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The effect of the FED's Quantitative Easing response on the US stock market

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Abstract

The aim of this paper is to examine the impact of QE implemented by the Fed on the prices of the three major stock indices (S&P500, Dow Jones & Nasdaq). The paper makes a distinction between QE implemented during and following the global financial crisis and QE during the Covid-19 pandemic. An ARDL model in a macro-economic setting is implemented to analyze the short run and long run results on stock prices. The robustness of the results are strengthened with the help of two Granger causality models. The findings indicate there is a cointegrating relationship amongst the variables for all three stock index models. In the short run there is evidence that a marginal increase in QE during the pandemic has a positive effect on the stock market. This is not the case for QE during the GFC, where the effect is either negative or negligible. In the long run, QE during both the pandemic and the GFC has a positive effect on stock prices. Both in the short run and the long run there is a substantially larger effect of QE during the pandemic on stock prices than the effect of QE during the GFC on stock prices. The Granger causality tests show that in the short run QE regarding the GFC unidirectionally Granger causes the S&P500 and the DOW, while QE regarding Covid bi-directionally Granger causes the NASDAQ. In the long run, there is bi-directional Granger causality between QE and the stock indices.

Keywords: quantitative easing, monetary policy, stock market, GFC, Covid-19 Pandemic, ARDL cointegration

Contents

Introduction

Investors all over the world have weathered many financial storms in the past 25 years: from the dotcom bubble and the global financial crisis to the Covid-19 pandemic more recently. In the meantime, central banks have played important roles in response to these events. The first question that arises is whether these central bank policies have had a consequent impact on asset markets. A logical second question that arises then is whether this monetary influence on the stock market has increased over time. If there is indeed a significant effect of monetary policy on stock prices, one would expect the impact on financial markets to be even more severe since March of 2020, given the extreme unconventional monetary policy that was witnessed. This paper answers these questions and hence investigates the effect of the Federal Reserve's quantitative easing (QE) response on the US stock market.

Quantitative easing is sometimes referred to as "the printing of currency". Although this is technically not true, since the size of a financial institution's balance sheet does not change, the hypothesis that financial institutions and retail investors use newly created currency to buy assets and therefore increase asset prices is a plausible one. QE lowers interest rates on government and corporate bonds. The lower rates then feed through to lower interest rates on savings and loans for households and businesses (B.O.E., 2022). This lowers the main revenue source of commercial banks, but also the returns investors and savers can get on 'safe' investments such as money market accounts, certificates of deposit or treasuries. As a result, retail investors, but especially institutional investors, feel forced into relatively riskier investments in the search for yield (see Gambacorta, 2009; De Nicolò et al., 2010; Altunbas et al., 2010). Since many investors weight their portfolios towards stocks, they push up equity prices.

This search for yield explanation can also be strengthened by a few statistics. The average annual return since QE has been implemented (2009-2021) has been 14.20%, while the average annual return of the previous 13-year period (1996-2008) has only been 5.23%. One could argue that the first 13 years included the market crash of the dot-com bubble and the crash during the global financial crisis (GFC), which have had a negative impact on returns. However, not only does the latter 13-year time span also contain a market crash (of March 2020), but the high returns are abnormal from an historical perspective as well. The average annual return for the period 1928-2021 has 'only' been 7.98%. This is a strong indication the above average returns are unusual to say the least and our chosen time periods likely do not suffer from selection bias.

Finding out whether monetary policy is driving the recent anomalous stock market performance is therefore of great interest.

A bird's-eye view on monetary policy literature shows much research has been done on the relationship between monetary policy and stock prices during times when conventional policy tools were used. A few prominent examples of research regarding effects of monetary policy on asset prices are the work of Thorbecke (1997) and Rigobon and Sack (2004). The same Rigobon and Sack (2003) and Gilchrist and Leahy (2002) have looked at this relationship in the opposite direction: the effect of asset prices on monetary policy. Since the GFC, unconventional monetary policy tools have been implemented and even more research has been made possible. There has been a vast array of literature on QE during and after the GFC on asset markets and the economy. For example, Kapetanios et al. (2012) examine the impact of the first round of (QE) by the Bank of England on real GDP and inflation. De Mendonca et al. (2016) note that QE in the USA, Japan, and the UK had a positive effect on their respective stock markets. Finally, although the literature of monetary policy during the Covid-19 pandemic is still in a nascent stage, research has already been taking place. Gormsen and Koijen (2020) show that news about U.S. monetary policy and the fiscal stimulus bill around March 24th boosted the stock market, but was unable to significantly increase short-term growth expectations. Hartley et al. (2022) state that the Fed played an important role in stabilizing bond markets and in solving the global dollar shortage that was triggered by the pandemic.

To contribute to the existing literature before QE, this paper sheds light on the literature of monetary policy when interest rates are zero or close to zero. Only since the global financial crisis has research been made possible in times of reaching this zero lower bound. This has led to the unique possibility to study the effects of unconventional monetary policy tools on asset prices. With regards to adding value to 'QE literature', research on monetary policy during the pandemic is as topical as it can get, since it has only been made possible since March of 2022. On March 9th of 2022 the Federal Reserve conducted their final open market purchase, effectively ending the covid QE program started in March of 2020. Whereas other papers were only able to focus on quantitative easing during and after the global financial crisis, this paper is fortuned with the opportunity to make a distinction between GFC QE and pandemic QE and make comparisons between the two periods.

The results of this research could impose great value for society as well. Not only do the results help market analysts, investors and companies themselves in understanding what is driving stock returns, it could also help central planners with regards to their policies. Wealth inequality, a reverse wealth effect and a misallocation of capital; three unwanted consequences that will be described more in depth later on could be averted to a certain degree if we have a better understanding of the effects of central bank policies on financial markets. In addition, the impact of this paper can be felt internationally as well. For example, there is a broad array of literature on spillover effects of US quantitative easing to emerging market (EM) countries. Bhattarai et al. (2021) find large capital inflows and stock market booms for "The fragile five" due to a positive US QE shock.[1] This is amplified by Bowman et al. (2015), who state that EM countries' asset prices reacted strongly to U.S. unconventional monetary policy announcements.

Finally, the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) provided the foundation for later multi-factor models to capture the cross section of stock returns. Incorporating QE into asset pricing models could help explain asset prices and therefore enhance the knowledge on this topic. Incorporating monetary policy in a multi-factor asset pricing model requires a broad array of literature on these topics to understand the individual QE exposure stocks have. Ozdagli and Velikov (2016) agree this is the main challenge in studying the impact of monetary policy on the cross-section of equity risk premia. In their paper, the authors examine how monetary policy influences the cross-section of expected stock returns by creating a monetary policy exposure index that is linked to how firms react to monetary policy. They find that stocks whose prices react more positively to expansionary monetary policy surprises earn lower average returns.

The next part of this paper will review the literature of QE on the stock market and the underlying theory for answering the research questions. Then, it describes and analyzes the data sources that are used and the methodology that will be implemented. Afterwards, the results will be discussed to answer the proposed hypotheses and research question. Finally, a discussion is presented, which will be followed up by concluding remarks.

[1] The fragile five contain Brazil, India, Indonesia, South Africa and Turkey.

Theoretical framework

A short history about quantitative easing

Quantitative easing was first implemented by the Bank of Japan (BOJ) to fight deflation in the early 2000s. The BOJ had maintained short-term interest rates at close to zero since 1999 and were seeking for other unconventional monetary policies to increase liquidity into the economy. The perceived solution to the problem was quantitative easing, where a central bank purchases predetermined amounts of government bonds or other financial assets like mortgage-backed securities in order to increase the liquidity of financial institutions. The newly injected liquidity is then loaned to businesses and consumers to kickstart the economy again. After the global financial crisis of 2007-2008, QE was also implemented in the US, the UK and the eurozone. The western central banks slashed interest rates close to zero and reached the previously mentioned zero lower bound, where conventional monetary policy tools could not give an extra boost to the economy. Therefore, the Federal Reserve implemented multiple QE programs, regularly referred to as QE 1, 2 and 3. When the covid-19 pandemic hit in 2020, the Fed launched QE 4 and decided to unleash the biggest QE program so far in March of 2020. The program ended 2 years later, in March of 2022.

