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MASTER'S THESIS

# Impact of Monetary Policy on the U.S. Stock Market

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Prague, July 22, 2024 Liusha Li

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# Abstract

With the U.S. capital market's rapid development and continuous improvement, the stock market has become an important financing channel. More and more people tend to participate in the stock investments. The proportion of stocks in the structure of residents' assets continues to increase, and the relationship between the stock price and the actual economic activities becomes increasingly closer.

The thesis first summarizes and compares the theories and opinions of relevant studies on the impact of monetary policy on the stock market. Then, the author empirically investigates the impact of monetary policy on the stock market using data from January 2013 to March 2024, divides the test interval into two periods, and adopts the vector autoregressive model to test the impact of money supply and interest rate on the stock market. Finally, the author analyzes and interprets the results of the empirical tests by combining the actual situation of the stock market and monetary policy, and finds out that for the data from March 2023 to March 2024, the interest rate is helpful to explain the changes in stock prices. Nonetheless, only considering the money supply or interest rate cannot explain the changes in stock prices. At the same time, the government is advised to further strengthen its regulatory efforts to enhance markets and financial stability.

| | |
|---|---|
| **Keywords** | Monetary policy, interest rate, stock market, VAR model |
| **Title** | Impact of Monetary Policy on the U.S. Stock Market |

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# Acronyms

**VAR** Vector auto-regression

**ADF** Augmented Dickey-Fuller

# 1 Introduction

After the financial crisis in 2008, the Federal Reserve launched the quantitative easing policy by purchasing $600 billion in mortgage-backed securities (MBS) from commercial banks. It also employed forward guidance and other non-conventional monetary policies. The four rounds of quantitative easing (QE), from 2008 to 2012, provided massive liquidity to financial markets and injected money into the financial system. In the face of COVID-19 in 2020, after the 3 major stock indexes bottomed out, the Federal Reserve launched the interest rate cut, lowering the interest rate to nearly 0, and implemented a new round of quantitative easing. The capital markets began to recover rapidly after the Fed's interventions. Specifically, in February 2020, the S&P 500 fell by over 30% from its peak in January 2020. After the Fed’s aggressive monetary policy actions, it reached pre-pandemic levels by August 2020. Consequently, we can presume that an easing or tightening monetary policy can stimulate stock markets and cause stock prices to rise or fall.

With rapid economic development, the scale of the U.S. stock market has expanded quickly. As of December 2023, the U.S. stock market had 5,704 listed domestic and international companies with a total market capitalization of $50.8 trillion. Among these, the New York Stock Exchange comprised 2,272 listed companies with a market capitalization of $25.56 trillion. On the other hand, 3,432 companies were listed on the Nasdaq with a market capitalization of $22.6 trillion. The total capitalization of companies listed on the OTCQX markets by December 2023 was estimated to be $2.64 trillion. The studies of stock prices and macroeconomic policies, such as interest rates and amounts of money supply, can improve the understanding of the impact of macroeconomic policies on capital markets. It has important theoretical and practical implications for the growth of stock markets and the development of related policies.

Empirical research addressing the impact of monetary policy stances on stock markets traces back to the last century. Scholars have used diverse econometric methods and data from different countries to come up with conclusions. Thorbecke (1997) uses the Vector Autoregression (VAR) methodology, which consists of monthly stock returns, inflation, output, and federal funds rates, and explores the response of stock returns to changes in monetary policies. He concludes that expansionary monetary policy has a substantial and statistically significant positive effect on stock returns. Jensen and Johnson (1995) argue that financial markets react fast to the announcements of changes in discount rates. Their findings reveal that, from 1962 to 1991, stock returns following a decrease in discount rate are higher and less volatile than those following an increase in interest rate. Cassola and Morana (2004) find that permanent positive monetary shocks temporarily impact asset prices. Rapach et al. (2005) examine the predictability of stock prices, utilizing macroeconomic variables in 12 developed countries, and conclude interest rates are the most reliable and predictable drivers of stock returns across the countries among all macroeconomic variables considered.

From the research results, we observe that regardless of the econometric methods or dataset used, there is no consistent conclusion on how monetary policy stances affect asset prices. This thesis employs the vector autoregressive (VAR) model and its extensions, including the Granger causality test and Impulse Response Functions, and the S&P 500 stock index prices (January 2013 to December 2023) so as to explore the following hypotheses:

Hypothesis #1: Money supply has a positive impact on stock prices, i.e., stock prices rise when the money supply increases.

Hypothesis #2: Interest rate has a negative impact on stock prices, i.e., stock prices rise when the interest rate declines.

Hypothesis #3: There is a lag effect in the impact of money supply or interest rate on stock prices.

The main findings of this thesis are as follows: firstly, monetary aggregates (M1, M2) do not Granger cause the S&P 500 stock index. For the data ranging from March 2013 to February 2020, the federal funds rate fails to Granger cause the stock prices, while for the data from March 2020 to March 2024, the Fed rate Granger causes the stock index. This suggests that interest rate helps predict the S&P 500 stock prices spanning from March 2020 to March 2024. Furthermore, according to the results of the impulse response functions, we observe that the response of the S&P 500 index price to both the money supply and interest rate is relatively brief. The reaction of stock price to money supply and interest rate becomes 0 at $t = 2$ (the second month). The stock price response to interest rates from March 2020 to March 2024 is comparatively more extended than in other periods but still short, around five months.

This thesis consists of six chapters. The first chapter is the introduction, which presents monetary policy and stock market developments, an overview of existing research, an outline of this thesis, and a summary of key conclusions. The second chapter is the literature review, which mainly describes the different studies and relevant theories on the impact of money supply and interest rates on stock markets. Chapter 3 is data analysis, which focuses on the data indicators and their definitions, and summaries of the U.S. stock market development and the monetary policies implemented by the Federal Reserve from January 2013 to March 2024. Chapter 4 introduces the econometric methodology used in this thesis. Chapter 5 is the empirical analysis, including the processing of data, the construction of the VAR model, and the model application. Chapter 6 is the conclusion of this thesis.

# 2 Literature review

## 2.1 Research on the Impact of Money Supply on Stock Markets

Research on the effect of money supply on stock prices can be traced back to the end of the last century, which has spanned different regions and countries. Some scholars believe that the money supply positively affects stock prices and employ statistical methods such as graph analytics and linear regression to confirm the influence. Sprinkel (1964) first examines the relationship between stock prices and money supply. Using a graphical analysis and the Standard and Poor's 500 from 1918 to 1960, he concludes that peaks in the money supply are about 15 months ahead of peaks in stock prices, while troughs in the money supply precede those in stock prices by approximately two months. The findings suggest a relationship between the U.S. money supply and the S&P 500 index and that monitoring the money supply can potentially serve as a tool for predicting future movements in stock prices. Similarly, Homa and Jaffee (1971) and Keran (1971) use simple linear regression and find that changes in the money supply can serve as predictors of stock prices. Their findings suggest that money supply changes affect stock prices indirectly by affecting inflation rates and corporate earnings expectations and directly by altering investor demands.

With the development of econometric methods, Sims (1980) proposes the vector autoregressions (VAR) model, which can simultaneously process multiple time series data and capture the dynamic relationship among them. Lastrapes (1998) uses a VAR model with five key variables: output (GDP), stock price index, interest rates, price level, and nominal money supply. This study explores the impact of monetary aggregates on asset prices in eight developed and developing economies. They find that, except for France and the United Kingdom, changes in the money supply have a significantly positive impact on asset prices in six other countries, while in France and the UK, the effect is positive but insignificant. Tang and Li (2000) apply the vector autoregressive model to examine the relationship between monetary policy and stock returns in Chinese stock markets using data from 1991 to 1997. Their analysis shows that stock returns are affected by money supply to a certain extent, and the central bank is advised to promptly adjust money supply in response to changes in macroeconomic indicators in order to influence stock markets effectively. Syed M. Ali and M. Aynul Hasan (1993), Mookerjee and Yu (1999), and Hu and Cheng (2003) present similar results that there is a long-term positive relationship between monetary aggregates and stock prices. Jalil, Mohammad, and Hussain (2009) focus on the relationship between several macroeconomic variables and asset prices. They conclude that the industrial production index (IPI), gross fixed capital formation (GFCF), and other macroeconomic indicators do not have a statistically significant relationship with stock price changes. In contrast, monetary policy factors such as money supply and exchange rates have a more notable impact on stock prices. More specifically, changes in the broad money supply (M2) can directly affect market liquidity and cause stock price fluctuations. They further confirm a significant positive relationship between money supply and stock prices and believe that money supply is one of the crucial factors that cannot be overlooked in future research.

In contrast to the enormous number of studies demonstrating a positive impact of monetary aggregates on stock prices, comparatively fewer studies are attempting to establish either a negative or no relationship between money and stock prices. Rozeff (1974) argues that the analyses in Sprinkel (1964), Homa and Jaffee (1971), and Keran (1971) are insufficient to prove that monetary variables can be used to forecast asset prices. Using regression models of stock returns on monetary variables, Rozeff's results support the efficient market hypothesis that all available information about monetary policy is fully reflected in stock prices and that past values of monetary aggregates cannot be used to forecast stock returns. Consequently, his findings conclude that the profitable trading strategies mentioned in Sprinkel (1964) using past money supply data to predict current stock prices do not exist. Rogalski and Vinso (1977) improve on Rozeff's analysis. Their results suggest that the direction of causality is not from money to stock prices but from stock prices to money. Hafer (1986) extends previous research using a broader data set from 1977 to 1984. In addition to examining the effect of money on stock prices, he also investigates whether this impact is uniform across different industry groups. He finds that unanticipated changes in the money supply have a statistically significant effect on stock prices and that this effect tends to be asymmetric. For instance, only positive unanticipated money supply changes appear to have a significant impact on the S&P 500 and S&P 400 measures. In contrast, anticipated movements never present a statistically significant effect. From the 1960s to the 1990s, the primary target of U.S. monetary policy was the money supply for most of the time. This approach was primarily influenced by monetarist theories, particularly those of Milton Friedman, who claimed that controlling the money supply was crucial to managing inflation and stabilizing the economy. As a consequence, earlier studies used the money supply to measure the effects of monetary policy. Starting in the 1980s, the Federal Reserve shifted from the money supply to the federal funds rate to target monetary policy. This approach allowed for more precise control of economic activities by influencing other interest rates, such as business loan interest rates and mortgage rates. Since then, most literature has focused on studying the impact of changes in federal funds rates on asset prices.

In addition to the U.S. stock markets, scholars have studied the relationship between monetary policy and stock markets in many other countries and regions. Darrat (1990) uses monthly percentage changes in the monetary base and examines the impact of monetary and fiscal policy on the Toronto Stock Exchange 300 Index returns. The results show that the money supply fails to Granger cause stock returns, indicating that changes in the money supply do not predict stock prices. On the other hand, he finds that fiscal policy, as measured by structural budget deficits, significantly negatively impacts stock returns in the subsequent 2-3 months. Sun and Ma (2003) employ rolling VAR, augmented VAR, and Granger causality tests on monthly data from 1993 to 2002. Their results suggest that if the central bank wants to influence stock market performance, it can only effectively use the interest rate rather than the money supply among its monetary policy instruments. Notably, bank interest rate significantly impacts stock returns in 15 subsamples, while money supply shows no impact in any subsamples. Yi and Wang (2002), Alatiqi and Fazel (2008), Madurapperuma (2022), Bhattacharjee and Das (2022), etc. reach similar conclusions that money supply has no explanatory power in predicting changes in stock prices.

From the above studies, we can conclude that, either using statistical methods or econometric models, scholars have reached different conclusions regarding the relationship between money supply and stock prices. Most academics, such as Homa and Jaffee (1971), Lastrapes (1998), and Jalil, Mohammad, and Hussain (2009), conclude that an expansionary monetary policy, such as increasing the money supply, causes stock prices to rise, while other scholars contend that changes in the money supply do not predict stock prices or that there is no relationship between the two variables, such as Hafer (1986), Rozeff (1974), Sun and Ma (2003), Bhattacharjee and Das (2022), etc. The reasons for this discrepancy may be as follows: 1. the money supply does not fully reflect the changes in the monetary policy enacted by the central bank; 2. scholars have used different periods; 3. scholars have adopted different research methodologies.

## 2.2 Research on the Impact of Interest Rates on Stock Markets

Changes in interest rates can affect stock prices. This effect can be realized in two approaches: through stock investors and publicly listed companies. Interest rates can affect stock prices through stock investors in the following ways.

i. Substitution Effect. This effect is based on asset portfolio theory (William F. Sharpe, 1970). Asset portfolio theory suggests that people hold low-yielding, low-risk assets, such as cash and bonds, and high-yielding, risky assets, such as stocks, and make asset allocations based on their risk preferences and asset returns to achieve their target portfolio return. As financial assets react differently to interest rates, changes in interest rates cause corresponding changes in the returns of assets. When interest rates fall, the returns on savings and bonds fall more than those on equities, and the opportunity cost of holding low-yielding assets increases, causing people to increase their holdings of equities and thus raising stock prices. On the other hand, a rise in interest rates causes stock prices to fall. The conduction pathway can be expressed as:

Interest rates ↑ → Opportunity costs of holding low-yield assets ↑ → Proportion of stocks in portfolio ↑ → Stock prices ↑

ii. Transaction cost. For investors, an increase in interest rates tends to have a significant impact on securities lending due to higher borrowing costs and the increased opportunity cost of using cash as collateral. This raises transaction costs for borrowers and reduces demands for equities, causing stock prices to fall. The conduction pathway can be expressed as:

Interest rates ↑ → Transaction costs ↑ → Demand of stocks ↓ → Stock prices ↓

iii. Expectation effect. If interest rate changes exceed investors’ expectations and current interest rates decline, more people will believe that interest rates will rise and choose to hold cash instead of stocks, causing stock prices to fall. In contrast, if interest rate movements are below investors' expectations and current interest rates decline, people will believe interest rates will continue to fall. This prompts people to buy stocks, leading to upward movements in stock prices. If interest rate changes align with investors' expectations, the demand for stocks remains constant, and stock prices remain steady. The conduction pathway can be expressed as:

Interest rates ↓ (above expectations) → Investors expect interest rates ↑ → Investors hold cash instead of stocks → Stock Prices ↓

Interest rates ↓ (below expectations) →Investors expect interest rates ↓ → Investors hold stocks instead of cash → Stock Prices ↑

Interest rates ↓ (in line with expectations) → No change in interest rate expectations → Stock demands unchanged → Stock prices unchanged

In addition to directly influencing investor behaviors, interest rates can also affect stock prices through the valuation of companies. Myron J. Gordon and Eli Shapiro (1956) proposed the Gordon Growth Model (GGM), which states that the value of a stock is equal to the net present value of the sum of all future dividend payments. The model is written as:

$$V = D(1+g)/(r+i-g)$$

where *V* is the stock's current value, *D* the dividend payment today, *g* the annualized dividend growth rate, *r* the risk-free interest rate, and *i* is the risk premium.

