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Influence of ecological innovation and green energy investment on unemployment in China: evidence from advanced quantile approach

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ABSTRACT
This study investigates the dynamic and asymmetric effects of ecological innovation and green energy investment on China's unemployment from 1995 to 2020. The study has applied Quantile Autoregressive Distribution Lag (QARDL) model to explore the association between the study variables at different grids of quartiles. The overall results reveal that environmental technology and clean energy investments have a negative employment impact in the short-run and long-run, while environmental technology's significance is high in the short-run only. It implies that environmental technology and clean energy investments create ample job opportunities in China's energy sector and significantly address the growing unemployment issue. Moreover, the study examines the directional association among the variables by applying the Quantiles Granger Causality. It suggests a bidirectional causality between clean energy investment and unemployment, while a unidirectional relationship is observed between environmental technology and unemployment. These findings offer relevant policy recommendations.

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1. Introduction

Sustainable economic growth is the primary focus of each economic, financial, and social activity without paying the high environmental cost. Countries worldwide move towards cost-effective clean energy resources considering the environmental repercussions (Dell'Anna, 2021). It has been proven that the energy transition and adoption of clean or environmental technology bring multiple socio-economic benefits to societies (Khan et al., 2021). In other words, the investment in clean energy projects and technology is a victorious situation for all the stakeholders, specifically in terms of jobs creations. After the massive surge in the renewable energy sector in

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2012, the swift placement of clean energy projects has increased the number of employment opportunities (Naqvi et al., 2022). However, the investment and technological advancement in clean energy resources' direct impact on employment has received scant attention in the existing literature. This study endeavours to provide empirical evidence of the dynamic effects of environmental technology and clean energy investment in the context of China.

In recent years, unemployment has become a serious socio-economic issue in China. China's unemployment rate has grown from 2.37% in 1991 to 5% in 2020 (Figure 1). The growing trend of unemployment results from high population growth, imbalanced development levels within the country's states, surplus labour in the industrial sector, and the rising competition in the domestic industry by foreign counties as per the WTO agreement. The unemployment challenge in China is difficult to handle because it interlinks with different structural factors. The government has taken various measures to overcome the issue of employment by reforming and establishing a new mechanism of the labour market. Despite the government's initiative, there is an urgent need for a sweeping solution to expand employment opportunities.

One of the potential solutions to reduce the issue of unemployment is environmental technology up-greats. Environmental technology, also known as green technology, is defined as 'the development of new technologies that aim to conserve, monitor or reduce the negative impact of technology on the environment and the consumption of resources'. These technologies are more energy efficient (Chen et al., 2021; Hu et al., 2022; Tao et al., 2021), for instance, self-sufficient buildings, systems of water-waste management, etc. Multiple technologies related to solar, geophysical (wind, water), or biological (biomass) sources provide increasingly cost-effective energy resources. They can supply electricity, thermal energy and mechanical energy, and liquid fuels while lowering GHG emissions from the energy systems (Dell'Anna, 2021). The components of environmental technology are electricity generation

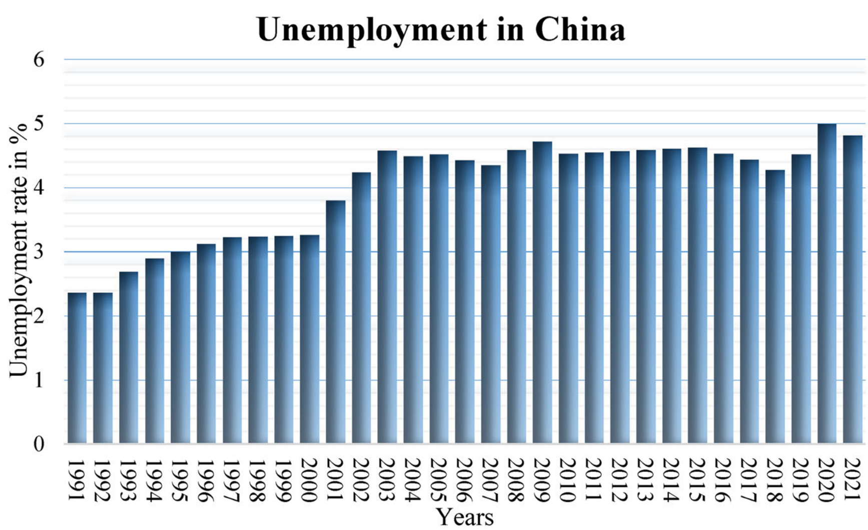

Figure 1. The unemployment rate in China from 1991 to 2021.
Source: https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?locations=CN

technologies, heat and power technologies, and storage technologies. Initially, the manufacturing and implementation costs of green technologies were so high. However, now the cost of these technologies has fallen across the board, and the benefits in terms of return skyrocketed.

The adaptation of environmental technology has different employment impacts. According to Valenti et al. (2016), the transition towards a green economy depends highly on green technologies and the implementation of labour markets (Irfan et al., 2022). These technologies reform the level of productivity, distribution, and work quality. Therefore, they require new skills, thus creating additional jobs. According to the International Energy Agency – IEA (2021a) report on China's energy sector roadmap towards carbon neutrality, China's accelerated progress towards environmental technology is expected to generate 3.6 million employment opportunities by 2030 compared to the expected jobs of 2.3 million in the non-renewable energy sector. These additional jobs are also expected to rise when the other countries' demand for Chinese environmental technology rises in the coming years. In contrast, environmental technologies are the reason for eliminating or transforming existing jobs in the market (Ram et al., 2022). These technological advancements lead to job losses in the unskilled or semi-skilled labour force. Besides these, the non-renewable energy sector labour may also suffer due to the green transition. Therefore, the unemployment trend due to environmental technology varies based on production, transmission, and distribution.

