Dean&Francis

ISSN 2959-6149

# To what extent do technological advancements and Government policy interventions contribute to unemployment in China?

**Anya Zhu**

**Abstract:**

This study empirically examines the impacts of technological advancements and government policy interventions on China's unemployment during 2015–2025, using Pearson correlation analysis and multiple linear regression analysis. It identifies a highly significant positive correlation between general public expenditure as a GDP share and China's unemployment rate, with clear reverse causality. However, national average minimum wage and R&D expenditure's GDP share show no statistical impact on overall unemployment, due to regional wage heterogeneity, offset R&D job displacement and creation, and long R&D employment lags. Limited by national aggregated data, incomplete variable measurement and a short empirical horizon, the study still provides evidence-based insights for China's targeted employment policies and balancing technological progress, policy regulation and employment stability.

**Keywords:** China's Unemployment Rate, Technological Advancements, Government Policy Intervention, Multiple Regression Analysis

## 1. Introduction

In contemporary China, unemployment has become a prominent socioeconomic challenge. Over the past decade, China's labor market has undergone profound shifts driven by economic restructuring, technological progress, and growing global uncertainties, turning unemployment into a pivotal issue. According to National Bureau of Statistics, youth unemployment rate among those aged 16-24 reached an astonishing 21.3% in June, while that for aged 25-59 stood at 4.1%. (Xinhua News Agency, 2023). From both figures presented, China's unemployment rate has surged over the last 30 years, skyrocketing to 5.1% in 2024, more than doubling the level from 1995. This striking unemployment rate has triggered widespread domestic concerns about social cohesion and economic development. It has also drawn close attention from international investors and policymakers, who are examining its potential ripple effects on

ISSN 2959-6149

China's future economic development.