The above equation shows that the stock prices positively correlate with the stock dividends and dividend growth rate but negatively with the interest rates and risk premium. When interest rates decrease, the risk-free rate may drop, and stock prices increase. A rise in stock prices gives investors a higher return on their investment, reducing their risk aversion and lowering the risk premium, pushing stock prices even higher. Concurrently, a lower interest rate usually reduces the cost of borrowing for companies, which helps businesses expand their operations and increase profitability, ultimately driving up stock prices. The conduction pathway can be expressed as:

Interest rates ↓ → Risk-free rates ↓ → Stock prices ↑ → Risk premiums ↓ → Stock prices ↑ ↑

Interest rates ↓ → Borrowing costs ↓ → Company profits ↑ →Stock prices ↑

From the analysis of the impact of interest rates on stock prices, we can see that the effect varies. Most theories suggest that when interest rates fall, stock returns increase. Therefore, it is vital to investigate further the impact of interest rates on stock prices through empirical studies.

Scholars have extensively studied the impact of interest rate changes on stock prices since the last century. Jensen and Johnson (1995) analyze stock returns from 1962 to 1991 to examine the effect of interest rate changes on long-term stock market performance. The results indicate that the stock market has significantly higher returns and lower volatility in periods following declines in discount rates than in periods following increases. Nonetheless, stock market performance cannot be attributed solely to short- or long-term interest rate changes. Many other factors affect stock market performance. Thorbecke (1997) uses various empirical techniques to examine how monetary policy shocks affect stock prices in the United States. Using a VAR model that includes monthly stock returns, output growth, inflation, and the federal funds rate, Thorbecke finds that monetary policy has a significant impact on both ex-ante and ex-post stock returns. Moreover, monetary policy shocks have a larger effect on small-cap stocks than on large-cap stocks. Similarly, Patelis (1997) uses a short-horizon vector autoregression model and long-horizon regressions introduced by Fama and French (1989) to examine whether changes in the stance of monetary policy can explain the predictability of excess stock returns. He concludes that while monetary policy variables significantly predict future stock returns, they do not fully explain the observed predictability of stock returns. Moreover, monetary policy shocks primarily affect expected excess returns and dividend growth, while having a minimal effect on expected real returns. Rigobon and Sack (2003) conducted a study using interest rates and stock market volatility. Their results show that a 25 basis point increase in short-term interest rates leads to a 1.9% decline in the S&P 500 index and a 2.5% decline in the NASDAQ index. Cassola and Morana (2004), Christos and Alexandros (2006), Lettau and Wachter (2011), and AL-Naif (2017) extend previous studies by suggesting that stock market returns are related to the monetary environment. Ehrmann and Fratzscher (2004) divide interest rate changes into expected and unexpected and utilize data from surveys conducted by Reuters on the Fridays before each FOMC meeting to measure investor expectations. They document that unexpected monetary policy shocks significantly impact stock prices. Moreover, monetary policy shocks have a larger effect on small-cap stocks than on large-cap stocks. Similarly, Patelis (1997) uses a short-horizon vector autoregression model and long-horizon regressions introduced by Fama and French (1989) to examine whether changes in the stance of monetary policy can explain the predictability of excess stock returns. His findings suggest that while monetary policy variables significantly predict future stock returns, they do not fully explain the observed predictability of stock returns. Moreover, monetary policy shocks primarily affect expected excess returns and dividend growth, while having a minimal effect on expected real returns. Rigobon and Sack (2003) conducted a study using interest rates and stock market volatility. Their results show that a 25 basis point increase in short-term interest rates leads to a 1.9% decline in the SP500 index and a 2.5% decline in the NASDAQ index. Cassola and Morana (2004), Christos and Alexandros (2006), Lettau and Wachter (2011), and AL-Naif (2017) extend previous studies by suggesting that stock market returns are related to the monetary environment. Ehrmann and Fratzscher (2004) divide interest rate changes into expected and unexpected ones and use data from Reuters surveys conducted on the Fridays before each FOMC meeting to measure investor expectations. They document that unexpected monetary policy shocks significantly impact stock prices.

From the above studies, we can see that there are three main empirical approaches to studying the impact of monetary policy on asset prices: linear regression models, event study methods, and vector autoregression models. The primary indicators used to measure monetary policy include monetary aggregates and interest rates. In addition, it is noticeable that regardless of the econometric method or indicators used, there is no consistent conclusion on how monetary policy shocks affect asset prices. The above studies provide a solid foundation for this thesis, which uses money supply and interest rates as indicators of monetary policy stances and the S&P 500 index price as an indicator of market returns to construct a VAR model. It aims to validate further and extend the results of previous studies and contribute to the existing research on the effect of monetary policy on stock prices.

# 3. Data

## 3.1 Data Collection

**Money Supply Measures:** The money supply in the United States is categorized according to the following spectrums: 1. M0 (the monetary base): the currency in circulation plus bank reserves; 2. M1: a narrower measure of money supply, including the currency in circulation and bank reserves. It also counts other liquid deposits, such as checkable deposits, demand deposits, and traveler's checks; 3. M2: M1 plus quasi-money assets, such as saving deposits, small-denomination time deposits, and retail money market mutual funds. The author uses M1 and M2 as the indicators for measuring changes in the money supply because M1 and M2 depict the day-to-day patterns of spending, consumption, investment, and long-term expenditure. Meanwhile, M1 and M2 also serve as common economic indicators the Federal Reserve uses to implement and guide monetary policy to manage liquidity and support economic growth. In March 2020, in response to the COVID-19 crisis, the Federal Reserve announced quantitative easing (QE) to inject more liquidity into the financial markets, which caused the amount of M1 to increase from USD 3,980 billion in February 2020 to USD 4,261 billion in March 2020. The author uses March 2020 as the dividing point and separates the money supply amounts into two periods: January 2013 to February 2020 and March 2020 to March 2024. The amounts of money supply are seasonally adjusted values obtained from the FRED database of the Federal Reserve Bank of St. Louis. The variables representing the monetary aggregates are denoted as M1 and M2 separately.

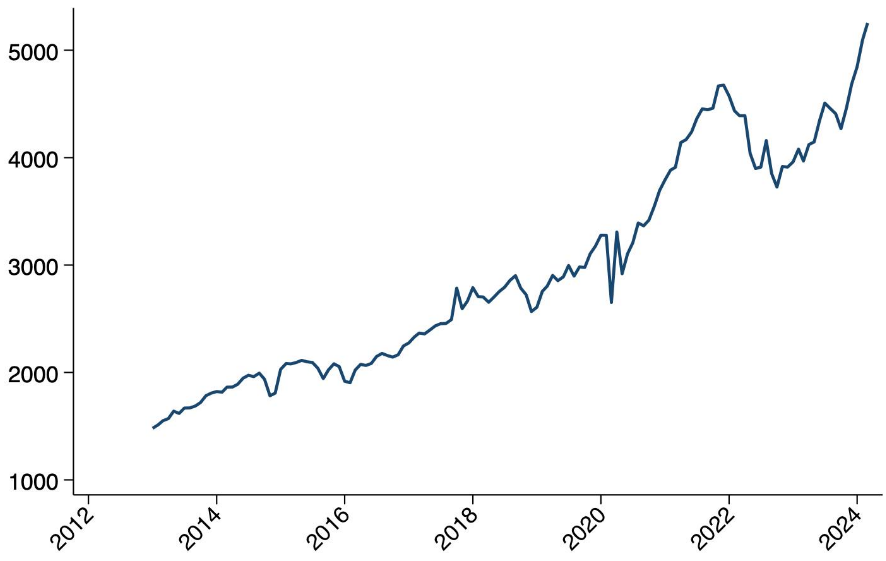
**Stock Market Index:** the author uses the Standard and Poor's 500 index as a benchmark for evaluating the performance of the U.S. stock market. Compared to other stock index indicators, the S&P 500 includes 500 large-cap U.S. companies from various sectors, including technology, healthcare, consumer discretionary, and so on. Additionally, the S&P 500 is a market capitalization-weighted index, meaning that the larger companies tend to have a greater impact on the index's performance. This more accurately reflects the size and performance of companies within the market and provides a more realistic view of market trends. The duration for the S&P 500 index in this thesis spans from January 2013 to March 2024. Monthly index prices obtained from Yahoo Finance are used. The variable representing the S&P 500 is denoted as SP.

**Market Interest Rate:** the author uses the effective federal funds rate (EFFR) as an indicator of market interest rates. The EFFR represents the interest rate at which the depository institutions borrow or lend to each other at an overnight market, and it aligns with the federal funds rate. The latter is established by the FOMC (Federal Open Market Committee) and set as a target range as a guidance for banks to follow. The volume-weighted median of overnight banking transactions becomes the EFFR. The Federal Reserve employs the federal funds rate as a crucial tool for communicating monetary policy stance and maintaining economic stability. The effective federal funds rate duration in this thesis is divided into two periods: January 2013 to February 2020 and March 2020 to March 2024. This division reflects the interest rate cut enacted by the Federal Reserve in March 2020. Following the Fed’s expansionary monetary policy actions, interest rates experienced a dramatic decline, plummeting from 1.58% in February 2020 to 0.65% in March 2020 (see Appendix A). The effective federal funds rates are monthly data sourced from the FRED database of the Federal Reserve Bank of St. Louis. The variable representing the EFFR is denoted as R.

## 3.2 Descriptive Statistics

### 3.2.1 Trend Analysis of the S&P 500 Stock Index

**Figure 3.1 Line Graph of the S&P 500 Stock Index from January 2013 to March 2024**




Source: Author's calculation in STATA 16

The S&P 500 index shows a general upward trend from January 2013 to March 2024, with significant fluctuations reflecting various economic events and market conditions. The performance of the US stock markets can be divided into the following stages.

During the period from 2013 to 2019, the S&P 500 exhibited a general upward trend characterized by consistent growth with intermittent periods of volatility. The index increased steadily from about 1,500 at the beginning of 2013 to approximately 3,300 by the end of 2019. This steady growth was driven by several factors, including economic recovery from the 2008 subprime crisis, robust corporate earnings, and supportive monetary policies from the Federal Reserve, such as low interest rates and quantitative easing. The market also experienced volatility, for instance, from 2015 to the first half of 2016 and 2018, due to various economic and geopolitical reasons. These fluctuations can be attributed to the global economic slowdown, declining oil prices, and the interest rate hikes by the Federal Reserve between 2015 and 2018.

The onset of COVID-19 in early 2020 led to a sharp and unprecedented decline in the S&P 500 index, with a significant drop observed around March 2020. The index fell from about 3,400 in February 2020 to approximately 2,200 in March 2020. In response to the stock market crashes, the Federal Reserve implemented several monetary policies to stabilize the financial markets and support the economy, including lowering the federal funds rate to near zero, quantitative easing, introducing various liquidity and credit facilities for businesses, and providing assistance to small businesses. Notably, the S&P 500 rebounded rapidly, returning to pre-pandemic levels by August 2020 and closing the year at around 3,700.

From 2021 to 2024, the S&P 500 index generally experienced a period of sustained growth and resilience. It rose steadily from around 3,800 at the beginning of 2021 to new highs, surpassing 5,000 in early 2024. Despite intermittent fluctuations, the overall trend has been characterized by upward momentum and positive performance. The upward trend can be attributed to the strong economic recovery, robust corporate earnings, and market participants' confidence.

