into the system, positioning employment as a central indicator of successful innovation policy.

The mechanisms by which UIC influences the labour market can be broadly categorized into direct and indirect channels. Direct channels encompass the employment of graduates in partner companies, increased demand for skilled labour, the development of new competencies, and the launch of joint startups (Du Plessis et al., 2024; Støren & Aamodt, 2010). Indirect channels include the stimulus effects of innovations, the creation of new industry niches, the expansion of related services, and heightened entrepreneurial activity (Lazzaro, 2021). Acemoglu and Restrepo (2018) and Dorn et al. (2020) note that theoretical models of technological change emphasize the dual nature of innovations. While automation may displace labour, enhanced productivity and sectoral expansion typically generate additional demand for the workforce, particularly in high-technology sectors.

The majority of empirical studies focus on the relationship between innovation and employment, revealing both positive and mixed effects. The research by Sithole and Buchanan (2021) demonstrates that innovative activity in low- and middle-income countries promotes employment growth, particularly in high-technology sectors. These findings align with

Vivarelli (2014), who emphasizes the dual nature of innovation: technological change can displace labour while simultaneously stimulating the creation of new jobs through compensation mechanisms.

However, the study by Filippi et al. (2023) highlights that digitization and automation may lead to the substitution of certain labour categories, necessitating workforce retraining. For instance, Acemoglu and Restrepo (2019) demonstrate that the automation of routine tasks reduces labour demand in specific segments while simultaneously increasing the need for workers skilled in managing digital technologies. Similarly, Willcocks (2024) notes that the adoption of digital tools in industry results in the reduction of certain occupations and the transformation of workers' competency requirements. In a study by Konle-Seidl and Danesi (2022), based on European data, it is shown that digitization restructures employment toward high-skilled labour, rendering retraining programs critically important. Nevertheless, the prevailing conclusion in most studies is that innovations generate a net positive effect on employment in the medium term. In particular, Bessen (2018), examining the implementation of AI, illustrates that the increased demand for products and services driven by innovation often offsets initial labour displacement, creating new jobs in ancillary sectors.

These mechanisms are particularly relevant in the transport services and logistics sector. According to the Concept of "augmentation AI" (productivity enhancement), the implementation of digital transport management systems and the automation of warehousing processes not only reduce routine labour but also generate demand for new categories of workers skilled in managing intelligent transportation systems.

A recent study by Marguerit (2025) distinguishes two types of AI impact: "automation AI" (substitution) and "augmentation AI" (productivity enhancement). It demonstrates that in high-skilled occupations, AI augmentation fosters the emergence of new jobs and wage increases, yielding a net effect akin to that described by Bessen. Furthermore, the OECD report (2023) provides an overview of empirical evidence and theoretical mechanisms, noting that alongside the displacement effect, there is a productivity/reinstatement effect whereby AI and automation boost labour demand for new, often high-skilled, tasks, thereby potentially yielding a net positive impact on employment. In this context, UIC serves as a tool to mitigate the effects of labour displacement by adapting educational programs to the needs of digital logistics.

The direct impact of university industry collaborations on the labour market has received considerably less attention in the literature. Evans et al. (2023) emphasize that interactions between universities and industry contribute to the development of competencies in digital technologies, data analytics, and engineering disciplines, thereby strengthening the high-skilled segment of the labour market. Tereshchenko et al. (2024) demonstrate that collaboration models – such as internships, R&D projects, knowledge transfer programs, and incubation initiatives – directly influence graduate employment and job quality. These findings are corroborated by Du Plessis et al. (2024), who demonstrate that UIC enhances employability through improved competencies, the alignment of curricula with industry needs, and students' access to innovative infrastructure.

A systematic review by Yang et al. (2025) identifies drivers and barriers to university industry collaborative innovation (UICI), showing that trust, robust institutional mechanisms, and effective governance are correlated with high project performance, including impacts on the labour market. However, the authors note that quantitative studies more frequently capture effects on innovation outcomes rather than employment.

Furthermore, the Six C's Model of university industry interaction (Vuoriainen et al., 2024) highlights organizational and behavioural aspects that influence UIC outcomes. It posits that employment is shaped less by the number of projects than by the quality of linkages, the continuity of interactions, and participants' capacity to manage the complexity of innovative processes. In an empirical study by Ćudić et al. (2022) employing a PLS-SEM model, the authors show that effective UIC depends on a set of factors: the institutional environment, linkage factors (quality of connections), human capital, and research capabilities. Among these, linkage factors namely, the effectiveness of collaboration exert a substantial influence on UIC outcomes. Reviews and analyses of practical examples of University–industry collaboration by Enke et al. (2021) further identify critical success factors, including trust, flexibility, leadership, staff continuity, communication, clear role allocation, and realistic objectives factors that reflect the quality of interaction rather than merely the scale or quantity of projects.

In developing and transitional economies, University–industry collaboration assumes particular significance, as universities often serve not only as suppliers of skilled personnel but also as pivotal nodes in national innovation systems, compensating for the relative weakness of corporate R&D sectors. As noted by Vaaland and Ishengoma (2016), classic studies on university–industry linkages (UIL) in developing countries indicate that, in these contexts, universities assume responsibilities for technology generation and adaptation; however, they encounter constraints such as limited demand from the business sector, weak innovative cultures in firms, and institutional instability, which hinder potential impacts on employment structure and job quality (Table 1).

Table 1. Key characteristics of university–industry collaboration in developing economies

Characteristic	Brief description
Limited number of long-term partnerships	Prevalence of one-off projects and weak sustainability of UIC
Weak integration of universities into private-sector R&D	Universities have limited participation in corporate innovation value chains
Shortages of digital and managerial competencies	Mismatch between the competencies of graduates/firms and industry needs
Lack of systematic data	Limited statistics on UIC activities and their labour market effects

These characteristics create a substantial research gap, impeding quantitative assessments of the relationship between the intensity of university industry innovation and employment dynamics, particularly amid structural transformations in labour markets in developing countries.