Likewise, clean energy plays a vital role in improving environmental quality. Moreover, it provides other environmental and economic benefits, such as energy security and import independence (Naqvi et al., 2022). This sector has a high tendency for year-on-year growth, and in the last few decades, the contribution of clean energy to electricity generation has significantly expanded. Solar PV has an approximate 66% share of the total clean energy growth. The investments in solar PV have created 33% of the jobs, which is around 11.5 million in 2019. According to International Renewable Energy Agency (IREA) (2021), the investments made in solar PV in Asia is accounted for more than 63% of the total jobs in the clean energy sector. European's wind energy powerhouse sector has created direct jobs and employed one hundred thousand people in the last couple of years, specifically in wind turbines and components supplied by domestic firms. The high investment in this sector reduces the total carbon emission and increases production and the level of employment.

However, the clean energy sector's direct contribution to the existing literature has not been consensual. Some studies argue that the contribution of this sector is not significant enough to create job opportunities or positively impact unemployment (Mu et al., 2018). While the other claim that the investment in the clean energy sector indirectly impacts unemployment based on the financing mechanism of the country (Proença & Fortes, 2020). The clean energy investment impacts unemployment in different scopes. For instance, direct, indirect, and induced (Ram et al., 2022). The direct employment opportunities are associated with the investment made to increase clean energy production capacity, while the indirect employment effect of clean energy investment is based on increased demand for the value chain. On the other hand, the induced employment effect of clean energy relies on the decline in investment in the non-renewable energy sector and the computation of capital (Almutairi et al., 2018; Mu et al., 2018; Razzaq et al., 2022).

Besides this, the study has incorporated another variable, such as economic policy uncertainty, as the control variable to evaluate its influence on China's unemployment rate. Sustainable economic and financial development relies on political stability (Tabash et al., 2022). The uncertainty in the government policies and initiatives hampered the foreign and domestic investment inflows by shaking the investors' confidence and cutting economic and business activities. Which ultimately reduces the social benefits of the society in terms of job creation or elimination of the existing jobs (Mu et al., 2018). At the same time, some recent studies argue that properly implementing environmental regulations for technology innovation and clean energy investments promotes high-skilled labour employment because of low economic policy uncertainty (Zhong et al., 2021). Therefore, it is essential to explore the actual impact of the EPU on employment or job creation in China.

The study has selected China as the sample based on various facts. For instance, China has global importance due to its high economic growth. Therefore, it has a wide range and lasting impact on the global economy. Moreover, the country is a significant suspect who emitted the highest GHGs. Also, the rapid population growth creates an alarming situation for achieving social and economic sustainability goals. The government has taken various initiatives to meet the social, economic, and environmental challenges. The energy sector has made significant progress in this regard. For instance, In 2021, China is responsible for catering to more than 50% of the clean energy production to generate electricity (IEA, 2021b).

Similarly, the 'Global Trends in Renewable Energy Investment 2019' report by United Nations Environment Program highlights that China has made the largest investments in clean energy in the last few years. The investment amount reached $760 billion from 2010 to 2019. In contrast, the United States has made half of these investments during the same period. The massive financial investment has increased the clean energy manufacturing capacity, providing ample employment opportunities in the domestic and international labour markets.

The current study contributes to the existing literature in various ways. For instance, previous studies have discussed various factors influencing the employment rate. However, the direct impact of environmental technology and clean energy investment has no empirical evidence. Based on the inconclusive discussion above related to the employment impact of these explanatory variables, this study is motivated to fill the knowledge gap by understanding the role of environmental technology and clean energy investments in reducing the unemployment rate in China. Besides this, the study employed the 'quantile autoregressive distribution lag' (QARDL) method to find detailed insights by exploring the long-run and short-run magnitude of the relationship, which is crucial due to the nature and indirect impact of the clean energy investment flows and expected high demand of environmental technologies in future. In addition, the clean energy transition of China needs strong government initiatives; the low carbon energy system further requires public and private investments contribution; therefore, the outcomes of the study provide a reliable and significant assessment of the employment effect of the environmental technology and clean energy investment to obtain further engagement of policymakers and stakeholders. The study's outcomes suggest that environmental technology and clean energy investment reduce the unemployment rate in China by providing ample job opportunities in clean energy production and value chain addition.

The result of the study comprises a literature review of section two discussing previous studies finding and establishing a theoretical framework. Section three discusses the proposed methodology and data summary, whereas the details discuss the empirical findings covered in section four. The conclusion section summarises the whole study and provides some policy recommendations.

2. Literature review

Recent studies have focussed significantly on the clean energy sector's environmental impact. In contrast, this sector is also a high economic contributor regarding investments and employment. The employment impact is one of the most crucial factors of society's wellbeing. However, very few have discussed the social benefits of employment created by the green energy sector. There are different groups of thoughts. Some researchers support the notion that the clean energy sector creates massive jobs due to its rapid growth, whereas others argue that the high implementation cost of clean energy projects and highly skilled labour-associated requirements slow down economic activities and cut down the jobs for nonskilled workers or low-skilled labour. The literature explains that the direct employment impact of clean energy investment and environmental technology is scant. However, some studies have measured the employment impact of the clean energy sector on environmental regulations and policies. For instance, Mu et al. (2018) examine the employment impact of renewable energy development in China. The authors used the CGE 'computable general equilibrium model' to gauge the change in job experience in the labour market due to the implementation of green technologies. The empirical finding of their study suggested that the expansion in solar PV and wind are significantly accounted for job creation in China. They also found the high indirect or induced employment impact of subsidies for renewable energy projects. These subsidies result from environmental taxes against the consumption or extraction of fossil fuels, depress the non-renewable energy sector, and become the reason for losses of jobs in this sector.

Hafstead and Williams (2018) found the strong influence of the renewable energy sector on total employment in environmental regulation. They explored that the strict regulations stimulate the green innovational capacity of the companies. Therefore, the high skilled workers' demand increases. However, in their study duration, they have found the upsurge in the non-relevant jobs also due to the expansion of the green energy sector. In addition, Zhong et al. (2021) also explore the association between the renewable energy sector performance at employment due to environmental regulations. The finding was based on the Cobb-Douglas production function and revealed that the clean energy sector expands employment opportunities for highly skilled workers with strict regulatory compliance, whereas the low-skilled job opportunities are suppressed in the same scenario.