### 3.2.2 Statistical Analysis of Federal Funds Rates

**Table 3.1 List of Adjustments to Federal Funds Rates and Stock Market Performance After Adjustments**

| FOMC Meeting Date | Rate Change (bps) | Federal Funds Rate | Change in the S&P 500 Index on the First Trading Day After the Adjustment |
|---|---|---|---|
| 12/17/2015 | 25 | 0.25% to 0.50% | -1.7797% |
| 12/15/2016 | 25 | 0.5% to 0.75% | -0.1751% |
| 3/16/2017 | 25 | 0.75% to 1.00% | -0.1314% |
| 6/15/2017 | 25 | 1.00% to 1.25% | 0.0284% |
| 12/14/2017 | 25 | 1.25% to 1.50% | 0.8974% |
| 3/22/2018 | 25 | 1.50% to 1.75% | -2.0967% |
| 6/14/2018 | 25 | 1.75% to 2.0% | -0.1017% |

| | | | |
|---|---|---|---|
| 9/27/2018 | 25 | 2.0% to 2.25% | -0.0007% |
| 12/20/2018 | 25 | 2.25% to 2.50% | -2.0588% |
| 8/1/2019 | -25 | 2.0% to 2.25% | -0.7283% |
| 9/19/2019 | -25 | 1.75% to 2.0% | -0.4896% |
| 10/31/2019 | -25 | 1.50% to 1.75% | 0.9662% |
| 3/3/2020 | -50 | 1.0% to 1.25% | 4.2203% |
| 3/16/2020 | -100 | 0% to 0.25% | 5.9955% |
| 3/17/2022 | 25 | 0.25% to 0.50% | 1.1662% |
| 5/5/2022 | 50 | 0.75% to 1.00% | -0.5674% |
| 6/16/2022 | 75 | 1.50% to 1.75% | 0.2201% |
| 7/27/2022 | 75 | 2.25% to 2.50% | 1.2133% |
| 9/21/2022 | 75 | 3.00% to 3.25% | -0.8428% |
| 11/2/2022 | 75 | 3.75% to 4.00% | -1.0586% |
| 12/14/2022 | 50 | 4.25% to 4.50% | -2.4922% |
| 2/1/2023 | 25 | 4.50% to 4.75% | 1.4699% |
| 3/22/2023 | 25 | 4.75% to 5.00% | 0.2985% |
| 5/3/2023 | 25 | 5.00% to 5.25% | -0.7219% |
| 7/26/2023 | 25 | 5.25% to 5.50% | -0.6425% |

The above information is based on the Forbes Advisor, Yahoo Finance

As the Federal Reserve maintained historically low interest rates between 0% and 0.25% for most of the period from 2013 to 2015 and kept interest rates within the range of 5.25% to 5.50% from July 2023 to support economic stability (see Appendix A), the author chooses the period from the first interest rate hike in December 2015 to the interest rate shift in July 2023 as the study period. In Table 3.1, only major interest rate changes are focused on to analyze the fluctuations of interest rates and stock prices.

From December 2015 to December 2018, it can be observed that the Federal Reserve consistently raised interest rates by 25 basis points at each FOMC meeting, and the target range for the federal funds rate rose steadily from 0.25% to 2.50% during this period. These interest rate hikes could be because the Fed was trying to prevent the economy from overheating and inflation. After years of keeping interest rates at historically low levels following the 2008 subprime crisis, the Federal Reserve aimed to normalize monetary policy by raising interest rates to more typical levels. Moreover, with the Federal Open Market Committee (FOMC) aiming for 2 percent inflation over the longer term, raising interest rates was seen as a tool to stimulate inflation to reach this target level. On the other hand, the reaction of the S&P 500 index seems to be mixed. Most reactions were negative, with the index falling on the first trading day after the interest rate hike. The largest decline was -2.1% on March 22, 2018. Nonetheless, there were a few positive reactions, most notably a 0.9% increase on December 14, 2017.

From August 1, 2019, to October 31, 2019, the Federal Reserve consistently lowered interest rates in 25 basis point increments, bringing the target range down to 1.50% to 1.75%. Nonetheless, stock price reactions still appear to be mixed. Prices fell after the first two cuts but increased after the third cut. This suggests that factors other than interest rates influence stock market performance.

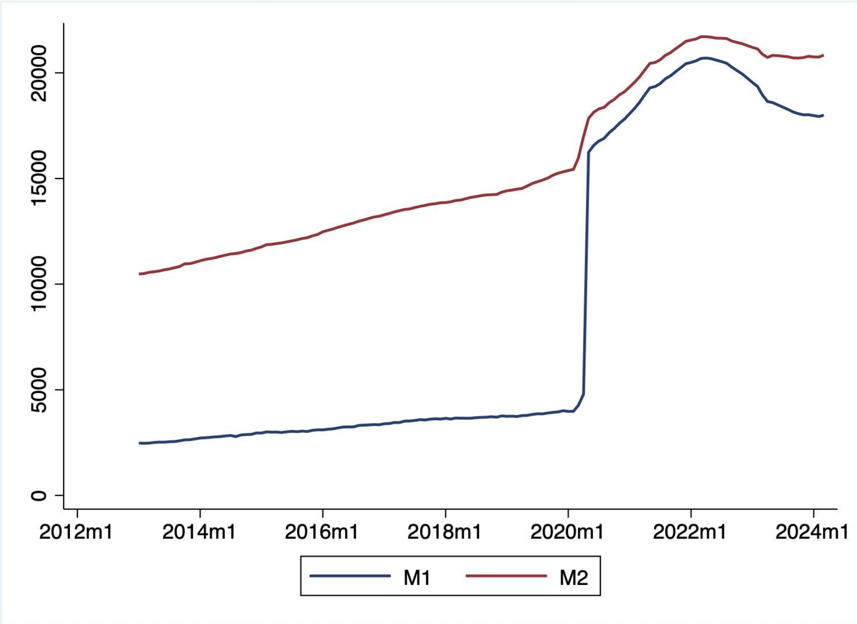
In order to stimulate the U.S. economy during the COVID-19 crisis, the Federal Reserve cut market interest rates by 50 and 100 basis points consecutively during March 2020, resulting in sudden spikes of 4.2% and 6% in stock market performance. This is consistent with the theoretical analysis in the previous chapter; that is, interest rates and the stock markets tend to have an inverse relationship. In addition to the rate cuts, the Federal Reserve offered forward guidance on the future path of the market interest rates in March 2020, using a tool honed during the Great Recession of 2007-2009. This commitment to forward guidance remained in place until December 2021, when labor markets were close to the Fed's "maximum employment" target, and inflation was well above the Fed's 2% target. In December 2021, the Federal Open Market Committee (FOMC) announced it expected to raise interest rates in three moves in 2022.

In contrast to the interest rate cuts in 2019 and 2020, from March 2022 to July 2023, the federal funds rates steadily increased from 0.25%-0.50% to 5.25%-5.50%. Specifically, from June 2022 to November 2022, there were four consecutive 75 basis point hikes during this period. Several reasons, such as policy normalization, drove this decision to raise interest rates. In early 2022, with labor market conditions improving significantly and inflation reaching levels not seen in decades, the Fed increased interest rates to slow the economy by making it more expensive to borrow and less attractive to save, thus reducing spending and investment. In addition, the Fed's raising interest rates helps prevent a wage-price spiral that could exacerbate inflationary pressures. From the analysis in the table, despite the rising interest rates, the immediate responses of stock prices are not consistently negative. The largest decline of -2.5% occurred after the December 2022 hike, while the biggest and second greatest increases of 1.5% and 1.2% showed up after the hikes in February 2023 and July 2022.

From Table 3.1, we can see that during the period from December 2015 to July 2023, there were a total of 25 interest rate changes. Within this period, interest rates increased 20 times and decreased 5 times. Of the 20 interest rate hikes, stock prices fell 13 times and increased 7 times. Of the 5 interest rate decreases, stock prices rose 3 times and fell 2 times. This is consistent with the theoretical analysis in the previous chapter. In Chapter 2, based on the theoretical analysis results, stock prices tend to have an inverse relationship with market interest rates; for instance, as interest rates rise, stock prices fall, whereas when interest rate decreases, stock prices rise. In the empirical part of Chapter 5, we will examine and verify the relationship between interest rates and stock closing prices.

### 3.2.3 Trend Analysis of the Monetary Aggregates (M1, M2)

**Figure 3.2 Line Graph of Monetary Aggregates (M1, M2) from January 2013 to March 2024 (billions of dollars)**




Source: Author's calculation in STATA 16

Figure 3.2 depicts changes in the measures of money supply, M1 and M2, from January 2013 to March 2024. The y-axis represents the money supply in billions of dollars, while the x-axis shows the timeline, with specific markers for the beginning of each year. The changes in M1 and M2 can be divided into the following phases.

From January 2013 to February 2020, both M1 and M2 show a steady increase. M1 starts from a lower base and rises gradually, while M2, which starts from a much higher base due to the inclusion of saving deposits and money market mutual funds, also shows a consistent upward trend. The reasons for this comparatively moderate rise may be stable economic growth, declining unemployment, and wage growth, which contribute to higher consumer spending and deposits and improve business confidence and investments.

Since March 2020, there has been a significant increase in both M1 and M2. On March 15, the Federal Reserve resumed quantitative easing. It announced it would purchase $500 billion of longer-term Treasury securities and $200 billion of agency mortgage-backed securities (MBS) over the upcoming months. Later, on March 23, 2020, the Fed announced that it would continue to purchase Treasuries and agency MBS in the amounts needed and include commercial MBS in the purchases. It is worth noting that there were significant changes in M1 and M2 due to the changes in the Reserve Requirements for Depository Institutions (Regulation D). In April 2020, the Federal Reserve announced an interim final rule that removed the six-month limit on convenient transfers from the definition of "savings deposits" in Regulation D. The funds previously classified as part of M2 (savings deposits) could be considered part of M1 if they were used for transactions. Removing the six-transaction limit increased the amount of M1, making savings deposits more liquid. This change is consistent with Figure 3.2, which illustrates that in April 2020, the value of M1 was more than $4000 billion, but in May 2020, the new M1 surged to approximately $16,000 billion. In June 2020, the Fed set the purchase rates at a minimum of $80 billion per month in Treasuries and $40 billion in residential and commercial MBS. In December 2020, the Fed updated its guidance to indicate that the tapering of asset purchases would begin once the economy has made "substantial further progress" toward the Fed's goals of maximum employment and price stability.

From 2021 to June 2022, we can observe that M1 and M2 continue to increase, peaking around mid-2022, before declining moderately. This gradual increase can be attributed to the significant economic stimulus measures implemented after the COVID-19 pandemic, such as direct payments to individuals, extended unemployment assistance, and business grant schemes. Continued low interest rates and asset purchase programs (quantitative easing) also provide liquidity to the financial system and contribute to the growth of both M1 and M2.

After 2023, there are slight fluctuations in both M1 and M2. M1 stabilizes at a higher level than it was before 2020, which indicates a sustained increase in the more liquid forms of money. M2 levels off and stabilizes, reflecting adjustments in savings and other quasi-money components as the economy moves toward normalization after COVID-19. The changes in M1 and M2 have been driven primarily by monetary policy actions, such as interest rate increases and the tapering of quantitative easing. These actions play a significant role in controlling inflation and stabilizing the overall economy.

# 4. Methodology

The vector autoregression model extends the concept of autoregression from a single variable time series to a system of multiple time series data. The VAR approach models each endogenous variable as a function of the lagged values of all endogenous variables in the VAR system. Below are relevant steps in building a vector autoregression model and applying the VAR model, including the Granger causality test, impulse response functions, forecast error variance decomposition, etc.

## 4.1 Time Series Stationarity Test

To avoid spurious regression, it is necessary to first determine whether the time series data contains a unit root or is stationary. The method for testing the stationarity of time series data is known as the unit root test.

The stationarity indicates that the mean and variance of a time series data remain constant and do not vary over time and that the covariance between any two observations $X_t$ and $X_{t+k}$ depends only on the time difference $|k|$ and not on the specific value of time $t$ or $t+k$. A time series that does not have a unit root tends to revert to its historical mean. If the time series itself is stationary, then the series is integrated of order 0, denoted as $I(0)$, and no differencing is required. If the first differencing is necessary to make the data stationary, then the time series can be considered integrated of order 1, denoted as $I(1)$. Assuming that $d$ refers to the degree of differencing, the time series that is differenced $d$ times is said to be integrated of order $d$ and denoted as $I(d)$.

The most popular methods for testing the stationarity of time series data are the DF (Dickey-Fuller) test, the ADF (Augmented Dickey-Fuller) test, the PP (Phillips-Perron) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The DF test examines whether a unit root is present in a first-order AR model, which requires that the disturbance $\{u_t\}$ has white noise properties and does not exhibit autocorrelation. The Phillips-Perron (PP) test applies a nonparametric correction and is appropriate when the error terms exhibit heteroscedasticity and autocorrelation. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test determines whether a time series can be considered stationary in a deterministic trend. The test statistic of the KPSS test is based on the variance of the residuals from an autoregressive (AR) model. The computation of the statistics is complex but can be implemented with statistical software or programming languages such as Python.

The Augmented Dickey-Fuller (ADF) test is the most commonly used method among these four approaches. The ADF test extends the requirements of the DF test. The former allows for autocorrelation in the disturbance term and introduces $p$ lags of the $\Delta y$ in the DF test to ensure that $\{u_t\}$ has the white noise properties. The regression model of the ADF test can be written as：

$$\Delta y_t = \beta_0 + \delta y_{t-1} + \gamma_1 \Delta y_{t-1} + \gamma_2 \Delta y_{t-2} + \cdots + \gamma_{p-1} \Delta y_{t-p+1} + \gamma t + \varepsilon_t$$

where $\Delta y_t$ is the lagged difference terms, i.e., $\Delta y_{t-1} = y_t$- $y_{t-1}$.

The null hypothesis of the ADF test is that the time series data $Y_t$ has a unit root ($\delta$= 0), and the alternative hypothesis is that the time series is stationary without a unit root ($\delta$< 0). If the t-statistic is higher than the critical value, we can reject the null hypothesis and confirm that there is no unit root and that the time series is stationary. If the time series data still shows a unit root after the first differentiation, more degrees of differentiation are required until the time series data achieves stationarity.

The result of the ADF test is usually sensitive to the lag order ($p$). The most commonly used approaches to determine the lag order are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The AIC and BIC criteria help select the optimal lag order by penalizing the number of parameters in a model. Typically, if the lag length yields the lowest AIC or BIC value, the model can be considered parsimonious, and there is no autocorrelation in the disturbance terms.

