Czech University of Life Sciences Prague

Faculty of Economics and Management

Department of Statistics

Bachelor Thesis

Statistical Analysis of Unemployment in the United States

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CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Economics and Management

BACHELOR THESIS ASSIGNMENT

Matvei Trifanov

Business Administration

Thesis title

Statistical Analysis of Unemployment in the United States

Objectives of thesis

The bachelor thesis aims to study the indicators of unemployment used to measure its state and development and subsequent comparison concerning gender and age. The thesis will also focus on finding indicators affecting the structure of unemployment in the United States.

Methodology

For the practical part, time series analysis methods will be elaborated to describe the development of selected unemployment indicators. Insofar as plenty of factors can influence unemployment, it makes sense to divide the analysis procedure into several categories, such as demographic, economic, and educational. This approach will allow a rational assessment of factors and causes and identify which of the categories affects the subject under study the most. Therefore, methods of regression analysis will be used to identify these factors.

The proposed extent of the thesis

30-40 pages

Keywords

Analysis, economics, regression, statistics, USA, unemployment, USA unemployment, unemployment analysis, unemployment data, unemployment rate.

Recommended information sources

FIELD, A P. *Discovering statistics using IBM SPSS statistics.* Thousand Oaks: SAGE Publications, 2013. ISBN 978-1-4462-4917-8.

CHRISTENSEN, R. *Analysis of variance, design and regression : applied statistical methods.* London ; Weinheim ; New York: Chapman & Hall, 1996. ISBN 0-412-06291-7.

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Declaration

I declare that I have worked on my bachelor thesis titled "Statistical Analysis of Unemployment in the United States" by myself and I have used only the sources mentioned at the end of the thesis. As the author of the bachelor thesis, I declare that the thesis does not break copyrights of any their person.

In Prague on 15.03.23 ______________________________

Trifanov Matvei

Acknowledgement

I would like to thank my supervisor Zuzana Pacáková for her help with writing this thesis. I would like to also thank my parent for their help throughout whole study.

Statistical Analysis of Unemployment in the United States

Abstract

This bachelor thesis examines the unemployment rate in the United States through statistical analysis. The research draws on data from the Bureau of Labor Statistics (BLS) for the period from 2000 to 2022, utilizing time-series models, regression analysis, and correlation analysis to explore trends in unemployment. The study aims to identify factors contributing to unemployment and to evaluate the impact of government policies and economic conditions on the labor market.

The practical part of this thesis involves using statistical models to analyze the relationship between the macroeconomic indicators and unemployment rates. Specifically, this study employs multiple regression analysis to investigate the extent to which changes in GDP growth, inflation, and interest rates affect the level of unemployment in the United States. The regression model's objective is to determine statistically significant independent variables that impact the unemployment rate while not being correlated with one another. As a result, it was found that only the GDP growth rate and employment in the information industry have a direct effect on the unemployment rate, while the rate of inflation did not show statistical significance for the model.

Keywords: unemployment, statistical analysis, unemployment rate, analysis of unemployment, unemployment in the USA, types of unemployment

Statistická analýza nezaměstnanosti v USA

Abstrakt

Tato bakalářská práce zkoumá míru nezaměstnanosti ve Spojených státech prostřednictvím statistické analýzy. Výzkum vychází z údajů Úřadu pro statistiku práce (BLS) za období od roku 2000 do roku 2022 a využívá modely časových řad, regresní analýzu a korelační analýzu ke zkoumání trendů nezaměstnanosti. Cílem studie je identifikovat faktory přispívající k nezaměstnanosti a zhodnotit dopad vládních politik a ekonomických podmínek na trh práce.

Praktická část práce zahrnuje využití statistických modelů k analýze vztahu mezi makroekonomickými ukazateli a mírou nezaměstnanosti. Konkrétně tato studie využívá vícenásobnou regresní analýzu ke zkoumání, do jaké míry ovlivňují změny růstu HDP, inflace a úrokových sazeb úroveň nezaměstnanosti ve Spojených státech. Cílem regresního modelu je určit statisticky významné nezávislé proměnné, které ovlivňují míru nezaměstnanosti a zároveň nejsou vzájemně korelovány. Výsledkem bylo zjištění, že přímý vliv na míru nezaměstnanosti má pouze míra růstu HDP a zaměstnanost v informačním sektoru, zatímco míra inflace nevykazuje pro model statistickou významnost.

Klíčová slova: nezaměstnanost, statistická analýza, míra nezaměstnanosti, analýza nezaměstnanosti, nezaměstnanost v USA, druhy nezaměstnanosti

Table of content

1 Introduction

Unemployment is a social and economic issue that affects individuals, families, communities, and the economy. The significance of studying unemployment cannot be overstated. The high levels of unemployment have dire consequences that ripple through the society and the economy. More importantly, unemployment has far-reaching effects on individuals, families, and communities. For the unemployed it means a loss of income, reduced standards of living, and diminished well-being. Research has shown that unemployment also has social and psychological impacts, such as loss of self-esteem, social isolation, and increased rates of depression and suicide, which can also lead to higher rates of crime and social unrest.

In addition to its effects on individuals and families, high levels of unemployment can have serious economic consequences: it can lead to decreased demand for goods and services due to reduced spending power, ultimately resulting in reduced economic growth. High levels of unemployment also place a strain on social welfare programs, increasing government expenditures and adding to the national debt.

In the US, unemployment trends are characterized by cyclical fluctuations, long-term trends, and regional variations. Factors such as economic cycles, demographic shifts, and changes in the labor market structure all contribute to these trends. For example, economic recessions often lead to increased unemployment, while periods of economic growth can reduce joblessness. Additionally, demographic factors, such as an aging population or changes in immigration patterns, can influence labor force participation and unemployment rates. Lastly, technological advancements and shifts in industry composition can create structural changes in the labor market, affecting the demand for specific skills and occupations.

Studying unemployment is crucial for understanding broader economic trends and providing insights into the effectiveness of policies and interventions aimed at reducing unemployment rates. By identifying factors that contribute to high levels of unemployment and developing strategies to mitigate its effects, we can work towards improving economic conditions. In this thesis, I will provide a comprehensive statistical analysis of unemployment in the US, offering insights that can contribute to a deeper understanding of this complex issue and inform more effective interventions.

2 Objectives and Methodology

2.1 Objectives

The objective of this thesis is to examine the statistical patterns and trends of unemployment in the United States over time. Through data analysis and modeling, the thesis aims to identify key factors that contribute to unemployment and provide a comprehensive understanding of its statistical nature.

The main objectives of this research are:

- Identify the key factors that contribute to unemployment in the USA.
- Analyze the relationship between unemployment and GDP growth rate, inflation rate, and employment in the information industry.
- Assess the statistical significance of the independent variables in predicting unemployment rates and determine their relative importance.

2.2 Methodology

The data for this study was obtained from the United States Bureau of Labor Statistics (BLS) website. The data covers the period from 2000 to 2022 and includes annual unemployment rates as well as several independent variables. The selection of these variables was based on previous research on the determinants of unemployment rates in the United States. It should be noted that the BLS data has some limitations. For example, it only includes individuals who are actively seeking work and does not capture those who have given up looking for work altogether.

The dependent variable in this study is the unemployment rate, which is defined as the percentage of the labor force that is unemployed and actively seeking work. This variable is measured on a monthly basis from 2000 to 2022 but data is provided as an annual average. The independent variables selected for this study include GDP growth rate, inflation rate and n the information industry.

The statistical analysis in this study will involve the use of multiple regression analysis to determine the relationship between the dependent variable (unemployment rate) and the selected independent variables using SPSS. Multiple regression model can be expressed as:

Formula 1 Multiple Regression Model

$$\mathbf{Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \varepsilon} \tag{1}$$

Where Y is the predicted dependent variable (unemployment rate), X1 to Xn are the independent variables, β0 is the intercept, β1 to βn are the coefficients, and ε is the error term. The coefficients β1 to βn represent the change in the predicted value of Y for a one-unit increase in the corresponding independent variable, while holding all other variables constant. The intercept β0 represents the predicted value of Y when all independent variables are equal to zero. The error term ε represents the variability in the dependent variable that cannot be explained by the independent variables included in the model (Hair, Black, Babin, & Anderson, 2019).