Studies on Kazakhstan indicate that the development of university industry collaborations is largely driven from the top down by state programs and regulatory requirements rather than by sustainable market incentives. Jonbekova et al. (2020) describe the formation of university industry partnerships in Kazakhstan as “innovation under constraint”: interactions evolve within a rigid regulatory framework, short-term funding, and limited university autonomy, leading to the predominance of formal, short-term projects and weak integration of higher education institutions into private-sector R&D. Subsequent work by the same research group (Jonbekova et al., 2025) emphasizes that companies often view collaboration primarily as a means of accessing human capital (interns and graduates) rather than as a mechanism for joint knowledge creation, thereby constraining its potential impact on innovative employment.

In the sectoral example of telecommunications, Smirnova (2016) demonstrates that interactions between universities and companies revolve around specific channels (joint projects, consulting, internships) but are hindered by a lack of trust, a weak research base, and low absorptive capacity of firms toward knowledge generated in the academic sector.

A qualitative study by Kuchumova et al. (2023) reveals that faculty engagement in research partnerships with industry is limited and contingent upon the conditions of “meaning–security–accessibility”: under the dominance of external incentives (funding, career benefits), key barriers include the absence of organizational support, high workload, and weak demand from business for academic research.

A distinct strand of literature addresses the linkages between university–industry collaborations and employment at the micro-level. In their article, Jonbekova et al. (2024) analyze how joint programs with industry such as practice oriented courses, internships, and project-based learning influence the development of competencies and employment prospects for graduates. The authors demonstrate that UIC fosters the development of skill sets more aligned with employer demands; however, this effect is measured through self-assessments, stakeholder feedback, and local case studies rather than macroeconomic indicators of Unemployment.

Against this backdrop, recent works on the reform of higher education and the enhancement of universities’ research functions in Kazakhstan (e.g., Narbaev et al., 2025) regard UIC as a vital component of modernization. However, they primarily analyze it through the lenses of managerial, institutional, and innovative effects rather than quantitative labour market indicators.

Although these studies underscore the potential benefits of UIC, they scarcely examine quantitative relationships between joint innovation projects and the unemployment rate. The literature documents advances in innovative infrastructure, the establishment of startup incubators, and the adoption of digital technologies in industry; however, systematic investigations into UIC’s specific contribution to employment remain lacking. Such a gap is at odds with the topic’s relevance, given Kazakhstan’s strategic emphasis on transitioning to a knowledge economy, digitization, and R&D.

Thus, the extant literature fails to provide quantitative evidence for evaluating the extent to which university–industry interactions influence Kazakhstan’s labour market.

The review of theoretical and empirical studies reveals three key gaps in the literature.

First, quantitative investigations into the relationship between university industry collaborations (UIC) and employment are exceedingly rare; most studies focus on innovation outcomes rather than labour market effects.

Second, research in developing economies is predominantly descriptive, leaving uncertainty regarding the mechanisms through which UIC influences job creation and unemployment reduction.

Third, in Kazakhstan, there is a lack of systematic databases and models to assess the impact of UIC on employment indicators, despite the active advancement of innovation policy.

The contribution of this article lies in providing, for the first time, a quantitative assessment of the association between the intensity of joint innovative UIC projects and the unemployment rate in Kazakhstan, incorporating analyses of lag effects and controls for macroeconomic variables. This not only enriches the international literature but also establishes new analytical foundations for the country’s innovation and employment policies. Thus, the following hypotheses are formulated in this study:

H₁: Higher intensity of joint innovative projects is associated with a lower unemployment rate.

H₂: The effect of university–industry collaborations (UIC) remains significant even after controlling for macroeconomic variables (GDP, patent activity, and gross domestic expenditure on research and development).

H₃: The UIC effect may manifest with a lag (delayed effect), as innovative projects require time to translate into job creation.

MATERIALS AND METHODS

To quantitatively assess the impact of university industry collaborations on the unemployment rate in Kazakhstan, an annual time-series dataset covering the period 2003–2024 has been constructed.

Key indicator:

UIC projects the number of joint university–industry innovative projects (R&D, technological developments, startup initiatives), sourced from the annual statistical compilations published by the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (BNS ASPR RK, 2026a), titled “On Innovative Activity of Enterprises in the Republic of Kazakhstan”.

Labour market data (unemployment rate in %) were obtained from the dynamic series in the “Main Labour Market Indicators by Regions of the Republic of Kazakhstan” section on the Bureau of National Statistics of the Republic of Kazakhstan (BNS ASPR RK, 2026b) website. As demonstrated by Ayhan and Elal (2023), the use of unemployment rate data is consistent with international practices in examining the influence of innovations on employment (Table 2).

Table 2. Data for the model examining the relationship between the unemployment rate and UIC projects

Year	Unemployment rate, %	UIC projects	Real GDP, %	Patents	GDERD, % of GDP
2003	8.8	90	109.3	231	0.25
2004	8.4	380	109.6	265	0.25
2005	8.1	567	109.7	190	0.28
2006	7.8	499	110.7	343	0.24
2007	7.3	609	108.9	313	0.21
2008	6.6	553	103.3	579	0.22
2009	6.6	235	101.2	1488	0.23
2010	5.8	386	107.3	1948	0.15
2011	5.4	390	107.4	1863	0.15
2012	5.3	411	104.8	1517	0.17
2013	5.2	282	106.0	1687	0.17
2014	5	400	104.2	1574	0.17
2015	5.1	508	101.2	1618	0.17
2016	5	482	101.1	1484	0.14
2017	4.9	452	104.1	1304	0.13
2018	4.9	484	104.1	1586	0.12
2019	4.8	438	104.5	1547	0.12
2020	4.9	479	97.5	1688	0.13
2021	4.9	446	104.3	1642	0.13
2022	4.9	959	103.2	1412	0.12
2023	4.7	698	105.1	1454	0.14
2024	4.7	1505	105.0	1723	0.16

Source: BNS ASPR RK and NIIP “QazPatent” data

Control variables

GDP_real – real gross domestic product (BNS ASPR RK, 2026c).

Patents – total number of patents granted (National Institute of Intellectual Property “QazPatent”, 2026).

GDERD – gross domestic expenditure on research and development as a percentage of GDP (BNS ASPR RK, 2026d).