## 4.2 Cointegration Tests

Not long after the concepts of spurious regression and unit root test were raised, Engle and Granger, Johansen, and Phillips introduced an approach to address the spurious regression problem, known as the cointegration test. Cointegration focuses on finding the long-term equilibrium relationship in two or more non-stationary time series. Studies have found that after putting two or more non-stationary time series together, the time series may display a similar pattern or linear combination, which results in a stationary time series. Only when the cointegration relationship exists among several non-stationary variables is the regression model formed by these variables regarded as meaningful. The cointegration test is also an effective way to distinguish between regression and spurious regression.

The cointegration test extracts the common stochastic trends of two or more time series data with unit roots. After being extracted, the linear combination of these time series may exhibit stationarity. Assuming two first-differenced time series $I(1)$ $\{x_t\}$, $\{y_t\}$:

$$\begin{cases} x_t = \alpha + \beta w_t + \varepsilon_t \\ y_t = \gamma + \delta w_t + u_t \end{cases}$$

where $w_t$ is the random walk, i.e., $w_t = w_{t-1} + v_t$; $e_t$, $u_t$ and $v_t$ are white noise.

The common stochastic trend $w_t$ in $\{x_t\}$ and $\{y_t\}$ can be eliminated by equation transformation. Hence, the linear regression of the two variables is:

$$\delta y_t - \beta x_t = (\alpha\delta - \beta\gamma) + (\delta\varepsilon_t - \beta u_t)$$

As there is no random walk in the model, we can conclude that $\{x_t\}$ and $\{y_t\}$ are cointegrated variables; the vectors $(\delta, -\beta)$ are cointegrating vectors.

The most common cointegration tests include the Engle-Granger test (1987) and the Johansen test (1988). The Engle-Granger test is a two-step method. It uses the ordinary least squares (OLS) technique to estimate the cointegration coefficient and then performs the ADF test on the residual series. The limitation of the Engle-Granger test is that the method is suitable for assessing the relationship between only two variables. If the scenario involves two or more non-stationary time series that are integrating together, the method cannot be used to check for cointegration. In addition, if errors arise in the first step of assessing the long-run equilibrium, the errors will inevitably be carried over into the subsequent ADF test performed in the second step.

Another cointegration test is the Johansen test. The Johansen test relies on the maximum likelihood estimation to determine the rank of the matrix (Π), known as the number of cointegrating vectors. The Johansen test consists of the trace test and the maximum eigenvalue test. The trace test is a likelihood ratio test where the test statistic is the trace, which is the sum of the diagonal elements of the matrix of generalized eigenvalues. The trace test evaluates whether the number of cointegrating vectors equals r (the null hypothesis) against the alternative hypothesis that the number of cointegrating vectors is greater than r. The maximum eigenvalue test focuses on the largest eigenvalue of a matrix in an estimated VAR model. The null hypothesis is that there are r cointegrating vectors, while the alternative hypothesis states that there are r+1 cointegrating vectors with the maximum eigenvalue test. The advantage of the Johansen test is that it permits more than one cointegrating relationship. Because of its advantages, this thesis uses the Johansen test for cointegration analysis.

## 4.3 Vector Autoregression (VAR) Analysis

The vector autoregression model is a statistical model used to analyze the dynamic relationship between multiple time series data. In contrast to univariate time series forecasting, which predicts future values of a single variable based on its past values, Sims (1980) proposed the vector autoregression model. The VAR model puts all the multiple time series together, and each variable in the model is a linear function of its own lagged values and the lagged values of other variables. A two-variable VAR($p$) can be written in matrix form as:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

where time series $\{y_{1t}, y_{2t}\}$ are dependent variables, lagged values of $\{y_{1,t-p}, y_{2,t-p}\}$ up to lag $p$ are explanatory variables, $\{\varepsilon_{1t}, \varepsilon_{2t}\}$ are uncorrelated white noise but maybe contemporaneous correlated:

$$\mathrm{Cov}(\varepsilon_{1t}, \varepsilon_{2s}) = \begin{cases} \sigma_{12} & t = s \\ 0 & \text{Other} \end{cases}$$

The main methods used to determine the optimal lag order for a VAR model include the information criteria, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The information criteria balance the model's goodness of fit and parsimony by penalizing models with more parameters. Lower AIC and BIC values indicate a better model fit.

## 4.4 Granger Causality Test

An important application of the VAR model is the Granger causality test. Introduced by Granger (1969), the econometric test states that the past values of one time series can predict the future values of another time series. When *X* is said to Granger-cause *Y*, it means that *X* improves the predictability of *Y*. The main methods for analyzing the potential relationship between two variables include the Sims test and the Granger causality test. Among them, the Granger causality test is the most widely used. The Granger causality test applies only to stationary or non-stationary cointegrated time series. The mathematical formulation of the Granger causality test can be written as:

$$y_t = \gamma + \sum_{m=1}^{p} \alpha_m y_{t-m} + \sum_{m=1}^{p} \beta_m x_{t-m} + \varepsilon_t$$

(Null hypothesis: $H_0\colon \beta_1 = \cdots = \beta_p = 0$)

Accepting the null hypothesis indicates the past values of *X* do not contribute to predicting the future values of *Y*, while failing to reject $H_0$ means that at least one lagged value of *X*, ranging from 1 to *p*, has the predictive power for *Y*. The Granger causality test is highly sensitive to the lag value, *p*. Different lag orders can produce different test results. Even minor differences in lag values can lead to completely opposite conclusions.

## 4.5 Impulse Response Functions

Since the vector autoregression model includes many parameters, and the economic meanings of the parameters can sometimes be difficult to explain, we usually report the impulse response functions of the VAR model. A change or "shock" in the *i*-th variable in a VAR model has a direct effect not only on the *i*-th variable itself but also on all other variables in the VAR system. The impulse response function (IRF) illustrates how the variation of one standard deviation in one or more variables causes changes in a specific variable over time. Assuming a VAR(*p*) model consists of *n* variables:

$$\boldsymbol{y}_t = \Gamma_0 + \Gamma_1 \boldsymbol{y}_{t-1} + \cdots + \Gamma_p \boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t$$

This equation can also be written as an infinite-order vector moving average process model:

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_t + \boldsymbol{\psi}_1 \varepsilon_{t-1} + \boldsymbol{\psi}_2 \varepsilon_{t-2} + \cdots = \boldsymbol{\alpha} + \sum_{i=0}^{\infty} \boldsymbol{\psi}_i \varepsilon_{t-i}$$

where the *n* x *n* matrix $\boldsymbol{\psi}_s$ is the partial derivative of the *n*-dimensional column vector $\boldsymbol{y}_{t+s}$ concerning the n-dimensional row vector $\boldsymbol{\varepsilon}_t'$:

$$\boldsymbol{\psi}_s = \frac{\partial \boldsymbol{y}_{t+s}}{\partial \boldsymbol{\varepsilon}_t'}$$

If we extend the matrix $\boldsymbol{\psi}_s$ in the one-dimensional case to the multidimensional case, the element of row $i$ and column $j$ becomes $(\partial \boldsymbol{y}_{i,t+s} / \partial \boldsymbol{\varepsilon}_{jt})$. It represents, assuming that the other variables and disturbance terms remain constant, the effect on the value $\boldsymbol{y}_{i,t+s}$ of the $i$-th variable in period ($t$+$s$) when the disturbance term $\boldsymbol{\varepsilon}_{jt}$ of the $j$-th variable in period $t$ increases by one unit. This allows us to view $(\partial \boldsymbol{y}_{i,t+s} / \partial \boldsymbol{\varepsilon}_{jt})$ as a function of the time interval $s$, represented as an impulse response function (IRF).

The limitation of the impulse response function is that it assumes that only $\boldsymbol{\varepsilon}_{jt}$ varies while all other disturbance terms remain constant. This assumption holds only if the disturbance terms are not contemporaneously correlated. In reality, nonetheless, contemporaneous correlation is prevalent. As a result, we use the orthogonalized impulse response function, denoted as the OIRF. The orthogonalized impulse response function separates the orthogonalized parts ($\boldsymbol{v}_t$) from the disturbance term. It calculates the effect on each variable in the VAR model over time when a component in $\boldsymbol{v}_t$ is changed. In this thesis, we will use the orthogonalized impulse response functions for analysis.

## 4.6 Variance Decomposition Analysis

Variance decomposition provides another approach to investigating the dynamic properties of the VAR model. It can provide similar information as impulse response functions, but unlike impulse response functions, variance decomposition decomposes the variance of an endogenous variable into shocks to all endogenous variables in the VAR model. It illustrates the importance of stochastic error terms of each variable.

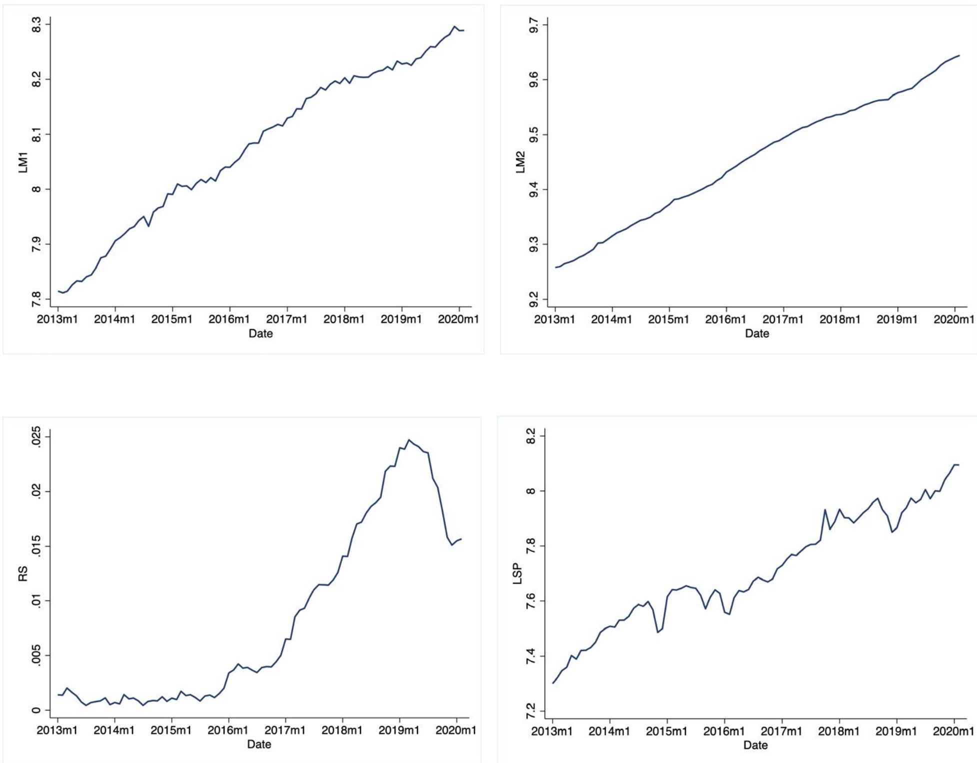
The variance decomposition attributes the proportion of each variable’s forecast error variance to its shocks and to shocks in other variables. Understanding each variable's contribution to the forecast error variance can lead to more accurate forecasts and improve the predictive power of the VAR model.

# 5. Empirical Results and Analysis

## 5.1 Data Processing

In order to eliminate heteroskedasticity in the time series data, this thesis applies the logarithmic transformation to all data mentioned in Chapter 3, except for the interest rate R. The transformed data is denoted by adding the letter "L" in front of it. After the transformation, variables such as the narrow measure of money supply M1, the broader measure of money supply M2, and the closing prices of the S&P 500 index are presented separately as LM1, LM2, and LSP.

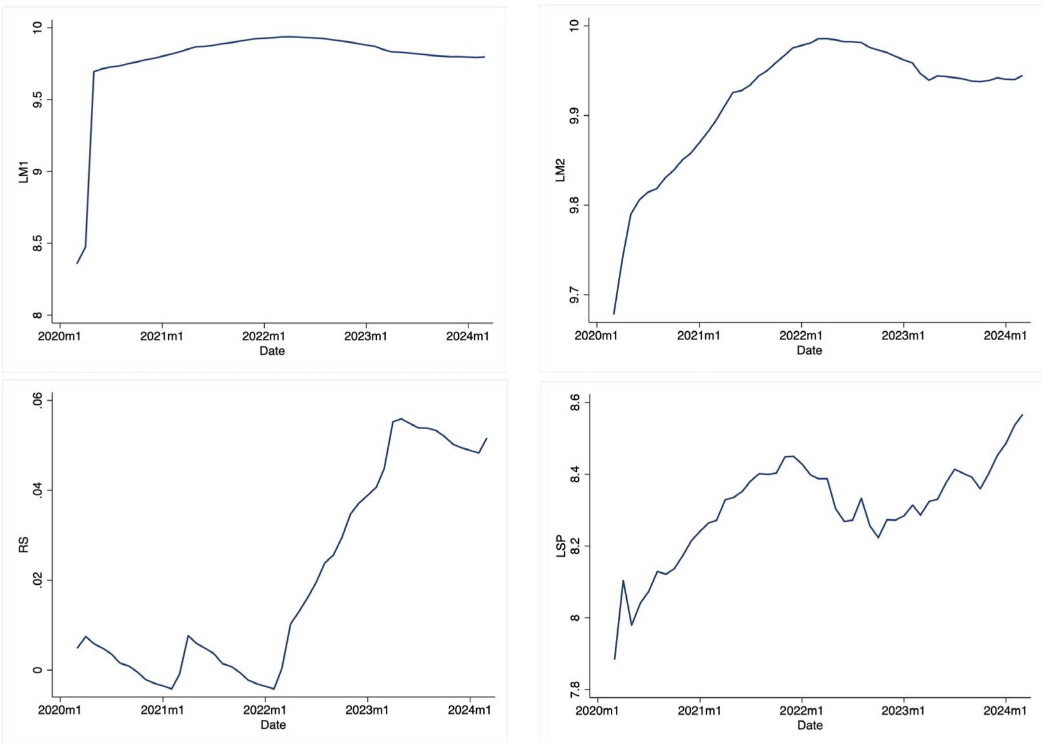
**Figure 5.1.1 LM1, LM2, RS, and LSP Trends, January 2013 - February 2020**




Source: Author’s calculation in STATA 16

Since the monthly data EFFRs are the same for specific periods, such as September 2020 to January 2021 and August 2023 to March 2024 (see Appendix A), applying first-order differencing to the raw data may result in zero values. (The author performed the Augmented Dickey-Fuller (ADF) test to examine unit-roots on the raw data before and after March 2020 without differencing and could not reject the null hypothesis for either period.) To improve model performance and data fitting, the author seasonally adjusted the federal funds rates before and after March 2020. Seasonal adjustment refers to the removals of seasonal components, such as weather, administrative measures, holidays, trading day effects, etc., from the time series data. In economic analysis, these seasonal and irregular components tend to complicate changes in economic trends, making it difficult to study and assess the current state of the economy. Thus, it is necessary to seasonally adjust time series data before performing economic analysis. Seasonal adjustment can also be used to smooth time series data, which makes it a better fit for the model.

