Economic Data Analysis

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Abstract

This paper examines the relationship between various economic variables and Gross Domestic Product (GDP) to gain insights into economic growth factors. The study draws upon a comprehensive dataset compiled from reputable sources, including the U.S. Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Federal Reserve Economic Data (FRED), and Congressional Budget Office (CBO). The analysis aims to uncover patterns, trends, and associations among the variables by applying correlation, descriptive statistics, and visualization techniques in Tableau. The paper begins with an introduction highlighting the significance of understanding the relationship between economic data and GDP. A literature review surveys existing scholarly works to provide a theoretical and empirical foundation for the research. The methodology section outlines the data collection process, data preprocessing techniques, and the statistical methods employed in the analysis. The analysis results offer valuable insights into the relationships between economic variables and GDP. The findings, presented through narrative, tables, and visualizations, shed light on the factors contributing to economic growth and their relative importance. These findings provide a basis for understanding the dynamics of the economy and inform policymakers, researchers, and practitioners in making informed decisions.

While the study contributes to the existing body of literature, it acknowledges certain limitations, such as the availability and reliability of data, potential biases, and the scope of the analysis. Future research directions are suggested, including exploring additional variables and examining the effects of external factors on GDP.

Keywords: Economic data analysis, Gross Domestic Product (GDP), forecasting, descriptive statistics, visualization, economic growth.

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Introduction of Economic Data Analysis

Analyzing economic data and its relationship with Gross Domestic Product (GDP) plays a crucial role in understanding the drivers of economic growth and formulating effective policy decisions. Exploring the intricate dynamics between various economic variables and GDP becomes essential as economies become increasingly complex and interconnected. This paper investigates the relationships between economic data and GDP, providing insights into the factors contributing to economic growth. GDP is a vital indicator of a nation's economic performance, representing the total value of goods and services produced within a specific period. However, GDP is influenced by many factors, including employment, inflation, government spending, consumer behavior, and financial indicators. Understanding the interactions among these variables and their impact on GDP is crucial for policymakers, economists, and researchers.

A comprehensive dataset has been compiled from reputable sources such as the U.S. Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Federal Reserve Economic Data (FRED), Congressional Budget Office (CBO), and other reliable repositories. This dataset encompasses various economic variables, including employment levels, inflation rates, household debt, government spending, and financial market indicators.

Various statistical techniques and models have been employed to explore the dataset and uncover meaningful insights. Generalized Linear Models (GLM) forecasting, descriptive statistics, and visualization techniques have been used to identify patterns, trends, and associations among the economic variables and GDP. Additionally, the analysis has been conducted using Tableau, a powerful data visualization tool, to present the findings intuitively and informally.

This study aims to contribute to the existing knowledge on economic growth by investigating the relationships between economic data and GDP. The findings will provide valuable insights into economic performance factors, enabling policymakers to make informed decisions and economists to refine their theoretical frameworks. Furthermore, the analysis will have implications for forecasting future economic trends and understanding the potential impacts of policy interventions. The remainder of this paper is organized as follows: The literature review provides an overview of existing research on the relationships between economic variables and GDP. The methodology section outlines the data collection process, data preprocessing techniques, and the statistical methods employed in the analysis. Subsequently, the analysis results are presented, followed by a discussion of the implications and limitations. Finally, the paper concludes with suggestions for future research and the importance of further understanding the relationships between economic data and GDP. This study contributes to a deeper understanding of the factors driving economic growth by delving into the intricate connections between economic variables and GDP. Ultimately, this knowledge can inform policymakers, researchers, and practitioners in their pursuit of fostering sustainable and resilient economies.

Overview of Economic Data Analysis

Importance

Accurate and comprehensive analysis of economic data plays a vital role in understanding the functioning of economies and informing policy decisions. By examining a wide range of economic variables and their relationships, economic data analysis provides valuable insights into the factors influencing economic growth, inflation, employment, and other critical aspects of an economy. This section highlights the importance of economic data analysis in understanding and interpreting the complexities of the economy.

1. **Informing Policy Decisions:** Economic data analysis is crucial for policymakers making informed decisions. Policymakers can identify the factors driving economic growth or contraction by examining the relationships between economic variables and GDP. This knowledge can guide the formulation of appropriate monetary, fiscal, and regulatory policies to achieve desired economic outcomes.
2. **Assessing Economic Performance:** Economic data analysis enables assessing an economy's performance over time. Analysts can evaluate an economy's overall health and stability by examining indicators such as GDP growth rates, inflation, and employment levels. These insights help identify areas of strength and weakness, allowing policymakers to focus on targeted interventions and policy adjustments.
3. **Understanding Macroeconomic Relationships:** Economic data analysis allows for exploring complex relationships among various macroeconomic variables. By analyzing factors such as consumer spending, investment, trade balances, and government expenditures, researchers can gain insights into how changes in one variable may affect others. This understanding helps predict the potential impacts of policy changes or external shocks and aids in designing appropriate policy responses.

4. **Forecasting Economic Trends:** Through statistical techniques, economic data analysis facilitates the forecasting of economic trends. Analysts can develop models that predict future outcomes by examining historical patterns and relationships among economic variables. These forecasts are invaluable for policymakers, businesses, and investors in making informed decisions and planning for the future.
5. **Identifying Risks and Vulnerabilities:** Economic data analysis helps identify potential risks and vulnerabilities within an economy. Analysts can detect emerging imbalances or weaknesses by monitoring indicators such as household debt, financial market indicators, and unemployment rates. Timely identifying such risks allows policymakers to take preemptive measures to mitigate their impact and ensure economic stability.
6. **Supporting Economic Research:** Economic data analysis is the foundation for academic research and contributes to developing economic theories and models. By examining empirical relationships among economic variables, researchers can test hypotheses, refine economic theories, and contribute to the broader body of economic knowledge.