Literature review

Before QE was implemented on a large scale, much research had already been done on relationships between monetary policy and the stock market. Early attempts of Geske and Roll (1983) and Kaul (1987) examine the relationship between stock market returns and inflation, where they incorporate aspects of monetary policy. Geske and Roll state that when stock prices decline, the government will likely run a budget deficit, which will be monetized by the central bank. Since rational people will anticipate this, expected inflation will rise, which on its own leads to a rise in unanticipated actual inflation as well. Kaul indicates that for the U.S., Canada, the U.K. and Germany there is a significant positive relation between budget deficits and the money growth rates, which supports the existence of a counter-cyclical monetary policy. This anti-cyclical policy amplifies the negative relationship between inflation and stock returns. Mishkin (2001) shows that asset prices are important in the monetary transmission mechanism and suggest that monetary policy works through its effect on asset prices. Rigobon and Sack (2004) find that an increase in short-term interest rates leads to a decline in stock prices. This observation is in line with the findings of Bernanke and Kuttner (2005) and Bjørnland and Leitemo (2009). The former explain that an unanticipated 0.25% cut in the Federal funds rate leads to a 1% increase in broad stock indexes. The latter find significant simultaneous interaction between the interest rate and shocks to real US stock prices. Real stock prices fall by seven to nine percent due to a rise in the federal funds rate by one percent.

Since the inception of QE, even more academic research has been published on this topic. Florackis et al. (2014), using data for the UK from 1989 till the second quarter of 2012, show a strong correlation between a lack of market liquidity and a fall in the stock market. De Haan et al. (2016) show that both conventional and unconventional ECB monetary policy surprises affect the Euro Stoxx 50 index, but that the strongest effects are found for unconventional monetary policy surprises. Meinush and Tillman (2016) find that a QE shock has modest effects on real economic activity, inflation, interest rates and stock prices, with an increase in stock prices due to QE shocks of close to 5 percentage points. On the other part of the spectrum, Galí and Gambetti (2015) find evidence that stock prices increase consistently in response to an exogenous tightening of monetary policy. Another study by Laopodis (2013) found that there was no consistent dynamic relationship between monetary policy and the stock market during the monetary regimes of Burns, Volcker and Greenspan. In conclusion, there seems to be a general consensus about the relationship between stock prices and monetary policy. While interest rates seem to have an inverse relationship with stock prices, the relationship between quantitative easing and the stock market seems to be positive, although the discussion on this topic is still not fully settled.

Early academic work by Modigliani (1971) seeked answers to the question whether an increase in wealth leads to an increase in consumption. This desired goal of the central banks, often referred to as ‘the wealth effect’, is broadly discussed in the economic literature. First of all, FOMC minutes and transcripts reveal that policy makers pay attention to the stock market due to their concern about the wealth effect (Cieslak and Vissing-Jorgensen, 2021). According to Joyce et al. (2011), higher asset prices reduce the cost of obtaining funding and increase the wealth of asset holders, which eventually boosts spending and demand. One of the most widely cited papers by Case et al. (2005) on wealth effects found a large and statistically significant effect of housing wealth on household consumption, while evidence of a stock market wealth effect was weak. At the same time, Peek (1983) found a larger spending response to gains from net financial assets than from owner-occupied housing. In addition, Juster et al. (2006) state that a one-dollar capital gain in corporate equities increases spending in a 5-year interval by 19 cents. A different view is held by Lettau and Ludvigson (2004), who state that permanent changes in wealth indeed affect consumer spending, but since most changes in wealth are temporary, they have no effect on consumption.

If it turns out that quantitative easing indeed plays a part in influencing stock market prices, it could also bring unwanted consequences. Some argue that monetary policy contributes to wealth inequality and even income inequality. Since on average the wealthier in society hold more assets like stocks than the less wealthy people, wealth inequality would tend to increase in a dovish monetary environment due to asset price appreciation. This is rebutted by Lenza and Slacalek (2018), who state that monetary policy only has negligible effects on wealth inequality. As mentioned before, QE lowers interest rates in the economy and injects liquidity in financial institutions. In line with Lenza and Slacalek, one could argue that this spurs investments and business growth and therefore has a positive impact on employment of lower income households and income equality. On the other hand, one could also argue that this new liquidity especially benefits the rich in the form of unproportionate high salaries, bonusses or company stock options, which would have an upwards effect on income inequality. Montecino and Epstein (2015) find similar results: while employment changes and mortgage refinancing were indeed equalizing, these factors were nonetheless overruled by the large inequality effects of stock price appreciations. According to both Coibion et al. (2017) and Furceri et al. (2018), contractionary monetary policy shocks increase U.S. income inequality.

Another potentially negative implication of QE is whether such a distortionary force in the market leads to efficient pricing. One could argue that the market to a large degree would be based on speculation of expectations of monetary policy instead of economic fundamentals. In simple terms: buy stocks in the anticipation of the Fed pumping liquidity into the financial system and sell vice versa, regardless of the idiosyncratic aspects of companies. The next step of the Fed, which some suspect would be the case in the next severe recession, could be the buying of stocks directly into the market. A rather philosophical follow up question to these statements is the degree to which a market is efficient in that case. What is the definition of an 'efficient market'? Is a market efficiently priced when prices reflect historical prices and other "obviously publicly available information", according to the semi-strong form of the efficient market hypothesis (Fama, 1970) or is this only possible in a 'free market' with limited market intervention, which is in line with the statements of Adam Smith in The Wealth of Nations (2010)? In the first case, this would mean that central bank intervention would be part of the process of efficient pricing, since monetary policy decisions and conferences are easily accessible to the public. In the latter, this would not be the case, since an undistorted market by governments and central banks would price stocks on a different level.

A third negative consequence of QE, in line with the previous point, could be the creation of excessive risk taking. When market participants believe that the Fed will always back the market up when the stock market declines significantly, referred to in the economic literature as the ‘Fed put’, they will adjust their risk appetite and therefore take more risk than they normally would. An indication of this moral hazard was the sharp reversal in equity prices after the stock market crash in March of 2020. This intervention in the bond market could lead to artificially high equity prices given the economic situation. Higher valuations in equities would spur even more excessive risk taking and eventually increase the chance on financial bubbles. This view is confirmed by Miller et al. (2002), who showed that a fully credible `Greenspan put' could accommodate highly overvalued stock prices without changed attitudes to risk. According to Cieslak and Vissing-Jorgensen (2021) these concerns do not seem to bother the Federal Open Market Committee. They argue that even though FOMC members are aware that the Fed put could induce risk-taking, moral hazard implications appear not to significantly affect their decision-making ex ante.

The final direct unwanted outcome, in line with the previous point, is with regards to stock market bubbles. A very simple definition of a financial bubble is something along the lines of a prolonged period of rising prices to levels greatly exceeding fundamentals values. The rising prices are subsequently followed by sharp declines or even price crashes. There has been a vast literature on financial bubbles, including the role central banks play in them. The most recent one, the housing bubble, has received much attention by economists. A Wall Steet Journal article in 2009 stated the Fed did not cause the housing bubble. ‘Coincidentally’, the article was written by Alan Greenspan, chairman of the Fed during the housing mania. McDonald and Stokes (2013) however, using Granger causality analysis and VAR modeling methods, find that the artificially low Fed funds rate in 2001–2004 indeed was a cause of the housing price bubble. An earlier example, more specific to a stock market bubble episode, was the dot-com bubble around the year 2000. The dot-com mania, highlighted by the “irrational exuberance” speech by the same Greenspan in 1996, was likely for the largest part caused by both limits to arbitrage and (ir)rational speculators (see Ofek and Richardson, 2003; Griffin et al. ,2011). Since the currency injection after the pandemic, some argue we are at the moment of writing in “the everything bubble”, given the high valuations across many asset classes. Again, if the Fed plays a part in creating financial bubbles, it indirectly has blame in the unwanted consequences and externalities that have been mentioned before, like excessive risk taking and income inequality.

Finally, an indirect negative effect of monetary policy on stock prices could be through the inflation channel. Western central banks have been ‘screaming’ for a very long time that we did not have enough inflation with regards to their respective 2% inflation target. In that sense, central banks have succeeded in creating more inflation since the pandemic. However, US inflation has been significantly overshooting this 2% target since the beginning of 2021, also in the eurozone. This goes at least against one of their two mandates: price stability. As mentioned in previous articles, there are arguments to make why quantitative easing has a positive impact on inflation. According to Reinhart and Rogoff (2009), the ‘printing’ of paper currency is simply a modern version of debasing content of coinage invented before the 1800s. So, assuming a central bank creates inflation through a ‘dovish’ monetary policy, it could lead to both a decrease in (discretionary) consumer spending as well as higher (input) costs for many businesses. Both these factors hurt the profit and growth of exchange-listed companies. Again, current valuations depend on the future expectation of the market. If the market expects future revenues and profits to be lower at time t + 1 due to higher inflation and the market is semi-strong efficient, stock prices should go down at time t.