**Figure 5.1.2 LM1, LM2, RS, and LSP Trends, March 2020 - March 2024**



Currently, there are five commonly used seasonal adjustment methods: Census X12, X-12-ARIMA, moving average, TRAMO-SEATS, and regression. The Census X12 method is mainly based on the moving average method, which tends to be not too precise at the beginning and end of the time series data. The X-12-ARIMA and TRAMO-SEATS methods are comparatively complicated. This thesis uses the regression method to adjust the data seasonally. The data after seasonal adjustment is denoted as RS.

## 5.2 Empirical Analysis of the VAR Model of the Impact of Money Supply on the Stock Market

### 5.2.1 Unit Root Test for Money Supply and S&P 500 Index Price

This thesis uses the Augmented Dickey-Fuller (ADF) unit root test to examine the stationarity of the time series data. Table 5.2.1 presents the test statistics of the first-differenced data for DLM1, DLM2, and DSLP, which cover the period from January 2013 to February 2020. The test statistics of the data are higher than the critical values at the 1% significance level, which means we can reject the null hypothesis and accept the alternative hypothesis that the first differenced data is stationary at the 99% confidence interval. The results also indicate that the variables are suitable for the cointegration test.

**Table 5.2.1 Unit Root Test Results for DLM1, DLM2 and DLSP, January 2013 - February 2020**

| Variable | DLM1 | DLM2 | DLSP |
|---|---|---|---|
| Test statistics | -13.520 | -7.945 | -9.038 |

N=84, 1% Critical value -3.532, 5% Critical value -2.903, 10% Critical value -2.586

The results of the unit root test on the time series data from March 2020 to March 2024, as illustrated in Table 5.2.2, show that the test statistics of the first-differenced data for DLM1, DLM2, and DSLP are larger than their critical values at the 1% significance level. This indicates that we can reject the null hypothesis. In addition, the results imply that the variables are suitable for the cointegration test.

**Table 5.2.2 Unit Root Test Results for DLM1, DLM2 and DLSP, March 2020 - March 2024**

| Variable | DLM1 | DLM2 | DLSP |
|---|---|---|---|
| Test statistics | -6.150 | -6.285 | -10.912 |

N=47, 1% Critical value -3.6, 5% Critical value -2.938, 10% Critical value -2.604

## 5.2.2 Johansen Cointegration Test for Money Supply and S&P 500 Index Price

In order to perform the Johansen cointegration test, the optimal lag length of the VAR model must be determined using information criteria. The results of the model selection are reported in Tables 5.2.3 and 5.2.4.

**Table 5.2.3 Optimal Lag Selection for DLM1, DLM2 and DLSP, January 2013 - February 2020**

| Lag | LL | LR | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|
| 0 | 844.899 | N/A | 2.4e-13 | -20.5341 | -20.4988 | -20.4461* |
| 1 | 858.922 | 28.046* | 2.1e-13* | -20.6566* | -20.5152* | -20.3044 |
| 2 | 866.702 | 15.558 | 2.2e-13 | -20.6269 | -20.3794 | -20.0105 |
| 3 | 871.605 | 9.8077 | 2.5e-13 | -20.527 | -20.1734 | -19.6465 |

It can be noted from Table 5.2.3 that the optimal lag length for the Johansen cointegration test is one (1). This conclusion is drawn from the observation that the Likelihood Ratio (LR) reaches its highest value while the values of FPE, AIC, and

HQIC are minimized, which indicates a better trade-off between model complexity and fitness.

**Table 5.2.4 Optimal Lag Selection for DLM1, DLM2 and DLSP, March 2020 - March 2024**

| Lag | LL | LR | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|
| 0 | 471.023 | N/A | 1.9e-13 | -20.801 | -20.7561 | -20.6806 |
| 1 | 544.284 | 146.52 | 1.1e-14* | -23.6571* | -23.4775* | -23.1753* |
| 2 | 546.163 | 3.757 | 1.5e-14 | -23.3406 | -23.0263 | -22.4975 |
| 3 | 557.403 | 22.481* | 1.4e-14 | -23.4401 | -22.9911 | -22.2357 |

As the AIC and SBIC criteria reach their minimum values while the optimal lag length is one (1), we adopt 1 as the lag value for the VAR model.

The Johansen cointegration test, proposed by Søren Johansen in 1988 and later refined with Katarina Juselius in 1990, is a method used to determine whether two or more time series are cointegrated, i.e., if the time series share a long-term equilibrium relationship despite being non-stationary in their levels. Cointegration refers to the time series moving together over time and the temporary deviations from this relationship. The author uses the Johansen cointegration test to examine the long-term cointegration relationship among the variables DLM1, DLM2, and DLSP. The results of the tests are presented in Tables 5.2.5 and 5.2.6.

**Table 5.2.5 Johansen Cointegration Test Results for Money Supply and S&P 500 Index, January 2013 - February 2020**

| Rank | LL | Eigenvalue | Trace Statistic | 5% Critical Value |
|---|---|---|---|---|
| 0 | 770.35672 | N/A | 179.6812 | 24.31 |
| 1 | 826.7289 | 0.73873 | 66.9369 | 12.53 |
| 2 | 857.28977 | 0.51695 | 5.8151 | 3.84 |
| 3 | 860.19732 | 0.06689 | | |

**Table 5.2.6 Johansen Cointegration Test Results for Money Supply and S&P 500 Index, March 2020 - March 2024**

| Rank | LL | Eigenvalue | Trace Statistic | 5% Critical Value |
|---|---|---|---|---|
| 0 | 254.24591 | N/A | 150.4734 | 24.31 |
| 1 | 295.49952 | 0.82717 | 67.9662 | 12.53 |
| 2 | 317.57724 | 0.60917 | 23.8108 | 3.84 |
| 3 | 329.48262 | 0.39747 | | |

Source: Author's calculation in STATA 16

Tables 5.2.5 and 5.2.6 suggest long-term equilibrium relationships among DLM1, DLM2, and DLSP for January 2013 to February 2020 and March 2020 to March 2024. Hence, the author conducts Granger causality and other tests on the economic data within these two periods.

### 5.2.3 Granger-causality Test for Money Supply and S&P 500 Index Price

The table below shows the results of the Granger causality test between DLM1, DLM2, and DLSP from January 2013 to February 2020.

**Table 5.2.7 Granger-causality Test Results for DLM1, DLM2 and DLSP, January 2013 - February 2020**

| Null Hypothesis | chi-square | p-value |
|---|---|---|
| DLM1 does not Granger cause DLSP | 1.6115 | 0.204 |
| DLSP does not Granger cause DLM1 | 2.1147 | 0.146 |
| DLM2 does not Granger cause DLSP | 3.392 | 0.066 |
| DLSP does not Granger cause DLM2 | .02716 | 0.869 |

N=84. Source: Author's calculation in STATA 16

From Table 5.2.7, for the period from January 2013 to February 2020, the probability that the narrow measure of money supply (DLM1) does not Granger cause the S&P 500 index price (DLSP) is 0.204, which means that the past values of DLM1 do not significantly explain the variations in stock prices. The probability that the S&P 500 index price does not Granger cause DLM1 is 0.146. For the broad measure of money supply (DLM2), the probability that DLM2 does not Granger cause the SP500 index price is 0.066. The F-statistic (3.392) indicates some, but not significant, explanatory power of the money supply measure M2 for variations in the S&P 500 price. The probability that the S&P 500 closing price does not Granger cause DLM2 is 0.869. Thus, we cannot reject the null hypothesis and conclude that neither DLM1 nor DLM2 Granger cause S&P 500 index prices (DLSP).

**Table 5.2.8 Granger-causality Test Results for DLM1, DLM2 and DLSP, March 2020 - March 2024**

| Null Hypothesis | chi-square | p-value |
|---|---|---|
| DLM1 does not Granger cause DLSP | 1.9692 | 0.161 |
| DLSP does not Granger cause DLM1 | 4.9527 | 0.026 |
| DLM2 does not Granger cause DLSP | 2.0375 | 0.153 |
| DLSP does not Granger cause DLM2 | .54741 | 0.459 |

Table 5.2.8 presents the results of the Granger causality test for DLM1, DLM2, and DLSP from March 2020 to March 2024.

From Table 5.2.8, for the period from March 2020 to March 2024, the probability that the narrow measure of the money supply (DLM1) does not Granger cause the S&P 500 closing price (DLSP) is 0.161. This means that the past values of DLM1 do not significantly explain the variation in stock prices. The probability that the S&P 500 index price does not Granger cause DLM1 is 0.026. For the broad measure of the money supply (DLM2), the probability that DLM2 does not Granger cause the S&P 500 index prices is 0.153, while the probability that the S&P 500 index price does not Granger cause DLM2 is 0.459. Thus, we can reject the null hypothesis that DLSP does not Granger-cause DLM1, but we cannot reject the null hypothesis that neither DLM1 nor DLM2 Granger-cause the S&P 500 index price (DLSP).

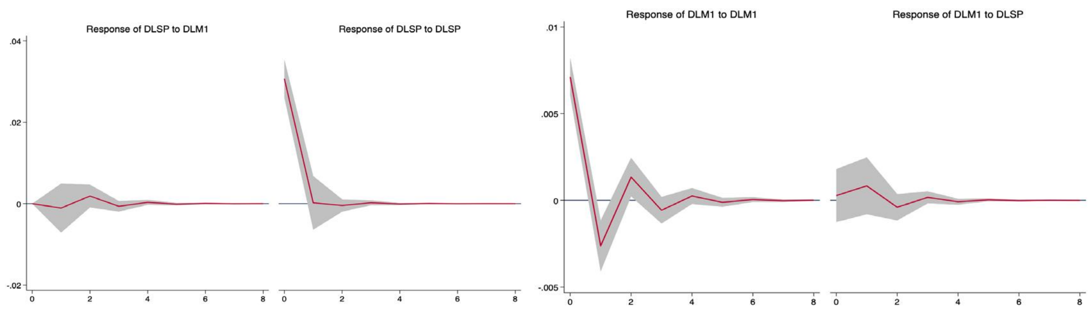
The Granger causality test results are inconsistent with most economic research. This is likely because this thesis uses recent economic data, and the changes in the capital markets in recent years appear drastic. At the same time, in terms of data processing and preparation, to prevent heteroskedasticity, this thesis uses log-normalized data for most variables instead of employing absolute values, as observed in several previous studies.

### 5.2.4 Impulse Response Analysis for Money Supply and S&P 500 Closing Prices

Tables 5.2.9 and 5.2.10 show the impulse response analysis results for the money supply DLM1, DLM2, and S&P 500 stock prices DLSP from January 2013 to February 2020.

**Figure 5.2.1 Impulse Response Analysis for DLM1 and DLSP, January 2013 - February 2020**

**Response to Cholesky One S.D. Innovations**

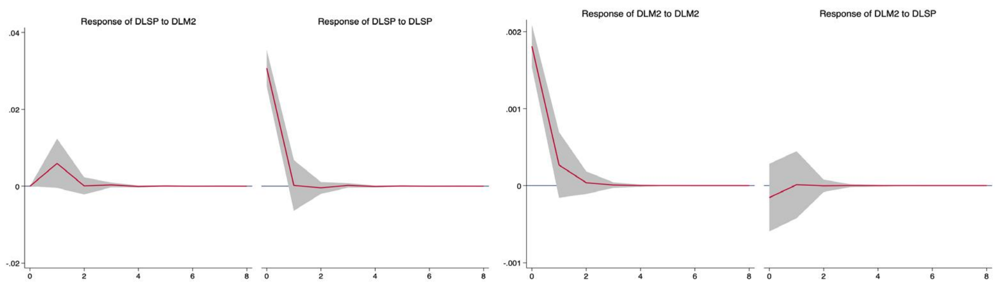



The first graph in Figure 5.2.1 illustrates the response of DLSP to a one-standard-deviation shock in DLM1. The response of DLSP is initially negative but shifts to positive at time 2. Nevertheless, the overall magnitude of the impact is minimal. The second graph shows how DLSP reacts to a one-standard deviation shock itself. The impact is 0.04 at time 0, then decreases rapidly and stabilizes at 0 since t=1. From the last graph, we see that the response of DLM1 to DLSP fluctuates between positive and negative values, but the overall impact is minimal.

The first graph in Figure 5.2.2 depicts the response of DLSP to DLM2. When there is a positive shock in DLM2, its effect on DLSPS peaks at t = 1 with a positive impact. The effect gradually decreases to zero as time progresses. The second graph represents the response of DLSP to a shock of one standard deviation from itself. The impact is 0.04 at time 0, then decreases rapidly and stabilizes at 0 since t=1. The last graph demonstrates that the response of DLM2 to DLSP is negative, with a negligible influence on the shock.