Economic data analysis is essential for understanding the complexities of the economy and informing policy decisions. The analysis provides insights into economic performance, macroeconomic dynamics, and future trends by examining relationships between economic variables and GDP. Policymakers, researchers, and businesses rely on robust economic data analysis to guide their decisions and navigate the ever-changing economic landscape.

Key Concepts

Before delving into the analysis of economic data and its relationship with the Gross Domestic Product (GDP), it is crucial to understand critical concepts underpinning economic data analysis. This section introduces and defines several fundamental concepts essential for comprehending the subsequent analysis.

1. **Gross Domestic Product (GDP):** Gross Domestic Product (GDP) is a widely used measure of economic activity within a country. It represents the total value of all goods and services produced within a specific period, typically a year. GDP is a critical indicator of a nation's economic health and is often used to compare the economic performance of different countries or to track changes in an economy over time.
2. **Economic Variables:** Economic variables are measurable factors that influence economic activity. These variables capture different aspects of the economy, such as employment levels, inflation rates, consumer spending, government expenditures, trade balances, and financial market indicators. Economic data analysis involves examining the relationships between these variables and GDP to gain insights into the factors driving economic growth or contraction.
3. **Descriptive Statistics:** Descriptive statistics provide a summary of data characteristics, helping to describe and summarize the distribution, central tendency, and variability of economic variables. Measures such as mean, median, standard deviation, and percentiles are commonly used in descriptive statistics to provide a snapshot of the data's key features.

4. **Data Visualization:** Data visualization involves representing data graphically to facilitate understanding and interpretation. Graphs, charts, and other visual representations depict the relationships, trends, and patterns in economic data. Visualization techniques are crucial in conveying complex information effectively, identifying insights, and facilitating the communication of findings.

Understanding these key concepts provides a solid foundation for conducting meaningful economic data analysis. By examining the relationships between economic variables and GDP using statistical techniques and visualization tools, researchers can uncover patterns, identify trends, and gain valuable insights into the factors that shape an economy's performance. In the subsequent sections of this paper, we will apply these key concepts to analyze a comprehensive dataset comprising various economic variables sourced from reputable institutions such as the U.S. Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Federal Reserve Economic Data (FRED), and Congressional Budget Office (CBO). Through descriptive statistics, GLM forecasting, and data visualization in Tableau, we aim to explore the relationships between economic variables and GDP, shedding light on the factors driving economic growth and their relative significance.

Literature Review

Forecasting Real GDP Rate through Econometric Models

An Empirical Study from Greece aimed to model and forecast Greece's real GDP rate using the Box-Jenkins methodology and an ARIMA model. The study found that Greece's real GDP rate showed a positive trend, indicating an improvement in the country's economic activity. The literature review highlighted similar studies that utilized ARIMA models for GDP forecasting in different regions. The empirical analysis involved testing for stationarity, model identification, estimation, and diagnostic checking. The results showed that the ARIMA(1,1,1) model was statistically significant, but its forecasting accuracy was limited. The study's findings provide insights for policymakers and business executives in making informed decisions based on GDP projections.

Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach

Presents a method for forecasting real GDP growth using machine learning models, specifically gradient boosting and random forest models. The study focuses on forecasting the real GDP growth of Japan from 2001 to 2018 and compares the forecasts with those of the International Monetary Fund (IMF) and the Bank of Japan (BOJ). The paper applies the cross-validation process to select the optimal hyperparameters for the machine learning models. The forecast accuracy is evaluated using mean absolute percentage error (MAPE), and root mean squared error (RMSE). The results show that the forecasts generated by the gradient boosting and random forest models are more accurate than the benchmark forecasts provided by the IMF and the BOJ for the 2001-2018 period. The gradient-boosting model outperforms the random forest model in terms of accuracy. The study highlights the advantages of machine learning models in macroeconomic forecasting. Machine learning models can produce predictions without such assumptions, unlike traditional econometric models requiring predetermined assumptions and judgments. Machine learning models' flexibility and predictive power make them suitable for forecasting macroeconomic variables like real GDP growth. The findings of this paper contribute to the literature by providing empirical evidence of the effectiveness of machine learning models in forecasting real GDP growth. Machine learning techniques should be increasingly utilized in macroeconomic forecasting and can aid in informed decision-making for economic policy design and implementation.

Nowcasting GDP Using Machine-learning Algorithms: A Real-time Assessment

This paper explores machine learning (ML) algorithms to improve the nowcast performance of macroeconomic variables, specifically real GDP growth in New Zealand. The study compares various ML models with traditional time-series regression models central banks use. Using multiple vintages of historical GDP data and approximately 600 predictors, the researchers found that ML algorithms outperformed a simple autoregressive benchmark and a dynamic factor model. The top-performing models were: boosted trees, support vector machine regression, and neural networks. These models had reduced nowcast errors by 20% to 30% compared to the benchmark. ML algorithms also added value to the official forecasts of the Reserve Bank of New Zealand, with boosted trees performing exceptionally well. The study contributes to the existing literature by evaluating a wide range of ML models and focusing on real-time forecasting performance. The research provides insights into practical applications by considering the revision properties of variables. The findings demonstrate that ML algorithms can significantly improve nowcast accuracy for real GDP growth. These algorithms outperform traditional techniques and enhance the official forecasts of the Reserve Bank of New Zealand.