Raff and Earnhart (2020) discussed two types of labour force relevant to the environment. One is the production labour dedicated to the energy production process, while the other is the environmental labour responsible for compliance with environmental regulations. The expansion of the clean energy sector is responsible for following all the environmental regulations; therefore, as a substitute for fossil fuel, clean energy production reduces production labours job. Thus, according to this study, the clean energy sector enhances unemployment. Likewise, Almutairi et al. (2018) measured the impact of implementing renewable and nuclear energy (RNE) on the social and economic benefits to the world. Their study has divided the sample into specific regions based on their economic structure and availability of natural resources, such as Saudi Arabia, China, India, the United States, Europe, and the rest of the world. The study explores the economic shift towards RNE negatively affects the GDP and decreases 4.45 million jobs.

Dell'Anna (2021) has investigated investment's environmental and social benefits in Italy's renewable energy sector (RES). The input-and-output analysis was applied to the power systems comprised of wind, solar PV, hydroelectric and geothermal infrastructure expected to install by 2040. The study's outcome confirms the positive association between these investments and economic growth. Also, RES creates more job and enhance job performance related to solar PV infrastructure. Similarly, Khan et al. (2021) analysed the energy transition impact on the economic growth of IEA countries and found that the low–CO2–emission technologies support the green energy transition and positively influence the labour and capital in these IEA economies. A recent study by Naqvi et al. (2022) analysed the role of enhanced clean energy production capacity in the digital societies' labour market. The study applied the NARDL-PMG method to the panel data of European countries. The study's outcomes explored that the enhancement in clean energy production capacity significantly reduced the unemployment in these countries from 1990 to 2019. Also, the technology innovations in the clean energy sector support employment growth in the long run.

The employment impact of technology has also been investigated by various other studies, such as (Van Roy et al., 2018), who found the positive effects on job creation by the innovation activities of the high-tech manufacturing sector of Europe. In contrast, Borys et al. (2021) found a different association between technology and unemployment in the USA. They determined that technology stocks are accountable for more than 42% fluctuation in the unemployment rate of the USA labour market. Similarly, Widarni et al. (2020) applied the method of ARIMA and TAR to evaluate the technological innovation impact on unemployment in Indonesia. They discovered that high technology innovation negatively affects the job creation mechanism. The increase in innovations upsurges unemployment in the high population growth scenarios. A recent study by Ram et al. (2022) also investigated the socio-economic benefits of the sustainable technology adopted by energy sectors of the world. Their study forecast the direct employment impact of the power, heat, transport, and biofuel sectors for energy transition and suggests that by the end of 2050, the energy-related jobs will reach 134 million, which is more than double the green jobs recorded in 2020.

Likewise, Saka et al. (2021) assessed the impact of technological progress on the unemployment of different labour skill levels. Their study tests two notions: technology advancement replaces labour with more technical efficiency, or technology expands the energy sector and raises employment. This study endorsed that technological advancement increased the unemployment of low-skilled labour. Focacci (2021) has also highlighted the ICT revolution's employment impact, technology innovation, and renewable energy consumption in China and South Korea. The author established the insignificant relationship between technology innovation and unemployment from 2008 to 2018. However, the finding considers clean energy consumption as the prime factor in fluctuating the unemployment rate in these countries.

3. Methodology

3.1. Data and variables construction

The empirical evidence of the study has been obtained from China's data from Q1-1990 to Q4-2020.[1] In doing so, the data of variables listed in Table 1 have been integrated to investigate the impact of environmental technology and clean energy investment on China's unemployment rate.

3.2. Model formation

The study gets inspiration from the model used by Van Roy et al. (2018) and Zhao and Luo (2017) to evaluate the employment impact of environmental technology, clean energy investment, economic growth, and economic policy uncertainty (EPU) in China. The functional form of the study variables' interconnection has exhibited in Equation (1)

Table 1. Description and source of study variables.

Variables	Acronyms	Variable description	Measurement	Source
Unemployment	UEMP	The labour force share which is currently not working but available for jobs or seeking employment	% of the total labour force	WDI
Environmental technology	ETEC	Patents on environmental technologies	% of total technology patents	OECD
Clean energy investment	CINV	It is referred to the investments made through various sources to align with the environmentally friendly business and conservation of natural resources	Amount (2019 prices USD millions)	China Statistical Yearbooks
Economic growth	GDP	Gross Domestic Production	Per capita USD Constant (2010)	WDI
Economic policy uncertainly	EPU	Uncertainty or risk related to the government's undefined economic policies for the future.	EPU Index	EPU website

Note: WDI: World Development Indicators. OECD: Organization for Economic Cooperation and Development, and EPU: Economic Policy Uncertainty website.
Source: Authors.

$$\text{UEMP} = f\ (\text{ETEC},\ \text{CINV},\ \text{GDP},\ \text{EPU}) \tag{1}$$

The dependent variable UEMP refers to the unemployment rate (percent of the labour force currently unemployed but seeking jobs). While the explanatory variables such as ETEC, CINV, GDP, and EPU illustrated environmental technology, clean energy investment, economic growth, and economic policy uncertainty, respectively (refer to Table 1 for the details of the variable).

The functional form of variables in Equation (1) has been constructed into the following econometric model as under

$$\text{UEMP}_\text{t} = \mu_0 + \mu_{ETEC}\ \text{ETEC}_\text{t} + \mu_{RINV}\ \text{CINV}_\text{t} + \mu_{GDP}\ \text{GDP}_\text{t} + \mu_{EPU}\ \text{EPU}_\text{t} + \varepsilon_\text{t} \tag{2}$$

't' represents the study duration from 1990 to 2020 in the above model, while the ε_t presents the error term in the model of Equation (2).