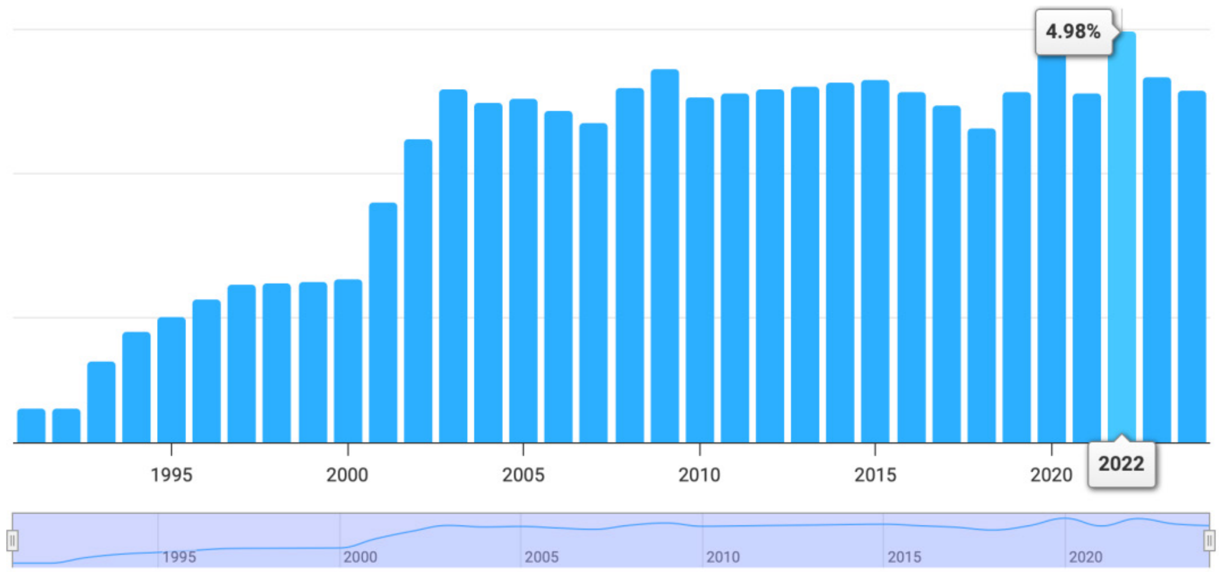


**Figure 1: China's Unemployment Rate from 2015 to 2024 (Source: macrotrends.net)**

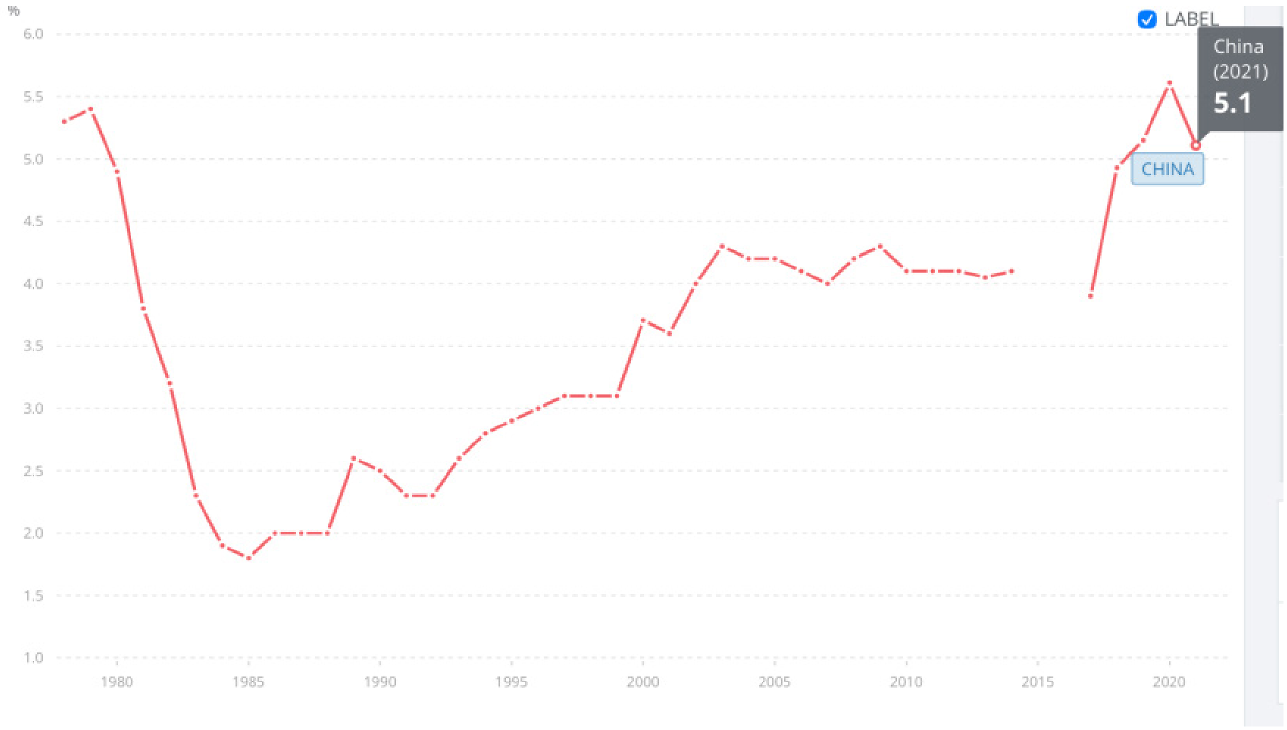


**Figure 2: Total unemployment as a % of total labor force. (International Labour Organization: Labor Force Statistics)**

A mix of factors has sparked public attention to the far-reaching impacts of unemployment, from individual livelihoods to national economic resilience. This underscores the urgent need for effective solutions. Among which, technological advancements and government policy interventions have emerged as the most profound catalysts. On the one hand, digital transformation and industrial upgrading have led to structural unemployment through substitution effect. Chiacchio et al. (2018) estimated that employment declines by 0.16-0.20 percentage points when a robot is added per 1,000 workers. Similarly, Yan et al. (2020) reported that for every 1 percentage point rise in robots, labor force jobs fell by 4.6 percentage points. On the other hand, restructuring policies and employment support measures exert a dual impact. While they alleviate unemployment pressures, poor alignment with real-world labor market conditions can exacerbate the issue. Unemployment also poses multifaceted harms, including reduced income, poorer mental health, weakened social cohesion, widening inequality, and slower growth in consumption, fiscal revenue and longterm economic growth.

This research intends to analyze and determine which of these two factors is more dominant in driving unemployment trends in China over the past decade. Given the ongoing economic restructuring in China, how these two intertwined forces contribute to unemployment is essential for deepening the understanding of the causes, but also for formulating more targeted strategies that reconcile technological advancements, policy regulation and employment stability. Ultimately, the dissertation aims to distill evidence-based insights on the significance of the factors, helping policymakers formulate better strategies, and thus promoting social stability and inclusive economic growth.

# 2. Literature review

## 2.1 Overview of Unemployment in the Chinese Context

According to international labor standards, unemployment generally refers to individuals aged 16–59 who are currently without work, have actively sought work in the past 4 weeks, and are available to start work immediately (International Labour Organization, 2022). Nevertheless, due to China's unique labor market characteristics, specifically its large migrant worker population and rural-urban migration, these require nuanced adjustments to this definition (National Bureau of Statistics of China, 2023). Unlike developed economies, China's official urban surveyed unemployment rate excludes rural workers not registered in urban areas, leading some scholars to argue that the actual unemployment rate may be 1.5–2 percentage points higher than reported (Fang & Lin, 2015).

## 2.2 Typologies of Unemployment

Unemployment is a complex labor market issue that can be classified into distinct typologies based on varying mechanisms, duration, and market performance.

### 2.2.1 Voluntary vs. Involuntary Unemployment

Voluntary unemployment describes individuals who exit the labor force by choice, such as those pursuing further education or a more desirable job, while involuntary unemployment refers to workers willing and able to work at current wages but unable to find employment (Caceres-Santamaria, 2024). This distinction is useful for policy design: voluntary unemployment often involves adjusting incentives, whereas involuntary unemployment requires demand-side interventions.

### 2.2.2 Cyclical vs. Structural Unemployment

Cyclical and structural unemployment both reflect macroeconomic conditions. Cyclical unemployment is transitory, closely linked to economic swings like recessions that reduce aggregate labor demand. By contrast, structural unemployment is long-lasting, driven by skill mismatches or industrial restructuring. Evidence shows that cyclical unemployment fades with economic recovery, whereas structural unemployment will persist without targeted measures. For instance, there were permanent job losses in the leisure and hospitality sector in 2020, as automation adopted during the pandemic stayed in place, even after consumer demand bounced back (Caceres-Santamaria, 2024).

### 2.2.3 Technological Unemployment

Technological unemployment describes job displacement caused by technological advancements, and existing studies have examined its impact across different occupations. Somers et al. (2022) identified a "labor replacement effect" in repetitive manufacturing roles via 127 empirical studies. Liu et al. (2024) confirmed this in China, where technological progress in industry suppressed demand for low-skill production workers, while increasing high-education worker opportunities. Yale University (2025) noted no economy-wide AI-induced unemployment as of 2025 but acknowledged gradual, sector-specific displacement.