Underlying theory for answering the problem

To answer the problem and hence the relevant research questions, the underlying theories behind them need to be evaluated first. The first part of the underlying theory is with regards to the model and variables that will be used with regards to the ARDL model. An ARDL or Autoregressive Distributed Lag Model is a model where the dependent variable is a function of its own past lagged values as well as current and past values of other independent variables. The ARDL model that is implemented in this paper has two major advantages in comparison with other previously used cointegration methods. The first major benefit is that the ARDL model does not require all the variables to be integrated of the same order, i.e. integrated of order I(0), I(1) or a combination of both. The second big advantage is that the ARDL test is robust in the case of small and finite sample sizes.

In terms of the model, there are other methods to investigate the effect of QE on the stock market, like looking at event studies. The first difficulty of looking at QE event studies is that you base your results on the expectation that the market prices the effect of the announcements in correctly in the short term and the long term. There is an argument to be made that this assumption of efficient pricing is unrealistic. For example, stock prices fell following the QE announcement on March the 15th; an indication that investors overreacted during the beginning of the pandemic and misvalued companies. The second problem and inconvenience with an event study is that quantitative easing has been implemented for many years already, meaning that it would be very difficult to decide which events you look at in the data. For example, Gagnon et al. (2010) identify eight event dates beginning with the 11/25/2008 announcement until the summer of 2009. Krishnamurthy & Vissing-Jorgensen (2011) only focus on the first five of these event dates. This shows that picking important events was already a debatable process when QE had only been recently implemented. This headache would grow much larger given the fact that QE 4 has already ended.

With regards to the variables, multiple papers have used inflation, (proxies of) real GDP, interest rates and measures (and proxies) of QE to investigate the effect on stock markets. For instance, Chen et al. (1986) test the effects of interest rates, inflation, industrial production, and the spreads between high- and low-grade bonds on stock market returns. Geske and Roll (1983) found that US stock returns are negatively related to expected and unexpected inflation and positively related to real economic activity. Gan et al. (2006) examine the relationship between the New Zealand Stock Index and seven macroeconomic variables including the CPI, real GDP and M1 money supply for the period 1990 to 2003. Kwon and Shin (1999) illustrate that the production index, exchange rate, trade balance and the money supply have a direct long-run equilibrium relation with each stock price index in the Korean stock market. In line with the methodology in 'our' paper, the authors in the previous two papers also implement cointegration tests to test these relationships. Finally, whereas most papers use measures of the money supply as a measure of QE or monetary policy, we use the size of the asset side of the balance sheet of the FED. This is in line with Ruman (2021), who finds a relationship between the Fed's balance sheet size and US stock market returns for the period 1926-2015.

The final part of the underlying theory has to do with the statistical methodology. With the help of the cointegration methodology paper of Pesaran et al. (2001), the authors try to establish "true" long term relationships between the variables. A true long term relationship in this context means a scenario where two or more non-stationary time series are integrated together in a way that they cannot deviate from equilibrium in the long term. The cointegration test was first introduced by Engle and Clive (1987), after Newbold and Granger (1974) published the spurious regression concept. According to them, linear regression was an incorrect approach for analyzing time series due to the possibility of producing a spurious correlation. In our case this would mean a potential spurious correlation between the balance sheet of the FED and the stock market indices.

Data

Timeline

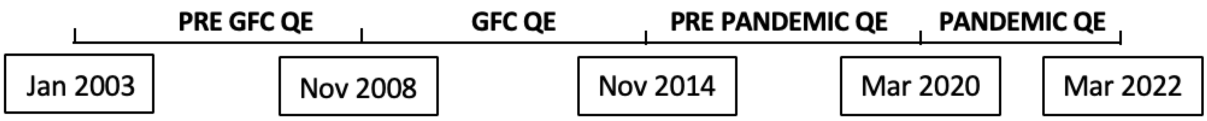

Figure 1 Timeline for the period 2003-2022, split up into periods regarding QE

The timeline in figure 1 can be motivated using Figure 2, which shows the assets of the balance sheet of the Federal Reserve. The timeline starts in January of 2003. Up until November of 2008, the assets were relatively flat. As a response to the GFC, the total assets spiked up and continued their uptrend until November of 2014. During this time, the Fed announced three QE programs in November of 2008 (QE1), November 2010 (QE2) and September 2012(QE3). Big upwards movements in the size of the balance sheet follow these dates (see figure 2). Between November 2014 and March of 2020, the balance sheet remained relatively flat and even decreased in 2019 due to quantitative tightening (QT). In that same year a liquidity crunch in the overnight repo market occurred, which caused a sudden spike in the interest rates on overnight repos. This led to a relatively small increase in the assets of the Fed until March of 2020. Then the pandemic came around the corner, to which the Fed responded with the launching of the largest QE program in history (QE4). The balance sheet spiked up significantly and continued going up steadily until March of 2022. March 2022 is when the Federal reserve stopped buying assets/doing QE, which means there is a complete QE 4 cycle from March of 2020 till March of 2022. The importance behind this visualization is to clearly state which periods are going to be analyzed. This paper aims to estimate the effect of GFC QE on the US stock market, as well as Covid QE on the US stock market. To distinguish the effects attributable to QE, the period where no QE took place needs to be investigated as well, meaning the period before the GFC and the period between GFC QE and Covid QE. This way it is possible to compare all the different time periods with each other and get a better view of what factors are playing a role in driving stock prices.

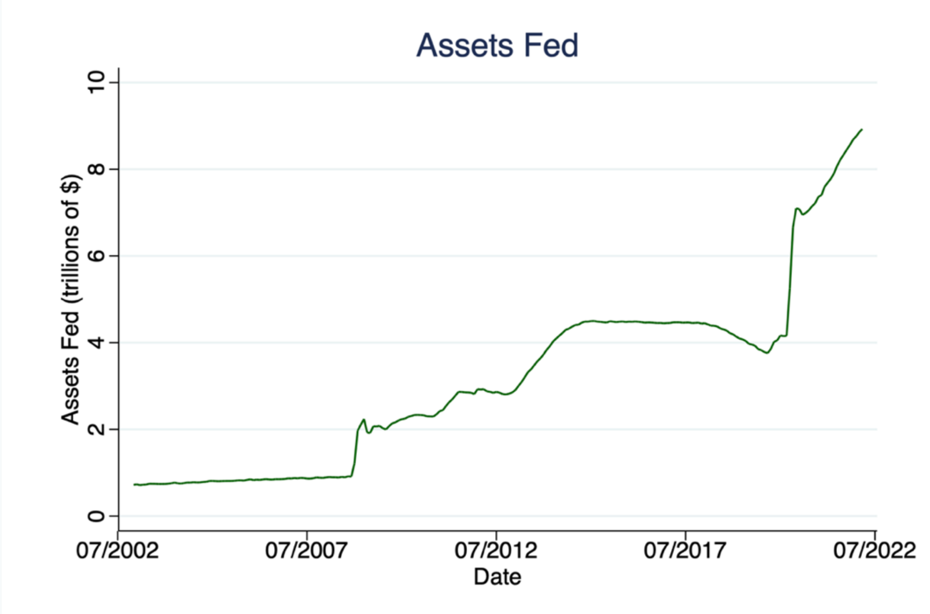

Figure 2 Assets Federal Reserve (trillions of $) 2003-2022

Variables

Table 1 presents an overview of each variable with the frequency, a short description and the source the variable has been retrieved from. The financial market data will be retrieved from Global Financial Data and the economic data from the FRED database of the St. Louis Fed. Global Financial Data provides data from 1265 to the present and spanning more than 200 global markets. The FRED database is an economic database maintained by the Research division of the Federal Reserve Bank of St. Louis. All variables will be used on a monthly basis.

The Monthly industrial production index (IPI) will be used as a proxy for real GDP, since GDP is only measured quarterly. This variable gives us the benefit of having 3 times more observations in the data than when real GDP is used. According to the Board of Governors of the Federal Reserve System (US), "The Industrial Production Index (INDPRO) is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories)". This definition indicates the IPI is in real terms. It is important to have a real proxy of GDP, since the CPI is already used to capture effects of inflation.