In order to obtain valid and reliable results from the multiple regression analysis, it is essential that the assumptions of the model are met, as these ensure that the analysis is appropriate and that the results are accurate and not biased. The linear regression assumptions are:

- Linearity: The dependent variable's relationship to each independent variable must be linear. This assumption may be tested by plotting the dependent variable against each independent variable in a scatterplot.
- Normality: The residuals must be normally distributed. This assumption can be checked by examining the distribution of the residuals using a histogram.
- Independence: The observations in the dataset should be independent of each other. This assumption may be verified by examining the data for systematic patterns or correlations.
- Homoscedasticity: Variance of the errors or residuals should be the same or constant for all levels of the predictor variables. This assumption can be checked by drawing plots of the residuals against the predicted values.
- No multicollinearity: The independent variables must not correlate with each other significantly. It can be tested by analyzing the correlation matrix between the independent variables, and calculating the variance inflation factor (VIF).

The estimated multiple regression equation allows us to estimate the values of the coefficients (β1 to βn) that quantify the relationships between the unemployment rate and the independent variables included in the model, thereby allowing us to assess the direction and magnitude of the effect of each independent variable on the dependent variable. The estimated regression equation can be expressed as:

Formula 2 Estimated Multiple Regression Equation

$$\hat{Y} = \mathbf{b0} + \mathbf{b1X1} + \mathbf{b2X2} + \ldots + \mathbf{bnXn} \tag{2}$$

Where Ŷ is the estimated value of the dependent variable, X1 to Xn are the independent variables, b0 is the intercept, and b1 to bn are the estimated coefficients obtained from the multiple regression analysis.

To estimate the regression coefficients, the ordinary least squares (OLS) method will be used, which minimizes the sum of squared errors between the observed and predicted values of the dependent variable and provides a measure of how well the linear regression model fits the data.

Formula 3 Ordinary least squares criterion (OLS)

$$\sum_{i=1}^{n} (\boldsymbol{y_i} - \boldsymbol{y'_i})^2 \rightarrow \boldsymbol{min} = \min_{b_0, b_1, \ldots, b_p} \sum_{i=1}^{n} \left(\boldsymbol{y_i} - \boldsymbol{b_0} - \boldsymbol{b_1 x_{i1}} - \boldsymbol{b_2 x_{i2}} - \cdots - \boldsymbol{b_p x_{ip}}\right)^2 \tag{3}$$

The coefficient of determination, which has an R^2 notation, is a statistical measure of the goodness of fit of a multiple regression model. R^2 represents the proportion of variation in the dependent variable that can be explained by the independent variables included in the model (Field, 2013).

Formula 4 Coefficient of determination

$$R^2 = \frac{SSR}{SST} \tag{4}$$

Where SSR stands for the sum of squares due to regression, and SST is the total sum of squares

For determining the statistical significance of coefficients in the multiple regression model, a t-test is used. Typically, the following steps are used to perform the t-test:

Formula 5 T-Test

$$t = \frac{\widehat{\beta_i} - 0}{SE\left(\widehat{\beta_i}\right)} \tag{5}$$

Where $SE\left(\widehat{\beta_i}\right)$ represents the standard error of the coefficient βi.

- Hypothesis formulation: null and alternative hypotheses about the parameters.

- Significance level selection: level of significance, typically 5%, 1% or 0,1%.
- T-value: calculation of t-value using the sample data and the estimated parameters.
- Critical value: determination of the t-critical value from a t-distribution table.
- Comparison: compare calculated t-value with the critical t-value to make a decision.
- Hypothesis testing: Test the null hypothesis and make a decision whether to reject or not reject it based on the comparison of the calculated t-value and the critical t-value

3 Literature Review

3.1 Introduction to Unemployment

3.1.1 Official definition of unemployment

The Bureau of Labor Statistics provides the official definition of unemployment in the United States, which is based on three criteria: individuals who are not currently employed, have actively looked for work within the past four weeks, and are currently available for work. This definition provides a clear and consistent framework for measuring unemployment across different regions and time periods.

However, some researchers have proposed alternative definitions of unemployment that take into account other aspects of labor market activity. For example, Dooley M.D defines "structural unemployment" as the persistent mismatch between the skills and abilities of workers and the requirements of available jobs, and "cyclical unemployment" as the temporary unemployment that results from fluctuations in economic activity (Dooley, 1984).

Other researchers have proposed even more nuanced definitions of unemployment that take into account different types of unemployment or the effects of unemployment on individuals and society. For instance, Molloy R. and Smith C. determine "involuntary nonemployment" as the condition of being not currently employed but willing and able to work. This definition is broader than the BLS definition and includes individuals who are not actively seeking work but would like to be working (Molley, 2011)

3.1.2 Unemployment measurement

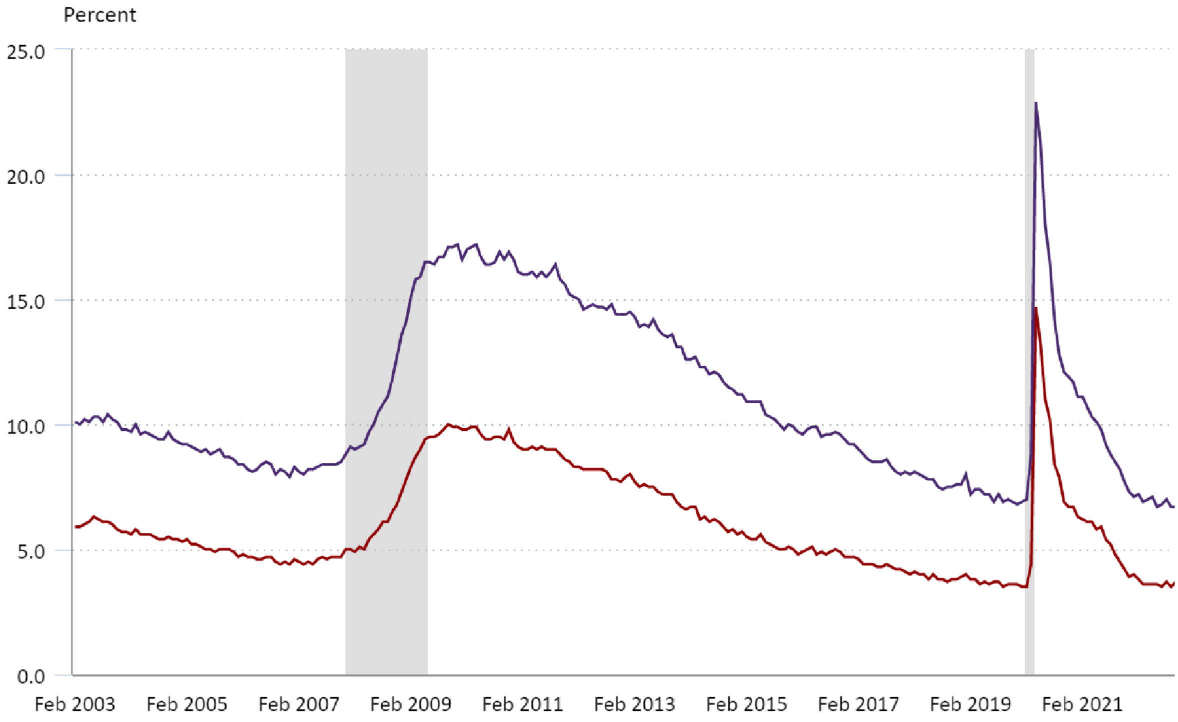
Unemployment is measured using a variety of different metrics that provide insight into various aspects of the labor market. The most commonly cited measure of unemployment in the United States is the U-3 measure provided by the Bureau of Labor Statistics. This measure counts individuals who are unemployed and actively seeking work as a percentage of the labor force. The labor force includes individuals who are either employed or unemployed but actively seeking work. The formula for calculating the U-3 unemployment rate is as follows:

Formula 6 U-3 Unemployment rate

$$U-3=\frac{\text{number of unemployed individuals}}{\text{labor force}}\times 100$$

However, it is important to note that the U-3 measure has limitations and may not provide a complete picture of labor market conditions. This measure does not include individuals who are marginally attached to the labor force, meaning those who would like to work but have given up looking for work, or those who are employed part-time but would prefer full-time employment. To address these limitations, the BLS also calculates several other measures of unemployment, such as the U-4, U-5, and U-6 measures. These measures include varying degrees of labor market slack, such as discouraged workers or those who are employed part-time for economic reasons.

Figure 1 U-3 and U-6 measurements over time



Source: U.S. BUREAU OF LABOR STATISTICS

Furthermore, some researchers have proposed alternative measures of unemployment that consider various aspects of the labor market. Thus, Barnichon and Nekarda introduced the "Barnichon-Nekarda measure," which includes individuals who are unemployed, marginally attached to the labor force, or employed part-time for economic reasons as a percentage of the potential labor force (Barnichon, 2012). This measure provides a broader view of labor market conditions and can be useful for analyzing unemployment trends over time.