## 2.3 Automation's Multifaceted Impact on Unemployment Dynamics in China

Several studies have found positive links between automation and unemployment in China's labor-intensive and routine-task-heavy sectors. Ozkan and Sullivan (2025) developed dual metrics to measure "AI exposure" (theoretical occupational vulnerability and real-world adoption) and found that manufacturing, administrative, and customer service roles face the highest displacement risk, where these sectors account for over 40% of China's low-skill employment (Cui et al., 2024). Their analysis of 2023–2025 data showed that provinces with high automation rates (e.g. Guangdong, Jiangsu) experienced a 5–7% decline in low-skill manufacturing jobs, directly linking automation to unemployment. This was exemplified in research, where Liu et al. (2024) analyzed hiring data from 1,200 Chinese enterprises and found that small- and medium-sized enterprises (SMEs) in textiles, electronics assembly, and toy manufacturing were most affected. Much of the literature suggests that those firms lack resources

ISSN 2959-6149

for workforce retraining, therefore they often respond to automation by eliminating positions involving rule-based work compared to non-routine roles, exacerbating unemployment among workers with limited education or specialized skills.

Despite these displacement effects, this finding risks overestimating automation's role in driving economy-wide unemployment in China. Instead, many present studies have highlighted that unemployment could be alleviated through restructuring roles in the economy. Yale University's Budget Lab (2025) analyzed national labor market data from 2019 to 2025. The study revealed that while employment in low-skilled manufacturing roles experienced an 8% decline, this reduction was counterbalanced by a 12% growth in automation-related jobs, such as AI maintenance and robot programming. Brij Dave (2025) noted this net positive employment trend was prominent in China's tech hubs, the city of Shenzhen alone added 230,000 automation-linked jobs (2022-2025), sufficiently offsetting traditional manufacturing employment losses. Cui et al. (2024) built on these findings by revealing a U-shaped relationship between automation and employment in China's manufacturing sector. Using panel data from 31 Chinese provinces from 2011 to 2020, the study outlined two sequential phases. The downward section of the U-curve shows an initial fall in employment, as automation replaces labour in routine tasks. The upward phase appears 2–3 years later, when employment rebounds, firms expand production with greater efficiency and create new roles for managing automated systems. Notably, by the end of the study period, provinces that adopted automation earlier had higher overall employment levels than those that integrated technologies later.

## 2.4 Government Policies' Impact on Unemployment. Effect of Minimum Wage on Unemployment

Multiple research have connected China's minimum wage reforms to aggravated unemployment, particularly for low-skilled workers. Fang and Lin (2015) conducted a seminal analysis of China's 2004 minimum wage policy and found that a 10% wage increase caused a 1–2% drop in employment among migrant workers. The effect was more obvious in Eastern China's manufacturing hubs, where the textile industry in Zhejiang province saw a 3% fall in employment. Subsequent studies have validated this pattern, firms with thin profit margins often respond to higher mandatory minimum wages by reducing staff or relocating to lower-wage regions. Prakash Loungani (2014) examined data from 2008–2013 and found that labor-intensive sectors such as assembly were twice as likely to reduce hiring after minimum wage hikes, compared with skill-intensive machinery manufacturing. More recently, LexChina (2025) documented the 2025 minimum wage adjustments, which lifted monthly rates above 2,000 RMB across 31 Chinese provinces. Their research showed that 15% of small manufacturers in Guangdong cut 5–10% of low-skill staff, while 20% moved production to inland provinces, diminishing coastal employment. Collectively, these findings highlight minimum wage policies disproportionately risk unemployment in labor-dependent sectors.

Despite these promising findings, other research has had contradictory findings, suggesting the potential to support jobs instead. Neumark (2015) addresses a key limitation in earlier studies by distinguishing between voluntary and involuntary unemployment: analyzing Chinese labor surveys, he found 40% of reported unemployment was voluntary, as workers gained bargaining power to reject substandard roles and seek better opportunities. This means job losses are often overstated when voluntary choices are conflated with involuntary layoffs. Furthermore, Huang (2024) identified minimum wages' indirect employment-creating role: higher wages increased disposable income for low-income households with a 0.9 marginal propensity to consume, boosting demand for retail, hospitality, and healthcare services, driving a 4% employment growth in these sectors. In Sichuan, this even offset 30% of manufacturing job losses tied to wage hikes. Taken together, this indicates minimum wages do not solely cause unemployment but can also support job creation.

## 2.5 Research gap

Although many studies examine the factors influencing unemployment, there are gaps in existing research in understanding how core drivers have evolved over time. Firstly, while numerous studies identify the elements affecting unemployment rate, they often fail to single out and compare the relative importance of each factor. This leaves a critical gap in understanding which drivers were most dominant during different stages of economic development.

Furthermore, empirical modeling in existing research is limited, while typical trends are discussed, there's a lack of mathematical analysis to examine the casual relationships between key variables, such as automation changes and minimum wage adjustments. Lastly, the examination of unemployment trends in 2025 and 2026 is incomplete. Although previous studies have focused on historical labor market patterns over the past decade, few have addressed the intensified prevalence of automation in recent years, especially the unprecedented peak of generative AI in 2025, which has reshaped China's labor demand at an accelerated pace.

In brief, given these gaps, the study uses statistical methods to quantify the impact of two key factors. It clarifies their relative importance, investigate the latest unemployment conditions, and extend prior research to contemporary Chinese labor market realities.

# 3. Methodology

## 3.1 Overview

This dissertation combines qualitative and quantitative methods. In order to synthesize existing insights regarding unemployment causes, and key patterns between the two factors and unemployment trends, the author adopts literature review and content analysis through secondary research, relying on credible academic journals, policy documents, and economic reports. The study aims to clarify their respective and combined influences, and derive targeted policy implications for balancing technological development, policy effectiveness, and employment stability. When collecting information, the author eliminated inaccurate or outdated sources to ensure data reliability and timeliness.