Table 1 Descriptions and sources of variables

Variable	Symbol	Frequency	Description	Source
Standard and Poor's 500	S&P500	Monthly	A market cap-weighted index of 500 leading publicly traded companies in the U.S.	Global Financial Data
Dow Jones Industrial Average	DOW	Monthly	a price-weighted index of 30 large, publicly-owned traded companies in the U.S.	Global Financial Data
Nasdaq Composite	NASDAQ	Monthly	A market cap-weighted index of more than 3,700 stocks listed on the Nasdaq stock exchange.	Global Financial Data
Assets Federal Reserve	QE	Monthly	Assets of the balance sheet of the Federal Reserve	Fred database St. Louis Fed
Federal Funds Effective Rate	FFR	Monthly	The interest rate at which commercial banks borrow and lend their excess reserves to each other overnight. It is set by the FOMC.	Fred database St. Louis Fed
Industrial Production Index	IPI	Monthly	A measure of real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories).	Fred database St. Louis Fed
Consumer Price Index for All Urban Consumers	CPI	Monthly	The average month over month change in the prices paid by urban consumers for a market basket of consumer goods and services.	Fred database St. Louis Fed
Global Financial Crisis	GFC	Monthly	Period of QE during and after the Global Financial Crisis	-
Covid-19 Pandemic	Covid	Monthly	Period of QE during the pandemic	-

Note. – means there is no source for the respective variable

To check the strength of the proxy, pearson's correlation coefficient between the IPI and GDP for the period January 2001 till January 2022 is 0.66. For the period January 1980 till January 2022 the correlation coefficient is 0.91 and for the period January 1950 till January 2022 the correlation coefficient is 0.93. This shows that the correlation between the variables used to be much higher, although the correlation is still moderately strong.

In addition, the Federal Funds rate (FFR), the size of the assets of the balance sheet of the Federal Reserve (QE) and the Consumer Price Index for All Urban Consumers (CPI) are used. Important to note and to avoid confusion in the rest of the paper, the variable QE refers to the assets of the Fed and not perse to QE. Since the assets of the Fed are a main function of buying of assets in the form of QE and out of notational simplicity, the variable is called QE. The financial market variables are the prices of the S&P500, Dow Jones and the Nasdaq. Finally, the dummy variables GFC and Covid and the interaction variables QE*GFC and QE*Covid are introduced. Important to note is that these variables do not necessarily imply when the global financial crisis and the pandemic took place. The dummies imply the response of the central banks to the respective crisis. For example, according to the U.S. National Bureau of Economic Research, the financial crisis lasted from December of 2007 till June of 2009. The QE rounds however, which were a response to the financial crisis, started in November of 2008 and lasted till November of 2014. The pandemic is also still going on in the middle of 2022, while Covid QE has stopped in March of 2022.

As a final remark, the asset side of the balance sheet of the Fed is preferred above monetary aggregates like M1 and M2. The assets of the Fed are a better reflection of the monetary policy implemented by the Federal Reserve, since it directly reflects the creation of currency by the purchasing of assets. The downside of regressing stock prices on monetary aggregates, which are used in the paper of De Mendonca et al. (2016) for example, is that it is not possible to fully isolate the part of the monetary base which is directly created by central banks. Most currency in circulation is created through loans by commercial banks (B.O.E., 2019). Although the central bank plays an important part in steering the direction of the money supply, the Fed does not fully control the amount of currency that households choose to hold as deposits in commercial banks, nor do they fully control the amount that depository institutions choose to lend. Sellin (2002) gives a literature overview of the interaction between monetary policy and the stock market and reiterates this issue multiple times. The author states that the problem with using money supply as a measure of monetary policy, which is often used in the literature, is that changes in it are attributable to both changes in money demand as changes in money supply. “The use of high-frequency data does not solve this problem.”

Descriptive statistics

Table 2 shows descriptive statistics of monthly US market returns of the respective stock indices and monthly (growth) rates of our economic variables.

Table 2 Descriptive statistics US financial and economic variables (monthly ret. 2003-2022)

Variable	Observations	Mean (%)	Std. Dev. (%)	Minimum (%)	Maximum (%)
S&P500	231	0.67	4.15	18.56	11.94
DOW	231	0.58	4.03	15.15	11.19
NASDAQ	231	0.99	4.37	24.25	13.62
QE	231	1.09	4.64	8.88	53.73
FFR[a]	231	1.27	1.58	4.86	5.27
IPI	231	0.06	1.33	14.61	6.01
CPI	231	0.19	0.32	1.79	1.37
GFC	231	31.17	46.42	0	100
Covid	231	10.82	31.13	0	100

[a]*The FFR is not calculated m.o.m.*

Among the three stock indices, it looks like the higher the standard deviation, the higher the average monthly returns. For example, the NASDAQ has the highest average monthly return, but also the highest standard deviation. This indicates that when the markets perform relatively well, the more volatile indices perform better. The QE variable has increased 1.09% every month on average, which is 13.08% on an annualized basis. Compared to the IPI, which proxies that the US economy has only grown at a 0.72% annualized rate, the expansion rate of the Fed's balance sheet has been remarkably high. The means of the dummy variables show what percentages of the data span fulfill the dummy criteria. The averages of GFC and Covid show that QE during and after the GFC lasted three times longer than QE since the beginning of the pandemic. The minima and maxima of the dummies are logically either 0 or 1. Since the statistics are in percentages, it means a value of 0 is equal to 0% and a value of 1 is equal to 100%.

Table 3 shows Pearson's correlation coefficient for US financial and economic variables. As expected, there is a high correlation between the stock indices. The correlation between QE and the stock indices is negative, relatively low and significant. One interpretation of the negative sign could be that initially when a crisis occurs, stock prices decrease significantly, whereas QE takes off. Since this happens simultaneous, it takes some time for the newly created liquidity to go through the financial system. This explains why there is a negative correlation between QE and the IPI and could also explain the negative correlation with the CPI, since recessions are deflationary most of the times. The second explanation could be that in the periods where no QE took place, there was no relationship between the two variables. As robustness check for this second argument, the correlations for the period March 2020 till March 2022 between QE and the S&P500, DOW and NASDAQ were -0.08, -0.11 and 0.35 respectively. Although the correlations became slightly more positive, especially for the NASDAQ, there is clearly not enough evidence to validate the second argument. This means our main explanation has to do with the fact that QE is initiated at same the time as stock markets are panicking and prices fall. In the results we will look at lags and interaction effects of QE, which will confirm if there is a lagged effect of QE on stock prices.

Table 3 Correlation table US financial and economic variables (monthly ret. 2003-2022)

Variable		1	2	3	4	5	6	7
1	S&P500	1						
2	DOW	0.97*	1					
3	NASDAQ	0.49*	0.45*	1				
4	QE	-0.21*	-0.17*	-0.14*	1			
5	FFR	-0.05	-0.03	-0.10	-0.11	1		
6	IPI	-0.02	-0.01	0.05	-0.35*	0.01	1	
7	CPI	0.08	0.05	-0.06	-0.33*	0.12	0.26*	1

$^*p < 0.05$

Methodology

As mentioned before, the main question this paper wants to answer is the following:
What is the effect of the quantitative easing response by the Federal Reserve on US stock prices?

The research question can be answered through the testing of three null hypotheses:
H_{01} *: There is no effect of quantitative easing on US stock prices during and following the Global Financial Crisis.*
H_{02} *: There is no effect of quantitative easing on US stock prices during the Covid-19 pandemic.*
H_{03} *: There is no different effect of quantitative easing on US stock prices between the two mentioned periods.*

Regarding the third hypothesis, intuitively the question arises why there would be an expected difference in effect of QE on US stock prices between the two periods ex ante. The explanation has to do with uncertainty and the nature of the different crises. The economic impact of the global financial crisis was very likely ‘easier’ to estimate than the economic impact of the once-in-a-lifetime health crisis in March of 2020. Since the uncertainty at the governments and central banks was much larger, the monetary approach to the problem was different as well. To avoid a deflationary spiral, the Federal Reserve tried to stimulate the economy to a much larger degree. If the hypothesized theory is correct, i.e. an x% increase in QE significantly increases the prices of U.S. stock indices with y%, a large difference is expected to occur between the two periods. According to the Board of Governors of the Federal Reserve System, the balance sheet of the Fed more than doubled in the period of March 2020 till March 2022, while the balance sheet only increased 36% in the period of March 2009 till March 2011. Therefore, a significantly larger increase in stock prices is expected in the pandemic QE period.