Understanding Patterns of Economic Growth: Searching for Hills among Plateaus, Mountains, and Plains

The paper examines the historical trends of gross domestic product (GDP) per capita, focusing on the growth experiences of both developed and developing countries. While developed countries, like the United States, exhibit relatively stable and modest growth patterns over time, developing countries show much greater instability in their growth rates. These growth patterns vary widely, including steady growth (hills), rapid growth followed by stagnation (plateaus), rapid growth followed by decline (mountains), catastrophic falls (cliffs), continuous stagnation (plains), or steady decline (valleys).

The author emphasizes the significant implications of these growth differences for human well-being. Even minor differences in growth rates, compounded over long periods, can result in substantial shifts in living standards. For instance, the United States' consistent growth outpaced Great Britain's, leading to a decline in the latter's economic superpower status. Similarly, Japan's sustained growth propelled its transformation into an economic powerhouse. The rapid growth experienced by certain East Asian countries in recent decades has also reshaped the global economic landscape. The paper challenges the prevailing focus on explaining long-run differences in growth rates and highlights the importance of understanding growth instability and volatility, particularly in developing countries. It argues that conventional econometric approaches relying on high-frequency panel data are insufficient for capturing the dynamics of growth rates. Instead, the author suggests directing research efforts toward investigating the determinants of growth shifts and policy changes. In terms of methodology, the paper utilizes chain-linked indexes of real GDP per capita measured in purchasing power parity dollars. Descriptive statistics are employed to analyze average levels, instability, and volatility of growth rates across a broad range of countries. The distinction between developing and industrial countries is made primarily based on membership in the Organisation for Economic Co-operation and Development (OECD), focusing on capturing the diverse growth experiences of developing nations.

Exploring What Stock Markets Tell Us about GDP in Theory and Practice

This paper examines the relationship between stock market movements, specifically the S&P 500 index, and GDP in the United States. The study finds that while the correlation between the stock market and real GDP is weak when examined contemporaneously, it becomes more robust and statistically significant with a one-quarter lag. This suggests that stock market trends provide valuable information about future GDP. Furthermore, the research highlights that the stock market is more closely related to final, revised GDP numbers released months later than to initial vintage GDP estimates.

This indicates that stock market movements can offer insights into the actual state of GDP, even before it is accurately reflected in official estimates. The paper emphasizes the importance of studying episodes of growth and policy changes rather than relying solely on high-frequency panel data for understanding long-run growth correlates. By considering the stock market as an information aggregator, researchers can gain a deeper understanding of the factors driving shifts in growth rates. Overall, this study contributes to understanding the stock market-GDP relationship and underscores the potential of stock market trends as an indicator of underlying economic conditions.

Methodology

Research Design and Data Collection

The data collection process involved downloading the data from the aforementioned sources as .CSV files and transforming it into a suitable format to import into Oracle SQL Developer.

Data Collection and Preparation

The resulting thirty-four tables were reduced to nine by merging them across the categories of consumer price index (CPI), federal reserve debt (FED_DEBT), federal reserve rate (FED_RATE), gross domestic product (GDP), mortgage delinquency rates (MORT), savings deposits (M2), personal consumer expenditures (PCE), unemployment rates (UNEMP), and median sales price of houses sold in the United States (MSPUS). The merging operation was based on the common column of RECORD_DATE, which provided a consistent timeline across all tables.

Indexes were created on all the tables to enhance query performance. The primary key (SURROGATE_KEY) of each dimension table and the foreign key (DATE_KEY) in the FACT_DATA table, corresponding to the JULIAN_DAY_KEY in the DATE_DIM table, were primarily used for establishing the indexes. The creation of these indexes allows for faster lookup and query execution.

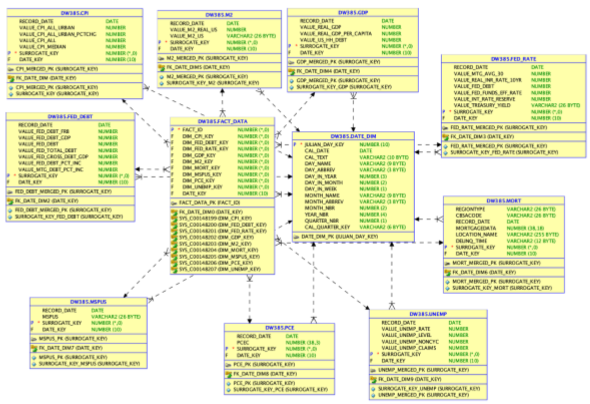
The FACT_DATA table was created to connect the dimension tables through foreign keys. The FACT_DATA table serves as the central element of the dimensional model, connecting each dimension table via their primary keys.The DATE_DIM table was created as a dimension table for dates, containing various useful time-based fields such as DAY_NAME, MONTH_NAME, YEAR_NBR, QUARTER_NBR, etc. This facilitated the connection of the timeline across all dimension tables and enabled efficient execution of complex temporal queries.

Database Design

This database design should ultimately enable the extraction of high-level business insights by providing the ability to conduct multidimensional analysis across various economic indicators over time.

Figure 1

Entity relationship diagram (ERD)



Transactional Models

Regarding the OLTP system, a similar schema could be designed, but without the use of a fact table. Instead, data from different sources would be normalized and stored in separate tables, with joining tables managing the many-to-many relationships. This would cater to the day-to-day transactional requirements of the system, such as data entry and simple queries. This would then feed into the data warehouse designed for complex analyses and reporting.