## 3.2 Secondary research

To ensure the credibility and relevance of the information, the CRAAP test (Currency, Relevance, Authority, Accuracy and Purpose) was employed to evaluate potential resources. The following criteria were used to select the references.

1. Currency: Preference was given to sources published within the last 10 years (2015–2026) to ensure the information reflects the most recent advancements and developments in China's economy. This also ensures that the analysis aligns with the latest economic policies and technological realities. Nevertheless, seminal works from earlier periods (e.g., 1995–2015) were included to provide essential historical context.
2. Relevance: Sources were selected based on their direct relevance to the two core factors: Chinese governmental policies and technological change. These include empirical studies, labor market policy analyses, technological impact assessments, and comprehensive economic reviews. Priority was given to sources explaining causal mechanisms between government intervention, technological progress, and unemployment dynamics.
3. Authority: Only sources published in reputable journals or produced by respected institutions were included. Examples include the Federal Reserve Bank of St. Louis, Investopedia, VoxEU, Yale University's Budget Lab, and the CSMAR database.
4. Accuracy: Sources were evaluated for accuracy based on the credibility of the publisher and the rigor of the content. Empirical studies, labor market policy analyses, technological impact assessments, and comprehensive economic reviews were prioritized as they are more likely to be accurate and up-to-date.
5. Purpose: The purpose of each source was assessed to ensure consistency with the overall research objective. Those providing comprehensive overviews, rigorous empirical evidence, and clear theoretical frameworks were favored, as they best support the analysis of how government policies and technology jointly influence unemployment in China.

## 3.3 Data collection

The author collected relevant macroeconomic indicators spanning the period 2010 to 2025 from official statistical databases and macroeconomic platforms, namely *Macrotrends, the Worldbank, Macromicro* and *tradingeconomics.com.* These indicators include China's unemployment rate, different types of government expenditure as a percentage of China's Gross Domestic Product (GDP), the ratio of Research and Development (R&D) expenditure to China's GDP, and the annual mean minimum wage.

## 3.4 Data analysis methods

### 3.4.1 Pearson Correlation analysis

The Pearson correlation coefficient is an indicator used to measure the strength and direction of the linear association between two variables, with the value of r ranging from −1 to +1. An r-value of −1 or +1 represents a perfect linear relationship, while an r-value of 0 indicates no linear relationship; a negative sign simply reflects the inverse direction of the association, meaning that as one variable increases, the other decreases (Ken Stewart, 2025). As a parametric correlation test, Pearson correlation can only be applied when variables follow a normal distribution, and it is mainly used to examine whether a linear relationship and corresponding dependence exist between quantitative variables. A correlation is considered statistically significant if $p<0.05$, and such a pretest is necessary before conducting further regression analysis, because a meaningful impact relationship can only be explored when a significant linear correlation is confirmed between variables.

### 3.4.2 Multiple linear regression analysis

Multiple regression analysis is a statistical technique used to examine the relationship between a single dependent

ISSN 2959-6149

variable and a set of independent variables. This method isolates the effect of each explanatory variable on the dependent variable, while accounting for the influence of other factors in the model (McKee, 2024). The author used the SPSSAU website to assist in the analysis of multiple linear regression equations.

The general form of the multiple regression equation is expressed as:

$Y=\beta0+\beta1X1+\beta2X2+\ldots+\beta nXn+\varepsilon$

In this equation: Y represents the dependent variable (China's unemployment rate). X1,X2,…,Xn are the independent variables ( in this case they are R&D's proportion of GDP, general public expenditure and government expenditure as a share of GDP, and minimum wage levels). Note that general public expenditure is a broader measure that includes social security and public funds, whereas government expenditure is narrower and only covers core budgetary spending, which is why their values as shares of GDP differ noticeably. β0 is the intercept, representing the value of Y when all independent variables are zero. β1,β2 ,…, βn are the regression coefficients, quantifying the magnitude and direction of the relationship between each independent variable and the dependent variable. ε is the error term, capturing the variation in Y that is not explained by the model.

# 4. Results

## 4.1 Descriptive Statistic

**Table 1. Summary Statistics of Key Macroeconomic Indicators and China's Unemployment Rate (2015-2025)**

| | Case number | Mean | Standard Deviation | Median |
|---|---|---|---|---|
| Unemployment rate in China (%) | 16 | 4.651 | 0.223 | 4.575 |
| Research & Development as a proportion of China's GDP (%) | 16 | 2.227 | 0.331 | 2.130 |
| General Public expenditure as a proportion of China's GDP (%) | 16 | 16.669 | 1.301 | 16.480 |
| Mean Minimum wage in China each year (RMB) | 16 | 2005.625 | 682.419 | 2360.000 |
| Government Expenditure as a proportion of China's GDP (%) | 16 | 30.949 | 2.924 | 31.960 |

China's unemployment rate has shown a fluctuating upward trend over the past decade from 2015 to 2025, eventually peaking at 5.20%. Meanwhile, government expenditure as a proportion of GDP (%) increased gradually over the years, and had the highest mean 30.949. General Public Expenditure as a proportion of GDP (%) showed extreme volatility, with the median of 16.480 recommended for its central tendency. The mean annual minimum wage (RMB) had the largest standard deviation with significant fluctuations. R&D as a proportion of GDP (%) had a low mean with mild volatility, performing as the most stable indicator.