**Figure 5.2.2 Impulse Response Analysis for DLM2 and DLSP, January 2013 - February 2020**

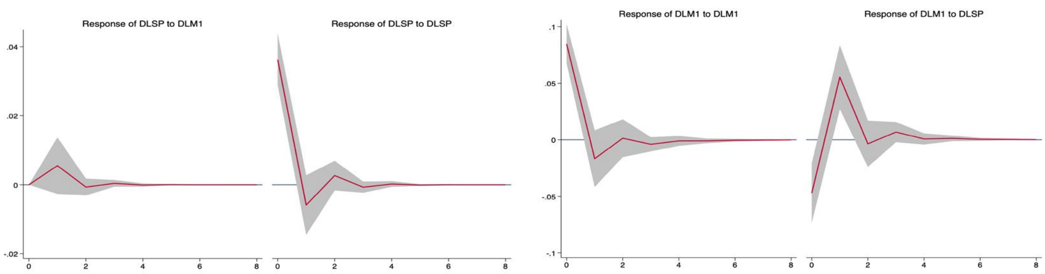
**Response to Cholesky One S.D. Innovations**




Tables 5.2.11 and 5.2.12 show the impulse response analysis results for the money supply measures DLM1, DLM2, and stock closing prices from March 2020 to March 2024.

**Figure 5.2.3 Impulse Response Analysis for DLM1 and DLSP, March 2020 - March 2024**

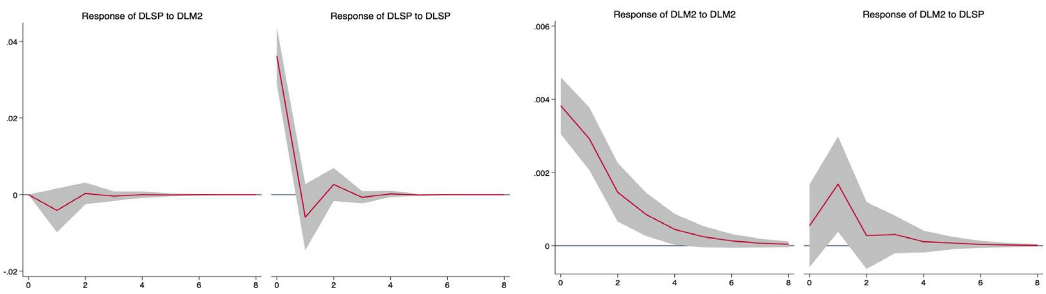
**Response to Cholesky One S.D. Innovations**




The first graph in Figure 5.2.3 illustrates how DLSP responds to DLM1. For a positive shock in DLM1, the effect on DLSP is negative. At t=0, the effect is 0, then it rises to its highest value of 0.01 at t=1 and disappears over time. The second graph shows how DLSP reacts to a shock of one standard deviation from itself. The impact is immediate, reaching about 0.04 at time 0, then it decreases rapidly, approaching approximately -0.005 at time 1 and rebounding to 0.003 at t=2, then the impact gradually weakens and approaches 0. From the last graph, we can observe that from March 2020 to March 2024, the response of DLM1 to DLSP varies between positive and negative values, but the magnitude of the impact is not significant.

**Figure 5.2.4 Impulse Response Analysis for DLM2 and DLSP, March 2020 - March 2024**

**Response to Cholesky One S.D. Innovations**




The first graph in Figure 5.2.4 illustrates how DLSP responds to DLM2. After a positive shock to DLM2, the effect on DLSP is negative, starting at 0 at t=0 and decreasing to approximately -0.005. The second graph shows how DLSP responds to a shock of one standard deviation from itself. The impact is immediate, reaching around 0.04 at time 0, then declines rapidly, approaching about -0.005 at time 1 and rebounding to 0.003 at t=2, then the impact gradually weakens and approaches 0. From the last graph, we can see that from March 2020 to March 2024, the response of DLM2 to DLSP is positive, but the magnitude of the impact is not significant.

### 5.2.5 Forecast Error Variance Decomposition Analysis for S&P 500 Closing Prices

The numbers in the forecast error variance decomposition table represent the contribution of each variable. The total contribution of each variable equals 100.

**Table 5.2.9 Variance Decomposition Analysis for DLSP, January 2013 - February 2020**

| t | DLSP | DLM1 | DLM2 |
|---|---|---|---|
| 1 | 1 | 0 | 0 |
| 2 | 96.277 | 0.1199 | 3.6031 |
| 3 | 95.936 | 0.474 | 3.5901 |
| 4 | 95.8839 | 0.5168 | 3.5993 |
| 5 | 95.8735 | 0.5268 | 3.5997 |
| 6 | 95.8715 | 0.5286 | 3.5999 |
| 7 | 95.8712 | 0.5289 | 3.5999 |

| | | | |
|---|---|---|---|
| 8 | 95.8711 | 0.529 | 3.5999 |

From Table 5.2.9, we can see that from January 2013 to February 2020, the contribution of DLM1 to DLSP is nominal, only about 0.5%. Although the contribution of DLM2 to DLSP appears to be higher, it is still modest at 3.6%. The main contribution of DLSPS is DLSPS itself, with an average explanatory power of approximately 95.8%.

**Table 5.2.10 Variance Decomposition Analysis for DLSP, March 2020 – March 2024**

| t | DLSP | DLM1 | DLM2 |
|---|---|---|---|
| 1 | 100 | 0 | 0 |
| 2 | 96.6081 | 2.1858 | 1.2061 |
| 3 | 96.5878 | 2.2055 | 1.2067 |
| 4 | 96.5673 | 2.2164 | 1.2163 |
| 5 | 96.567 | 2.2167 | 1.2163 |
| 6 | 96.5667 | 2.2168 | 1.2165 |
| 7 | 96.5667 | 2.2168 | 1.2165 |
| 8 | 96.5667 | 2.2168 | 1.2165 |

From Table 5.2.9, we can notice that for the period from March 2020 to March 2024, the contributions of DLM1 and DLM2 to DLSPS appear to be minimal but stable, with 2.22% and 1.22%, respectively. The main contributor to DLSP is DLSP itself, which is 100% at t=1 and remains about 96.5% from time 2 to 8.

## 5.3 Empirical Analysis of the VAR Model of the Impact of Interest Rates on the Stock Market

### 5.3.1 Unit Root Test for Interest Rate and S&P 500 Index Price

As the unit root test on the S&P 500 stock prices was carried out in the previous section, the author performs the ADF test on the interest rates *R* only in section 5.3.1 to assess the stationarity of the time series.

The Augmented Dickey-Fuller (ADF) test results on the first-differenced data from January 2013 to February 2020 show that interest rates are stationary at the 1%

critical value. This also indicates that the variable is suitable for a cointegration test in the next section.

**Table 5.3.1 Unit Root Test Results for DRS, January 2013 - February 2020**

| Variable | Test statistic | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| DRS | -6.229 | -3.532 | -2.903 | -2.586 |

**Table 5.3.2 Unit Root Test Results for DRS, March 2020 - March 2024**

| Variable | Test statistic | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| DRS | -3.994 | -3.600 | -2.938 | -2.604 |

After applying a unit root test to the variable DRS from March 2020 to March 2024, the results show that the DRS is non-stationary in this period. As a result, a first-order difference is applied to the data. The results of the ADF test on the first-order differenced data show that the time series is stationary from March 2020 to March 2024. A cointegration test is then applied to examine the existence of a long-run equilibrium relationship between the two variables.

### 5.3.2 Johansen Cointegration Test between Interest Rates and S&P 500 Closing Prices

Tables 5.3.3 and 5.3.4 below show the results of the optimal lag selection for the VAR models, which consist of interest rates and S&P 500 stock prices for the two specified time periods.

**Table 5.3.3 Optimal Lag Selection for DRS and DLSP, January 2013 – February 2020**

| Lag | LL | LR | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|
| 0 | 595.778 | N/A | 6.9e-10 | -15.4228 | -15.3984 | -15.3619* |
| 1 | 601.86 | 12.165 | 6.5e-10 | -15.4769 | -15.4038 | -15.2943 |
| 2 | 610.393 | 17.065* | 5.8e-10* | -15.5946* | -15.4729* | -15.2902 |
| 3 | 612.717 | 4.6475 | 6.0e-10 | -15.5511 | -15.3806 | -15.1249 |

The results in Table 5.2.3 indicate that the optimal lag length for the Johansen cointegration test is two (2). This conclusion is drawn from the fact that the Likelihood Ratio (LR) reaches its highest value while the values of FPE, AIC, and HQIC are minimized, which suggests a better trade-off between model complexity and fitness.

**Table 5.3.4 Optimal Lag Selection for DRS and DLSP, March 2020 - March 2024**

| Lag | LL | LR | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|
| 0 | 278.573 | N/A | 1.2e-08 | -12.5715 | -12.5414 | -12.4904 |
| 1 | 290.777 | 24.408* | 8.2e-09* | -12.9444* | -12.8542* | -12.7011* |
| 2 | 292.162 | 2.7706 | 9.2e-09 | -12.8256 | -12.6752 | -12.4201 |
| 3 | 292.982 | 1.6381 | 1.1e-08 | -12.681 | -12.4705 | -12.1133 |

According to the LR test result and the AIC criterion, we choose a lag value of 2 for the data of money supply and stock closing prices in both VAR models.

Tables 5.3.5 and 5.3.6 give the results of the Johansen cointegration test for interest rates and S&P 500 closing prices for the two specified time periods.

**Table 5.3.5 Johansen Cointegration Test Results for Money Supply and S&P 500 Index, January 2013 - February 2020**

| Rank | LL | Eigenvalue | Trace Statistic | 5% Critical Value |
|---|---|---|---|---|
| 0 | 623.10383 | N/A | 48.7507 | 12.53 |
| 1 | 641.72195 | 0.36150 | 11.5144 | 3.84 |
| 2 | 647.47918 | 0.12954 | | |

**Table 5.3.6 Johansen Cointegration Test Results for Money Supply and S&P 500 Index, March 2020 - March 2024**

| Rank | LL | Eigenvalue | Trace Statistic | 5% Critical Value |
|---|---|---|---|---|
| 0 | 265.24154 | N/A | 68.9624 | 12.53 |
| 1 | 294.54219 | 0.71259 | 10.3611 | 3.84 |
| 2 | 299.72274 | 0.19784 | | |

Table 5.3.5 reports the existence of cointegrating relationships between DLSP and DRS from January 2013 to February 2020 at the 5% significance level. In the same

way, Table 5.3.6 shows a cointegrating relationship between DLSP and DRS from March 2020 to March 2024 at the 5% significance level. Thus, we will perform Granger causality and other tests on the economic data for these two periods.

### 5.3.3 Granger-causality Test for Interest Rates and S&P 500 Closing Prices

Tables 5.3.7 and 5.3.8 show the results of the Granger causality test for interest rates and S&P 500 closing prices.

**Table 5.3.7 Granger-causality Test Results for DRS and DLSP, January 2013 - February 2020**

| Null Hypothesis | chi2 | Probability |
|---|---|---|
| RSA does not Granger cause DLSP | 0.26171 | 0.190 |
| DLSP does not Granger cause RSA | 0.43148 | 0.902 |

Table 5.3.7 indicates that for the period between January 2013 and February 2020, the probability that interest rates DRS do not Granger-cause the S&P 500 stock index prices DLSP is 0.19. The probability that the S&P 500 stock index prices do not Granger-cause the interest rates DRS is 0.902. Therefore, we can conclude that the interest rates of DRS do not Granger cause the S&P 500 index prices of DLSPS during this period.

**Table 5.3.8 Granger-causality Test Results for DRS and DLSP, March 2020 - March 2024**

| Null Hypothesis | chi square | p-value |
|---|---|---|
| DRS does not Granger cause DLSP | 5.8586 | 0.016 |
| DLSP does not Granger cause DRS | 6.4389 | 0.011 |

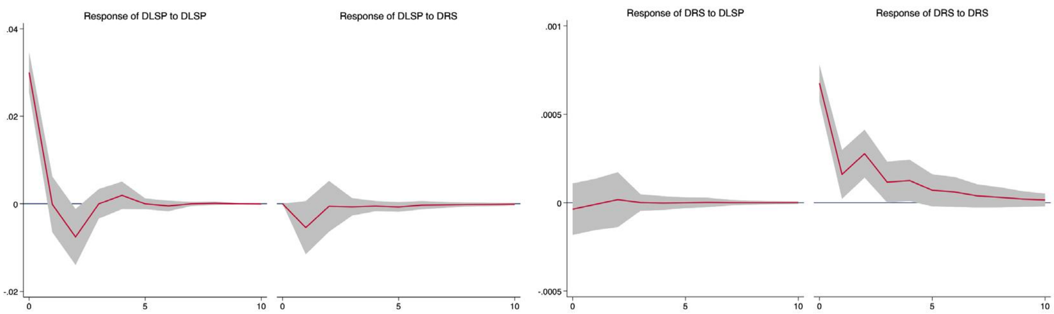
As the p-value (0.016) is less than the significance level of 0.05, we reject the null hypothesis that DRS does not Granger cause DLSP, indicating that the past values of interest rates can help predict the S&P 500 stock index prices. Similarly, the p-value of DLSP does not Granger-cause DRS is 0.011, which is also less than the 0.05 significance level. Thus, we reject the null hypothesis that DLSP does not Granger cause DRS. This indicates that the past values of S&P 500 stock index prices can help predict market interest rates. Hence, we can conclude that bidirectional Granger causality exists between market interest rates and S&P 500 index prices. This mutual predictive relationship might also indicate that changes in one variable can be used to predict those in the other within the timeframe of March 2020 to March 2024.