3.2 Types of Unemployment

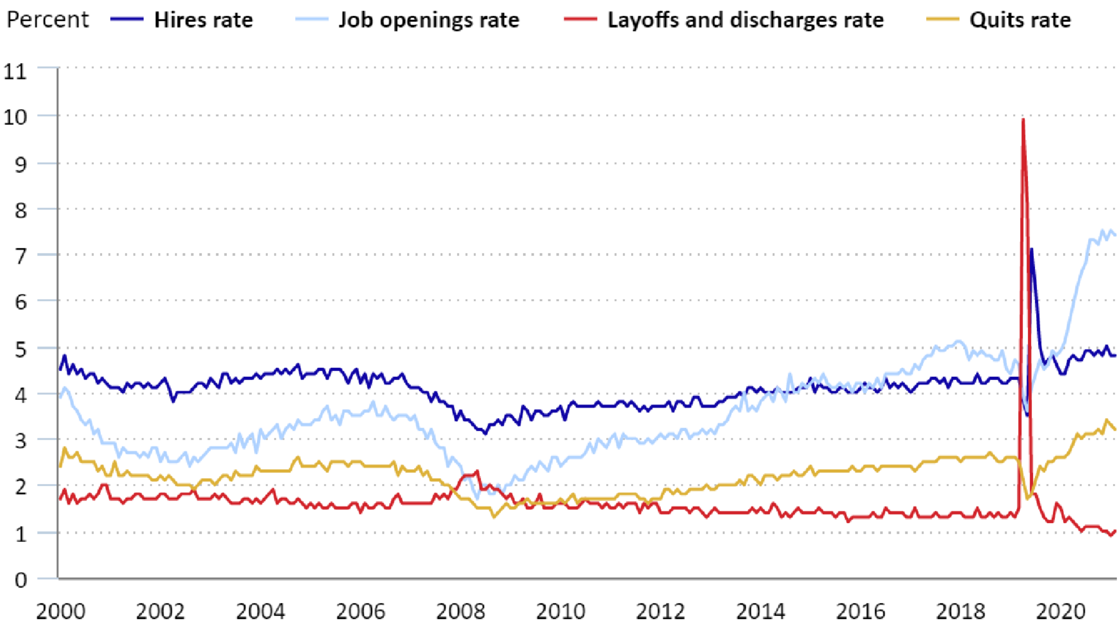
3.2.1 Frictional Unemployment

Frictional unemployment constitutes a key component of labor market fluctuations, resulting from the natural progression of job searching and the process of matching employees with suitable employment opportunities (Mankiw, 2014). This form of unemployment is typically short-term and arises when individuals voluntarily leave their jobs in pursuit of improved prospects, career transitions, or due to personal factors such as relocation. The duration of frictional unemployment is influenced by variables such as the effectiveness of job search mechanisms, the accessibility of information regarding job openings, and the preferences and skills of job seekers.

As an inherent feature of labor market dynamics, frictional unemployment is considered an inevitable and necessary component of a well-functioning economy (Tasci, 2010). Even when an economy operates at its full potential, frictional unemployment will persist due to the inherent imperfections in matching job seekers with vacancies. Furthermore, frictional unemployment can contribute to labor market adaptability and facilitate the efficient allocation of resources (Mortensen & Pissarides, 1999).

Governments and policy-makers can implement strategies to minimize frictional unemployment, including enhancing job search services, improving labor market information systems, and providing targeted training programs that align workers' skills with job market demands. However, it is crucial to maintain a balance between reducing frictional unemployment and preserving the natural flexibility of the labor market (Tasci, 2010).

Figure 2 Rates for hires, job openings, layoffs and discharges, and quits. December 2000 - January 2021



Source: U.S. BUREAU OF LABOR STATISTICS

While frictional unemployment is a natural aspect of labor market fluidity, it is essential to recognize its implications for individuals and the economy. One of the primary consequences of frictional unemployment is the temporary loss of income for job seekers, which can create financial instability and impact consumer spending (Tasci, 2010). Additionally, prolonged frictional unemployment can result in the depreciation of human capital, as individuals lose touch with the skills and knowledge relevant to their professions (Mankiw, 2014). Another important aspect to consider is the role of technology and the internet in reducing frictional unemployment. In recent years, online job search platforms and professional networking sites have significantly improved the job search process by providing job seekers with better access to information about job openings and simplifying the application process (Autor, 2001). As a result, the time and effort required to find a suitable job have decreased, potentially reducing the duration of frictional unemployment.

To further address frictional unemployment, government and policy-makers can also focus on enhancing the education and training systems to ensure that they are aligned with the evolving needs of the labor market. By fostering a workforce with adaptable skills, individuals can more seamlessly transition between jobs, thereby reducing the duration of frictional unemployment (Mortensen & Pissarides, 1999).

3.2.2 Structural Unemployment

Structural unemployment arises from a misalignment between the skills and expertise of job seekers and the requirements of available job positions within an economy (Mankiw, 2014). This type of unemployment is characterized by a long-term shift in the labor market, often due to technological advancements, globalization, or changes in consumer preferences that render specific industries or occupations obsolete. As a result, workers in declining sectors may find it challenging to secure employment without the necessary skillset or qualifications demanded by growing industries (Autor, 2010).

The persistence of structural unemployment can have significant social and economic implications. Long-term unemployment can lead to the erosion of human capital and reduced lifetime earnings, as well as increased reliance on social welfare systems (Mortensen & Pissarides, 1999). Moreover, high levels of structural unemployment can hinder economic growth and exacerbate income inequality (Tasci, 2010). Policy interventions aimed at addressing structural unemployment typically focus on facilitating the adaptation and retraining of the workforce to align with the evolving demands of the labor market (Mankiw, 2014). These initiatives may include targeted education and training programs, vocational guidance services, and financial incentives to encourage skill development in high-demand sectors. Additionally, policies that promote labor mobility and remove barriers to job transitions can further support workers in adapting to structural changes in the economy.

In addition to the factors previously discussed, technological change and globalization significantly contribute to structural unemployment. Rapid advancements in technology can render certain skills obsolete, leading to job displacement for workers who do not possess the required competencies for emerging industries. Furthermore, the rise of automation and artificial intelligence can exacerbate structural unemployment as machines increasingly perform tasks that once required human labor (Acemoglu & Restrepo, 2018).

Globalization, characterized by the growing interconnections of economies, can also exacerbate structural unemployment. As companies seek cost efficiency by outsourcing production to countries with lower labor costs, domestic workers in certain industries may face unemployment (Krueger, 2008). Consequently, the integration of global markets and the competitive pressures it creates can contribute to the displacement of workers in higher-cost economies.

To address the challenges posed by technological change and globalization, policy-makers can consider measures such as investing in lifelong learning programs, providing career counseling services, and promoting collaboration between educational institutions and industries to ensure that curricula are aligned with labor market needs (Mankiw, 2014). Furthermore, social safety nets and income support programs can be strengthened to mitigate the adverse effects of structural unemployment on affected workers and their families (Tasci, 2010).

3.2.3 Seasonal Unemployment

Seasonal unemployment occurs when the demand for labor varies due to seasonal factors, such as changes in weather, holidays, or other cyclical patterns that influence certain industries (Mankiw, 2014). Industries such as agriculture, tourism, and retail experience fluctuations in labor demand throughout the year, leading to periods of increased hiring followed by layoffs or reduced working hours for some workers. As a result, seasonal unemployment is typically short-term and predictable, as workers in affected sectors expect the fluctuations in employment opportunities. The economic impact of seasonal unemployment is generally less severe than other types of unemployment, as it is often anticipated and temporary in nature (Borjas, 2016). However, it can still pose challenges for workers in seasonal industries, who may face income instability and uncertainty. To mitigate these challenges, governments and employers can adopt various strategies, such as promoting flexible work arrangements, offering temporary employment opportunities in other sectors during low-demand periods, or providing income support to seasonal workers during times of unemployment (Kahn, 2010).

Furthermore, statistical agencies often adjust unemployment data for seasonality to obtain a clearer picture of underlying labor market trends. By using seasonal adjustment techniques, policy-makers can better assess the true state of the labor market and distinguish between seasonal and non-seasonal fluctuations in unemployment. Regional variations can also play a significant role in seasonal unemployment. Areas with climates that are strongly influenced by the seasons, such as regions with harsh winters or prominent tourist destinations, may experience more pronounced seasonal unemployment patterns (Mankiw, 2014). A common example, ski resorts and other winter tourist attractions often face high demand for labor during colder months, while beach destinations see increased demand for workers during the summer season. These regional variations can lead to disparities in the distribution of seasonal unemployment across different geographic areas.