Endogeneity issues

Before the model is discussed, some endogeneity issues need to be addressed. The first issue that arises is with regards to simultaneity bias. While asset prices could be influenced by the Federal funds rate and QE, these regressors could simultaneously be affected by asset prices due to the influence on monetary policy expectations. The same argument could be made for the IPI, since a stronger economy should lead to higher asset prices, while higher asset prices then again incentivize companies to invest more into their businesses. If a company however buys back its own shares, this simultaneity might not hold, since share buybacks typically reduce cash positions that could otherwise be used for investments.

The second issue that could arise is multicollinearity. The variables QE and the real industrial production index suffer from a high negative correlation with each other (see table 3). One reasoning for this negative relationship could be that monetary policy and hence QE is based on the current and future view of the economic situation, something which especially became aware during the Covid-19 crisis. During that short lived recession, where the IPI decreased significantly, the Fed acted quickly with the help of large amounts of QE and the lowering of interest rates.

Thirdly, there is a case to be made for omitted variable bias, since there are variables like macroeconomic indicators or risk preferences that influence both stock prices and our independent variables but are not included in the models. This could lead to our QE variable to capture the effect of the missing variables. On the other hand, one could argue that the FFR and QE variables are exogeneous, since omitted variables only indirectly influence the amount of

QE and the level of the Federal funds rate. At the end of the day, the Federal Reserve has the final saying on these policy tools. When the decision was made to use monetary aggregates and other forms of short-term interest rates, the argument of market forces endogenously influencing these variables would be stronger. Furthermore, it is important to note that this research is done in a macro-economic setting. Company specific data or discounted cash flow methods are not incorporated into the model. These omitted variables do however play an important role, since some companies have a significant weighting in the index and hence their prices can influence the price of the index to a large degree.

In defense of the authors behind the applied ARDL methodology, Pesaran and Smith (1995) argue that under specific conditions such as a unique cointegrating relationship, estimates of the long run parameter vector β are consistent. In other words, when the variables are I(1), the authors argue that the estimates of the coefficients are very consistent. Pesaran (1997) even argues that the ARDL model is applicable if the independent variables are endogenous, irrespective of whether the variables are I(1) or not. With regards to serial correlation, modification of the order of the ARDL model is sufficient to deal with this problem in the error process (Pesaran and Shin, 1999). The results section will test whether the variables are I(1) and whether the residuals suffers from serial correlation with the help of the Breusch–Godfrey test. It will also cover to what degree endogeneity is an issue and whether appropriate changes to the methodology are needed.

Finally, the following equation notes that there is a proxy bias for real GDP:

$$\widetilde{GDP} = IPI + \epsilon$$

This proxy bias can be classified as a measurement error, even though a measurement error is often referred to as a variable that is not observable. Real GDP is observable in our application, but the extra number of observations in the dataset are preferred. As discussed before, the correlation between the industrial production index and real GDP is 0.66 for the last 20 years. The reason for the decrease over time in correlation has to do with the US shifting away from an industrial heavy economy into a service sector economy. This measurement error is sometimes referred to as the Classical Errors-in-Variables (CEV) problem and could lead to attenuation bias in the parameters of our model. This means we need to take caution if our proxy is interpreted as real GDP. Of course this endogeneity problem does not hold if we only make statements about the industrial production index.

Model

The model implements an autoregressive distributed lag model, where it uses lags of the dependent variable as well as current and past values of the independent variables. With regards to the explanatory variables, it seems convincing that there is a lag between the moment a central bank increases QE or lowers interest rates and the effect on the stock market. A similar interpretation holds for the proxy of real GDP and the CPI. The first reaction of these variables with stock prices has to do with the technicality that economic data in databases correspond correctly with the appropriate time period, while in reality the reaction of the market on the released GDP and CPI numbers is lagged. This is because the release of the economic data points most of the time falls in the subsequent month. The second reaction is more fundamental, since current economic data influence economic data in the future. With regards to inflation, you can think about psychological factors or a wage-price spiral for example. Therefore, lags of the independent variables could be very useful in determining current stock prices.

The model uses natural logarithms for all variables except the dummies and the FFR. First of all, taking natural logarithms of macro-economic variables to avoid problems of scale is very common in economic literature. Second, taking away the exponential trend of a timeseries helps in reducing heteroskedasticity and leads to more accurate linear regression predictions. Figure 3 shows four graphical examples of the variables QE and S&P500. The top panel fits an exponential line through the data and indicates that this is a better fit than when a linear model would be used. The lower panel applies logarithmic transformation to the variables and visually shows that a linear model fits the data better than before. Third, the dummy and interaction term coefficients will likely have extreme coefficients without logarithms due to the relatively small data span for each dummy. The pandemic period contains only 24 observations e.g., meaning that extreme and uninterpretable coefficients arise when stock indices go up fast in that period. Since this scenario has played out in real life, natural logarithms are used to avoid such sensitivities. Finally, interpreting the coefficients becomes much easier. Without the use of logarithms, it is only possible to make conclusions about absolute values with regards to the short run coefficients. For example, if the CPI goes up with 1, the S&P500 goes down with 500 points. Since differenced logarithms are implemented, we can now interpret the coefficients as if it was a normal OLS regression. For example, a 1% increase in the CPI month over month leads to a 1% increase in the S&P500. With regards to the FFR, it makes no sense to take a logarithm of this variable. The interpretation would be less intuitive, since interest rates are already expressed in percentages and there is no exponential trend to linearize.

One potential problem in the data that will be observed is that the sample size could be quite small. This is especially the case for the period March 2020 till March 2022, where there are only 24 monthly observations. The problem manifests itself in the reliability of the cointegration test results if we use e.g. the Engle and Granger (1987), Johansen (1988) or Johansen and Juselius (1990) cointegration techniques. Narayan and Smith (2005) discuss that the bounds test approach has the advantage that it has better small sample properties than other popular methods as previously mentioned. Therefore, the boundary test approach of Pesaran et al. (2001) is used to establish the cointegrating relationships between our dependent variable and regressor variables.

Before the ARDL bounds test for cointegration is performed, testing for a unit root is necessary to make sure that there are no variables integrated of order 2. The well-known Augmented Dickey-Fuller (ADF) test, the Dickey-Fuller generalized least square (DF-GLS) de-trending test and the Philips-Perron (PP) test are implemented. For the unit root tests the optimal lag structure is chosen based on the lowest value of the Schwarz information criterion (SIC). The DF-GLS test as recommended by Elliot et al. (1996) has the best overall performance in terms of small-sample size and power compared the ADF test. Though the PP test is similar to the ADF test, the primary difference is in how the tests each manage serial correlation. Where the PP uses Newey-West standard errors to account for serial correlation, the ADF uses additional lags of the first-differenced variable.

A final important notion to make is about structural breaks. It needs to be confirmed whether our dummies with regards to QE are indeed structural breaks. The Bai-Perron test (1998) for structural breaks will be used. Afterwards, it is important to see if the structural breaks influence the unit root properties. The logarithmic time series of QE might still not look stationary at first glance, but accounting for structural breaks during the GFC and the pandemic might yield a stationary result. This can be visually presented as well. Figure 4 accounts for three structural breaks at the beginning and end of GFC QE and the beginning of the pandemic. The fitted lines seem to fit the data better overall. In this case, the structural breaks are suspected to be both in intercept and trend. Structural breaks in other variables will also be checked if it turns out a variable is neither I(0) nor I(1) in the three previously mentioned unit root tests. In case of non-stationary variables, we will perform the Zivot-Andrews unit root test for structural breaks (1992) on those variables.