3.3. Theoretical framework

The green economic transition has various benefits. The deployment of clean energy enhances economic growth (Naqvi et al., 2022). At the same time, implementing environmental technology to support green economic transition has positive and negative employment impacts. Technology innovation in environmental aspects requires highly skilled labour. Therefore, it creates job additions (Valenti et al., 2016) in the manufacturing, distribution, and storage of parts of clean energy projects. Besides this, the rapid growth in the energy sector increases the demand for energy-efficient technology, which also upsurges the overall employment rate globally. At the same time, technology has reduced jobs in the non-renewable energy sector. Moreover, the high demand for technically sound labour has significantly cut down the low-skilled labour jobs related to the clean energy sector (Saka et al., 2021). Therefore, the expected outcome of the relationship between environmental technology and unemployment in China can be positive $\left(\mu_{ETEC} = \frac{\text{UEMP}}{\text{ETEC}} > 0\right)$ or negative $\left(\mu_{ETEC} = \frac{\text{UEMP}}{\text{ETEC}} < 0\right)$.

Likewise, the employment effect of clean energy investment is also inconclusive in the existing literature. Investing in clean energy projects enhances the production capacity of green energy, therefore expanding economic activities and creating jobs in the form of a direct employment effect (Ram et al., 2022). In contrast, the high investment in the industry discourages the pay of high wages to get maximum return against the investment, thus promoting efficient and skilled labour and discouraging the employment of low or nonskilled workers. Also, the high investment in clean energy ensures the availability of clean energy to meet future energy demand. Consequently, the labour-related to the non-renewable energy sector lost their jobs (Almutairi et al., 2018). Based on these facts, the expected coefficient to demonstrate the association between clean energy investment and unemployment is positive $\left(\mu_{CINV} = \frac{\text{UEMP}}{\text{CINV}} > 0\right)$ or negative $\left(\mu_{CINV} = \frac{\text{UEMP}}{\text{CINV}} < 0\right)$.

The study has incorporated economic growth and policy uncertainty into the control variables. The economic growth impact on employment has been well studied. Economic growth enhances per capita income and provides domestic and international investors with various opportunities to establish their businesses. This has indirectly created a strong demand in the job market (Dell'Anna, 2021). Therefore, as the investments increase in clean energy projects, the economic growth becomes stable in China, which leads to a reduction in the unemployment rate; thus, the expected outcome to measure the environmental impact of economic growth is negative $\left(\mu_{GDP} = \frac{\text{UEMP}}{\text{GDP}} < 0\right)$. In contrast, the economic policy uncertainty discourages investment flow and minify the economic growth therefore cause unemployment (Mu et al., 2018). Hence the anticipated coefficient value of the nexus of economic policy uncertainty and unemployment in the clean energy sector is positive $\left(\mu_{EPU} = \frac{\text{UEMP}}{\text{EPU}} > 0\right)$ as the level of EPU increases the unemployment rate also rise.

3.4. Econometric method

To obtain reliable and unbiased results, it is essential to determine the integrated order of the study variables or stationarity in empirical studies before implementing an empirical analysis. The study addresses the issue of unit root presence by incorporating the test of existence by applying the Augmented Dickey-Fuller (ADF) test introduced by Dickey and Fuller (1981) and Zivot and Andrews (ZA) tests referred by Zivot and Andrews (1992) to determine the stationarity in the data series of the study variables. The Zivot and Andrews (ZA) test is advantageous as it highlights the structural break along the stationarity property of the data series to justify the inevitable change in the trend due to economic shocks or any uncertain occurrence. Subsequently, the long-run and short-run coefficients are obtained through the Quantile Autoregressive Distributed Lag (QARDL) to represent the dimension of the association among variables. This methodology has introduced by Cho et al. (2015) to explore the magnitude of the interaction between dependent and independent variables. This proposed econometric strategy has the edge over another traditional regression method in various ways. For instance, it provides details of the variable's association at different quantiles (the economic condition) for the long-run and short-run, which enables the study to evaluate within the conditional distribution the possible location-wise asymmetries. Besides this, it also provides non-linear association dynamics (He et al., 2021; Jiang et al., 2021). Also, according to the quantile innovations, this method enables the adjustment of cointegration parameters.

The study applied the Wald test to analyse the long-run and short-run equilibrium and the consistency of the parameters via time-varying integration across the quantiles. Additionally, the econometric strategy has also added the Quantiles Granger Causality to determine the directional relationship of unemployment with other independent variables. The conventional model of ARDL has been established to obtain the non-linear and asymmetric linkage among variables as under:

$$\begin{aligned}\text{UEMP}_t = {} & \mu_0 + \sum_{i=1}^{p} \varphi_{\text{UEMPi}}\, \text{UEMP}_{t-i} + \sum_{i=0}^{q1} \omega_{\text{ETECi}}\, \text{ETEC}_{t-i} + \sum_{i=0}^{q2} \lambda_{\text{CINVi}}\, \text{CINV}_{t-i} \\ & + \sum_{i=0}^{q3} \theta_{\text{GDPi}}\, \text{GDP}_{t-i} + \sum_{i=0}^{q4} \Psi_{\text{EPUi}}\, \text{EPU}_{t-i} + \varepsilon_t \end{aligned} \tag{3}$$