## 4.2 Results of Normality Test

**Table 2. Normality Test Results for the discussed factors**

| Normality Test Results | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Name | N | Mean | Standard Deviation | Skewness | Kurtosis | | | Shapiro-Wilk Test33 |
| | | | | | | Statistic W | P value | |
| Unemployment rate in China (%) | 16 | 4.651 | 0.223 | 1.319 | 1.630 | 0.825 | 0.006** | |
| Research & Development as a proportion of China's GDP (%) | 16 | 2.227 | 0.331 | 0.277 | -0.954 | 0.953 | 0.544 | |
| General Public expenditure as a proportion of China's GDP (%) | 16 | 16.669 | 1.301 | 2.378 | 7.824 | 0.766 | 0.001** | |
| Mean Minimum wage in China each year (RMB) | 16 | 2005.625 | 682.419 | -0.690 | -1.283 | 0.826 | 0.006** | |
| General Government Expenditure as a proportion of China's GDP (%) | 16 | 30.949 | 2.924 | -0.851 | -0.295 | 0.898 | 0.074 | |
| * $p$<0.05 ** $p$<0.01 | | | | | | | | |

Normality tests were conducted for five variables above in Table 1 using the Shapiro-Wilk test, given the sample size of fewer than 50 observations. The results demonstrated that R&D as a proportion of GDP and general government expenditure as a proportion of GDP were normally distributed ($p > 0.05$). By contrast, the unemployment rate, general public expenditure as a proportion of GDP, and mean minimum wage showed significant deviations from absolute normality ($p < 0.05$). Nevertheless, strict normality requirements are often difficult to satisfy in empirical research. Furthermore, all variables exhibited absolute skewness values below 3 and absolute kurtosis values below 10, which are widely accepted as indicative of approximate normality. Consequently, all variables satisfied the normality assumption required for Pearson correlation analysis.

### 4.3 Results of correlation analysis of influencing factors of China's unemployment rate

**Table 3. Pearson Correlation Results for China's Unemployment Rate and Related Variables**

| Pearson Correlation | | |
|---|---|---|
| | Unemployment rate in China (%) | P value |
| Research & Development as a proportion of China's GDP (%) | 0.583* | 0.018 |
| General Public expenditure as a proportion of China's GDP (%) | 0.689** | 0.003 |
| Mean Minimum wage in China each year (RMB) | 0.328 | 0.215 |
| Government Expenditure as a proportion of China's GDP (%) | 0.380 | 0.147 |
| * *p*<0.05 ** *p*<0.01 | | |

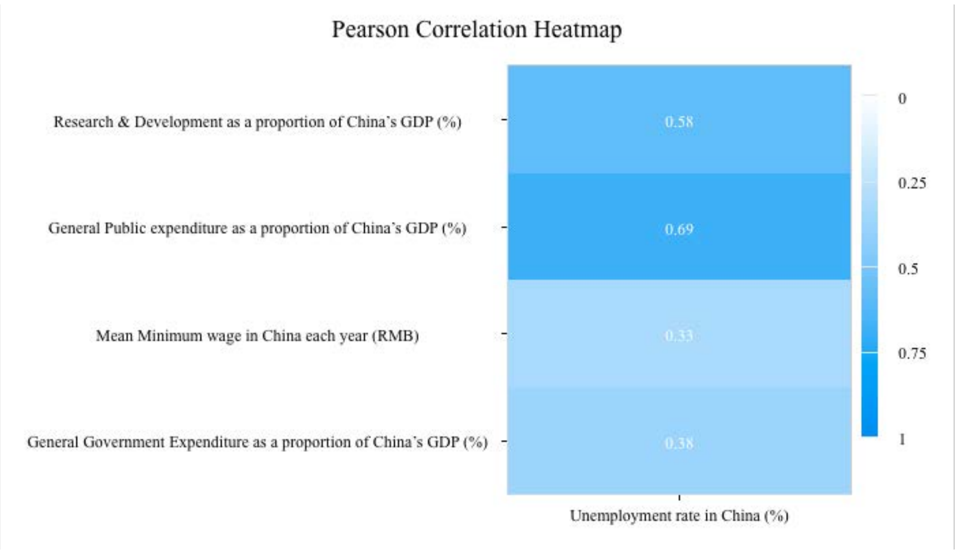


**Figure 3: Pearson Correlation Heatmap**

As shown in Table 3, Pearson correlation analysis was conducted to examine the relationship between China's unemployment rate (%) and four macroeconomic variables, with the correlation strength and significance measured by Pearson's r and p-values respectively. The results indicated a significant positive correlation between China's unemployment rate and R&D as a proportion of GDP, with a correlation coefficient of 0.583 and a p-value of 0.018 ($p<0.05$). A highly significant positive correlation was also found between China's unemployment rate and general public expenditure as a proportion of GDP, with a correlation coefficient of 0.689 and a p-value of 0.003 ($p<0.01$). By contrast, no significant correlation was observed between China's unemployment rate and the mean annual minimum wage, where the correlation coefficient was 0.328 and the p-value was 0.215 ($p>0.05$). Similarly, no significant correlation existed between China's unemployment rate and general government expenditure as a proportion of GDP, with a correlation coefficient of 0.380 and a p-value of 0.147 ($p>0.05$).

As shown in figure 3, the Pearson correlation heatmap intuitively presents the positive correlation trend among all variables. Overall, only R&D expenditure as a proportion of GDP and general public expenditure as a proportion of

ISSN 2959-6149

GDP were significantly positively correlated with China's unemployment rate, while the other two variables failed to reach the statistical significance level of 0.05.