3.2.4 Cyclical Unemployment

Cyclical unemployment arises as a consequence of economic downturns or recessions, when the overall demand for goods and services declines, leading to a decrease in labor demand (Mankiw, 2014). During economic contractions, businesses may cut back on production or reduce their workforce to lower costs, resulting in higher unemployment rates. Conversely, as the economy recovers and expands, the demand for labor typically increases, reducing cyclical unemployment.

The severity and duration of cyclical unemployment can vary depending on the depth of the economic downturn and the effectiveness of policy responses (Blanchard, 2017). Monetary and fiscal policies can be employed to counteract the negative effects of recessions and stimulate economic growth. For instance, central banks can lower interest rates or implement quantitative easing measures to increase the money supply, encouraging borrowing and investment. Similarly, governments can implement expansionary fiscal policies, such as increasing public spending or cutting taxes, to boost aggregate demand and promote job creation (Gali, 2015).

It is important to distinguish between cyclical unemployment and other types of unemployment, as policy responses to each type can differ. While cyclical unemployment requires macroeconomic interventions to stimulate demand, other forms of unemployment, such as structural or frictional, necessitate targeted measures aimed at addressing specific labor market imbalances or skill mismatches (Tasci, 2010).

3.3 Causes and Consequences of Unemployment

3.3.1 Macro-economic factors

Macro-economic factors, such as economic growth, inflation, and interest rates, play a crucial role in shaping the overall level of unemployment in an economy. Economic growth, typically measured by the Gross Domestic Product, influences labor demand as an expanding economy generally leads to increased job opportunities and lower unemployment rates (Mankiw, 2014). On the contrary, during economic contractions businesses may reduce their workforce and hiring, contributing to higher unemployment levels.

Alternatively, inflation, the rate at which the general level of prices for goods and services is rising, can also impact unemployment. The relationship between inflation and unemployment is often described using the Phillips curve, which suggests that there exists a short-run trade-off between inflation and unemployment (Blanchard, 2017). Central banks often aim to achieve low and stable inflation rates, as persistently high inflation can erode purchasing power and negatively affect economic stability. By adjusting interest rates, central banks can influence borrowing costs, investment, and consumption, which in turn affect the overall demand for labor. Monetary and fiscal policies are key tools employed by policymakers to manage macro-economic factors and address unemployment. Monetary policy, conducted by central banks, typically involves adjusting interest rates and influencing money supply to promote price stability and full employment (Gali, 2015). Fiscal policy, implemented by governments, involves altering government spending and taxation to influence aggregate demand and stabilize the economy. As an example to it, during economic downturns, expansionary fiscal policies, such as increased public spending or tax reductions, can help stimulate demand and support job creation (Blanchard, 2017). Furthermore, exchange rates and fiscal multipliers can also impact unemployment levels in an economy. Exchange rates affect the competitiveness of a country's exports and imports, which can influence the demand for labor in various industries (Mankiw, 2014). A depreciation of a country's currency can make exports more competitive, potentially increasing the demand for labor in export-oriented industries. On the other hand, an appreciation of the currency can make imports cheaper, potentially reducing labor demand in import-competing sectors.

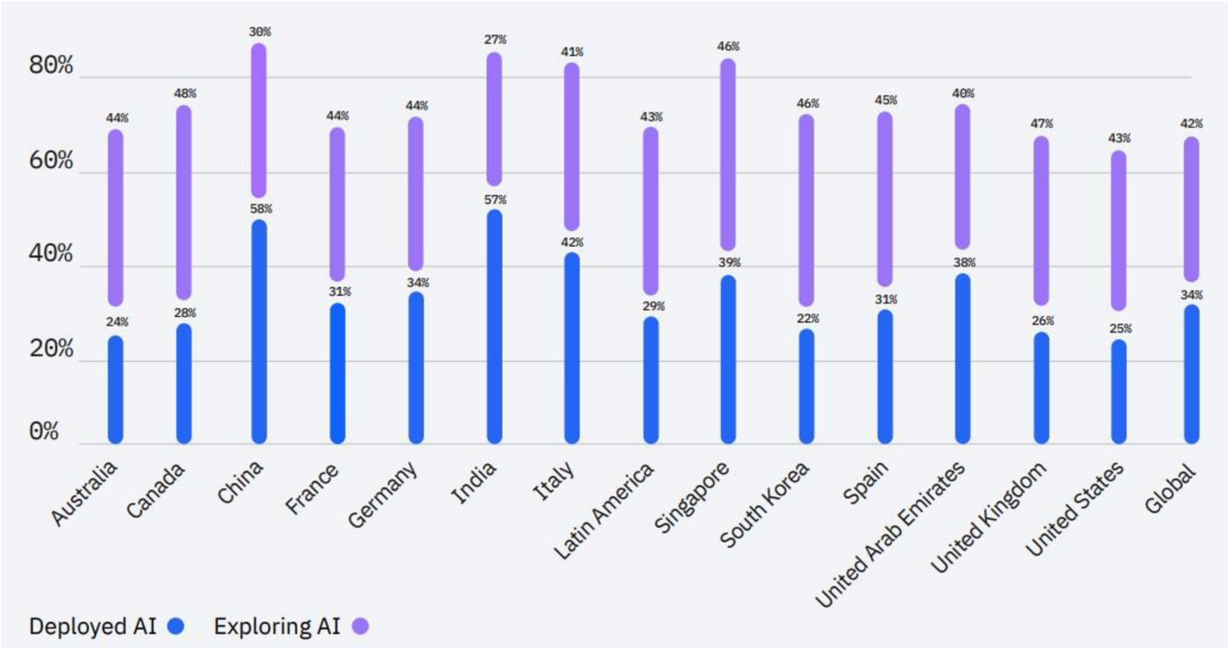
On the other hand, fiscal multipliers, which measure the change in output resulting from a change in government spending or taxation, can provide insights into the effectiveness of fiscal policies in addressing unemployment (Blanchard, 2017). A higher fiscal multiplier implies that a given change in fiscal policy has a larger impact on output and employment. The size of fiscal multipliers depends on various factors, such as the openness of the economy, the degree of economic slack, and the monetary policy response. Understanding the role of fiscal multipliers can help policymakers design more effective fiscal interventions to support employment during economic downturns.

3.3.2 Technological advancements

Technological advancements have a profound influence on unemployment levels, as they can both create new job opportunities and displace existing jobs. The process of creative destruction, coined by the economist Joseph Schumpeter, describes how innovation leads to the creation of new industries and the decline of old ones (Schumpeter, 1942). While technological advancements can lead to increased productivity and the emergence of novel occupations, they can also render certain jobs obsolete, causing workers in those industries to face unemployment. Thus, automation and artificial intelligence are two significant technological trends that have the potential to reshape the future of work. Automation involves replacing human labor with machines or algorithms, often in repetitive, routine tasks. AI, on the other hand, refers to the development of computer systems that can perform tasks requiring human intelligence, such as problem-solving, learning, and decision-making (Brynjolfsson & McAfee, 2014). These technologies have the potential to dramatically increase productivity and reduce the demand for labor in almost most industries.

For example, according to IBM's recent Global AI Adoption Index 2022 study, Figure 3 shows AI adoption rates around the world, with India and China leading the way. In 2022, 35% of companies reported using AI in their businesses, a 4% increase from 2021. Key drivers of adoption included improved accessibility and cost reduction through task automation.