Dimensional Models

This model features dimension tables surrounding the central fact table with each dimension table linked to the fact table by date. This star schema design simplifies querying and provides fast data retrieval for complex queries. The data cubes represent the multidimensional views of this data, facilitated by the use of ROLLUP, CUBE, and other aggregate functions.

Results

Exploratory Data Analysis (EDA)

Comprehensive exploratory data analysis was performed on the dataset, including both descriptive statistics and advanced analytical SQL queries. Queries were conducted to display simple measures such as average, maximum, minimum, and count for various economic metrics. The ROLLUP operator was utilized to create subtotals and grand totals across various combinations of the dimensions specified in the GROUP BY clause. Additionally, the CUBE operator was employed to compute subtotals for all combinations of the values in the selected columns. These functions enabled the creation of complex reports and facilitated multidimensional analysis.

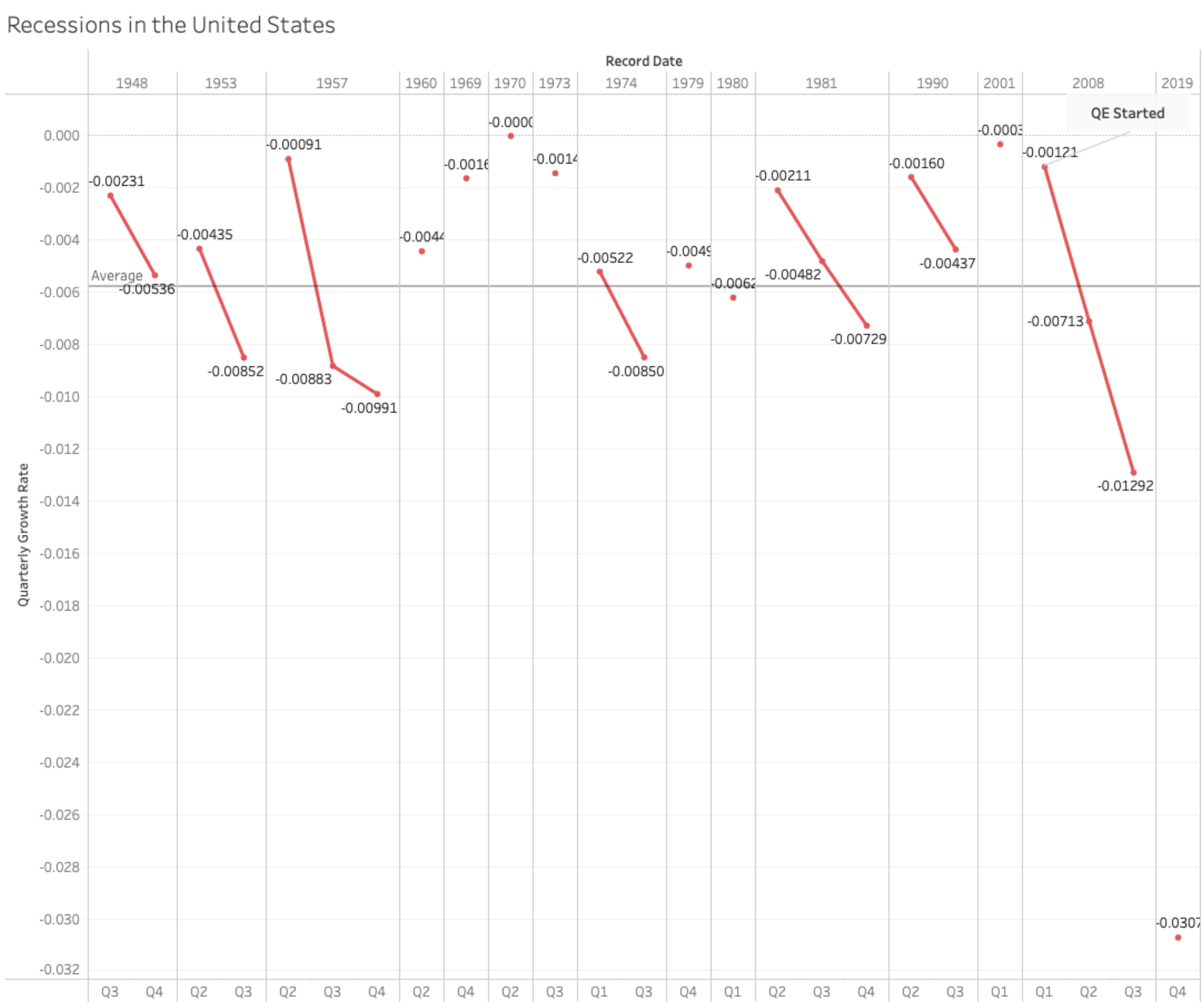
A handful of correlation analyses were conducted, looking at relationships such as the correlation between CPI and the Federal Reserve Rate, as well as the correlation between Unemployment Rate and Median Sales Price of Houses Sold. These analyses revealed interesting connections between various economic indicators, but ultimately reflect only a small portion of the multitude of factors affecting these economic measures

Reporting, Modeling and Storytelling

Quantitative easing (QE) is a monetary policy tool central banks use to stimulate the economy and address recessions. Its primary objective is to combat economic downturns and prevent or mitigate recessions. Central banks increase the money supply and lower interest rates by purchasing government bonds and other financial assets. This liquidity injection aims to encourage lending, boost economic activity, and stabilize financial markets. QE can help mitigate recessions by providing liquidity during times of crisis, reducing borrowing costs, and promoting investment and consumption. Lower interest rates resulting from QE can incentivize borrowing, driving economic growth. However, the effectiveness of QE in preventing recessions and its long-term consequences are influenced by various factors, such as economic conditions, the scale and duration of the QE program, and the overall policy framework. It is an ongoing topic of debate and analysis among economists. Throughout the history of the US economy, there has been a recession at least every ten years except for after QE started. The critical question is, is QE preventing the inevitable while increasing inflation, or are the extra liquidity injections necessary to survive during globalization?