The composition of the error term in Equation (3) is based on $\text{UEMP}_t - E\left[\frac{\text{UEMP}_t}{\sigma_{t-1}}\right]$ where the smallest field of white noise is demonstrated as 'σ' which is created by the current and preceding values of study variables such as $UEMP_t$, $ETEC_t$, $CINV_t$, GDP_t, EPU_t and $UEMP_{t-1}$, $ETEC_{t-1}$, $CINV_{t-1}$, GDP_{t-1}, EPU_{t-1}. The lag values are presented by p, q1, q2, q3, and q4 under the criterion of Schwarz information criteria (SIC). According to Cho et al. (2015) the ARDL model of Equation (3) can be transformed into the quantile version of ARDL as under:

$$UEMP_t = \mu_0(\tau) + \sum_{i=1}^{p} \varphi_{UEMPi}(\tau)UEMP_{t-i} + \sum_{i=0}^{q1} \omega_{ETECi}(\tau)ETEC_{t-i} + \sum_{i=0}^{q2} \lambda_{CINVi}(\tau)CINV_{t-i} + \sum_{i=0}^{q3} \theta_{GDPi}(\tau)GDP_{t-i} + \sum_{i=0}^{q4} \Psi_{EPUi}(\tau)EPU_{t-i} + \varepsilon_t \tag{4}$$

where the quantile range varies from zero to one ($0 > \tau < 1$). The Equation (4) has to be modified by considering the conditional distribution of the quantiles and the probability of the potential sequential correlation in the white noise error. The new form of Equation (4) presents the QARDL model as under:

$$UEMP_t = \mu_0(\tau) + \rho UEMP_{t-1} + \mu_{ETEC} ETEC_{t-1} + \mu_{RINV} CINV_{t-1} + \mu_{GDP} GDP_{t-1} + \mu_{EPU} EPU_{t-1} + \sum_{i=1}^{p} \varphi_{UEMPi} \Delta UEMP_{t-i} + \sum_{i=0}^{q1} \omega_{ETECi} \Delta ETEC_{t-i} + \sum_{i=0}^{q2} \lambda_{CINVi} \Delta CINV_{t-i} + \sum_{i=0}^{q3} \theta_{GDPi} \Delta GDP_{t-i} + \sum_{i=0}^{q4} \Psi_{EPUi} \Delta EPU_{t-i} + \varepsilon_t \tag{5}$$

The QARDL model in Equation (5) considers the error correction term and reconstructed as under:

$$UEMP_t = \mu_0(\tau) + \rho(\tau)(UEMP_{t-1} - \mu_{ETEC}(\tau)ETEC_{t-1} - \mu_{RINV}(\tau)CINV_{t-1} - \mu_{GDP}(\tau)GDP_{t-1} - \mu_{EPU}(\tau)EPU_{t-1}) + \sum_{i=1}^{p} \varphi_{UEMPi}(\tau)\Delta UEMP_{t-i} + \sum_{i=0}^{q1} \omega_{ETECi}(\tau)\Delta ETEC_{t-i} + \sum_{i=0}^{q2} \lambda_{CINVi}(\tau)\Delta CINV_{t-i} + \sum_{i=0}^{q3} \theta_{GDPi}(\tau)\Delta GDP_{t-i} + \sum_{i=0}^{q4} \Psi_{EPUi}(\tau)\Delta EPU_{t-i} + \varepsilon_t(\tau) \tag{6}$$

In Equation (6), the speed of adjustment presented as ‘ρ’ is assumed to be significantly negative, and its value must be varied between 0 and −1. to support the degree of correction. In addition, the model applied the delta method, which measures the accumulated effects of past and lagged values of UEMP on the recent value of UEMP in the short-run as $\varphi_{UEMPi} = \sum_{i=1}^{p-1} \varphi_{UEMPj}$. Similarly, the other variables such as ETEC, CINV, GDP, and EPU influenced the current value of unemployment with their aggregate value of previous and lagged values. Which are presented as $\omega_{\mathrm{ETECi}} = \sum_{i=0}^{q1-1} \omega_{\mathrm{ETECj}}$, $\lambda_{\mathrm{CINVi}} = \sum_{i=0}^{q2-1} \lambda_{\mathrm{CINVj}}$, $\theta_{\mathrm{GDPi}} = \sum_{i=0}^{q3-1} \theta_{\mathrm{GDPj}}$, and $\Psi_{\mathrm{EPUi}} = \sum_{i=0}^{q4-1} \Psi_{\mathrm{EPUj}}$ respectively. In contrast, long-run estimates of QARDL illustrated as $\mu_{ETEC*} = -\frac{\mu_{ETEC}}{\rho}$, $\mu_{RINV*} = -\frac{\mu_{RINV}}{\rho}$, $\mu_{GDP*} = -\frac{\mu_{GDP}}{\rho}$, and $\mu_{EPU*} = -\frac{\mu_{GEPU}}{\rho}$ for ETEC, CINV, GDP and EPU, respectively.

As mentioned earlier in the econometric strategy, the Wald test is employed to examine the asymmetric impact of dependent variables such as ETEC, CINV, GDP, and EPU on the dependent variable of UENP for both the long and short duration of the study. Similar to the QARDL model, the parameter of adjustment has also been donated by ρ and supports the following null hypothesis:

$$\text{Null hypothesis} = \rho*(0.05) = \rho*(0.10), = \rho*(0.20)\ldots. = \rho*(0.90) = \rho*(0.95)$$

For the long-run parameters of $\mu_{ETEC*}, \mu_{RINV*}, \mu_{GDP*}$, *and* μ_{EPU*}And the shirt-run parameters φ_{UEMPi}, ω_{ETECi} , λ_{CINVi}, θ_{GDPi}, Ψ_{EPUi} the same Wald test has been applied.

4. Results and discussions

The empirical analysis begins with the descriptive analysis of the study variables. Such as UEMP ('unemployment'), ETEC ('environmental technology'), CINV ('clean energy investments'), GDP ('economic growth'), and EPU ('economic policy uncertainty'). Table 2 exhibit the highest mean value of EUP, while the least mean value is shown by environmental technology. In contrast, the highest volatility has been shown by ETEC, while the least desperation has been observed for the data series of UEMP, which expresses the high growth and frequent change in the environmental technology while the unemployment rate remains stable in China. Besides this, the table shows the results of the Jargue-Bera test, which assume that the data of the variables is normally distributed. This notion has been presented in the form of the null hypothesis. According to the results, all the study variables have rejected the null hypothesis at a 1% significance level which confirms the asymmetric properties of the variables or, in other words, the data distribution is not normal. Based on these outcomes, the study has motivated to apply the quantile ARDL approach to examine the quantile based association among the variables of interest (Song et al., 2021).