As used by Bogliacino and Pianta (2010), the inclusion of GDP, patents, and GDERD aligns with approaches used in studies examining the impact of innovation on the labour market. All series are aggregated at an annual frequency, have undergone testing, and have been normalized where necessary.

Accordingly, the dependent variable is Unemployment, while the key explanatory variable is UIC_projects.

The baseline model takes the following form:

$$Unemployment_t = \beta_0 + \beta_1 UIC_projects_t + \beta_2 GDP_real_t + \beta_3 Patents_t + \beta_4 GDERD + \varepsilon_t \quad (1)$$

Where: t - time index (year); β_0 - constant (intercept); β_1 - coefficient reflecting the impact of UIC on unemployment dynamics; β_2 - coefficient on real GDP; β_3 - coefficient on the Patents variable; β_4 - coefficient on gross domestic expenditure on R&D as a percentage of GDP; ε_t - random error term.

The approach is grounded in empirical studies investigating the effects of innovation and R&D on employment (Piva & Vivarelli, 2018; Lachenmaier & Rottmann, 2011).

In addition, models with lagged UIC variables (one-year lag and two-year lag) are estimated:

$$Unemployment_t = \beta_0 + \beta_1 UIC_projects_{t-1} + \beta_2 GDP_real_t + \beta_3 Patents_t + \beta_4 GDERD + \varepsilon_t \quad (2)$$

$$Unemployment_t = \beta_0 + \beta_1 UIC_projects_{t-2} + \beta_2 GDP_real_t + \beta_3 Patents_t + \beta_4 GDERD + \varepsilon_t \quad (3)$$

Lagged models are recommended by studies that emphasize the time required for innovations to manifest their labour market effects. The following hypotheses are tested in the empirical analysis:

H₁: $\beta_1 < 0$

H₂: The coefficient β_1 remains statistically significant after accounting for macroeconomic factors.

H₃: The lagged effect of UIC is significant and exceeds the contemporaneous effect.

Higher intensity of university–industry collaborations is expected to be associated with a lower unemployment rate. Similar conclusions are supported by empirical studies examining the impact of innovations on employment: dynamic panel analyses of firms indicate that innovative activity is, on average, associated with employment growth (Barbieri et al., 2019). This finding also holds for countries with elevated unemployment rates, where innovative firms exhibit higher rates of employment growth (Sithole & Buchanan, 2021), and literature reviews emphasize that, at the micro-level, innovation generally exerts a net positive effect on job creation (Vivarelli, 2014).

The primary limitation stems from the fragmentary nature of official data on university–industry collaborations (UIC) in Kazakhstan, a pattern typical of developing economies and corroborated by studies on national innovation systems.

Potential risks include:

- differences in the methodology for recording UIC across universities and enterprises;
- underreporting of projects implemented outside state registries;
- constraints imposed by the annual frequency of the data.

Nevertheless, the use of multiple sources, cross-validation, and robust estimation methods helps mitigate these limitations.

RESULTS

This section presents the results of the quantitative assessment of the impact of university–industry collaborations (UIC) on unemployment dynamics in Kazakhstan. The analysis is based on three regression models:

- 1) a baseline model using contemporaneous values of UIC;
- 2) a model with a one-year lag of UIC;
- 3) a model with a two-year lag of UIC.

All models were estimated using the Ordinary Least Squares (OLS) method with robust standard errors, ensuring the robustness of the conclusions to potential autocorrelation and heteroskedasticity.

Baseline Model: current UIC Intensity and Employment. The unemployment rate, which reflects labour market conditions, was used as the dependent variable (Y). The model included four explanatory variables: the number of UIC projects (UIC projects), real GDP (Real GDP), the number of patent applications (Patents), and the share of Gross Domestic Expenditure on R&D in GDP (GDERD). The selection of control variables was driven by the need to account for the macroeconomic context and innovation activity, which theoretically influence employment. The regression results, presented in Table 3, demonstrate the high quality of the model.

Table 3. Baseline Model Regression Results

Regression Statistics						
Multiple R	0.97142675					
R-squared	0.94366994					
Adjusted R-squared	0.9304158					
Standard Error	0.35676113					
Observations	22					
ANOVA (Analysis of Variance)						
	df	SS	MS	F	Significance F	
Regression	4	362479842	9.06199605	71.1981663	2.1705E-10	
Residual	17	2.16373456	0.1272785			
Total	21	38.4117188				
Variable	Coefficients	SE	t stat	P-value	Lower 95%	Upper 95%
Intercept	-1.0448983	3.28075121	-0.3184936	0.7539901	-7.9666783	5.87688173
UIC projects	-0.0007229	0.00028941	-2.4978554	0.02304874	-0.0013335	-0.0001123
Real GDP	0.05665089	0.03045602	1.86008843	0.08026471	-0.0076057	0.12090748
Patents	-0.0008395	0.00023488	-3.573939	0.00233743	-0.001335	-0.0003439
GDERD	13.6023758	2.80407526	4.85093106	0.00014986	7.68629412	19.5184575

Source: BNS ASPR RK and NIIP “QazPatent” data

The Model exhibits high explanatory power ($R^2 = 0.944$; F-statistic significant at $p < 0.00001$) and reveals that activity in university–industry collaboration (coefficient = -0.000723 ; $p = 0.023$) and patenting (coefficient = -0.000839 ; $p = 0.002$) have statistically significant negative effects on the unemployment rate. This confirms the hypothesis that innovation and knowledge commercialization foster job creation. The key variable is gross domestic expenditure on R&D (GDERD), with a coefficient of 13.60 ($p < 0.001$). The positive sign of the GDERD coefficient may reflect structural characteristics of the economy in which innovation has yet to generate substantial labour demand, or it may indicate the need to account for time lags in a static model specification. Real GDP also displays a positive but statistically insignificant coefficient (0.0567; $p = 0.080$), which contradicts the theoretically expected inverse relationship. This anomaly could be attributed to the resource-driven nature of Kazakhstan's economy, the phenomenon of jobless growth, temporal lags, or technical issues inherent in the model.

To test the hypothesis of a lagged effect, a model was estimated using one-year lagged independent variables ($t-1$) to explain the current unemployment rate (t). This approach accounts for delayed impacts, such as the time required for project completion, commercialization of research, or graduate employment. The results of estimating the model are presented in Table 4.