### 4.4 Multiple linear regression process of mentioned influencing factors

**Table 4. The Impact of General Public Expenditure on China's Unemployment Rate**

| Linear Regression Analysis Results (n=16) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Unstandardized coefficients | | Standardized coefficients | *t* | *p* | Collinearity Diagnostics | |
| | *B* | Std. Error | *Beta* | | | VIF | Tolerance |
| Constant | 2.682 | 0.556 | - | 4.828 | 0.000** | - | - |
| General Public expenditure as a proportion of China's GDP (%) | 0.118 | 0.033 | 0.689 | 3.554 | 0.003** | 1.000 | 1.000 |
| $R^2$ | 0.474 | | | | | | |
| Adjusted $R^2$ | 0.437 | | | | | | |
| *F* | $F$ (1,14)=12.632, $p$=0.003 | | | | | | |
| D-W | 1.759 | | | | | | |
| Dependent variable = Unemployment rate in China (%) | | | | | | | |
| * $p$<0.05 ** $p$<0.01 | | | | | | | |

Building on the preliminary findings from the correlation analysis, mean minimum wage and General Government Expenditure as a percentage of China's GDP were therefore excluded from the subsequent multiple regression analysis, leaving R&D expenditure and General Public Expenditure as a proportion of China's GDP as the retained predictors. In the initial model, the partial effect of R&D expenditure as a proportion of GDP was not statistically significant (p = 0.613>0.05), this variable was manually removed to refine the specification. A revised multiple regression model was then estimated, with General Public Expenditure as a proportion of China's GDP as the sole independent variable, shown in Table 4. The regression equation is:

Unemployment rate in China (%)=2.682+0.118×General Public expenditure as a proportion of China's GDP (%)

The final model yielded an R-squared=0.474, indicating that General Public expenditure as a proportion of China's GDP (%) explains 47.4% of the variance in China's unemployment rate. The F-test confirmed the model's overall significance (F(1,14)=12.632, p=0.003<0.05), meaning General Public expenditure has a statistically significant impact on the unemployment rate, supporting the model's validity.

**Table 5. Reverse Causality: The Impact of China's Unemployment Rate on General Public Expenditure**

| Linear Regression Analysis Results (n=16) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Unstandardized coefficients | | Standardized coefficients | *t* | *p* | Collinearity Diagnostics | |
| | *B* | Std. Error | *Beta* | | | VIF | Tolerance |
| | -2.007 | 5.260 | - | -0.382 | 0.708 | - | - |
| Unemployment rate in China (%) | 4.016 | 1.130 | 0.689 | 3.554 | 0.003** | 1.000 | 1.000 |
| $R^2$ | 0.474 | | | | | | |
| Adjusted $R^2$ | 0.437 | | | | | | |
| *F* | $F$ (1,14)=12.632,$p$=0.003 | | | | | | |
| D-W | 0.967 | | | | | | |
| Dependent variable= General Public expenditure as a proportion of China's GDP (%) | | | | | | | |
| * $p$<0.05 ** $p$<0.01 | | | | | | | |

A reverse causality test was performed to resolve the counterintuitive primary finding, swapping the dependent and independent variables. Table 5 presents a linear regression with China's Unemployment Rate (%) as the predictor and General Public Expenditure as a proportion of GDP (%) as the outcome. The regression equation is defined as:

General Public Expenditure (%)=−2.007+4.016×Unemployment Rate (%)

Specifically, the unstandardized regression coefficient for the unemployment rate was B=4.016, illustrating a significant positive effect: a 1% increase in the unemployment rate is associated with a 4.016 percentage point increase in General Public Expenditure as a proportion of GDP. Collinearity diagnostics suggested no multicollinearity was detected (VIF = 1.000, Tolerance = 1.000).

# 5. Discussion

## 5.1 Higher General Public Expenditure as a Proportion of GDP associated with higher Unemployment Rate: Empirical Evidence and Explanation

One explanation for the strong relation ($p=0.003<0.01$) is the crowding-out effect. Higher government borrowing and public spending push up interest rates, which dampens private investment (Cuestas et al., 2020). Since private enterprises account for over 80% of urban employment in China, weaker private investment leads to slower job creation (National Bureau of Statistics, 2024). In this case, public spending does raise total employment but replaces private-sector job generation, potentially pushing up the overall unemployment rate.

Addtionally, evidence from developed countries suggests that expanded government spending on unemployment benefits can drive up measured unemployment, caused mainly by voluntary labor force withdrawal rather than involuntary job loss. Generous welfare narrows the income gap between benefits and potential wages, which encourages some individuals to voluntarily reduce job search intensity or delay reentering the workforce. Per the U.S. Bureau of Labor Statistics (BLS, 2025), these individuals still meet official definition of unemployed, thus inflating the rate. Post-pandemic U.S. evidence confirms this: the CARES Act's $600 weekly UI supplement meant benefits exceeded pre-unemployment wages for many, with 24% of respondents admitting aid discouraged active job hunting. This voluntary behavior coincided with a drop in labor force participation to 62–63% post-2021, highlighting that the observed unemployment rise reflects welfare-driven choices, not a lack of job opportunities. A similar mechanism may also exist in China, suggesting that public spending and welfare-related policies could similarly influence China's official unemployment rate.

## 5.2 Reverse Causality Verification: Unemployment Rate Drives the Increase of General Public Expenditure

This reverse causality explains empirical results between general public expenditure and unemployment rate in the primary regression model, unemployment drives spending, not the opposite. This study's regression results illustrate that unemployment rate exerts a significant positive effect on general public expenditure as a proportion of GDP ($p=0.003<0.01$), demonstrating China's fiscal responsiveness to labour market weakness. In practice, the government increases expenditure on social security and employment assistance to respond to rising unemployment. For example, it has expanded unemployment insurance benefits, provided social insurance subsidies for unemployed graduates, and required enterprises to allocate at least 60% of training funds to frontline workers. Recent policies further support fresh graduates: the government has extended the fresh graduate identity to unemployed graduates within 2 years of graduation, offered a one-off job expansion subsidy of 1,500 yuan per person to firms hiring eligible young people, and expanded recruitment in civil service, public institutions and state-owned enterprises (MOE, 2025). Public investment in infrastructure and job-creating projects has also been increased, especially amid the youth unemployment rate of 18.8% in August 2024 (Jiang, 2024). These policies lead to a passive rise in general public expenditure as unemployment increases.