The next step of the econometric strategy is to diagnose the unit root presence in the data series. The stationary data provide reliable results as its statistical properties

Table 2. Results of descriptive statistics.

Variables	UEMP	ETEC	CINV	GDP	EPU
Mean	1.038	0.104	1.02	0.146	1.051
Min.	0.115	0.062	0.154	0.07	0.2
Max.	1.103	1.011	1.085	1.005	1.131
Std. Dev.	0.11	1.052	1.027	0.123	1.045
J-B Stats	16.126***	21.071***	17.110***	23.052***	19.143***

Note: *** $= p < 0.01$.
Source: Authors.

Table 3. ADF and ZA tests for stationarity.

Variable	ADF (Level)	ADF (Δ)	ZA (Level)	Year	ZA (Δ)	Year
UNEMP	−0.157	−5.367***	−0.559	2010 Q1	−6.886***	2012 Q4
ETEC	−0.657	−5.302***	−1.572	2016 Q4	−7.057***	2016 Q4
CINV	−1.308	−4.334***	−0.622	2009 Q1	−5.998***	2010 Q3
GDP	−1.061	−6.355***	−1.859	2012 Q1	−8.134***	2007 Q4
EPU	−0.336	−5.174***	−0.956	2017 Q2	−8.660***	2011 Q1

Note: ***$p < 0.01$. The values under −5.57(1%), −5.08 (5%) and −4.82 (10%) present the critical values for the ZA test.
Source: Author estimations.

remain stable over time. Therefore, it is crucial to determine the stationary form of the data series to obtain valid results to illustrate the impact of environmental technology and clean energy investments on unemployment in China. In doing so, this study has applied the Augmented Dickey-Fuller (ADF) test and Zivot and Andrews (ZA) tests. The outcomes of these tests are demonstrated in Table 3. According to the ADF and ZA test outcomes, all the data series are stationary at first. In addition, the ZA test explores various structural breaks, which are the abrupt change in the data series due to the involvement of other economic factors. The conspicuous integration order of I(1) provides the unique integration order and motivates the study to proceed further with QARDL estimates.

The QARDL estimates presented in Table 4 illustrate the long-run dynamics and short-run association among variables at different grids of quantiles from low to high (0.05 − 0.95). The coefficient of error correction term is observed as negative and significant at low to high quantiles, which shows the reversion of the variables to obtain equilibrium. However, at the highest quantile (0.7-0.95), the convergence to the equilibrium is insignificant in the long run for the suggested model. Likewise, the coefficient values of environmental technology are significantly negative at low quantile only (0.05-0.10), which exhibits its effectiveness in reducing the unemployed only in slow economic growth in the long-run. While in the medium and high economic growth situations, the environmental technology contribution to providing job opportunities is insignificant. The negative relationship between environmental technology and unemployment is similar to the relationship explored by Ram et al. (2022). It is suggested that environmental technology has a high potential to create jobs related to power, heat, transport, and biofuel sectors.

Similarly, the coefficient of clean energy investment is negatively significant at medium to high quantiles (0.50-0.95) at a 5% level of significance which demonstrates that in the high economic growth scenario, the investment in clean energy projects boosts employment due to the high demand of clean energy in long-run. Proença and Fortes (2020) and Naqvi et al. (2022) endorse the negative and significant association between clean energy investment and unemployment. They stated that the investment in clean energy resource production capacity significantly enhances direct employment. The findings are inconsistent with the study outcomes of Almutairi et al. (2018). They argue that the high investment in clean energy projects depresses fossil fuel demand, creating unemployment in non-renewable energy sectors.

Likewise, in the long run, the economic growth associated with unemployment has been negatively correlated at high quantiles at a 5% (0.60) and 1% (0.70 to 0.95) level

Table 4. Long run & short run estimates of Quantile Autoregressive Distributed Lag (QARDL).