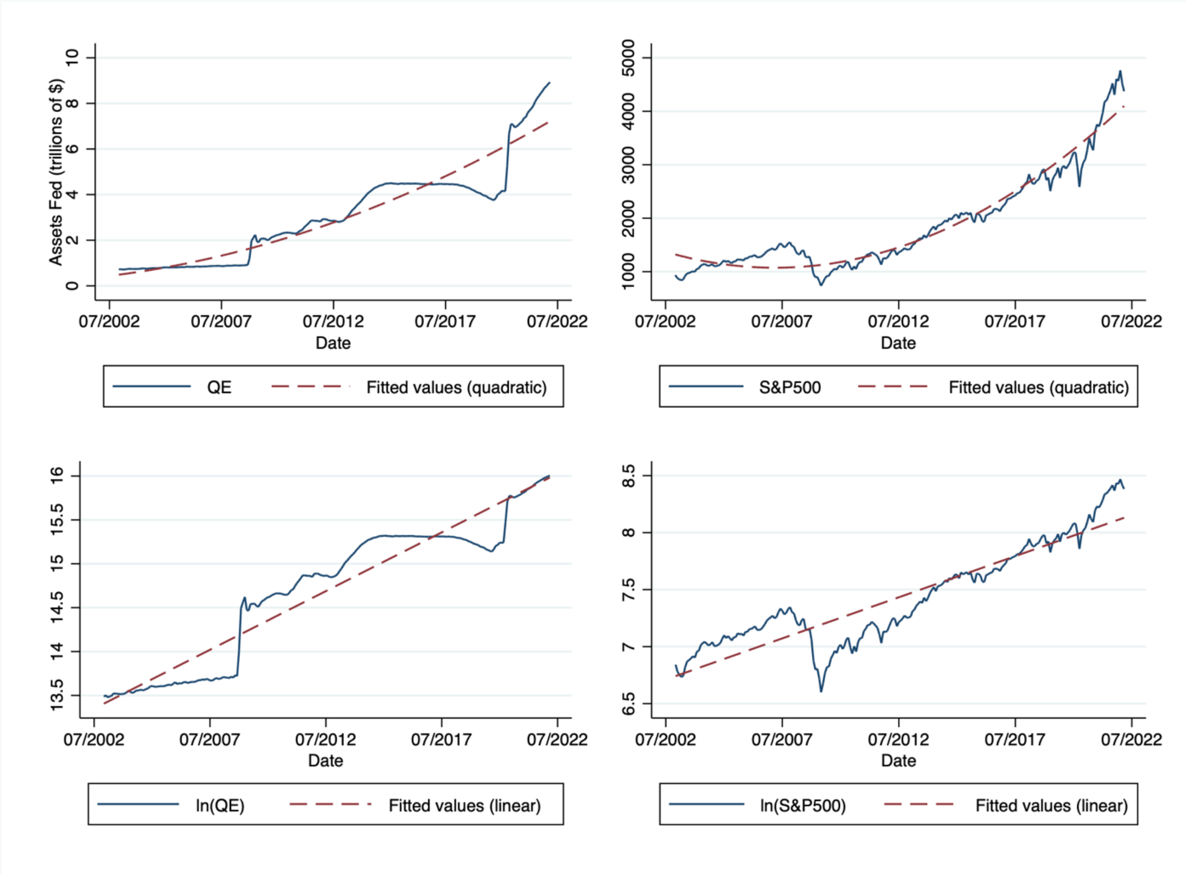

Figure 3 Linearizing exponential trends (QE and S&P500, 2003-2022)

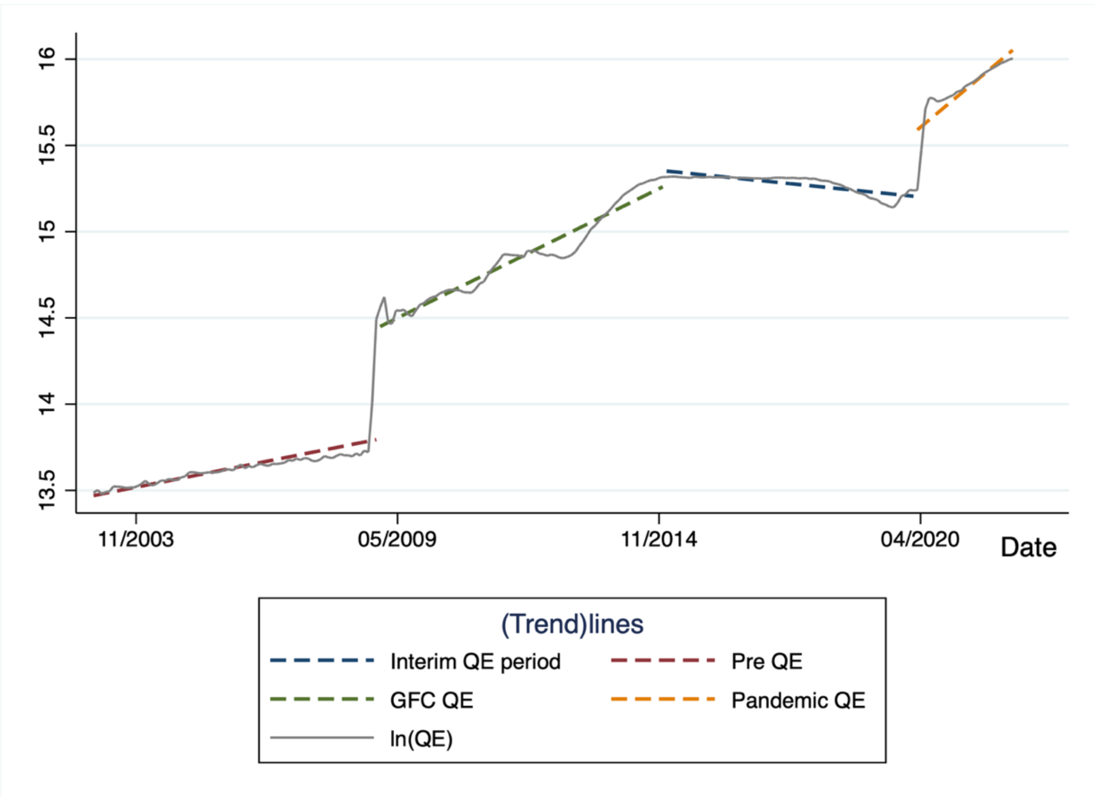

Figure 4 Linear trend lines ln(QE) for periods in 2003-2022

Model specifications

In its basic form, an ARDL(p,q) regression model looks like this:

$$\mathrm{y_t} = \alpha_0 + \beta_1 \mathrm{y}_{t-1} + \cdots + \beta_p \mathrm{y}_{t-p} + \theta_0 \mathrm{x_t} + \theta_1 \mathrm{x}_{t-1} + \theta_q \mathrm{x}_{t-q} + \varepsilon_t \qquad (1)$$

The general conditional error correction model (ECM) in equation (8) in Pesaran et al. (2001) can be written as follow:

$$\Delta \mathrm{y_t} = \alpha_0 + \alpha_1 \mathrm{trend} + \pi_{yy} \mathrm{y}_{t-1} + \boldsymbol{\pi}_{yx.x} \mathbf{x}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\psi}_i' \Delta \mathbf{z}_{t-i} + \boldsymbol{\delta}' \Delta \mathbf{x}_t + \varepsilon_t \qquad (2)$$

They test the following hypotheses for equation (2):

$\mathrm{H}_0^{\pi_{yy}}: \pi_{yy} = 0,\ \mathrm{H}_0^{\boldsymbol{\pi}_{yx.x}}: \boldsymbol{\pi}_{yx.x} = \mathbf{0}'$ (No long run levels relationship)

$\mathrm{H}_1^{\pi_{yy}}: \pi_{yy} \neq 0,\ \mathrm{H}_1^{\boldsymbol{\pi}_{yx.x}}: \boldsymbol{\pi}_{yx.x} \neq \mathbf{0}'$ (Long run levels relationship)

The full equation for the conditional ARDL in the context of this paper can therefore be written in the following manner:

$$\Delta(\ln(P_t)) = \alpha_0 + \alpha_1 t + \alpha_2 GFC_t + \alpha_3 Covid_t + \beta_1(\ln(P_{t-1})) + \beta_2 FFR_{t-1}$$

$$+\beta_3(\ln(IPI_{t-1})) + \beta_4(\ln(CPI_{t-1})) + \beta_5(\ln(QE_{t-1})) + \beta_6((\ln(QE_{t-1} * GFC))$$

$$+\beta_7((\ln(QE_{t-1} * Covid)) + \sum_{i=1}^{p} \gamma_{1i}\Delta(\ln(P_{t-i})) + \sum_{i=0}^{q1} \gamma_{2i}\Delta(FFR_{t-i}) + \sum_{i=0}^{q2} \gamma_{3i}\Delta(\ln(IPI_{t-i}))$$

$$+\sum_{i=0}^{q3} \gamma_{4i}\Delta(\ln(CPI_{t-i})) + \sum_{i=0}^{q4} \gamma_{5i}\Delta(\ln(QE_{t-i})) + \sum_{i=0}^{q5} \gamma_{6i}\Delta\big((\ln(QE_{t-i} * GFC)\big)$$

$$+\sum_{i=0}^{q6} \gamma_{7i}\Delta((\ln(QE_{t-i} * Covid)) + \varepsilon_t \qquad (3)$$

In equation 3, a is a constant, t a time trend, P is the price of the stock market index, FFR the federal funds rate, GDP the industrial production index, CPI the CPI, QE the size of the assets of the FED's balance sheet, *GFC* a dummy which is 1 for the period Nov 2008 - Nov 2014, *Covid* a dummy which is 1 for the period March 2020 – March 2022, *QE*GFC* the interaction term between *QE* and *GFC*, *QE*Covid* the interaction term between QE and Covid and ε the error term. p and q represent the optimal lag structure based on the lowest value of the SIC. The dummies enter the model as exogenous variables.