Figure 2

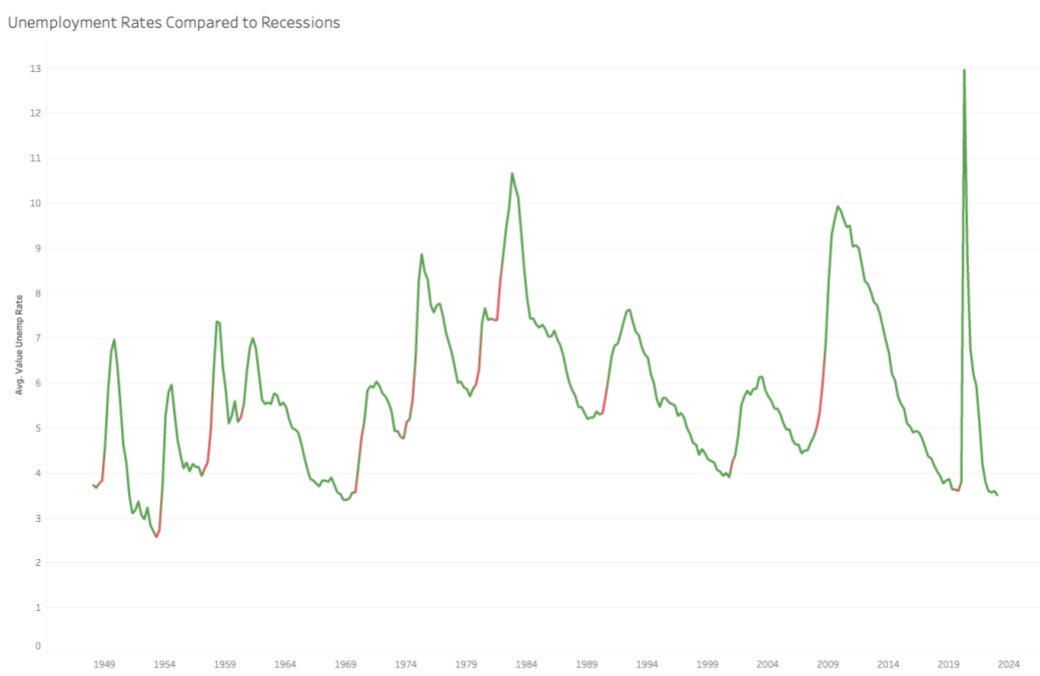
Recessions in the United States



During economic recessions, the behavior of the unemployment rate reveals a distinct pattern where it tends to exhibit lagging characteristics. This means that the unemployment rate often reaches its highest point after the economy has already entered a downturn or during the early stages of the recovery phase. The reason behind this phenomenon lies in the response of businesses to changing economic conditions. When faced with a decline in demand, companies often strive to retain their existing workforce by minimizing layoffs. Consequently, the unemployment rate may only partially reflect the full extent of the economic downturn. As the recession progresses and economic conditions worsen, businesses may eventually reach a point where they can no longer sustain their current workforce. This leads to increased layoffs, resulting in a rising unemployment rate. Therefore, the unemployment rate peak tends to occur relatively later in the recessionary phase.

Figure 3

Recessions in the United States



When the central bank engages in QE, it typically purchases government bonds and other financial assets from commercial banks and financial institutions. This process injects money into the economy to boost lending and spending. As a result, the federal debt can increase because the government is issuing more debt to finance its spending or to accommodate the central bank's purchases. The relationship between QE and the federal debt is complex. QE is often implemented as a response to an economic downturn or financial crisis, which can lead to decreased tax revenues and increased government spending on stimulus measures. These factors can independently contribute to higher levels of federal debt. The impact of QE on the federal debt depends on various factors, including the size and duration of the QE program, the pace of bond purchases, and the government's fiscal policies. If the economy recovers as intended, with increased economic activity and tax revenues, it can help mitigate the long-term impact on the federal debt.

Figure 4

The Effect of Quantitative Easing on Federal Debt

Feature Selection

Feature selection plays a crucial role in economic analysis, and when choosing variables to include in a model, several factors are considered. GDP, Federal Debt, and Unemployment rates are often selected as essential features due to their significance in understanding the overall economic landscape. Researchers and policymakers can fully understand the economic landscape by including GDP, Federal Debt, and Unemployment rates in economic analysis. These variables capture critical dimensions of economic performance, fiscal sustainability, and labor market dynamics. Their inclusion allows for a more nuanced analysis, providing insights into the interplay between economic growth, government debt, and employment trends, ultimately supporting informed decision-making and policy formulation.

Discussion

Our work on the dimensional database design and exploratory data analysis in this project have yielded some fascinating insights and pointed out some noteworthy aspects of this economic data. The key highlights include:

Correlation between Unemployment Rate and Federal Interest Rate

One result from our exploratory data analysis was the discovery of a moderately strong negative correlation (-0.611) between the unemployment rate and the federal interest rate. This suggests that as the unemployment rate increases, the federal interest rate tends to decrease, and vice versa. The relationship between unemployment and interest rates in reality is influenced by a multitude of factors, including the policies of the Federal Reserve, which typically lowers interest rates during periods of high unemployment to stimulate economic activity.