Quantiles	Constant	ECM	Long-run estimates				Short-run estimates					
(τ)	$\alpha^*(\tau)$	$\rho^*(\tau)$	$\mu_{ETEC}(\tau)$	$\mu_{CINV}(\tau)$	$\mu_{GDP}(\tau)$	$\mu_{EPU}(\tau)$	$\varphi_1(\tau)$	$\omega_0(\tau)$	$\omega_1(\tau)$	$\lambda_0(\tau)$	$\theta_0(\tau)$	$\Psi_0(\tau)$
0.05	0.021	−0.647***	−0.308*	−0.125	−0.186	0.356***	0.459***	−0.062**	−0.077	−0.037***	−0.080***	0.051**
	(0.100)	(−4.010)	(−1.661)	(−0.740)	(−0.515)	(3.120)	(3.350)	(−1.980)	(−1.347)	(−1.971)	(−3.018)	(2.002)
0.10	0.208	−0.898***	−0.421*	−0.209	−0.241	0.341***	0.460***	−0.053**	−0.068	−0.069***	−0.077***	0.043**
	(0.020)	(−6.088)	(−1.650)	(−0.821)	(−0.448)	(4.074)	(3.252)	(−2.305)	(−0.567)	(−2.069)	(−4.077)	(1.689)
0.20	0.056	−0.758***	−0.332*	−0.246	−0.175	0.478***	0.538***	−0.070**	−0.045	−0.042***	−0.066***	0.062**
	(0.036)	(−5.111)	(−1.792)	(−1.075)	(−0.610)	(3.202)	(3.302)	(−1.974)	(−1.064)	(−2.182)	(−5.066)	(2.044)
0.30	0.078	−0.514**	−0.520	−0.250	−0.300	0.370***	0.314***	−0.059**	−0.075	−0.033	−0.027***	0.036**
	(0.108)	(−2.031)	(−1.243)	(−1.114)	(−0.795)	(4.014)	(3.410)	(−2.051)	(−0.757)	(−1.555)	(−3.022)	(1.660)
0.40	0.056	−0.246**	−0.209	−0.210	−0.268	0.428***	0.464***	−0.064	−0.054	−0.052	−0.025***	0.049**
	(0.001)	(−2.016)	(−1.101)	(−1.437)	(−1.053)	(3.128)	(3.101)	(−0.811)	(−1.515)	(1.365)	(−4.105)	(2.009)
0.50	0.372	−0.510**	−0.416	−0.301**	−0.156	0.301***	0.623***	−0.063	−0.060	−0.040	−0.035***	0.068**
	(0.070)	(−2.015)	(−1.115)	(−1.994)	(−0.600)	(5.015)	(2.977)	(−1.208)	(−1.606)	(−1.144)	(−4.022)	(1.650)
0.60	0.158	−0.020*	−0.325	−0.380**	−0.203**	0.308***	0.486***	−0.078	−0.058**	−0.025	−0.046***	0.041**
	(0.010)	(−1.125)	(−1.156)	(−2.689)	(−2.469)	(3.256)	(3.306)	(−1.100)	(−2.333)	(−1.086)	(−6.006)	(2.001)
0.70	0.003	−0.309*	−0.401	−0.429**	−0.342***	0.292***	0.550***	−0.055**	−0.050***	−0.012	−0.100***	0.058**
	(0.070)	(−1.700)	(−1.084)	(−2.027)	(−3.142)	(4.117)	(2.992)	(−2.005)	(−4.009)	(−1.401)	(−4.003)	(1.681)
0.80	0.050	−0.003	−0.0210	−0.563**	−0.274***	0.286***	0.352**	−0.080**	−0.030***	−0.038	−0.061***	0.049**
	(0.070)	(−0.013)	(−1.132)	(−1.970)	(−3.374)	(3.041)	(2.701)	(−2.222)	(−5.030)	(−1.228)	(−3.361)	(2.006)
0.90	0.612	−0.277	−0.353	−0.382**	−0.310***	0.315***	0.499**	−0.072	−0.044***	−0.032	−0.076***	0.051**
	(0.106)	(−0.001)	(−0.850)	(−2.035)	(−3.773)	(6.002)	(2.176)	(−1.608)	(−3.004)	(−0.821)	(−5.006)	(1.668)
0.95	0.191	−0.155	−0.600	−0.442**	−0.220***	0.306***	0.362*	−0.060	−0.090***	−0.037	−0.150***	0.031**
	(0.010)	(−0.033)	(−1.100)	(−1.980)	(−3.281)	(4.124)	(1.762)	(−1.617)	(−3.090)	(−1.017)	(−5.305)	(2.101)

Note: The table reports the quantile estimation results. The t-statistics are between brackets. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
Source: Author estimations.

of significance. This has confirmed the constructive role of economic growth towards employment. In other words, when economic growth is at its peak, employment opportunities also accelerate due to extensive economic and investment activities. The results meet the expected outcome mentioned in section 3.3 of a theoretical framework for the employment impact of economic growth, as Dell'Anna (2021) suggested. The estimates of QARDL estimation for EUP presented in Table 4 show the positive and significant association between EUP and unemployment at all quantile (0.05-0.95) in the long-run, which expresses that low, medium or high economic growth EPU always creates hurdles for the economy. Despite the economic losses, it also creates social losses in the form of shutdowns or slows down the industries and loss of jobs.

Table 4 also presents the short-run estimates of the QARDL estimator for all the study variables. The outcomes present a positive coefficient for the unemployment lagged value at all quantile, for low to high quantile (0.05-0.70), the significance level is 1%, at higher quantile ($0.80-0.90$) it is 5% while at highest quantile (0.95) the level of significance is 10%. It has been declared that the previous high level of unemployment enhances the current unemployment in all economic growth scenarios in the short-run. In contrast, the previous and lagged environmental technology negatively impacts the current unemployment rate of China at low (0.05-0.30) and high quantile (0.70-0.95) at 5% and 1% levels of significance, respectively. This has explained that when the economic growth is slow and very high, implementing environmental technology boosts employment, whereas, in a stable economic condition, the employment impact of environmental technology is not significant.

Similarly, in the short-run, the association between clean energy investment and unemployment was only observed in the low quantile (0.05-0.20) at a 1% level of significance, which illustrate that in the slow economic growth the past and lagged clean energy projects investment reduce the current employment rate in China. The GDP also shows a negative and significant association with unemployment in the short-run at all quantile. In contrast, the EPU has a positive and significant coefficient to explain the relationship with unemployment at all quantiles. This has demonstrated the past and lagged negative influence on China's current employment rate.

The study applied the Wald test to investigate parameter consistency. Table 5 exhibited the outcomes of the Wald test. According to the results, the parameter consistency for the speed of adjustment was established as the null hypothesis was rejected at a 1% significance level. In addition, the test outcomes for the other variables, such as environmental technology, clean energy investments, economic growth, and policy uncertainty, also reject the null hypothesis and show the dynamic relationship with unemployment in the long run across all quantiles at a significance level of 1%. Similarly, the short-run outcomes also demonstrate the significant non-linear association of variables such as environmental technology, clean energy investments, economic growth, and policy uncertainty with unemployment in China by rejecting the null hypothesis of linearity.

Table 6 illustrates the Granger causality test results to demonstrate the directional association of environmental technology, clean energy investments, economic growth, and policy uncertainty with unemployment in China across various quantiles.

Table 5. Wald Test for the constancy of parameters.

Variables	Wald-statistics
ρ	12.110*** (0.000)
$\mu_{ETEC}(\tau)$	8.654*** (0.000)
$\mu_{CINV}(\tau)$	5.361*** (0.000)
$\mu_{GDP}(\tau)$	17.256*** (0.000)
$\mu_{EPU}(\tau)$	24.565*** (0.000)
φ_1	5.980*** (0.000)
ω_0	4.741*** (0.000)
ω_1	0.632 (0.593)
λ_0	7.805*** (0.000)
θ_0	6.641*** (0.000)
Ψ_0	10.501*** (0.000)
Cumulative short-term effect:	
ω^*	1.210 (0.368)

*** and * indicate significance level at 1% and 10% levels, respectively.
Source: Author estimations.

Table 6. Results of Granger causality test.