In addition to the dummies GFC and Covid, a time trend is introduced to the model as well. Regressing the dependent variable $\ln(P_t)$ on the time trend variable t yields highly significant results at the 1% level (see table 4 in Appendix). In addition, Pearson's correlation coefficients between the respective variables are at least 0.913 for all dependent variables. This shows there is a strong relationship between the independent variables and the time. The problem is that the dummies in the model only capture a fraction of the unobserved effects that change over time. The period before QE and the period between the two periods of QE (Nov. 2014 – March 2020) are not accounted for in the model, since the dummies indicate a zero in both scenarios. Pesaran et al. (2001) face the same problem, where equation (30) contains two time dummies that are 1 for the time dummy 1974q1-1975q4 and 1 for the time dummy 1975q1-1979q4. In all other scenarios the dummies state 0: before 1974q1 and after 1979q4. To solve this issue an additional time trend variable is implemented, which captures all possible correlation between the time and the dependent variable.

The first step in the ARDL bounds approach is to estimate equation 3 with OLS. The estimation tests for the existence of a long-run relationship among the variables by conducting an F-test for the joint significance of the coefficients of the lagged levels of the variables.

We test the following hypotheses for equation (3):

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$ (No long run levels relationship)

H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 = 0$ (Long run levels relationship)

If the F-statistic is greater than the critical value for the upper bound I(1) the null hypothesis of no long run relationship can be rejected: there is cointegration. The series are related and can be combined in a linear fashion. In other words, even if there are significant shocks in the short run, the series would eventually converge to the long run equilibrium. The speed of this convergence to long run equilibrium is called the error correction term (ECT). The ECT_{t-1} is the lagged OLS residuals obtained from the regression of the long run equation ($P_{t-1} - \alpha - \boldsymbol{\beta X_{t-1}}$). The coefficient of the ECT φ represents the speed of adjustment to equilibrium. A positive coefficient indicates a divergence and means the model is explosive, while a negative coefficient indicates convergence. The ECT_{t-1} and its coefficient φ are translated in the following error correction model (ECM):

$$\Delta(\ln(P_t)) = \alpha_{01} + \alpha_{11}t + \alpha_{21}GFC_t + \alpha_{31}Covid_t + \sum_{i=1}^{p} \gamma_{1i}\Delta(\ln(P_{t-i})) + \sum_{i=0}^{q1} \gamma_{2i}\Delta(FFR_{t-i})$$

$$+ \sum_{i=0}^{q2} \gamma_{3i}\Delta(\ln(IPI_{t-i})) + \sum_{i=0}^{q3} \gamma_{4i}\Delta(\ln(CPI_{t-i})) + \sum_{i=0}^{q4} \gamma_{5i}\Delta(\ln(QE_{t-i}))$$

$$+ \sum_{i=0}^{q5} \gamma_{6i}\Delta\big((\ln(QE_{t-i} * GFC)\big) + \sum_{i=0}^{q6} \gamma_{7i}\Delta((\ln\,(QE_{t-i} * Covid)) + \varphi ECT_{t-1} + \varepsilon_t \qquad (4)$$

,where φECT_{t-1} replaces the long run ARDL component:

$$\beta_1(\ln(P_{t-1})) + \beta_2 FFR_{t-1} + \beta_3(\ln(IPI_{t-1})) + \beta_4(\ln(CPI_{t-1})) + \beta_5(\ln(QE_{t-1}))$$

$$+ \beta_6((\ln\,(QE_{t-1} * GFC)) + \beta_7((\ln(QE_{t-1} * Covid))$$

The other option is no cointegration or long run relationship, which means the F-statistic is lower than the critical value for the lower bound I(0). It is not possible to reject the null hypothesis and only the short run ARDL model can be estimated:

$$\Delta(\ln(P_t)) = \alpha_{02} + \alpha_{12}t + \alpha_{22}GFC_t + \alpha_{32}Covid_t + \sum_{i=1}^{p} \gamma_{1i}\Delta(\ln(P_{t-i})) + \sum_{i=0}^{q1} \gamma_{2i}\Delta(FFR_{t-i})$$

$$+ \sum_{i=0}^{q2} \gamma_{3i}\Delta(\ln(IPI_{t-i})) + \sum_{i=0}^{q3} \gamma_{4i}\Delta(\ln(CPI_{t-i})) + \sum_{i=0}^{q4} \gamma_{5i}\Delta(\ln(QE_{t-i}))$$

$$+\sum_{i=0}^{q5}\gamma_{6i}\Delta\big((\ln(QE_{t-i}*GFC)\big)+\sum_{i=0}^{q6}\gamma_{7i}\Delta((\ln(QE_{t-i}*Covid))+\varepsilon_t \tag{5}$$

If the F-statistic falls between the lower bound I(0) and the upper bound I(1), the test is inconclusive.

With regards to coefficient expectations, the expectation of the lagged coefficient signs of stock index prices is that they are random in the short term, in line with the random walk theory by Malkiel (1973). The (lagged) coefficients of the FFR are expected to be negative, since an increase in the FFR means borrowing in the economy becomes more expensive. This negatively presses on business investments, consumer spending and eventually profits. If the market prices this future deterioration of companies into the indices, it is expected that stock prices will go down. The (lagged) coefficients of IPI are expected to be positive, which can be reasoned in the same way as the FFR but then the other way around. A higher IPI means a stronger economy, more consumer demand, more investment opportunities and therefore more (expected) profits. This will likely be priced into the price of the stock indices. The next (lagged) coefficients are for the CPI, which are expected to be negative. Higher prices hurt both the companies and the consumer directly and indirectly, as mentioned before. This leads to lower profits and hence lower future stock prices, given the market argues the same way. However, the CPI has been relatively low in the past 20 years, according to US government statistics. Famous economists like Paul Krugman even claimed there was not enough inflation (Krugman, 2013). In that sense, market participants could view higher CPI readings as an improvement in the economy, which creates positive sentiment and subsequently boosts stock prices. As comprehensively discussed before, it is expected that QE will have a positive effect on the stock market and therefore to have a significantly positive sign. Finally, the coefficients of the interaction effects of QE with the dummies GFC and Covid are expected to both have a positive sign, with $\ln(QE_{t-i}*Covid)$ to have a larger effect than $\ln(QE_{t-i}*GFC)$. As mentioned earlier, we anticipate the QE coefficient to be positive, but it depends on the time period we are in. Covid QE had a much bigger impact on the Fed's balance sheet than the GFC period had, which means stock prices during the pandemic should have risen faster than during the GFC if our hypothesis holds.

Granger causality

Important to note is that if a cointegrating relationship is found between the variables and the coefficients of the respective variables are significant, it does not tell the reader anything about the direction of 'causality'. In a macro-economic setting, it is extremely difficult or even impossible to find causal relationships, but it is desirable to at least find out whether quantitative easing induced by the Fed has a granger causal effect on stock prices. If so, the argument can be made that the Fed simply reacts to the economy and the subsequent QE rounds 'happen' to influence stock prices. If there is no evidence of such one-way or unidirectional granger causality, it means the causality could run in either direction or both directions (bi-directional causality). In the case where causality runs the other way, there is an indication that the Fed responds to deviations in the stock market. Since a proxy of GDP is used in the models, it is possible to examine whether the state of the economy unidirectionally granger causes QE. If not, then there is reason to say the Fed solely responds to the stock market and not the economy.