Figure 3 AI deployment in different countries. Research commissioned by IBM in partnership with Morning Consult

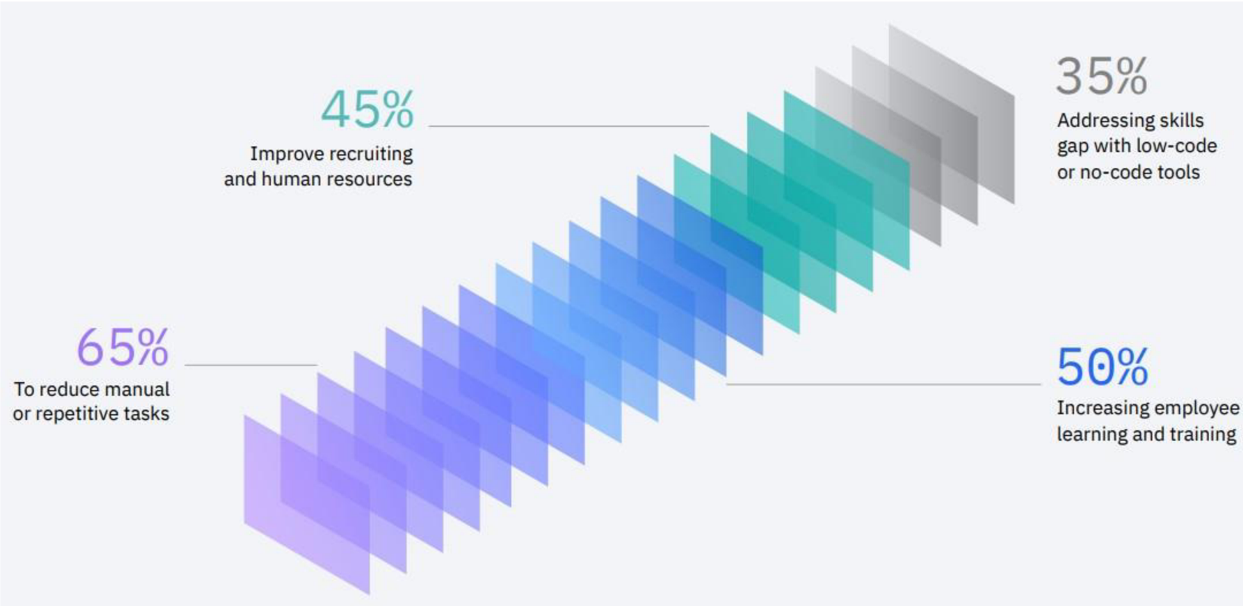


Source: IBM Global AI Adoption Index Research 2022

The impact of technological advancements on unemployment is not uniform across all sectors and skill levels. Research suggests that workers performing routine tasks, especially in middle-skilled jobs, are more likely to be displaced by automation and AI (Acemoglu & Restrepo, 2018). In contrast, high-skilled workers in non-routine cognitive jobs and low-skilled workers in non-routine manual jobs may be less vulnerable to technological displacement. That being said, bank tellers could be displaced by automation in the form of ATMs and digital banking platforms. Nevertheless, high-skilled workers in non-routine cognitive jobs, such as software engineers, may be less vulnerable due to their specialized skills and ability to adapt to technological advancements. Similarly, low-skilled workers in non-routine manual jobs, such as janitors or home health aides, might be less susceptible to displacement, as their tasks are challenging to automate and require human dexterity and flexibility.

Thus, Figure 4 of the same IBM study on the AI Adoption Iindex in 2022 focuses on the most common patterns occurring in the labor market. A significant proportion (35%) of organizations are currently addressing the skills gap by training and reskilling employees to work with new AI and automation tools. Larger companies and industries such as automotive, chemical, oil and gas, and aerospace and defense are particularly proactive in this regard. IT professionals in countries like China, India, Singapore, and the UAE are more likely to report their organizations' involvement in employee training for AI and automation technology adaptation

Figure 4 Labor market patterns in 2022



Source: IBM Global AI Adoption Index Research 2022

To mitigate the potential negative impacts of technological advancements on unemployment, policymakers and educators can focus on promoting workforce development programs that foster upskilling and reskilling. Such initiatives aim to equip workers with the skills necessary to adapt to changing labor market demands and reduce the risk of unemployment due to technological displacement.

Another dimension of technological advancements is the concept of the gig economy, which has emerged as a result of advances in digital platforms and communication technologies. The gig economy refers to a labor market characterized by the prevalence of short-term contracts or freelance work, as opposed to permanent jobs (Friedman, 2014). While the gig economy offers increased flexibility for both employers and workers, it can also contribute to underemployment and job insecurity, as gig workers often lack access to traditional employment benefits and protections.

Moreover, technological advancements can impact the spatial distribution of jobs, as certain industries and regions may be more susceptible to technological displacement than others (Autor, 2019). For example, regions with a higher concentration of manufacturing jobs may be more vulnerable to the effects of automation, leading to localized unemployment and wage disparities. This uneven distribution of the impacts of technology on employment highlights the importance of regional and sector-specific policy interventions to address potential labor market dislocations.

Policymakers can also consider implementing policies that promote a more equitable distribution of the benefits of technological advancements, such as progressive taxation and social safety nets. These policies can help cushion the potential negative effects of technology-induced unemployment on income inequality and social cohesion (Stiglitz, 2019).

Furthermore, the role of education in preparing individuals for the future labor market cannot be overstated. Educational systems should be adapted to better equip students with the skills required in a technology-driven economy, such as critical thinking, creativity, and digital literacy . In this context, lifelong learning initiatives can play a pivotal role in ensuring that individuals can continuously adapt to changing labor market demands.

3.3.3 Education and skills mismatch

Education and skill mismatch is a significant contributor to unemployment because it occurs when employees' talents do not meet the criteria of available jobs. This mismatch can occur in various forms, such as overeducation, undereducation, and skills obsolescence.

Overeducation refers to situations where individuals possess higher levels of education than required for their current jobs, resulting in underutilization of their skills (Verhaest & Omey, 2006). On the other hand, undereducation occurs when workers have lower educational qualifications than needed for their positions, leading to suboptimal job performance and potential productivity losses. Both overeducation and undereducation can contribute to unemployment by creating inefficiencies in the labor market, as employers may struggle to find suitable candidates, and workers might face challenges in securing appropriate jobs (McGuinness, 2006).

Skills obsolescence is another aspect of the skills mismatch problem, as it occurs when workers' skills become outdated or irrelevant due to technological advancements or changes in the labor market (De Grip & Van Loo, 2002). To address this issue, lifelong learning and continuous skills development are essential for maintaining employability and adapting to changing labor market demands.

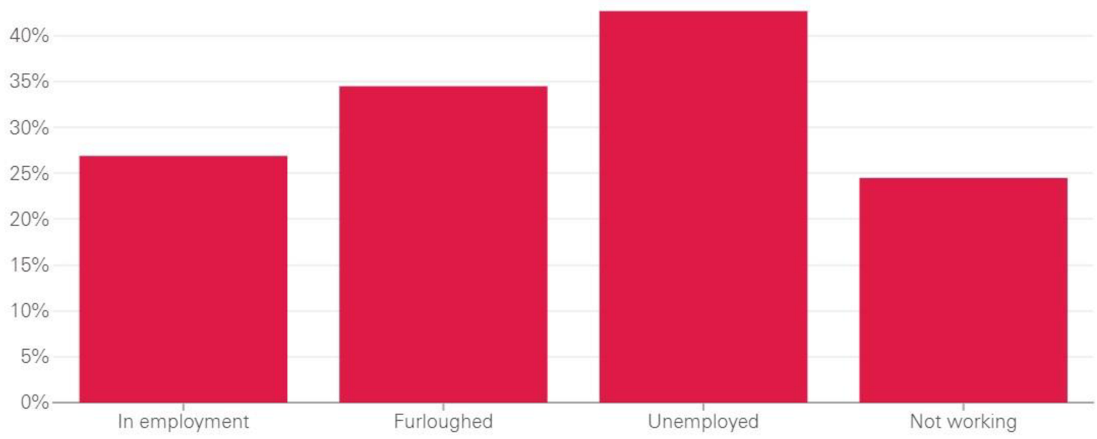
3.3.4 Individual consequences

Unemployment has substantial individual effects that can influence people's well-being and long-term potential. The financial, psychological, and social implications of unemployment can be widely categorized. Financial consequences are perhaps the most visible and obvious effects of unemployment. Income loss can result in decreased spending, higher debt, and decreased savings, possibly culminating in financial distress and poverty. Moreover, long-term unemployment can have lasting effects on individuals' future earnings, as skills depreciation and employer discrimination against the long-term unemployed can hinder reemployment prospects and lead to lower wages when reemployed (Arulampalam, 2001).

Psychological consequences of unemployment include increased stress, anxiety, and depression, which can adversely affect mental health and overall well-being (Paul & Moser, 2009). These negative psychological consequences are not only harmful to the individual, but they can also have an influence on family members and personal relationships. Long periods of unemployment may also result in a loss of self-esteem and self-efficacy, making it more difficult to re-enter the labor field and succeed in future employment. Less social engagement, social isolation, and the degradation of social networks that might give emotional support and job prospects are all social impacts of unemployment. What is more, unemployment may lead to increased crime rates, as financial strain and a lack of social integration can contribute to engagement in criminal activities (Fougère, Kramarz, & Pouget, 2009).

Thus, from an analysis of "Unemployment and mental health" by The Health Foundation, shown in Figure 5, it can be clearly seen that those on furlough had a lower frequency of poor mental health (34%) and more lower for those who working (27%). Findings indicate that furloughing appears to provide some protection against mental health decline.