### 5.3.4 Impulse Response Analysis for Interest Rates and S&P 500 Closing Prices

The results of the impulse response analysis for the interest rates and S&P 500 closing prices are listed in Figures 5.3.1 and 5.3.2.

**Figure 5.3.1 Impulse Response Analysis for DRS and DLSP, January 2013 - February 2020**

**Response to Cholesky One S.D. Innovations**

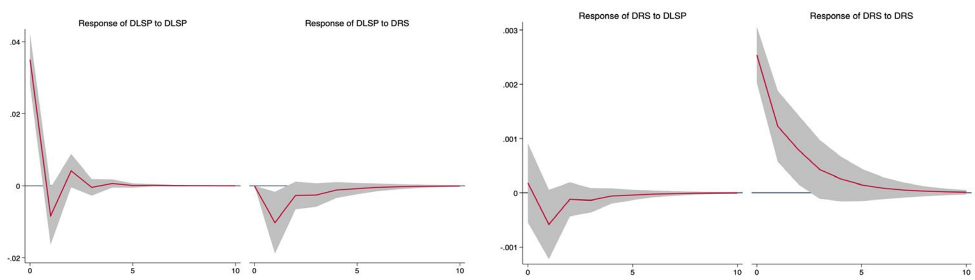



The first graph in Figure 5.3.1 illustrates that when DLSP experiences a shock of one standard deviation, the effect is positive, peaking before t=1, then declining rapidly and gradually approaching zero. For a positive shock in DRS, the impact on DLSP is initially negative. At t=1, it reaches a minimum value of approximately -0.01 and gradually increases. The impact reaches zero at t=3. The third graph illustrates the response of DRS to a shock of one standard deviation in DLSP. The impact is mostly positive but with a negligible level of influence.

The first graph in Table 5.3.2 illustrates that the response of DLSP to a shock of one standard deviation in DLSP is positive overall. The effect is largest at t=0 and then gradually decreases to 0. The second graph shows that for a positive shock in DRS, the impact on DLSP is 0 before t=1. After that, the impact gradually decreases and reaches its lowest peak at t=2, then increases until it reaches 0 at t=10. The third graph illustrates the response of DRS to a shock of one standard deviation in DLSP. The impact varies between positive and negative, but with an insignificant level of impact.

**Figure 5.3.2 Impulse Response Analysis for DRS and DLSP, March 2020 – March 2024**

**Response to Cholesky One S.D. Innovations**




## 5.3.5 Forecast Error Variance Decomposition Analysis for S&P 500 Index Closing Prices

Tables 5.3.9 and 5.3.10 present variance decomposition analysis between DRS and DLSP for the two specified time periods.

**Table 5.3.9 Variance Decomposition Analysis for DLSP, January 2013 to February 2020**

| t | DLSPS | DRS |
|---|---|---|
| 1 | 100 | 0 |
| 2 | 96.8202 | 3.1798 |
| 3 | 96.9736 | 3.0264 |
| 4 | 96.9265 | 3.0735 |
| 5 | 96.9117 | 3.0883 |
| 6 | 96.8618 | 3.1382 |
| 7 | 96.8536 | 3.1464 |
| 8 | 96.8482 | 3.1518 |
| 9 | 96.8454 | 3.1546 |
| 10 | 96.8434 | 3.1566 |

From Table 5.3.9, we can observe that from January 2013 to February 2020, DRS contributed only about 3% to DLSP. The main contributor to DLSP is the S&P 500 stock prices, with an average explanatory power of 96%.

**Table 5.3.10 Variance Decomposition Analysis for DLSP, March 2020 to March 2024**

| t | DLSP | DRS |
|---|---|---|
| 1 | 100 | 0 |
| 2 | 92.5195 | 7.4805 |
| 3 | 92.1401 | 7.8599 |
| 4 | 91.7127 | 8.2873 |
| 5 | 91.6273 | 8.3727 |
| 6 | 91.5885 | 8.4115 |
| 7 | 91.5774 | 8.4226 |
| 8 | 91.5733 | 8.4267 |
| 9 | 91.5720 | 8.4280 |
| 10 | 91.5716 | 8.4284 |

Table 5.3.10 shows that from January 2013 to February 2020, the contribution of DRS to DLSP is only about 8%. The main contributor to DLSP is DLSP itself, with an average explanatory power of 91%.

## 5.4 Result Analysis

From the results of the Granger causality test, we can conclude that the money supply measures, M1 and M2, and federal funds rate from January 2013 to February 2020 do not provide significant information about the future values of the changes in the closing prices of the S&P 500 index. Therefore, we do not reject the null hypothesis that all three variables do not Granger cause the S&P 500 index prices. For the period from March 2020 to March 2024, the results of the Granger causality test indicate that the money supply measures, M1 and M2, do not provide significant information about the future values of the S&P 500 index prices at the 5% significance level. Therefore, we cannot reject the null hypothesis that M1 and M2 do not Granger cause the S&P 500 prices. On the other hand, the federal funds rates provide significant information about the future values of the changes in the S&P 500 prices, so we reject the null hypothesis and confirm that the federal funds rates Granger cause the changes in the closing prices of the S&P 500 index during March 2020 to March 2024.

The impulse response analysis was conducted to examine the response of S&P 500 closing prices to a one-standard-deviation shock in monetary aggregates, M1 and M2, and the federal funds rate. From the results of the two periods, we can observe that stock prices respond positively to a shock in M1, which is consistent with the theoretical analysis in Chapter 2, which states that stock prices are positively related to changes in monetary aggregates. It's worth noting that the lag of the response of S&P 500 prices to M1 is about one month for January 2013 to February 2020. The response is around 0 at t=1 and then increases to 0.005 at t=2. On the other hand, the results for the monetary aggregate measure M2 seem to be different. From January 2013 to February 2020, the impact of a one-standard-deviation shock in M2 is positive, while it becomes negative from March 2020 to March 2024. This may be due to economic uncertainties; for example, large increases in the money supply may signal that the central bank is trying to combat economic weakness. With the higher risk premium demanded by investors due to COVID-19, market participants may become more concerned about the economy's underlying health, reducing confidence in future corporate earnings and, thus, stock prices. Regarding interest rates, the response of the S&P 500 Index prices to a shock in the federal funds rate is negative for both periods, and the responses are immediate. More specifically, a shock to the federal funds rate causes an initial decline in stock prices, with the decline reaching a minimum at t=1 and gradually increasing. The results are consistent with the theoretical analysis that an increase in interest rates leads to a decline in stock prices. In addition, it's worth noting that the magnitude of the S&P 500's response to a shock in the federal funds rate from January 2013 to February 2020 appears to be larger than that for the period from March 2020 to March 2024. This may be because from March 2020 to the end of December 2022, the Federal Reserve lowered market interest rates to almost 0 in response to the COVID-19 crisis. It's also noticeable that the impact for both periods disappears only at t=10, indicating that the time lag of the stock price response to interest rates is relatively short, less than one year.

From the results of the variance decomposition, we can observe that for the period January 2013 to February 2020, with respect to the role of M1, M2, and the federal funds rate in the S&P 500 price movements, most of the variance of the forecast error in the stock price can be attributed to shocks within the stock price itself. M1, M2, and the federal funds rate contribute only 0.53%, 3.6%, and 3.16%, respectively. From March 2020 to March 2024, the contribution of the money measures M1 and M2 appears to be still modest, accounting for only 2.2% and 1.2% of the forecast error variance of stock index prices. In contrast, the contribution of the federal funds rate is much larger than in the previous period, and the effect is immediate. At t=2, 7.5% of the forecast error variance in stock prices is due to fed funds rate shocks. At t=10, the contribution of interest rates is 8.4%. This indicates that after March 2020, the rate cuts have had an effective impact on stock market performance.

From the above results, we can summarize that for the period from January 2013 to February 2020, all three monetary policy indicators, M1, M2, and the federal funds rate, cannot effectively influence stock market performance. From March 2020 to March 2024, the monetary aggregates, M1 and M2, cannot effectively impact the stock markets, but the federal funds rate has an impact on the U.S. stock markets.

In 2020, in response to COVID-19, the Federal Reserve enacted a series of aggressive monetary policy actions, which aimed at providing liquidity to financial markets, lowering borrowing costs, and supporting economic activity. The Fed began reducing its target federal funds rate by 50 basis points in early March, followed by another 100 basis point reduction on March 15. In addition, the Fed launched large-scale asset purchase programs, commonly called quantitative easing (QE), to purchase Treasuries and mortgage-backed securities, further lowering long-term interest rates and providing liquidity to credit markets. These monetary policy actions helped stabilize financial markets and restore investor confidence. By lowering borrowing costs for businesses and households, the Fed's monetary stimulus supported consumer spending, business investment, and housing market activity, bolstering overall economic activity. In addition, the Federal Reserve implemented several emergency lending facilities to support key sectors of the economy, including the corporate bond market, the municipal bond market, and small and medium-sized businesses. These facilities helped alleviate strains in credit markets and ensure the smooth functioning of financial intermediation, preventing a liquidity crisis and supporting the flow of credit to businesses and households. Feldkircher, Huber, and Pfarrhofer (2021) propose a new mixed-frequency vector autoregressive (MF-VAR) model to examine the effects of the Federal Reserve's monetary policy stance in response to the COVID-19 recession. They use weekly and monthly data from the first week of 2011 to the 24th week of 2020, including the response of the CPI to monetary easing, the money supply (M2), the NASDAQ composite index, and nine other variables. By simulating the effects of expansionary monetary policy in the model, they conclude that it stimulates economic growth through higher stock prices and more favorable long-term financing conditions. In addition, monetary policy caused a depreciation of the U.S. currency and supported the external competitiveness of the economy.

Nevertheless, based on the results from March 2020 to March 2024 in this thesis, the effect of monetary aggregates and interest rates on stock market performance still seems limited. We believe that this might be due to the following reasons:

i. A variety of factors affect stock market performance. In addition to interest rates and money supply, other factors such as corporate events, corporate earnings, investor sentiments and geopolitical conditions, etc. can affect the S&P 500 stock index prices. This might lead to biased test results. This explains the fact that whether it is from January 2013 to February 2020 or from March 2020 to March 2024, the degree to which the stock price itself is explained in the FEVD is greater than 90 percent. If other factors are considered, the degree of explanation of the stock index price itself would be lower, and the results of other tests, such as the Granger causality test and impulse response analysis, would also be more significant.

ii. Speculative behaviors still tend to dominate the capital markets. Despite the fact that market participants have become more rational in their decision-making, a considerable number of participants still trade stocks based on speculation rather than investments. This prevalence of speculative activity can potentially disrupt the normal reaction of stock prices to changes in market interest rates.

iii. We use the vector autoregressive (VAR) model to examine the relationship between interest rates, money supply, and S&P 500 stock index prices. There are also other models for exploring the relationship between stock prices and monetary policy, such as the vector error correction model (VECM), autoregressive distributed lag (ARDL) model, structural equation modeling (SEM), etc. At the same time, we applied log normalization and first differencing on stock prices, M1 and M2, and seasonally adjusted the market interest rates. This data processing process may lead to missing information in the raw data.

iv. The economic data for the thesis is from January 2013 to March 2024, a total of 135 time series data observations. We divided the data into 86 observations from January 2013 to February 2020 and 49 observations from March 2020 to March 2024. The latter is a relatively short period, which might lead to biases in the empirical results. The results might be different if we extend the time frame of the second phase.

# 6. Conclusion

This thesis examines the importance of monetary policy on the stock markets in the United States. Monetary policy is measured from two aspects: interest rates and money supply measures, M1 and M2. The data spans from January 2013 to March 2024 and is segregated with March 2020, the peak of the COVID-19 crisis. Since we are exploring the linear interdependence among multivariate time series data, we use the Vector Autoregressive (VAR) model in this thesis. To understand the predictability of one variable on another and a shock of one standard deviation in a variable on the current and further values of other variables, the author uses the Granger causality test and impulse response analysis to investigate these dynamics. In addition, the Forecast Error Variance Decomposition (FEVD) approach is used to study the forecast error variance of a variable due to shocks in each variable in the VAR system. The conclusions of the thesis are as follows: 1. the long-run relationships exist between stock prices and monetary aggregates and between stock prices and interest rates; 2. for the period from March 2020 to March 2024, the federal funds rate can help predict the S&P 500 stock index prices, and we can argue that the federal funds rate Granger-causes the S&P 500 stock prices; 3. for both periods, stock prices react positively to shocks to the S&P 500 stock index itself. Specifically, stock prices react positively to an initial shock, and the reaction declines rapidly and converges to 0 by the 5th month. Stock prices react positively to a shock in M1 with a comparatively small magnitude. Stock prices react negatively to a shock in the federal funds rate with a minimal magnitude; 4. from the FEVD, we can see that the forecast error variance of stock prices is mainly explained by itself, with a contribution of over 90% for both periods. This indicates that stock prices are mainly influenced by their own innovations.

The results of this thesis provide us with some insights. Firstly, for investors, we can see that the price movement of a stock index does not depend solely on changes in interest rates or the amount of money supply. That is, a rise or fall in interest rates or the money supply does not fully explain the movement in stock prices. A series of other factors, such as investor sentiments, political factors, corporate events, or corporate earnings, should also be considered in the investment decision-making process. Moreover, we find that the interest rate is an effective indicator of the impact of monetary policy on stock markets to a certain extent. Governments are advised to adjust economic activities by controlling interest rates, playing the critical role of market interest rates.