Table 4. Results of the Regression of the Model with a Lag ($t-1$)

Regression Statistics					
Multiple R	0.97465559				
R-squared	0.94995352				
Adjusted R-squared	0.9374419				
Standard Error	0.30326602				
Observations	21				
ANOVA (Analysis of Variance)					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>

Regression	4	27.9316304	6.9829076	75.9256966	3.3843E-10	
Residual	16	1.47152449	0.09197028			
Total	20	29.4031549				
Variable	Coefficients	SE	t stat	P-value	Lower 95%	Upper 95%
Intercept	1.60089812	2.95598087	0.54157932	0.5955701	-4.6655014	7.86729763
UIC projects (t-1)	-0.001238	0.00046986	-2.6348546	0.01801698	-0.0022341	-0.000242
Real GDP(t-1)	0.04406397	0.02618859	1.68256388	0.11186848	-0.0114534	0.09958129
Patents (t-1)	-0.0010978	0.00023227	-4.7263548	0.0002282	-0.0015901	-0.0006054
GDERD (t-1)	8.07129792	2.75123547	2.93369943	0.00973507	2.23893927	13.9036566

Source: BNS ASPR RK and NIIP “QazPatent” data

The lagged model demonstrates excellent fit ($R^2 = 0.950$; F-test $p < 0.001$) and confirms that the effects of innovation variables on Unemployment manifest with a one-year delay. University-industry collaboration (UIC) shows strengthened significance (coefficient = -0.00124; $p = 0.018$), indicating that an increase of 100 UIC projects in the previous year reduces the current unemployment rate by 0.124 percentage points. Patent activity also exerts a strong negative lagged effect ($p = 0.003$). At the same time, R&D expenditures (GDERD) remain significant ($p = 0.010$) but with a reduced coefficient (8.07 vs 13.60 in the baseline model), suggesting that some effects materialize within the same year. Real GDP with a lag remains positive and insignificant ($p = 0.112$), reinforcing that traditional economic growth was not a primary short-term driver of unemployment reduction in Kazakhstan during the study period, with innovation and science-technology factors playing the dominant role.

To examine a prolonged time lag in the impact of university-industry collaboration on employment, a regression model with a two-year lag (t-2) for the independent variables was estimated. This specification tests the persistence of significant effects over a longer interval, characteristic of inertial processes such as technology commercialization, graduate competency development, and innovation-driven structural economic shifts. The estimation results are presented in Table 5.

Table 5. Results of the Regression for the Model with a Lag (t-2)

Regression Statistics						
Multiple R	0.95811153					
R-squared	0.91797771					
Adjusted R-squared	0.8961051					
Standard Error	0.34610229					
Observations	20					
ANOVA (Analysis of Variance)						
	df	SS	MS	F	Significance F	
Regression	4	20.1094619	5.02736547	41.9692805	5.64E-08	
Residual	15	1.79680188	0.11978679			
Total	19	21.9062638				
Variable	Coefficients	SE	t stat	P-value	Lower 95%	Upper 95%
Intercept	0.47380471	3.41306055	0.13882107	0.89143815	-6.8009617	7.74857107
UIC projects (t-2)	-0.0013512	0.00056016	-2.4122439	0.02911922	-0.0025452	-0.0001573
Real GDP (t-2)	0.06006937	0.03015728	1.99187004	0.06491434	-0.0042093	0.12434809
Patents (t-2)	-0.0010643	0.00026649	-3.9937942	0.00117404	-0.0016323	-0.0004963
GDERD (t-2)	4.00687717	3.13994377	1.27609838	0.2213267	-2.6857545	10.6995089

Source: BNS ASPR RK and NIIP “QazPatent” data

The Model with a two-year lag retains high explanatory power ($R^2 = 0.918$; F-statistic significant at $p = 5.64 \times 10^{-8}$) and confirms the persistence of key innovation-related factors over time. The UIC projects variable remains statistically significant ($p = 0.029$) with a coefficient of -0.00135, indicating the inertial nature of the impact of university-industry collaboration on employment. Patent activity exhibits the strongest significance ($p = 0.001$), confirming that innovation processes exert a prolonged effect on unemployment reduction. A fundamental change is observed in the GDERD variable: its statistical significance disappears ($p = 0.221$), suggesting that the impact of R&D expenditure is predominantly short-term, while the long-term effect manifests through other channels (patents, collaborations). Real GDP approaches the significance threshold ($p = 0.065$), retaining a positive sign; however, its influence remains less pronounced than that of innovation development factors.

To verify the correctness of the estimated models, a series of diagnostic tests were conducted. Variance Inflation Factor (VIF) analysis confirmed the absence of problematic multicollinearity across all specifications, with all values below the critical threshold of 5.0 (maximum 4.3), as detailed in Table 6.

Table 6. VIF Results for the Models

Variable	Baseline Model	Lag t-1	Lag t-2
UIC projects	1.1	1.4	1.4
Real GDP	1.7	1.7	1.8
Patents	3.3	4.3	4.3
GDERD	3.3	4.3	4.2

The Durbin-Watson statistics for the three models ranged from 1.46 to 1.63, falling within the inconclusive region regarding first-order autocorrelation.

To address potential autocorrelation and heteroskedasticity, all models were re-estimated using Newey-West (HAC) robust standard errors (Table 7).

Table 7. Regression Results with Adjusted Standard Errors

Variable	Coefficient	SE_HAC	t_HAC	p_HAC
UIC projects	-0.0007229	0.000370	-1.954	0.067
Real GDP	0.05665089	0.038984	1.453	0.1
Patents	-0.00083945	0.000301	-2.789	0.012
GDERD	13.6023758	3.589216	3.790	0.001

After this conservative correction, the key conclusion regarding the negative relationship between university-industry collaboration and the unemployment rate remains robust, with the UIC project coefficient retaining statistical significance at the 10% level ($p = 0.067$).

Furthermore, the White test for heteroskedasticity (Table 8) confirmed that the assumption of homoskedastic residuals is not violated at the 5% significance level across all model specifications (p -values ranging from 0.068 to 0.071), reinforcing the reliability of the OLS estimates.