Figure 5 Proportion of working age adults (age 18-65) with poor mental health by economic status: UK, January 2021



Source: The Health Foundation

One more individual consequence of unemployment is the potential deterioration of physical health. Unemployed individuals may experience increased health issues, because they are less likely to engage in health-promoting activities, have limited access to healthcare services, or face difficulties in maintaining a healthy lifestyle due to financial constraints (Bartley, 1994).

Unemployment can also have an inter - generational impact, as children of jobless parents may experience poor effects in terms of educational achievement, future labor market performance, and general well-being. Research suggests that parental unemployment can lead to reduced investments in children's education, lower educational aspirations, and an increased likelihood of children experiencing unemployment themselves in the future (Rege, Telle, & Votruba, 2011). These intergenerational effects highlight the importance of addressing unemployment not only for the well-being of individuals directly affected but also for the long-term prospects of their families and future generations.

4 Practical Part

4.1 Descriptive analysis of variables

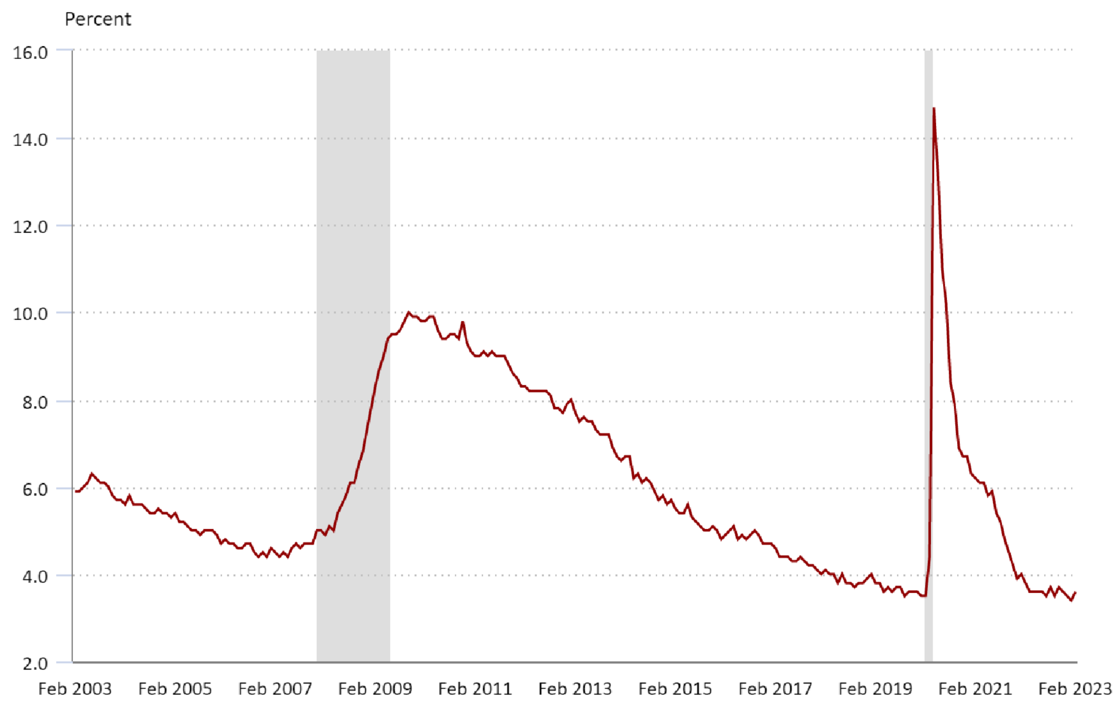
4.1.1 Unemployment rate

Between 2000 and 2022, the U.S. unemployment rate experienced substantial fluctuations, with several distinct periods marked by varying trends. The early 2000s saw a mild recession, with the unemployment rate increasing from 4.0% in 2000 to a peak of 6.0% in 2003. Following the recession, the unemployment rate gradually declined, reaching 4.6% in 2006.

The period between 2007 and 2009 was characterized by the housing bubble collapse and the onset of the Great Recession, resulting in a sharp increase in the unemployment rate. The rate reached its peak of 9.9% in 2009, marking the highest level since the early 1980s. The subsequent recovery period saw a gradual decline in the unemployment rate, falling to 6.2% by 2014.

Between 2015 and 2019, the U.S. economy continued to recover, with the unemployment rate reaching a 50-year low of 3.5% in 2019. This period marked a sustained period of low unemployment, signaling strong labor market conditions. The COVID-19 pandemic had a significant impact on the U.S. labor market, with widespread business closures and economic disruptions leading to a rapid increase in the unemployment rate. In 2020, the rate reached 11%, reflecting the pandemic's adverse effects. However, as the economy began to recover and adapt to new conditions, the unemployment rate started to decline again, reaching approximately 4.6% by the end of 2022.

Figure 6 US Unemployment Rate 2000-2023



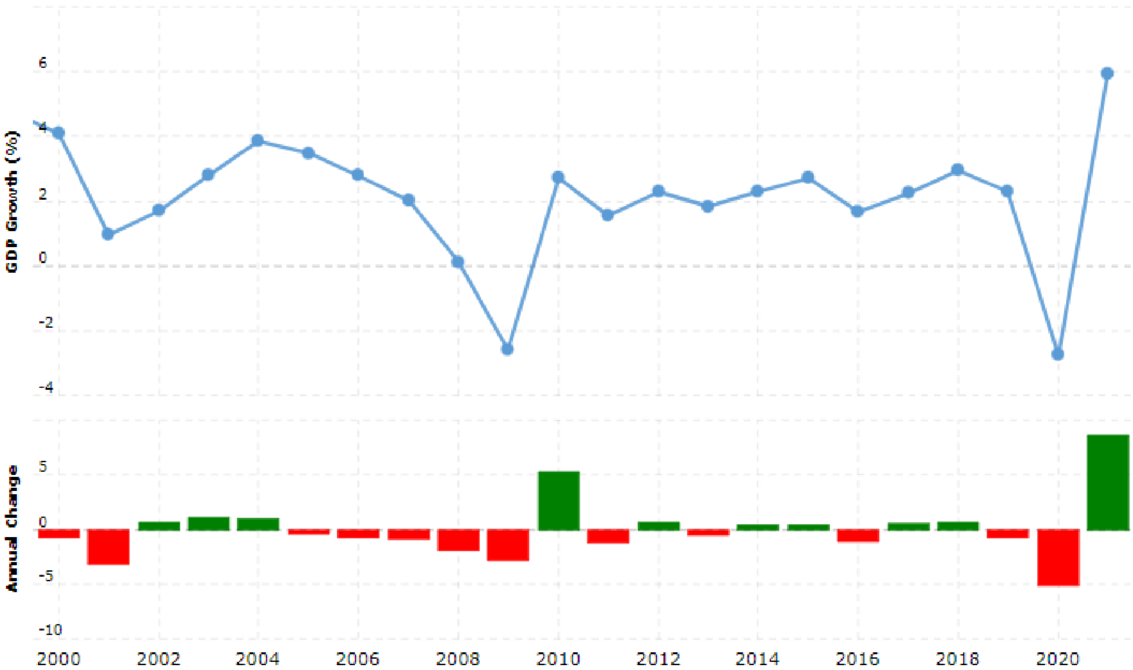
Source: U.S. BUREAU OF LABOR STATISTICS

4.1.2 GDP Growth Rate

Between 2000 and 2007, the U.S. economy experienced a period of moderate growth. The early 2000s saw the recovery from the dot-com bubble burst, with the GDP growth rate reaching its peak at 3.5% in 2004. However, the economy began to slow down in 2007 due to the subprime mortgage crisis, culminating in the Great Recession of 2008-2009. In 2009, the U.S. GDP growth rate reached its lowest point, registering a decline of 2.5%.

The period from 2010 to 2019 marked a slow but steady recovery for the U.S. economy. The GDP growth rate remained relatively stable, fluctuating between 1.6% and 2.9%. The U.S. experienced its longest economic expansion during this time, driven by factors such as low-interest rates, strong consumer spending, and fiscal stimulus measures. However, the COVID-19 pandemic struck in early 2020, disrupting the global economy and causing a sharp contraction in the U.S. GDP growth rate. In 2020, the GDP growth rate declined by 3.5% as businesses closed, and millions of workers lost their jobs.