This correlation was efficiently computed through our dimensional model by joining the FACT_DATA table with the UNEMP and FED_RATE dimension tables. This demonstrates the power of dimensional modeling and its capacity to generate meaningful insights.

Benefits of Pre-Aggregation

We utilized the power of pre-aggregated data with our quarterly rolled-up tables, such as "CPI_Q", "GDP_Q", etc. An example to highlight is the simplicity of computing averages over the year when data is pre-aggregated by quarter. Without pre-aggregation, we'd need to implement complex calculations to average over the correct date intervals ourselves. The usage of pre-aggregated tables substantially enhances the performance of queries and makes it easier to perform temporal analysis.

Correlation between Unemployment Rate and Median Sales Price of Houses Sold

We also discovered a weak negative correlation (-0.0813) between the unemployment rates and the median sales price of houses sold. This indicates that to a very minor extent, as unemployment rates go up, the median sales price of houses sold tends to go down, and vice versa. This underlines that housing prices are influenced by a broad array of factors and that while unemployment might have an impact, it is relatively small.

Dimensional Database Schema

Finally, the overall dimensionality of our database schema is worth mentioning. We adopted a star schema with the FACT_DATA table at the center and multiple dimension tables, including DATE_DIM, CPI, FED_DEBT, FED_RATE, GDP, MORT, M2, PCE, UNEMP, and MSPUS, connected to it. Each dimension table provided specific economic indicators corresponding to a date, and the fact table linked them all together through keys. This structure facilitated efficient querying, high data integrity, and the ability to perform complex, multi-dimensional analysis.

This project has clearly demonstrated the power and versatility of dimensional modeling in a data warehousing environment. The insights we've generated show how such a design can be effectively utilized to make high-level business decisions and generate actionable insights from large datasets.

Conclusion

Key Findings

In this project, we leveraged the power of dimensional modeling and data warehousing to perform an in-depth analysis of various economic indicators. The principal findings from this project are:

1. *Correlations*: We discovered insightful correlations such as the moderately strong negative correlation between the unemployment rate and the Federal Interest Rate. Additionally, we noticed a weak negative correlation between unemployment rates and the median sales price of houses sold, highlighting complex dynamics of the housing market.
2. *Pre-aggregation Benefits*: The pre-aggregation of data on a quarterly basis significantly improved the performance of our analytical queries and simplified our calculations. This strategy of rolling up tables made it easier to conduct temporal analysis and trend identification over longer periods.
3. *Dimensional Modeling Efficiency*: The design of our database using a star schema allowed us to effectively link a wide variety of economic indicators for multi-dimensional

analysis. The design also ensured high data integrity and made complex querying more efficient.

4. *Value of EDA*: The exploratory data analysis we performed unearthed vital insights and trends hidden within our economic data. From computing aggregates to utilizing Oracle's ROLLUP and CUBE functions, we extracted valuable insights and highlighted the critical role of EDA in data warehousing.

Implications for Economic Data Analysis

Based on our findings, there are several implications for Economic Data Analysis and research:

1. Include additional relevant economic indicators such as inflation rates, consumer spending, investment levels, trade data, and government expenditure.
2. Include other countries' financial information to account for globalization.
3. Explore advanced time series analysis techniques like ARIMA, VAR, or state-space models to capture the temporal dependencies and relationships between GDP and other variables.
4. Analyze structural breaks and regime shifts using techniques like Chow tests or change-point analysis to account for significant changes in economic conditions.
5. Consider non-linear modeling approaches like artificial neural networks, support vector machines, or random forests to capture complex patterns and non-linear relationships in GDP dynamics.
6. Incorporate external factors and events, such as government policies, global economic events, or natural disasters, to better understand their impact on GDP fluctuations.
7. Validate and assess model performance using techniques like out-of-sample testing and diagnostic checks.

8. Consider a multi-dimensional approach by exploring alternative economic well-being and development measures, such as GNI, HDI, or inclusive wealth index.

In conclusion, enhancing the modeling of GDP requires a comprehensive approach that incorporates relevant economic indicators, employs advanced time series analysis techniques, considers structural breaks and regime shifts, explores non-linear modeling approaches, incorporates external factors, and validates model performance. By implementing these suggestions, researchers can develop more robust and accurate models to better understand and predict GDP dynamics. This will contribute to a deeper understanding of economic growth, inform policy decisions, and provide valuable insights for various stakeholders in the field of economics.