Quantiles	$\Delta UEMP_t \downarrow \Delta ETEC_t$	$\Delta ETEC_t \downarrow \Delta UEMP_t$	$\Delta UEMP_t \downarrow \Delta CINV_t$	$\Delta CINV_t \downarrow \Delta UEMP_t$	$\Delta UEMP_t \downarrow \Delta GDP_t$	$\Delta GDP_t \downarrow \Delta UEMP_t$	$\Delta UEMP_t \downarrow \Delta EPU_t$	$\Delta EPU_t \downarrow \Delta UEMP_t$
[0.05–0.95]	0.000	0.000	0.000	0.000	0.000	0.000	0.018	0.000
0.05	0.000	0.000	0.000	0.000	0.002	0.000	0.033	0.007
0.10	0.000	0.000	0.000	0.000	0.006	0.000	0.021	0.019
0.20	0.000	0.012	0.000	0.000	0.010	0.000	0.011	0.010
0.30	0.000	0.069	0.000	0.000	0.005	0.000	0.004	0.013
0.40	0.000	0.145	0.000	0.000	0.011	0.000	0.001	0.011
0.50	0.000	0.197	0.000	0.000	0.004	0.000	0.001	0.009
0.60	0.000	0.088	0.000	0.000	0.009	0.000	0.002	0.000
0.70	0.000	0.005	0.000	0.000	0.003	0.000	0.001	0.000
0.80	0.000	0.001	0.000	0.000	0.007	0.000	0.006	0.002
0.90	0.000	0.006	0.000	0.000	0.001	0.000	0.000	0.001
0.95	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's estimation.

According to the outcomes, unemployment and environmental technology have a unidirectional association. The change in unemployment significantly brings the change in environmental technology. However, environmental technology does not significantly affect unemployment at middle quantiles, demonstrating that ETECH cannot predict unemployment in a stable economic scenario. On the other hand, the other variables such as clean energy investments, economic growth, and policy uncertainty, have a significant bi-directional association with unemployment in China in all economic scenarios and are considered a significant predictor of unemployment.

5. Conclusion and recommendation

The importance of clean energy in environmental and economic sustainability has been well documented. However, its social benefits are not explored attentively. Despite the rapid economic growth, China's unemployment rate has shown an upward trend since 1990. Unemployment is a significant economic issue for any country. Various factors cause the rise in the unemployment rate, such as the high population growth, imbalance in development levels within the country's states, surplus labour in the industrial sector, and rising competition in the domestic industry. As discussed in the introduction section, renewable energy or clean energy has shown exceptional progress in the last couple of years, and its future demand to meet the economic and environmental suitability goals is expected to be too high. For the green economic transition, technology and investment are the key factors. At the same time, the employment impact of these two factors needs to be analysed to create more jobs, environmental regulation, and policy implementation. The study investigates the role of environmental technology and investment in clean energy in reducing unemployment in China from 1990 to 2020.

The study employed the QARDL ('Quantile Autoregressive Distributed Lag') method to determine the quantile-based association among the variables such as environmental technology, clean energy investment, economic growth, economic policy uncertainty, and unemployment. The QARDL method is an advanced method that provides better insights (magnitude) into the influence of one variable on the other compared to the other traditional regression approaches. The study began with the descriptive analysis where the Jargue-Bera test confirmed that the data series is not normally distributed. The integration order of variables at the first difference I(1) has been affirmed by the Augmented Dickey-Fuller (ADF) and Zivot and Andrews (ZA) tests. The primary analysis through QARDL estimation explored the negative and significant association of environmental technology, clean energy innovation, and economic growth unemployment in the long run, which illustrates that unemployment has reduced with the increase in ETECH, CINV, and GDP. Whereas the economic policy uncertainty empirically inflates unemployment. In short-run estimates, the QARDL estimator endorses the long-run associations and suggests ETECH, CINV, and GDP as constructive factors in creating jobs and supporting the green energy transition in China.

Similarly, the Wald test results also affirm the significance of these variables in reducing unemployment in China during the study period. However, the quantile Granger Causality test found slightly different results. The test diagnosed the unidirectional link between environmental technology and unemployment. It illustrates that environmental technology cannot predict unemployment in a stable economic situation. At the same time, the other variables cause a significant change in unemployment and show a bidirectional association. Based on the empirical finding, the study suggests the following policy implications to promote environmental technology implementation and investment in clean energy projects to mitigate the growing issue of unemployment.

The government can handle the severe issue of unemployment urgently by enhancing economic development, which will create new job opportunities. They must reform the employment system and establish a new labour market mechanism. Moreover, to accelerate the direct employment impact of clean energy investment, they need to promote domestic and foreign investment in the green energy sector by providing relaxation and other incentives. Also, to avoid technological unemployment, they need to increase the investment in the education of the labour to provide the technical training and skill which enhance their compatibility and secure the advanced technology-based jobs. In addition, they need to focus specifically on the remote areas and ensure the accessibility of the funds for higher education to the low-income group. In addition, they should expand the channels to supply highly skilled labour to the energy industry. They should relocate the rural labour for new clean energy projects.

Unemployment is a universal issue for sustainable socio-economic growth. This study has limited its sample to China only due to the large population of the country and proportionally high rate of unemployment; futures studies for the panel data can provide better employment impact of environmental technology and green investment in developing countries such as Asian or South Asian countries where the growing unemployment rate is alarming for the counties growth.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. This study used quadratic match sum approach to convert annual data into quarters following Razzaq, Sharif, et al. (2021) and Razzaq, Wang, et al. (2021).

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