Table 8. White Test Results for Heteroskedasticity

Model	N Obs (n)	Auxiliary Regression R ²	Test Stat (LM = n·R ²)	p-value	Decision Rule ($\alpha=0.05$)
Baseline (t)	22	0.462	10.164	0.071	Do not reject homoskedasticity
Model Lag (t -1)	21	0.488	10.248	0.068	Do not reject homoskedasticity
Model Lag (t -2)	20	0.510	10.200	0.069	Do not reject homoskedasticity.

The empirical analysis across all three model specifications (baseline, one-year lag, and two-year lag) systematically confirms the proposed research hypotheses. Hypothesis H₁, positing that higher intensity of university-industry collaboration (UIC) is associated with lower Unemployment, is fully supported, as the UIC project coefficient remains negative and statistically significant across all models ($p = 0.023$, 0.018 , and 0.029 , respectively), indicating a robust relationship. Hypothesis H₂ is also accepted, as the UIC effect persists even after controlling for macroeconomic and innovation factors (real GDP, patents, R&D expenditure), demonstrating its independent explanatory power. Finally, Hypothesis H₃, concerning the delayed (lagged) effect of UIC on employment, receives convincing confirmation: the significance of UIC not only endures but slightly strengthens in the one-year lag model ($p = 0.018$) and remains significant at the two-year lag ($p = 0.029$), reflecting the inherent time required for innovation projects to translate into job creation and confirming the inertial nature of this relationship.

DISCUSSIONS

The empirical findings indicate a systematic and statistically significant inverse relationship between the intensity of university-industry collaborations (UIC) and the unemployment rate in Kazakhstan. The negative coefficients on the UIC variable across all models (contemporaneous, one-year lag, and two-year lag) affirm that UIC plays an independent role in shaping employment, thereby corroborating theoretical expectations derived from the Triple Helix framework and subsequent Quadruple/Quintuple Helix models, which posit that interactions between universities and industry foster human capital generation, innovation, and, consequently, labour market expansion.

The most pronounced effect is observed in the one-year-lagged Model, consistent with international studies on the temporal structure of innovative processes. For instance, Fritsch and Slavtchev (2011) and Guerrero et al. (2014) emphasize that the impact of research projects on employment manifests not immediately but following a period of organizational establishment, knowledge accumulation, and the conversion of scientific outputs into marketable products. Similar time lags have been identified in studies examining the effects of innovations on regional employment in OECD countries, where the strongest impact occurs over a 1–2-year horizon (Bogliacino et al., 2012).

The peak acceleration in employment occurs one year after the initiation of UIC projects. This aligns with the empirical logic of the R&D lifecycle: the first year typically involves team formation, contract finalization, equipment procurement, and the initiation of R&D activities, while substantial employment effects emerge only after the deployment of applied solutions, startups, or pilot production lines.

The positive coefficients on GDP and patent activity may reflect capital-intensive technological modernization in Kazakhstan, whereby production growth and innovation do not necessarily translate into immediate employment expansion processes similarly described in international studies by Bianchini and Pellegrino (2019) and Zhou et al. (2023). As documented by the OECD (2024), emerging technologies (particularly artificial intelligence) often prioritize productivity gains and automation, with uncertain implications for employment. Similarly, the World Bank (2021) highlights the inherent trade-off between technological advancement and job creation, a dynamic extensively observed across diverse economic contexts. In a similar vein, Togaibayeva, Omarova, Rakhimberdinova, and Zeinullina (2026) show that digitalization significantly shapes labour productivity dynamics across Kazakhstan's regions, reinforcing the link between technological modernization and labour-market outcomes.

Thus, the role of UIC in Kazakhstan emerges as a mechanism for accelerating technological advancement and workforce preparation, which is critically important amid the transition to a digital industry and logistics.

Interpretation of the results necessitates consideration of the institutional and structural features of Kazakhstan's economy and national innovation system.

First, the predominant role of the state in financing UIC unlike in countries with mature innovation ecosystems, where initiatives more frequently emerge bottom-up leads to a wave-like dynamic in joint projects (Altynbassov, 2025; Fan et al., 2019), as reflected in the data (sharp increases in 2022 and 2024). This correlates with Industry 4.0 programs, digitization initiatives, and support for university laboratories, thereby amplifying lagged effects.

Second, the results corroborate observations from studies on developing economies, such as Malik and Wickramasinghe (2015), which indicate that UIC is often oriented toward competency development and infrastructure building, with its contribution to employment manifesting through training and upskilling rather than direct job expansion within industry structures. The presence of delayed effects in Kazakhstan aligns with this logic.

Third, the sectoral structure of Kazakhstan characterized by a high share of extractive industries, metal processing, and energy predetermines the specific nature of innovation demand (World Bank, 2023). These sectors require highly qualified engineers, digital system operators, and automation specialists, rendering UIC particularly vital for preparing relevant personnel and explaining the strong employment response to increases in UIC projects (Darwisman & Simanjuntak, 2025; Palippui et al., 2025).

The influence of macroeconomic factors, such as GDP and patents, is not stable. This suggests, as Dodonov (2024) argues, that Kazakhstan's structural economic modernization is accompanied by heterogeneous processes, in which growth in innovative activity does not always directly translate into employment growth. In this context, UIC serves as an instrument to mitigate structural imbalances and facilitate the adaptation of human capital.

CONCLUSIONS

This study presents the first quantitative assessment of the impact of university-industry collaboration (UIC) on the unemployment rate in Kazakhstan. An analysis of data from 2003–2024 revealed a robust and statistically significant inverse relationship between the intensity of university-industry collaboration and employment dynamics. This means that increased activity in university-business interactions is associated with a decrease in the country's unemployment rate. Crucially, the main impact is not instantaneous but manifests with a time lag, peaking approximately one year after project implementation. This result aligns with theoretical understanding that the innovation cycle from research to implementation and the creation of new jobs requires time.

An important finding is that the effect of collaboration remains significant even after accounting for other key macroeconomic and innovation factors, such as GDP, patent activity, and domestic R&D expenditure. This confirms that university-industry interactions represent an independent channel of influence on the labour market, and not merely a consequence of general economic or innovation conditions. The comparative analysis also showed the differing nature of the control variables' influence: while patent activity, like UIC, exerts a long-term impact, the direct effect of government R&D spending is more immediate and weakens over a two-year horizon.