## 5.3 Non-Significant Impact of Mean Minimum Wage on Unemployment Rate

Unlike regional studies, this study finds no statistically significant impact of the mean minimum wage on China's overall unemployment rate, where the p-value was 0.215 ($p>0.05$). The fundamental reason is the regional heterogeneity of China's minimum wage standards. Decentralized implementation allows provinces to formulate standards based on local conditions, creating enormous gaps (Huang et al., 2024). For instance, the minimum wage standards in first-tier cities such as Shanghai are more than twice as high as those in the western regions. Using national average minimum wage in macro regression offsets substantial regional wage differences, masking the actual impact of minimum wage adjustments on unemployment.

Additionally, China's minimum wage adjustment of "small steps and frequent adjustments", accounting for enterprises' affordability when revising standards, weakens labor

ISSN 2959-6149

market shocks. Its average ratio to the median wage is only about 20%, which is far below the 40–50% in most developed countries (Neumark and Corella, 2020). This low level keeps it well below the threshold for significant labor market disruptions, so even continuous adjustments do not trigger large-scale national job losses or significantly affect the overall unemployment rate.

Lastly, rather than raising unemployment, minimum wage hikes can boost employment through stronger aggregate demand. The minimum wage policy increases disposable income for lowwage households, and the marginal propensity to consume (MPC) associated with this additional income is close to 1 (Huang et al., 2024). Higher purchasing power stimulates domestic consumption and supports the real economy, which in turn creates more jobs. This forms a positive cycle: wage increase – consumption growth – employment promotion.

### 5.4 Non-Significant Impact of R&D Expenditure as a Proportion of GDP on Unemployment rate

This study finds no statistically significant impact of R&D expenditure as a proportion of GDP on China's overall unemployment rate ($p=0.613>0.05$). For one, R&D-driven technological progress generates mutually offsetting job displacement and creation effects, which neutralize each other. Dave (2025) notes that R&D investment in China’s manufacturing intelligent transformation has replaced 10–13% of low-skilled jobs, such as assembly line workers, as machines take over routine and repetitive tasks. In terms of job creation, new technologies spawn entirely new industries and occupations. Cui et al. (2024) confirm that R&D in the digital economy has created over 8 million new positions, such as AI trainers and digital operation analysts. Critically, these two effects are roughly balanced nationally: the number of displaced low-skilled jobs matches the number of newly created roles, resulting in no significant net change in the overall unemployment rate.

For another, the impact of R&D on employment has a long time lag that short-term data cannot capture. Given the rapid advancement of technology in recent years, such long-term effects are even harder to detect with limited short-run observations.Unlike public expenditure, which affects employment quickly through interest rates or welfare policies, R&D requires a multi-stage cycle. Liu et al. (2024) note that China’s R&D investment takes 1–2 years to translate into technical patents, a period known as the "breakthrough phase." After that, enterprises need another 1–2 years to apply these patents to production and adjust labor demand, a period called the "application phase." This 2–4 year lag means the annual data used in this study cannot reflect R&D’s true employment impact. Ozkan & Sullivan (2025) further verify this in cross-country research, finding that R&D’s effect on unemployment only becomes statistically significant after a 3-year lag. This explains why the short-term regression results show no correlation between the two.

## 6. Evaluation

### 6.1 Research Strengths

This study adopts authoritative secondary data from renowned databases and official Chinese statistical sources, all vetted to ensure data authenticity. It employs rigorous quantitative analyses, including Pearson correlation and multiple linear regression, generating reproducible conclusions through SPSSAU. All empirical findings are theoretically grounded in established economic theories and literature, linking evidence to analysis and ensuring academic validity.

#### 6.2.1 Aggregated Macroeconomic Data Limitations

The core limitation is the use of national aggregated data, which conceals regional, industrial and labor group heterogeneity in China and precludes refined sub-regional and industrial analysis. Stark disparities in minimum wage and R&D expenditure exist between eastern coastal and western inland regions, across labor-intensive and high-tech industries. Aggregated indicators fail to capture these variables’ affect on unemployment among vulnerable groups, merely reflecting national-level correlations and oversimplifying micro-level labor market dynamics.

#### 6.2.2 Incomplete Variable Measurement and Scope

Only four core independent variables are examined, with critical control variables of unemployment dynamics omitted, including industrial restructuring speed, inter-sector AI adoption intensity and migrant worker mobility. These omissions may alter the magnitude and direction of the observed variable-unemployment relationships, reducing the model’s explanatory power for real-world labor market changes.

#### 6.2.3 Short-Term Empirical Time Horizon and Data Frequency

The empirical analysis uses 2015–2025 annual macroeconomic data, with a short time window failing to capture the 2-4 year lag effects of factors like R&D expenditure, Annual data lacks the granularity of quarterly or monthly indicators, making it impossible to identify short-term fluctuations in unemployment driven by policy shocks or technological adoption spurts, limiting the accuracy of causal inference.

### 6.3 Future research Directions

Future research can use provincial and industrial panel data to analyze regional and industrial variations in policy impacts on unemployment and explore relevant moderating effects. It is also advised to expand the variable set with labor human capital, AI intensity and GDP growth rate, and shift research focus from aggregate unemployment to China's prominent specific types (youth, structural, urban-rural) for targeted policy insights.