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# Appendix A

A.1 Monthly data of S&P 500 price, effective federal funds rate, money supply

| Date | S&P 500 Index | Effective Federal Funds Rate | M1 | M2 |
|---|---|---|---|---|
| 2013/1/1 | 1,480.40 | 0.14% | 2,476.70 | 10,482.90 |
| 2013/2/1 | 1,512.31 | 0.15% | 2,468.90 | 10,501.30 |
| 2013/3/1 | 1,550.83 | 0.14% | 2,476.30 | 10,558.30 |
| 2013/4/1 | 1,570.70 | 0.15% | 2,504.90 | 10,586.30 |
| 2013/5/1 | 1,639.84 | 0.11% | 2,523.50 | 10,621.00 |
| 2013/6/1 | 1,618.77 | 0.09% | 2,521.00 | 10,678.70 |
| 2013/7/1 | 1,668.68 | 0.09% | 2,542.30 | 10,718.40 |
| 2013/8/1 | 1,670.09 | 0.08% | 2,551.30 | 10,776.60 |
| 2013/9/1 | 1,687.17 | 0.08% | 2,585.50 | 10,837.20 |
| 2013/10/1 | 1,720.03 | 0.09% | 2,631.20 | 10,961.60 |
| 2013/11/1 | 1,783.54 | 0.08% | 2,638.80 | 10,969.70 |
| 2013/12/1 | 1,807.78 | 0.09% | 2,674.20 | 11,035.00 |
| 2014/1/1 | 1,822.36 | 0.07% | 2,714.10 | 11,105.70 |
| 2014/2/1 | 1,817.03 | 0.07% | 2,730.20 | 11,171.20 |
| 2014/3/1 | 1,863.52 | 0.08% | 2,749.30 | 11,208.10 |
| 2014/4/1 | 1,864.29 | 0.09% | 2,774.20 | 11,253.10 |
| 2014/5/1 | 1,890.26 | 0.09% | 2,785.30 | 11,317.90 |
| 2014/6/1 | 1,947.09 | 0.10% | 2,817.20 | 11,373.50 |
| 2014/7/1 | 1,973.64 | 0.09% | 2,837.30 | 11,427.40 |
| 2014/8/1 | 1,961.53 | 0.09% | 2,787.00 | 11,451.90 |
| 2014/9/1 | 1,993.69 | 0.09% | 2,861.20 | 11,493.70 |
| 2014/10/1 | 1,937.27 | 0.09% | 2,880.40 | 11,568.10 |
| 2014/11/1 | 1,783.54 | 0.09% | 2,888.20 | 11,608.80 |
| 2014/12/1 | 1,807.78 | 0.12% | 2,955.80 | 11,692.00 |
| 2015/1/1 | 2,029.18 | 0.11% | 2,952.90 | 11,764.60 |
| 2015/2/1 | 2,082.94 | 0.11% | 3,009.90 | 11,870.80 |
| 2015/3/1 | 2,079.99 | 0.11% | 2,996.80 | 11,883.60 |
| 2015/4/1 | 2,093.59 | 0.12% | 2,999.10 | 11,923.20 |
| 2015/5/1 | 2,112.62 | 0.12% | 2,978.60 | 11,954.40 |
| 2015/6/1 | 2,099.28 | 0.13% | 3,013.40 | 12,000.50 |
| 2015/7/1 | 2,093.39 | 0.13% | 3,034.40 | 12,049.90 |
| 2015/8/1 | 2,039.87 | 0.14% | 3,017.60 | 12,100.20 |
| 2015/9/1 | 1,943.35 | 0.14% | 3,044.80 | 12,160.70 |

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|---|---|---|---|---|
| 2015/10/1 | 2,024.81 | 0.12% | 3,026.10 | 12,200.80 |
| 2015/11/1 | 2,081.01 | 0.12% | 3,083.40 | 12,289.80 |
| 2015/12/1 | 2,054.38 | 0.24% | 3,104.10 | 12,350.60 |
| 2016/1/1 | 1,918.60 | 0.34% | 3,103.40 | 12,480.00 |
| 2016/2/1 | 1,904.42 | 0.38% | 3,131.60 | 12,546.70 |
| 2016/3/1 | 2,021.95 | 0.36% | 3,152.80 | 12,609.30 |
| 2016/4/1 | 2,075.54 | 0.37% | 3,197.70 | 12,692.80 |
| 2016/5/1 | 2,065.55 | 0.37% | 3,236.50 | 12,763.30 |
| 2016/6/1 | 2,083.89 | 0.38% | 3,242.40 | 12,828.70 |
| 2016/7/1 | 2,148.90 | 0.39% | 3,241.70 | 12,889.60 |
| 2016/8/1 | 2,177.48 | 0.40% | 3,312.70 | 12,976.20 |
| 2016/9/1 | 2,157.69 | 0.40% | 3,326.70 | 13,039.10 |
| 2016/10/1 | 2,143.02 | 0.40% | 3,338.50 | 13,109.20 |
| 2016/11/1 | 2,164.99 | 0.41% | 3,354.40 | 13,179.70 |
| 2016/12/1 | 2,246.63 | 0.54% | 3,345.10 | 13,212.50 |
| 2017/1/1 | 2,275.12 | 0.65% | 3,393.20 | 13,283.50 |
| 2017/2/1 | 2,329.91 | 0.66% | 3,403.10 | 13,348.10 |
| 2017/3/1 | 2,366.82 | 0.79% | 3,451.30 | 13,416.70 |
| 2017/4/1 | 2,359.31 | 0.90% | 3,450.40 | 13,477.40 |
| 2017/5/1 | 2,395.35 | 0.91% | 3,516.20 | 13,535.70 |
| 2017/6/1 | 2,433.99 | 1.04% | 3,525.30 | 13,559.50 |
| 2017/7/1 | 2,454.10 | 1.15% | 3,547.30 | 13,623.50 |
| 2017/8/1 | 2,456.22 | 1.16% | 3,586.50 | 13,682.00 |
| 2017/9/1 | 2,492.84 | 1.15% | 3,570.50 | 13,727.40 |
| 2017/10/1 | 2,785.46 | 1.15% | 3,607.80 | 13,781.60 |
| 2017/11/1 | 2,593.61 | 1.16% | 3,629.40 | 13,807.60 |
| 2017/12/1 | 2,664.34 | 1.30% | 3,613.30 | 13,853.00 |
| 2018/1/1 | 2,789.80 | 1.41% | 3,651.10 | 13,861.80 |
| 2018/2/1 | 2,705.16 | 1.42% | 3,614.40 | 13,899.40 |
| 2018/3/1 | 2,702.77 | 1.51% | 3,664.50 | 13,958.00 |
| 2018/4/1 | 2,653.63 | 1.69% | 3,656.60 | 13,980.70 |
| 2018/5/1 | 2,701.49 | 1.70% | 3,654.00 | 14,046.20 |
| 2018/6/1 | 2,754.35 | 1.82% | 3,655.60 | 14,107.10 |
| 2018/7/1 | 2,793.64 | 1.91% | 3,681.50 | 14,145.30 |
| 2018/8/1 | 2,857.82 | 1.91% | 3,695.00 | 14,193.20 |
| 2018/9/1 | 2,901.50 | 1.95% | 3,702.20 | 14,224.60 |
| 2018/10/1 | 2,785.46 | 2.19% | 3,726.10 | 14,234.70 |
| 2018/11/1 | 2,723.23 | 2.20% | 3,704.20 | 14,245.00 |
| 2018/12/1 | 2,567.31 | 2.27% | 3,764.30 | 14,355.30 |
| 2019/1/1 | 2,607.39 | 2.40% | 3,744.40 | 14,417.10 |
| 2019/2/1 | 2,754.86 | 2.40% | 3,751.20 | 14,454.40 |
| 2019/3/1 | 2,803.98 | 2.41% | 3,735.00 | 14,496.70 |

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|---|---|---|---|---|
| 2019/4/1 | 2,903.80 | 2.42% | 3,779.30 | 14,531.00 |
| 2019/5/1 | 2,854.71 | 2.39% | 3,788.00 | 14,643.40 |
| 2019/6/1 | 2,890.17 | 2.38% | 3,832.10 | 14,765.40 |
| 2019/7/1 | 2,996.11 | 2.40% | 3,865.00 | 14,847.20 |
| 2019/8/1 | 2,897.47 | 2.13% | 3,862.00 | 14,928.80 |
| 2019/9/1 | 2,982.16 | 2.04% | 3,901.20 | 15,019.90 |
| 2019/10/1 | 2,977.68 | 1.83% | 3,931.60 | 15,154.50 |
| 2019/11/1 | 3,104.90 | 1.55% | 3,952.80 | 15,252.60 |
| 2019/12/1 | 3,176.75 | 1.55% | 4,008.40 | 15,313.70 |
| 2020/1/1 | 3,278.20 | 1.55% | 3,977.60 | 15,380.60 |
| 2020/2/1 | 3,277.31 | 1.58% | 3,979.60 | 15,432.30 |
| 2020/3/1 | 2,652.39 | 0.65% | 4,260.90 | 15,962.00 |
| 2020/4/1 | 3,307.64 | 0.05% | 4,788.80 | 16,983.90 |
| 2020/5/1 | 2,919.62 | 0.05% | 16,245.50 | 17,850.90 |
| 2020/6/1 | 3,104.66 | 0.08% | 16,574.10 | 18,142.80 |
| 2020/7/1 | 3,207.62 | 0.09% | 16,774.50 | 18,293.30 |
| 2020/8/1 | 3,391.71 | 0.10% | 16,898.80 | 18,365.20 |
| 2020/9/1 | 3,365.52 | 0.09% | 17,171.20 | 18,592.00 |
| 2020/10/1 | 3,418.70 | 0.09% | 17,369.10 | 18,746.90 |
| 2020/11/1 | 3,548.99 | 0.09% | 17,619.50 | 18,965.80 |
| 2020/12/1 | 3,695.31 | 0.09% | 17,812.80 | 19,107.10 |
| 2021/1/1 | 3,793.75 | 0.09% | 18,075.70 | 19,335.60 |
| 2021/2/1 | 3,883.43 | 0.08% | 18,338.30 | 19,575.80 |
| 2021/3/1 | 3,910.51 | 0.07% | 18,615.00 | 19,818.50 |
| 2021/4/1 | 4,141.18 | 0.07% | 18,968.60 | 20,143.40 |
| 2021/5/1 | 4,167.85 | 0.06% | 19,291.10 | 20,450.10 |
| 2021/6/1 | 4,238.49 | 0.08% | 19,352.30 | 20,494.10 |
| 2021/7/1 | 4,363.71 | 0.10% | 19,492.20 | 20,618.80 |
| 2021/8/1 | 4,454.21 | 0.09% | 19,718.90 | 20,830.10 |
| 2021/9/1 | 4,445.54 | 0.08% | 19,861.00 | 20,959.80 |
| 2021/10/1 | 4,460.71 | 0.08% | 20,055.00 | 21,140.00 |
| 2021/11/1 | 4,667.39 | 0.08% | 20,244.00 | 21,314.40 |
| 2021/12/1 | 4,674.77 | 0.08% | 20,434.10 | 21,495.00 |
| 2022/1/1 | 4,573.82 | 0.08% | 20,496.30 | 21,552.40 |
| 2022/2/1 | 4,435.98 | 0.08% | 20,574.30 | 21,608.60 |
| 2022/3/1 | 4,391.27 | 0.20% | 20,684.20 | 21,711.60 |
| 2022/4/1 | 4,391.30 | 0.33% | 20,701.70 | 21,714.30 |
| 2022/5/1 | 4,040.36 | 0.77% | 20,674.90 | 21,688.20 |
| 2022/6/1 | 3,898.95 | 1.21% | 20,600.70 | 21,644.40 |
| 2022/7/1 | 3,911.73 | 1.68% | 20,536.70 | 21,640.90 |
| 2022/8/1 | 4,158.56 | 2.33% | 20,456.10 | 21,624.40 |
| 2022/9/1 | 3,850.52 | 2.56% | 20,270.90 | 21,507.10 |

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|---|---|---|---|---|
| 2022/10/1 | 3,726.05 | 3.08% | 20,111.70 | 21,440.90 |
| 2022/11/1 | 3,917.49 | 3.78% | 19,954.80 | 21,385.50 |
| 2022/12/1 | 3,912.38 | 4.10% | 19,756.40 | 21,294.00 |
| 2023/1/1 | 3,960.66 | 4.33% | 19,548.10 | 21,207.60 |
| 2023/2/1 | 4,079.68 | 4.57% | 19,356.20 | 21,134.80 |
| 2023/3/1 | 3,968.56 | 4.65% | 18,964.30 | 20,888.10 |
| 2023/4/1 | 4,121.47 | 4.83% | 18,646.00 | 20,732.20 |
| 2023/5/1 | 4,146.17 | 5.06% | 18,595.80 | 20,829.00 |
| 2023/6/1 | 4,345.37 | 5.08% | 18,485.80 | 20,816.40 |
| 2023/7/1 | 4,508.08 | 5.12% | 18,381.40 | 20,789.10 |
| 2023/8/1 | 4,457.36 | 5.33% | 18,270.90 | 20,763.40 |
| 2023/9/1 | 4,409.10 | 5.33% | 18,150.40 | 20,710.10 |
| 2023/10/1 | 4,269.40 | 5.33% | 18,071.50 | 20,698.70 |
| 2023/11/1 | 4,460.06 | 5.33% | 18,014.70 | 20,724.90 |
| 2023/12/1 | 4,685.05 | 5.33% | 18,022.00 | 20,786.10 |
| 2024/1/1 | 4,845.65 | 5.33% | 17,976.90 | 20,754.20 |
| 2024/2/1 | 5,096.27 | 5.33% | 17,935.20 | 20,748.60 |
| 2024/3/1 | 5,254.35 | 5.33% | 17,997.50 | 20,841.20 |