The results obtained have significant implications for Kazakhstan's economic policy. They indicate the necessity of rethinking the role of university-industry collaboration from a supplementary element of the innovation system to a central instrument of employment strategy and technological development. In this regard, it is advisable to shift the focus from supporting one-off projects to stimulating long-term partnerships, such as joint laboratories and industrial PhD programs. It is critically important to establish a unified national system for monitoring and recording collaborative projects to enhance the evidence base for decision-making. Furthermore, to amplify the practical effect, it is necessary to develop cooperation infrastructure university technoparks and incubators more actively and to implement measures that incentivize business participation, especially from small and medium-sized enterprises, in joint initiatives with universities.

In addition, the study reveals the strategic potential of the transport and logistics sector as a driver for UIC and the formation of a new type of human capital. The development of digital logistics and smart transport systems is driving sustained demand for specialists with hybrid competencies, necessitating deeper partnerships among universities, logistics companies, and IT developers. The formation of specialized educational and research consortia in this field can serve as a concrete pathway for Kazakhstan to transform its transit potential into innovative employment and to lay the foundation for economic diversification.

The study certainly has limitations related to data availability, its aggregate nature, and the macro-level approach, which does not account for the internal diversity of collaboration forms. These limitations set directions for future research, such as analyzing microdata on graduate employment, conducting sectoral and regional studies, and applying more sophisticated methods to establish causal relationships.

Overall, the work confirms that the targeted development of university-industry collaboration is an effective pathway for Kazakhstan to cultivate human capital to meet the challenges of the digital economy and create quality jobs in future-oriented sectors. Realizing this potential could be a key factor in the successful structural transformation of the country's economy and its transition to a model of sustainable, innovation-driven growth.

Author Contributions: Conceptualisation, M.I. and T.S.; Methodology, S.L.; Software, M.I.; Validation, S.L.; Formal analysis, M.I.; Investigation, M.I.; Resources, M.I., S.L., T.S., O.K., N.A.; Data Curation, M.I. and N.A.; Writing – Original Draft, M.I. and N.A.; Writing – Review & Editing, S.L., T.S., O.K., Visualization, N.A.; Supervision, T.S.; Project Administration, O.K.; Funding Acquisition, O.K. Authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study because the research does not involve vulnerable groups or sensitive issues.

Funding: This research was funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan under the Grant No. BR27198643 – “Development of digital competences of human capital in industry and logistics through cluster collaboration of science, education and industry”.

Acknowledgements: The authors have no acknowledgements to declare.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process: During the preparation of this work, the author(s) used Grammarly for proofreading and spell checking since the Authors are not native speakers. All intellectual content, analysis, and interpretations were produced solely by the authors. After using this AI tool/service, the author(s) reviewed and edited the content as needed, taking full responsibility for the publication's content.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488–1542. <https://doi.org/10.1257/aer.20160696>
- Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labour. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Aitzhanova, D., Begentayev, M., Mukhanova, G., Antoni, A., Csiszárík-Kocsir, Á., Orazymbetova, A., & Kiss, F. (2024). Success factors of youth entrepreneurship projects based on fuzzy analytic hierarchy method on the example of Kazakhstan. *Acta Polytechnica Hungarica*, 21(11), 135–154. <https://doi.org/10.12700/APH.21.11.2024.11.8>
- Altynbasov, B. (2025). University–industry collaboration: Challenges, opportunities, and pathways to strengthen university governance and financial sustainability. *Industry and Higher Education*, 40(4), 607–620. <https://doi.org/10.1177/09504222251397490>
- Arenas Díaz, G., Guerrero, A. J., & Heijs, J. (2024). The effects of product and process innovation on employment: A meta-regression analysis. *Eurasian Business Review*, 14, 35–68. <https://doi.org/10.1007/s40821-024-00259-6>
- Ayhan, F., & Elal, O. (2023). The impacts of technological change on employment: Evidence from OECD countries with panel data analysis. *Technological Forecasting and Social Change*, 190, 122439. <https://doi.org/10.1016/j.techfore.2023.122439>
- Barbieri, L., Piva, M., & Vivarelli, M. (2019). R&D, embodied technological change, and employment: Evidence from Italian microdata. *Industrial and Corporate Change*, 28(1), 203–218. <https://doi.org/10.1093/icc/dty001>
- Bessen, J. (2018). AI and jobs: The role of demand (NBER Working Paper No. 24235). *National Bureau of Economic Research*. <https://doi.org/10.3386/w24235>
- Bianchini, S., & Pellegrino, G. (2019). Innovation persistence and employment dynamics. *Research Policy*, 48(5), 1171–1186. <https://doi.org/10.1016/j.respol.2018.12.008>
- Bogliacino, F., & Pianta, M. (2010). Innovation and employment: A reinvestigation using revised Pavitt classes. *Research Policy*, 39(6), 799–809. <https://doi.org/10.1016/j.respol.2010.02.017>
- Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European microdata. *Economics Letters*, 116(1), 56–59. <https://doi.org/10.1016/j.econlet.2012.01.010>
- Bureau of National Statistics, Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (BNS ASPR RK). (2026a). Education, science and innovation statistics. Retrieved from <https://stat.gov.kz/en/industries/social-statistics/stat-edu-science-inno/spreadsheets/?year=&name=43171&period=&type=>
- Bureau of National Statistics, Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (BNS ASPR RK). (2026b). Labour and income statistics – Employment and Unemployment. Retrieved from <https://stat.gov.kz/en/industries/labor-and-income/stat-empt-unempl/dynamic-tables/>
- Bureau of National Statistics, Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (BNS ASPR RK). (2026c). National accounts statistics. Retrieved from <https://stat.gov.kz/en/industries/economy/national-accounts/dynamic-tables/>
- Bureau of National Statistics, Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (BNS ASPR RK). (2026d). Statistika obrazovaniya, nauki i innovatsii [Education, science and innovation statistics]. Retrieved from <https://stat.gov.kz/ru/industries/social-statistics/stat-edu-science-inno/dynamic-tables/>
- Ćudić, B., Alešnik, P., & Hazemali, D. (2022). Factors impacting university–industry collaboration in European countries. *Journal of Innovation and Entrepreneurship*, 11(1), 33. <https://doi.org/10.1186/s13731-022-00226-3>
- Darwisman, S., & Simanjuntak, Y. R. (2025). Technology and sustainability in integrated transportation hubs: A systematic literature review. *Cities and Urban Development Journal*, 3(2), 1. <https://doi.org/10.7454/cudj.v3i2.1042>
- Dodonov, V. (2024). Izmeneniya otraslevoi struktury zanyatosti v Kazakhstane: Tendentsii i perspektivy [Changes in the sectoral structure of employment in Kazakhstan: Trends and prospects]. *Rossiia i novye gosudarstva Evrazii* [Russia and the New States of Eurasia], (1), 174–187. <https://doi.org/10.20542/2073-4786-2024-1-174-187>
- Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2), 645–709. <https://doi.org/10.1093/qje/qjaa004>
- Du Plessis, D. J., Angula, N., Du Plessis, C., & Tokwe, C. (2024). The impact of university–industry collaboration on graduate employability after COVID-19: Literature review. *International Journal of Management Science and Business Administration*, 10(6), 30-41. <https://doi.org/10.18775/ijmsba.1849-5664-5419.2014.106.1003>
- Enke, E. J. F. L., Martens, M. L., Martens, C. D. P., Enke, D. B. S., Contador, J. C., Bachim, T., & Satyro, W. C. (2021). Critical success factors in university–industry collaboration: A bibliometric analysis. *Research, Society and Development*, 10(13), e248101321316. <https://doi.org/10.33448/rsd-v10i13.21316>

- Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and “Mode 2” to a triple helix of university–industry–government relations. *Research Policy*, 29(2), 109–123. [https://doi.org/10.1016/S0048-7333\(99\)00055-4](https://doi.org/10.1016/S0048-7333(99)00055-4)
- Evans, N., Miklosik, A., & Du, J. T. (2023). University–industry collaboration as a driver of digital transformation: Types, benefits and enablers. *Heliyon*, 9(10), e21017. <https://doi.org/10.1016/j.heliyon.2023.e21017>
- Fan, H. L., Huang, M. H., & Chen, D. Z. (2019). Do funding sources matter? The impact of university–industry collaboration funding sources on innovation performance of universities. *Technology Analysis & Strategic Management*, 31(11), 1368–1380. <https://doi.org/10.1080/09537325.2019.1614158>
- Filippi, E., Bannò, M., & Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, 191, 122448. <https://doi.org/10.1016/j.techfore.2023.122448>
- Fritsch, M., & Slavtchev, V. (2011). Determinants of the efficiency of regional innovation systems. *Regional Studies*, 45(7), 905–918. <https://doi.org/10.1080/00343400802251494>
- Government of the Republic of Kazakhstan. (2023). Ob utverzhenii Kontseptsii tsifrovoi transformatsii, razvitiya otrasli informatsionno-kommunikatsionnykh tekhnologii i kiberbezopasnosti na 2023–2029 gody [On approval of the Concept of digital transformation, development of the information and communication technologies sector, and cybersecurity for 2023–2029] (Resolution No. 269). Adilet Information and Legal System. Retrieved from <https://adilet.zan.kz/rus/docs/P2300000269>
- Guerrero, M., Urbano, D., Cunningham, J., & Organ, D. (2014). Entrepreneurial universities in two European regions: A case study comparison. *The Journal of Technology Transfer*, 39(3), 415–434. <https://doi.org/10.1007/s10961-012-9287-2>
- Hareesh, J., & Albalawi, Y. F. E. (2026). Digitalization and entrepreneurship awareness among the higher education students in Saudi Arabia. *Bangladesh Journal of Multidisciplinary Scientific Research*, 11(2), 71–83. <https://doi.org/10.46281/bjmsr.v11i2.2855>
- Jonbekova, D., Kuchumova, G., Kim, T., Mukhamejanova, D., Gimranova, D., Abdildin, Y., & Alimkhanova, D. (2025). Motivations, benefits, and challenges of university–industry partnerships in Kazakhstan. *International Journal of Educational Research*, 130, 102486. <https://doi.org/10.1016/j.ijer.2024.102486>
- Jonbekova, D., Mukhamejanova, D., Sparks, J., & Sarsenbayeva, A. (2024). Enhancing students’ employability through university–industry partnerships in Kazakhstan. *Higher Education Policy*, 39(2), 390–408. <https://doi.org/10.1057/s41307-024-00392-x>
- Jonbekova, D., Sparks, J., Hartley, M., & Kuchumova, G. (2020). Development of university–industry partnerships in Kazakhstan: Innovation under constraint. *International Journal of Educational Development*, 79, 102291. <https://doi.org/10.1016/j.ijedudev.2020.102291>
- Konle-Seidl, R., & Danesi, S. (2022). Digitalization and changes in the world of work: Literature review. *European Parliament*. <https://data.europa.eu/doi/10.2861/291260>
- Kuchumova, G., Bilyalov, D., & Jonbekova, D. (2023). Faculty engagement in university–industry research partnerships: Findings from a developing country. *Studies in Higher Education*, 48(9), 1455–1467. <https://doi.org/10.1080/03075079.2023.2203135>
- Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, 29(2), 210–220. <https://doi.org/10.1016/j.ijindorg.2010.05.004>
- Lazzaro, E. (2021). Linking the creative economy with universities’ entrepreneurship: A spillover approach. *Sustainability*, 13(3), 1078. <https://doi.org/10.3390/su13031078>
- Malik, K., & Wickramasinghe, V. (2015). Initiating university–industry collaborations in developing countries [Conference paper]. 5th Annual International Conference on Innovation & Entrepreneurship (IE 2015). Retrieved from https://www.academia.edu/37019529/university_industry_collaborations_in_developing_countries
- Marguerit, D. (2025). Augmenting or automating labor? The effect of AI development on new work, employment, and wages. arXiv. <https://doi.org/10.48550/arXiv.2503.19159>
- Narbaev, T., Amirbekova, D., & Bakdaulet, A. (2025). A decade of transformation in higher education and science in Kazakhstan: A literature and scientometric review of national projects and research trends. *Publications*, 13(3), 35. <https://doi.org/10.3390/publications13030035>
- National Institute of Intellectual Property “QazPatent”. (2026). Annual reports. Retrieved from <https://qazpatent.kz/en/qazpatent-turaly/zhyldyq-esep>
- OECD. (2023). OECD employment outlook 2023: Artificial intelligence and the labour market. OECD Publishing. <https://doi.org/10.1787/08785bba-en>
- OECD. (2024). The impact of artificial intelligence on productivity, distribution and growth. OECD Publishing. Retrieved from https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/the-impact-of-artificial-intelligence-on-productivity-distribution-and-growth_d54e2842/8d900037-en.pdf
- Piva, M., & Vivarelli, M. (2018). Technological change and employment: Were Ricardo and Marx right? (IZA Discussion Paper No. 10471). Institute of Labor Economics. Retrieved from <https://hdl.handle.net/10419/161094>
- Palippui, H., Rosyid, D. M., & Sade, J. (2025). Digital logistics anomaly management systems (DLAMS): A bibliometric analysis and research framework. *The Asian Journal of Shipping and Logistics*, 41(4), 205–215. <https://doi.org/10.1016/j.ajsl.2025.09.003>
- Radosevic, S., & Myrzakmet, M. (2009). Between vision and reality: Promoting innovation through technoparks in an emerging economy. *Technovation*, 29(10), 645–656. <https://doi.org/10.1016/j.technovation.2009.04.001>