## 7. Conclusion

This paper examines the effects of technological advancements and government interventions on China's unemployment from 2015 to 2025, using Pearson correlation and multiple linear regression models. It aims to quantify the relative effects on aggregate unemployment and address empirical gaps in existing research. The result states a highly significant positive correlation between the general public expenditure-to-GDP ratio and unemployment with evident reverse causality, whereas the national average minimum wage and R&D expenditure-to-GDP ratio have no statistically significant impact on overall unemployment. Although the study is constrained by national aggregated data, incomplete variables and a short research period, it effectively quantifies the relative influence of major drivers of China's unemployment.

These findings deepen the understanding of the interaction between technological progress, government policy and unemployment in China's economic restructuring, and provide evidence-based insights for targeted policies to balance technological development and employment stability. They also lay an empirical foundation for future research, which can explore the heterogeneous impacts of relevant factors with more detailed regional data, and expand the variable set to investigate specific types of targeted unemployment.

## 8. References

1. Andrea Caceres-Santamaria. (2024). Exploring the Dynamics of Unemployment. The Federal Reserve Bank of St. Louis. Retrieved May 3, 2024, from https://www.stlouisfed.org/publications/page-one-economics/2024/05/03/exploring-the-dynamics-of-unemployment.

2. Greg Daugherty. (2025). Exploring the Dynamics of Unemployment. Investopedia. Retrieved January 1, 2025, from https://www.investopedia.com/articles/personal-finance/013015/how-minimum-wage-impacts-unemployment.asp.

3. Serdar Ozkan and Nicholas Sullivan. (2025). Is AI contributing to rising unemployment? The Federal Reserve Bank of St. Louis. Evidence from occupational variation. Retrieved August 26, 2025, from https://www.stlouisfed.org/on-the-economy/2025/aug/is-ai-contributing-unemployment-evidence-occupational-variation.

4. Melline Somers, Angelos Theodorakopoulos, and Kerstin Hötte. (2022). The fear of technology-driven unemployment and its empirical base. VoxEU. Retrieved June 22, 2022, from https://cepr.org/voxeu/columns/fear-technology-driven-unemployment-and-its-empirical-base.

5. Yale University's Budget Lab. (2025). Evaluating the impact of AI on the labor market: September CPS update. https://budgetlab.yale.edu/research/evaluating-impact-ai-labor-market-september-cps-update.

6. LexChina. (2025). Navigating China's Shifting Labor Cost Landscape: An October 2025 Minimum Wage Update. Retrieved October 21, 2025, from https://lexchina.org/navigating-chinas-shifting-labor-cost-landscape-an-october-2025-minimum-wage-update/.

7. Yan Cui, Jing Ruan, and Qingqing Huo. (2024). Frontiers in Artificial Intelligence. "Machine replacement" or "job creation": How does artificial intelligence impact employment patterns in China's manufacturing industry? doi:10.3389/frai.2024.1337264.

8. Jianmin Liu, Yifeng Shen, Wenye Fan, and Xiya WuIndustrial. (2024). Technological advance and the employment demand for China's labour force: Micro evidence from labour hiring in companies. PLOS ONE. doi: 10.1371/journal.pone.0307564.

9. Yi Huang. (2024). Boosting consumption in China: The Effectiveness of Minimum Wages article. PLOS ONE. Retrieved November 7, 2024, from https://voxdev.org/topic/labour-markets/boosting-consumption-china-effectiveness-minimum-wages.

10. Prakash Loungani. (2014). Does Raising the Minimum Wage Hurt Employment? Evidence from China. Retrieved October 23, 2014, from https://www.imf.org/en/blogs/articles/2014/10/23/does-raising-the-minimum-wage-hurt-employment-evidence-from-china.

11. *Global Economics Science.* (2023). The impact of technological advancement on unemployment in Turkey. http://ojs.wiserpub.com/index.php/GES/.

12. *ShodhSamajik: Journal of Social Studies.* (2025). Technology and AI -impact on country's growth and unemployment. doi:10.29121/ShodhSamajik.v1.i1.2024.3.

13. *International Monetary Fund (IMF).* (2018). Youth minimum wages and youth employment. doi:10.1186/s40173-018-0098-4.

14. David Neumark. (2015). The effects of minimum wages on employment. *Federal Reserve Bank of San Francisco.* Retrieved December 21, 2015, from https://www.frbsf.org/wp-content/uploads/el2015-37.pdf.

15. Tony Fang and Carl Lin. (2015). Minimum wages and

ISSN 2959-6149

employment in China. *IZA Discussion Paper.* Retrieved November 27, 2015, from https://docs.iza.org/dp7813.pdf.
16. *Global Economics Science.* (2018). Will this time be different? A review of the literature on the Impact of Artificial Intelligence on Employment, Incomes and Growth. https://www.econstor.eu/bitstream/10419/202236/1/jrc-dewp201808.pdf.
17. Qian Zhou. (2026). *China Briefing.* China Minimum Wage Standards 2026. Retrieved January 22, 2026, fromhttps://www.china-briefing.com/news/minimum-wages-china.
18. *Doc's Research Glossary.* (2024). Multiple regression analysis. https://docmckee.com/cj/docs-research-glossary/multiple-regression-analysis-definition/#google_vignette.
19. *Universitat Jaume I, Tallinn University of Technology and Eesti Pank.* (2020). Is government consumption really crowding out investment? Evidence from the EU28. Retrieved May, 2022, from https://www.doctreballeco.uji.es/wpficheros/Cuestas_et_al_05_2020.pdf.
20. *U.S. Chamber of Commerce.* (2022). Data Deep Dive: How Government Benefits Programs Are Contributing to the Labor Shortage. Retrieved September 29, 2022, from https://www.uschamber.com/workforce/data-deep-dive-how-government-benefits-programs-are-contributing-to-the-labor-shortage.