Github Project Code

https://github.com/andersonbdalton/ISM6208_Econ_DBProject

https://github.com/andersonbdalton/ISM6208_Econ_DBProject/branches

https://github.com/andersonbdalton/ISM6208_Econ_DBProject/tree/main/SQL

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Figures

Figure 1. *Entity Relationship Diagram (ERD)*

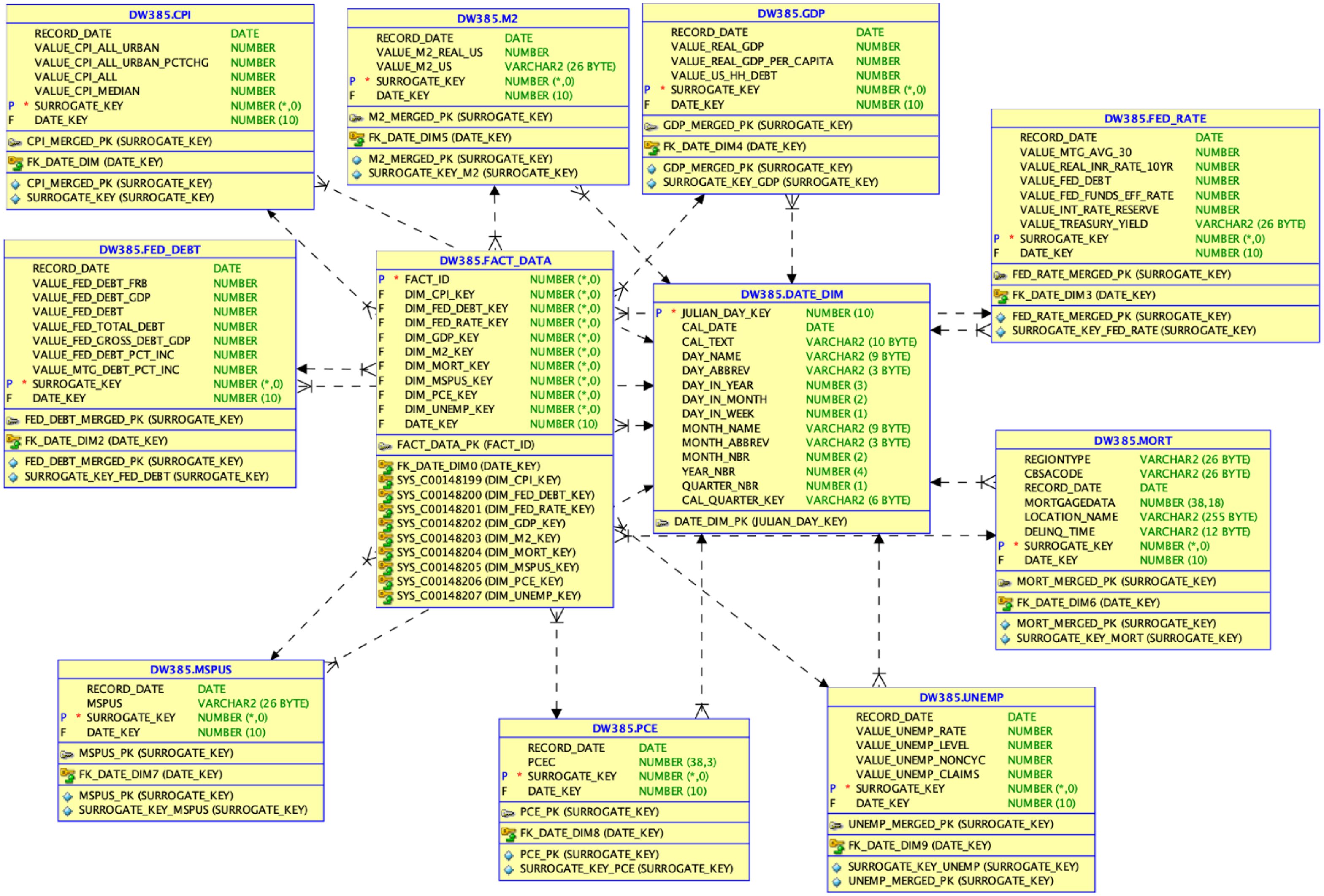

Figure 2. *Recessions in the United States*

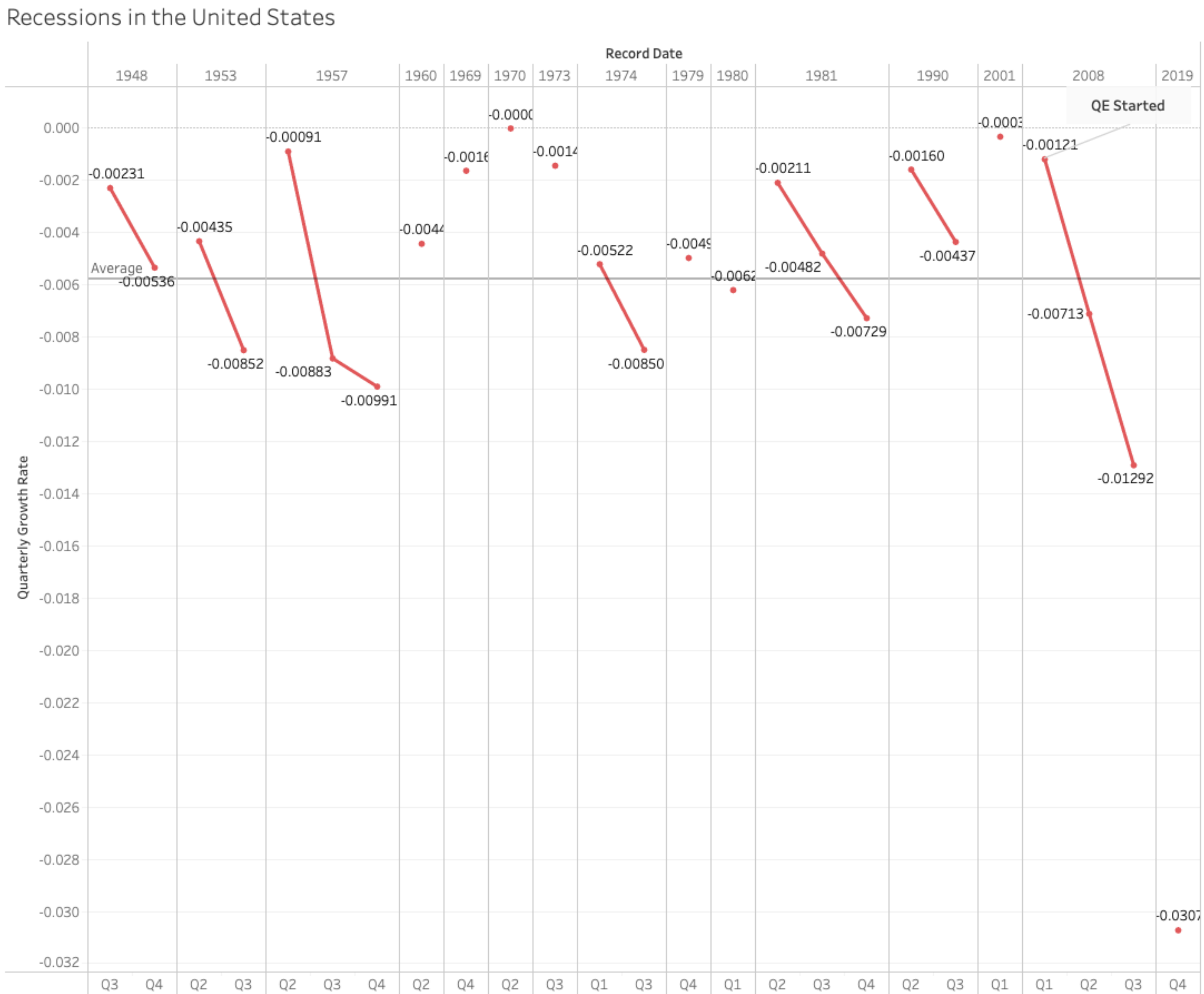

Figure 3. *Recessions in the United States*

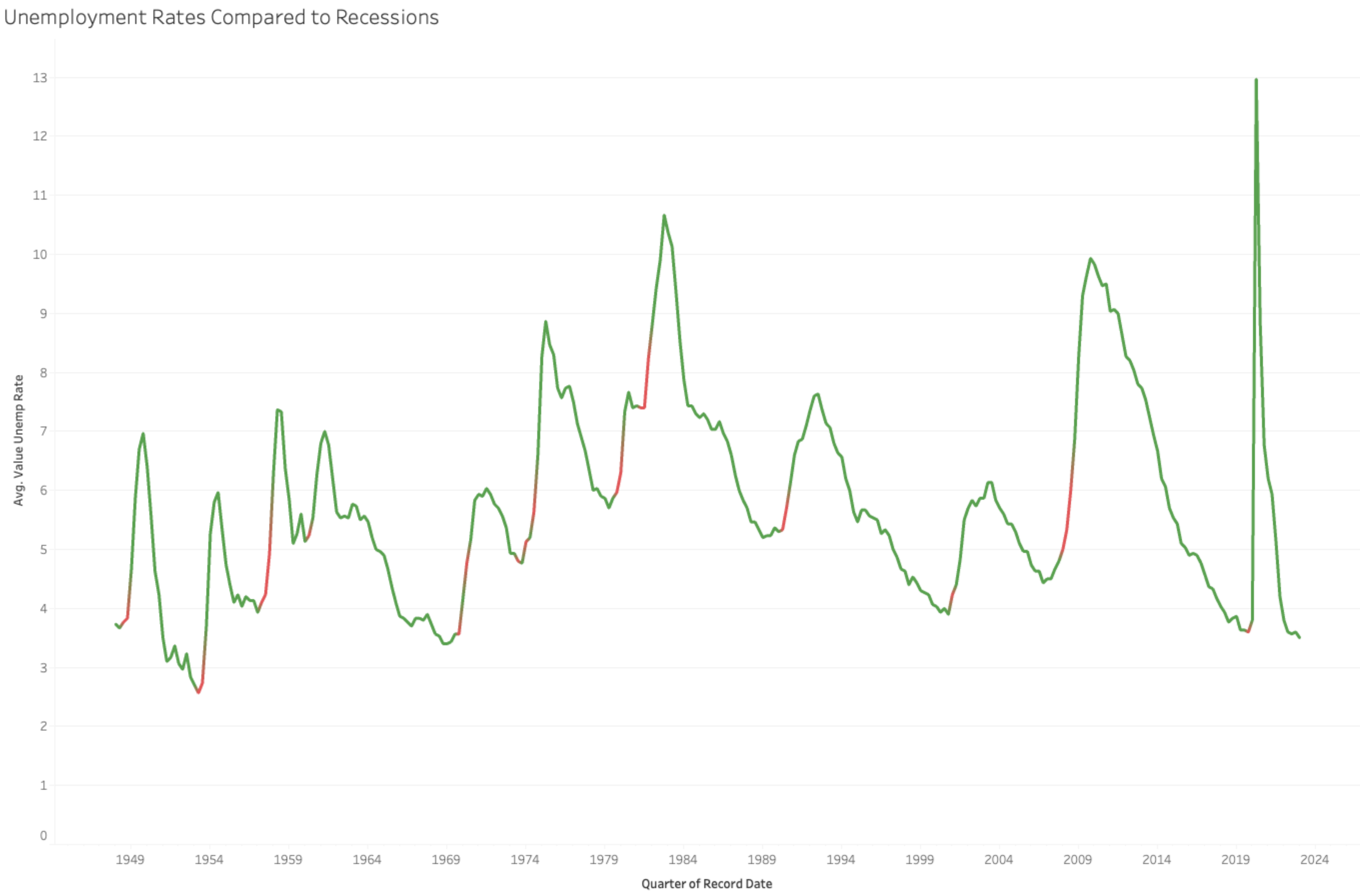

Figure 4. *The Effect of Quantitative Easing on Federal Debt*