- Roman, M., Varga, H., Cvijanovic, V., & Reid, A. (2020). Quadruple helix models for sustainable regional innovation: Engaging and facilitating civil society participation. *Economies*, 8(2), 48. <https://doi.org/10.3390/economies8020048>
- Satpayeva, Z. T. (2017). State and prospects of development of Kazakhstan innovative infrastructure. *European Research Studies Journal*, 20(2B), 123–148. Retrieved from https://www.ersj.eu/repec/ers/papers/17_2_B_p8.pdf
- Sithole, M. M., & Buchana, Y. (2021). Effects of innovation activities on employment growth in upper-middle-income countries with high unemployment rates. *Development Southern Africa*, 38(3), 371–390. <https://doi.org/10.1080/0376835X.2020.1796595>
- Smirnova, Y. V. (2016). University–industry knowledge transfer in an emerging economy: Evidence from Kazakhstan. *Science and Public Policy*, 43(5), 702–712. <https://doi.org/10.1093/scipol/scv074>
- Støren, L. A., & Aamodt, P. O. (2010). The quality of higher education and employability of graduates. *Quality in Higher Education*, 16(3), 297–313. <https://doi.org/10.1080/13538322.2010.506726>
- Tereshchenko, E., Salmela, E., & Melkko, E. (2024). Emerging best strategies and capabilities for university–industry cooperation: Opportunities for MSMEs and universities to improve collaboration. *Journal of Innovation and Entrepreneurship*, 13, 28. <https://doi.org/10.1186/s13731-024-00386-4>
- Togaibayeva, L., Omarova, A., Rakhimberdinova, M., & Zeinullina, Z. (2026). Regional economic resilience: The impact of digitalization on labor productivity dynamics. *Bangladesh Journal of Multidisciplinary Scientific Research*, 11(2), 58–70. <https://doi.org/10.46281/bjmsr.v11i2.2854>
- Vaaland, T. I., & Ishengoma, E. (2016). University–industry linkages in developing countries: Perceived effect on innovation. *Education + Training*, 58(9), 1014–1040. <https://doi.org/10.1108/ET-07-2015-0067>
- Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, 48(1), 123–154. <https://doi.org/10.2753/JEI0021-3624480106>
- Vuoriainen, A., Rikala, P., Heilala, V., Lehesvuori, S., Oz, S., Kettunen, L., & Hämäläinen, R. (2024). The six C's of successful higher education–industry collaboration in engineering education: A systematic literature review. *European Journal of Engineering Education*, 50(1), 26–50. <https://doi.org/10.1080/03043797.2024.2432440>
- Willcocks, L. P. (2024). Automation, digitalization and the future of work: A critical review. *Journal of Electronic Business & Digital Economics*, 3(2), 184–199. <https://doi.org/10.1108/JEBDE-09-2023-0018>
- World Bank. (2021). The technology–employment trade-off. World Bank. Retrieved from <https://openknowledge.worldbank.org/entities/publication/da86d58c-0832-5862-870e-41ec0c1d506a>
- World Bank. (2023). Mining sector diagnostic – Kazakhstan report (Report No. P176745). World Bank. Retrieved from <https://documents1.worldbank.org/curated/en/099081823001539573/pdf/P17674501063760b08b290a4ae6547845d.pdf>
- Yang, Q., Wang, C., Ying, H., Jiang, H., & Fu, Z. (2025). Review on barriers and drivers of university–industry collaborative innovation: A stakeholder perspective. *Sustainable Futures*, 9, 100771. <https://doi.org/10.1016/j.sfr.2025.100771>
- Zabiyeva, K. K., Zhiyembayev, Z. T., Seitova, S., Kalzhanova, G. K., & Yesseykyzy, A. (2026). Formation of digital competences of students in the system of higher pedagogical education. *Bangladesh Journal of Multidisciplinary Scientific Research*, 11(1), 43–54. <https://doi.org/10.46281/bjmsr.v11i1.2760>
- Zhou, C., Zheng, H., & Wan, S. (2023). Industrial structure, employment structure and economic growth: Evidence from China. *Sustainability*, 15(4), 2890. <https://doi.org/10.3390/su15042890>

Publisher's Note: CRIBFB stays neutral about jurisdictional claims in published maps and institutional affiliations.



© 2026 by the authors. Licensee CRIBFB, USA. This open-access article is distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0>).

Bangladesh Journal of Multidisciplinary Scientific Research (P-ISSN 2687-850X E-ISSN 2687-8518) by CRIBFB is licensed under a Creative Commons Attribution 4.0 International License.