Figure 7 GDP Growth Rate



Source: U.S. BUREAU OF LABOR STATISTICS

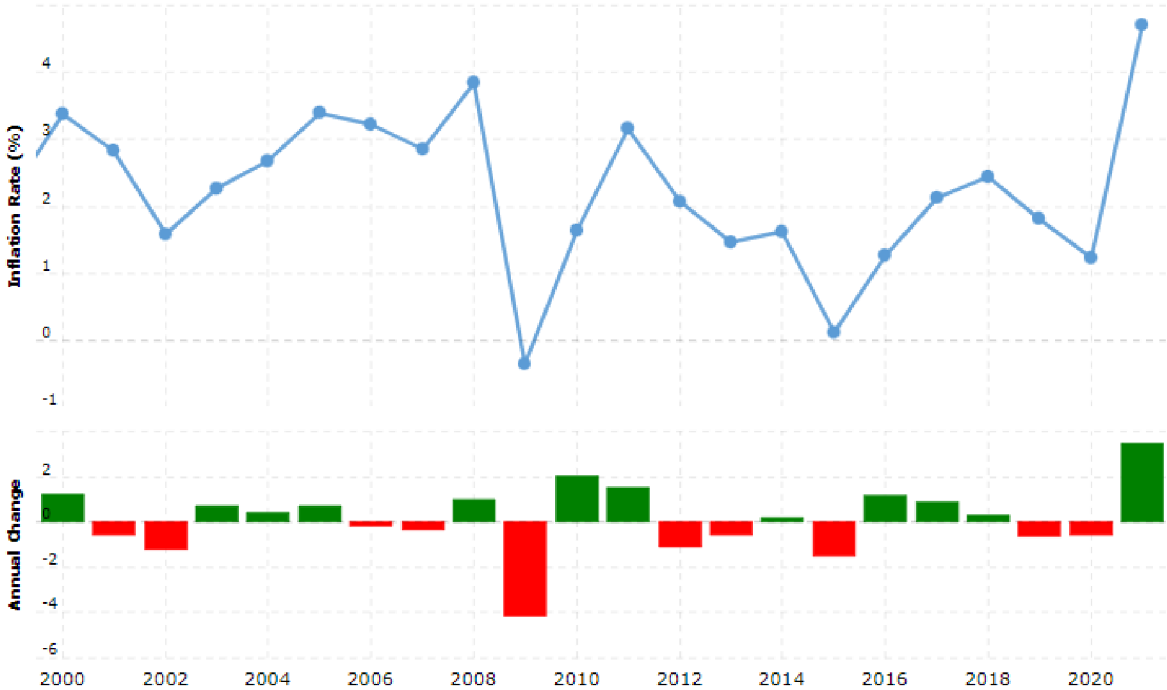
4.1.3 Inflation rate

From 2000 to 2022, inflation in the United States varied greatly due to different economic factors and major events. There were several changes in the inflationary environment, each with unique challenges and implications for monetary policy.

In the early 2000s, inflation was low, ranging from 2-3%, thanks to the Federal Reserve's monetary policy and the aftermath of the dot-com bubble. Between 2002 and 2007, inflation slightly increased and peaked at 3.8% in 2008 due to rising global commodity prices, specifically crude oil.

After the 2008 financial crisis, there was a significant shift in the inflationary landscape. Consumer demand declined, resulting in a period of disinflation, and the US experienced deflation in 2009 with an inflation rate of -0.4%. From 2010 to 2019, inflation was low, averaging around 1.5% per year, as the Federal Reserve implemented accommodating monetary policies to support economic recovery.

Figure 8 Inflation rate for 2000-2022 years

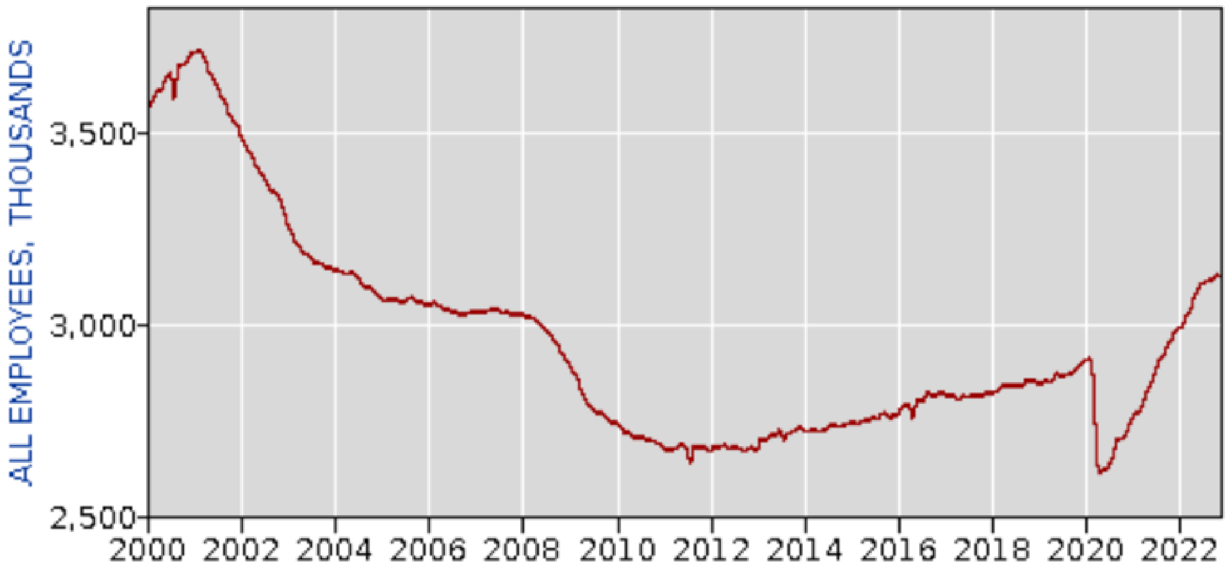


Source: U.S. BUREAU OF LABOR STATISTICS

4.1.4 Employment in Information Sector

As for employment in the information sector, it, like previous indicators, experienced similar trends. In 2002, for example, employment in the information sector peaked at more than 3,700,000 people across America. However, after 2002, the number of people employed in this industry went down, including a sharp drop from 2008 to 2012. It is interesting to note that during COVID-19 this industry was experiencing a maximum surge of new people into the industry and after about 300 thousand people left, it gained about seven hundred thousand again during 2020-2022.

Figure 9 Employment in Information Industry, thousands



Source: U.S. BUREAU OF LABOR STATISTICS

4.2 Time series data

The Table 1 of Time series below is based on 2000-2022 data for the following variables: unemployment rate, GDP growth rate, inflation rate, employment in informarion industry.

Table 1 Annual Time Series for 2000-2022

Year	Unemployment Rate, %	GDP Growth Rate, %	Inflation Rate, %	Employees in information industry, thousands
2000	4,0	4,1	3,4	3630,42
2001	4,7	1	2,8	3629,00
2002	5,8	1,7	1,6	3394,42
2003	6,0	2,8	2,3	3188,33
2004	5,5	3,9	2,7	3117,42
2005	5,1	3,5	3,4	3060,92
2006	4,6	2,8	3,2	3038,25
2007	4,6	2	2,8	3031,83
2008	5,8	0,1	3,8	2983,50
2009	9,3	-2,6	-0,4	2803,50
2010	9,6	2,7	1,6	2707,08
2011	8,9	1,5	3,2	2672,92
2012	8,1	2,3	2,1	2674,92
2013	7,4	1,8	1,5	2704,75
2014	6,2	2,3	1,6	2726,50
2015	5,3	2,7	0,1	2750,00
2016	4,9	1,7	1,3	2793,75
2017	4,4	2,2	2,1	2812,25
2018	3,9	2,9	2,4	2837,42
2019	3,7	2,3	1,8	2863,42
2020	8,1	-2,8	1,2	2720,75
2021	5,4	5,9	4,7	2856,67
2022	3,6	2,1	8	3073,00

Source: U.S. BUREAU OF LABOR STATISTICS

4.3 Regression model and its estimation

The model from Methodology was utilized in the following regression model. The final estimation of the regression model offers a clear picture of the relationships between the dependent variable (unemployment rate) and the independent variable (GDP growth rate, inflation rate, employment in information industry, and time series). The regression model is defined as:

$$\mathbf{Y = \beta 0 + \beta 1x1t + \beta 2x2t + \beta 3x3t + t + \varepsilon}$$

Where:

Y – unemployment rate in %

β0 – intercept

$x1_t$ – GDP growth rate

$x2_t$ – inflation rate

$x3_t$ – employment in information industry

t – time series

ε – error term

The objective is to determine whether variables are statistically significant.Variables that are statistically insignificant will be excluded from the model. Using SPSS embedded functions the unemployment rate is selected as a dependent variable, and GDP growth rate, inflation rate and employment in information sector are selected as independent ones.

Table 2 shows the results for the first estimation, and it can be noticed that P-value of inflation rate (0.627) is greater than alfa 0.05, meaning that the variable is not statistically significant. One more regression model will be created without x2 variable in order to achieve statisticall signigicance for all independent variables.

Table 2 Variables estimation

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,797[a]	,636	,555	1,2191	,636	7,862	4	18	<,001

a. Predictors: (Constant), YEAR, not periodic, GDP Growth Rate, Inflation Rate, Employment in the Information Industry

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	46,739	4	11,685	7,862	<,001[b]
	Residual	26,753	18	1,486		
	Total	73,492	22			

a. Dependent Variable: Unemployment Rate

b. Predictors: (Constant), YEAR, not periodic, GDP Growth Rate, Inflation Rate, Employment in the Information Industry

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	431,880	126,863		3,404	,003		
	GDP Growth Rate	-,349	,152	-,360	-2,303	,033	,829	1,207
	Inflation Rate	,099	,201	,091	,494	,627	,600	1,667
	Employment in the Information Industry	-,006	,002	-,973	-4,106	<,001	,360	2,776
	YEAR, not periodic	-,202	,061	-,751	-3,294	,004	,389	2,569

a. Dependent Variable: Unemployment Rate

Source: Own calculation, SPSS

4.4 Final regression model

The final regression model estimation is presented in Table 3, where the dependent variable is the unemployment rate and the independent variables are the following:GDP growth rate, employment in information industry and time series. Inflation rate was removed from the initial model due to statistical insignificance.

Furthermore, from Table 3 it can be seen that P-values for both independent variables are less that 0.05 meaning that they have statistical significance. And the same thing with the time series: it has P-value of 0.002. In this regression model's An R-squared of 63.1% means that 63.1% of the variation in the dependent variable is explained by the independent variable in the model. However, it is important to note that the remaining 39% of the variation is not explained by the model and could be due to other factors.

Table 3 Final regression model

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,794[a]	,631	,573	1,1946	,631	10,832	3	19	<,001

a. Predictors: (Constant), YEAR, not periodic, GDP Growth Rate, Employment in the Information Industry

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	46,377	3	15,459	10,832	<,001[b]
	Residual	27,116	19	1,427		
	Total	73,492	22			

a. Dependent Variable: Unemployment Rate

b. Predictors: (Constant), YEAR, not periodic, GDP Growth Rate, Employment in the Information Industry

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance	VIF
1	(Constant)	401,093	108,271		3,705	,002		
	GDP Growth Rate	-,322	,139	-,332	-2,325	,031	,951	1,051
	Employment in the Information Industry	-,006	,001	-,912	-4,597	<,001	,493	2,026
	YEAR, not periodic	-,188	,053	-,696	-3,571	,002	,511	1,956

a. Dependent Variable: Unemployment Rate

Source: Own calculation, SPSS

Thus, final multiple regression model equation is the following:

$$\mathbf{Y = 401,093 - 0,322}x\mathbf{1}t \mathbf{- 0,006x2t - 0,188}$$

4.5 Model diagnostics

As mentioned above, in the final model all variables are statistically significant. Moreover, the coefficient of variance inflation for all variables also has a satisfactory value. According to the rule of thumb, VIF less than 10 means that there is no multicollinearity in the model, or in other words, the independent variables are not strongly correlated with each other. Thus, for GDP growth rate VIF is 1.051, for employment in information industry it is 2.025 and 1.956 in case of time series.

Table 4 Model diagnostics

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	401,093	108,271		3,705	,002		
	GDP Growth Rate	-,322	,139	-,332	-2,325	,031	,951	1,051
	Employment in the Information Industry	-,006	,001	-,912	-4,597	<,001	,493	2,026
	YEAR, not periodic	-,188	,053	-,696	-3,571	,002	,511	1,956

a. Dependent Variable: Unemployment Rate

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Variance Proportions GDP Growth Rate	Variance Proportions Employment in the Information Industry	Variance Proportions YEAR, not periodic
1	1	3,628	1,000	,00	,02	,00	,00
	2	,367	3,146	,00	,94	,00	,00
	3	,006	25,116	,00	,03	,50	,00
	4	2,712E-6	1156,596	1,00	,01	,50	1,00

a. Dependent Variable: Unemployment Rate

Source: Own calculation, SPSS

5 Results and Discussion

In the results and discussion section of this thesis, the statistical analysis of unemployment in the United States has yielded several key insights into the labor market's dynamics and the factors that contribute to different types of unemployment. By examining historical trends, macroeconomic factors, and the causes and consequences of unemployment, this study has provided a holistic perspective on the intricacies of the U.S. labor market.

Furthermore, the examination of the various types of unemployment – frictional, structural, cyclical, and seasonal – has emphasized the importance of recognizing the distinct factors that drive each type. For instance, frictional unemployment is an inevitable aspect of the labor market, whereas structural unemployment stems from a mismatch between worker skills and labor market demands. This nuanced understanding allows for the development of targeted policies and interventions to address each type of unemployment effectively.

The study of macroeconomic factors, such as GDP growth and inflation, has demonstrated their influence on the labor market. Periods of economic growth tend to be associated with lower unemployment rates, while high inflation can exacerbate unemployment by reducing real wages and purchasing power. Additionally, technological advancements have emerged as a double-edged sword, with the potential to displace jobs while also creating new opportunities for growth and development.

6 Conclusion

In conclusion, this thesis has provided a comprehensive statistical analysis of unemployment in the United States, focusing on different types of unemployment, their causes and consequences, and the impact of various macroeconomic factors on the labor market. The study has also examined the historical trends and patterns of unemployment in the U.S., shedding light on the dynamics of the labor market over time and the effectiveness of policies and interventions aimed at reducing unemployment rates.

A primary finding of this thesis is that unemployment is a multifaceted phenomenon, with frictional, structural, cyclical, and seasonal factors contributing to its existence. The analysis has underscored the importance of understanding the nuances of each type of unemployment in order to devise effective strategies to tackle them. Frictional unemployment, for example, is a natural and unavoidable part of the labor market, as workers transition between jobs and search for new opportunities. Structural unemployment, on the other hand, arises due to a mismatch between the skills and qualifications of workers and the demands of the labor market. Cyclical unemployment results from fluctuations in the business cycle, while seasonal unemployment is tied to the changing demands for labor across different industries throughout the year.

The study has also highlighted the critical role of macroeconomic factors in shaping the labor market, including GDP growth, inflation, and technological advancements. It has been demonstrated that periods of strong economic growth tend to be associated with lower unemployment rates, while recessions often result in higher levels of joblessness. Technological advancements have emerged as both a potential cause and solution to unemployment, as they can lead to job displacement but also create new opportunities for growth and development. Education and skills development have been identified as essential factors in addressing the skills mismatch that contributes to structural unemployment.

Moreover, this thesis has delved into the various individual and societal consequences of unemployment, emphasizing the far-reaching effects it has on individuals, families, and communities. Unemployment can lead to reduced income, lower standards of living, and diminished well-being for those affected, with additional social and psychological impacts such as loss of self-esteem, social isolation, and increased rates of depression and suicide. Furthermore, high levels of unemployment can have negative economic consequences, such as decreased demand for goods and services, reduced economic growth, and increased strain on social welfare programs.

The analysis presented in this thesis has important implications for policymakers, businesses, and individuals alike. By understanding the complex factors that drive unemployment and the consequences it has on society, informed decisions can be made to address the issue and minimize its adverse effects. For policymakers, this may involve implementing targeted interventions, such as job training programs, education reforms, and investment in infrastructure projects, to stimulate economic growth and create new employment opportunities. Businesses can also play a role by investing in workforce development, adopting new technologies that create jobs, and fostering an inclusive and diverse labor market. Finally, individuals can contribute by seeking continuous education and training to enhance their skills and adaptability in the face of changing labor market conditions.

Looking forward, it is crucial to continue monitoring and analyzing unemployment trends and patterns in the United States, as new challenges and opportunities emerge in the rapidly evolving global economy. The recent COVID-19 pandemic, for instance, has underscored the importance of understanding the labor market's resilience and adaptability in the face of unprecedented disruptions. By leveraging the insights gained from this thesis and building upon them through future research, it is possible to develop a deeper understanding of the dynamics of unemployment and devise effective strategies to mitigate its effects, ultimately fostering a more prosperous and inclusive society.

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