Although the original Granger causality theory (1969) only implies a VAR(p) model with two variables that use the same number of lags p, the intuition behind the theory does not exclude the possibility to implement a multivariate model with different lags. The only difference is that it takes more computing power to get a combination of lags that yield the lowest information criterion. The benefit of time series data is that time does not run backwards. This way we can make stronger statements about causality. The basic idea behind granger causality is that a variable X Granger causes Y if past values of X can help explain Y above and beyond the information contained in past values of Y alone. The Wald test tests whether the lagged short run coefficients are jointly different from zero. The null hypothesis is that the respective lagged coefficients are jointly equal to zero. If at least one of the past values of the independent variables is statistically significant, it means it has explanatory power for the dependent variable at time t and we can reject the null hypothesis of no short run granger causality. The long run causal effects are examined through the t-statistic of the ECT. The null hypothesis in this case is that there is no long run Granger causality. By incorporating a second error correction model of the variables under investigation where QE is the dependent variable (equation 6), it is possible to examine which way the granger causality effects run per stock index:

$$\Delta(\ln(QE_t)) = \alpha_{03} + \alpha_{13}t + \alpha_{23}GFC_t + \alpha_{33}Covid_t + \sum_{i=1}^{p} \gamma_{1i}\Delta(\ln(QE_{t-i}))$$

$$+\sum_{i=0}^{q1}\gamma_{2i}\Delta(FFR_{t-i})+\sum_{i=0}^{q2}\gamma_{3i}\Delta(\ln(IPI_{t-i}))+\sum_{i=0}^{q3}\gamma_{4i}\Delta(\ln(CPI_{t-i}))+\sum_{i=0}^{q4}\gamma_{5i}\Delta(\ln(P_{t-i}))$$

$$+\sum_{i=0}^{q5}\gamma_{6i}\Delta\big((\ln(P_{t-i}*GFC)\big)+\sum_{i=0}^{q6}\gamma_{7i}\Delta((\ln\,(P_{t-i}*Covid))+\varphi ECT_{t-1}+\varepsilon_t \quad (6)$$

Model diagnostics

Every model will undergo robustness checks and residual diagnostics checks will be performed along the way. For example, the residuals will be checked for heteroskedasticity, serial correlation, normality and stability. Violations of the main OLS assumptions will be tackled when deemed necessary.

Results

Structural breaks

In the methodology the possibility of structural breaks for the variable ln(QE) was briefly discussed. In this section structural breaks for ln(QE) will be tested using the Bai-Perron structural break test (1998). The reason QE is examined is not only to validate that the dummy dates in the timeline are approximately well chosen, but also to account for structural breaks in the unit root tests if QE turns out to be I(2).

Table 5 presents the Bai-Perron test for multiple structural breaks at the level for the 95% trimmed time period. The 5% trim is introduced to avoid outliers. The column - Break date (unknown) - states the estimated break dates of the test. This is in contrast with the column – Break date (known) -, which present the break dates that are predicted ex ante in line with our timeline in figure 1. The test shows ln(QE) is highly significant at the 1% level. This means the null hypothesis of no structural breaks can be rejected. Although not given in the table, the test with two breaks also yielded highly significant t-statistics. As expected, the t-statistic is higher for the break dates the test generates. Regardless, the break dates that were chosen ex ante are highly significant at the 1% level. In addition, the estimated break dates for QE are quite close to our predicted break dates. This shows the choice of the breaks are approximately well chosen.

Table 5 Bai-Perron test for QE structural breaks at the level

Variable	(% trim)	Breaks	T-statistic	1% Critical value	Break date (unknown)	Break date (known)
Ln(QE)	5	3	4640.16	9.37	- 10/2008 - 04/2013 - 04/2020	
Ln(QE)	5	3	1476.97	9.37		- 11/2009 - 11/2014 - 03/2020

Note. (% trim) indicates what percentage of the data is trimmed at the tails

Unit root tests

Table 6 shows the results of the stationarity tests on the levels of variables using the optimal lag per variable. The letters in the top corner indicate whether the variable contains a constant and trend (^{c}), a constant without trend (^{b}) or neither a constant nor a trend (^{a}). Since the DF-GLS test makes no distinction between intercept or not, the letter is always at least ^{b} for this test. The optimal lag for the unit root tests is chosen based on the lowest value of the SIC. To not lose too many degrees of freedom, the maximum lag will be set at 12. As a robustness check we set the maximum number of lags at 24, but this yielded the same results as for a maximum lag length of 12.

Table 6 shows ln(IPI) is I(0) according to the ADF test, since the t-statistic is lower than the 5% critical value. One must be careful with this interpretation though. First of all, the DF-GLS and PP test decline this rejection of the hypothesis of possessing a unit root at the level. In addition, ‘true’ real GDP numbers for the period 2003-2022 showed a steady trend, while IPI numbers did not. This means our critical value would be -3.43 if this trend aspect was added to the model. This would mean the t-statistic is above the critical value and therefore it not possible to reject the hypothesis of the presence of a unit root at the level. So, in reality there is a high probability GDP is in fact I(1) if it would be included in the tests. Regardless of whether the proxy of GDP is I(0) or I1), the benefit of the bounds test of Pesaran et al. is that both I(0) and I(1) variables are valid in the ARDL model. Therefore, it is allowed to continue with IPI in testing for cointegration.

Table 6 ADF, DF-GLS and PP unit root test on levels of variables

Variable	ADF			DF-GLS			PP		
	Lags (SIC)	**t-stat**	**5% Critical value**	**Lags (SIC)**	**t-stat**	**5% Critical value**	**Lags (SIC)**	**t-stat**	**5% Critical value**
Ln(QE)	3	-1.87[c]	-3.43	2	-1.96[c]	-2.92	3	-1.92[c]	-3.43
FFR	2	-1.46[c]	-3.43	3	-1.58[c]	-2.91	2	-1.38[c]	-3.43
Ln(IPI)	3	-2.23[b]	-1.65	2	-2.62[c]	-2.92	3	-2.31[b]	-2.88
Ln(CPI)	3	-1.35[c]	-3.43	2	-1.26[c]	-2.92	3	-1.43[c]	-3.43
Ln(S&P500)	1	-1.65[c]	-3.43	1	-1.76[c]	-2.92	1	-1.59[c]	-3.43
Ln(DOW)	1	-1.98[c]	-3.43	1	-2.02[c]	-2.92	1	-2.00[c]	-3.43
Ln(NASDAQ)	2	-1.73[c]	-3.43	1	-1.95[c]	-2.92	2	-1.64[c]	-3.43
Ln(QE*GFC)	1	-1.28[a]	-1.95	1	-1.31[b]	-2.03	1	-1.28[a]	-1.95
Ln(QE*Covid)	1	0.11[a]	-1.95	1	-0.04[b]	-2.03	1	0.13[a]	-1.95

[a]model without constant and trend, [b]model without trend, [c]model with constant and trend

Table 7 shows the results of the stationarity tests of the first differenced variables using the optimal lag per variable.

Table 7 ADF, DF-GLS and PP unit root test on first differenced variables

Variable	ADF			DF-GLS			PP		
	Lags (SIC)	**t-stat**	**5% Critical value**	**Lags (SIC)**	**t-stat**	**5% Critical value**	**Lags (SIC)**	**t-stat**	**5% Critical value**
Ln(QE)	3	-7.32[b]	-1.65	1	-9.09[b]	-2.03	3	-8.96[b]	-2.88
FFR	2	-6.06[a]	-1.95	2	-5.43[b]	-2.02	2	-16.52[a]	-1.95
Ln(IPI)	3	-7.56[b]	-1.65	1	-9.86[b]	-2.03	3	-12.19[b]	-2.88
Ln(CPI)	3	-5.94[b]	-1.65	1	-8.81[b]	-2.03	3	-8.28[b]	-2.88
Ln(S&P500)	1	-10.87[b]	-1.65	3	-2.25[b]	-2.02	1	-13.86[b]	-2.88
Ln(DOW)	1	-11.37[b]	-1.65	3	-2.11[b]	-2.02	1	-14.41[b]	-2.88
Ln(NASDAQ)	2	-8.12[b]	-1.65	1	-9.50[b]	-2.03	2	-11.91[b]	-2.88
Ln(QE*GFC)	1	-10.70[a]	-1.95	1	-10.39[b]	-2.03	1	-15.11[a]	-1.95
Ln(QE*Covid)	1	-10.41[a]	-1.95	1	-10.13[b]	-2.03	1	-14.90[a]	-1.95

[a]model without constant and trend, [b]model without trend, [c]model with constant and trend

All variables are I(1) according to the unit root tests in table 7. This means it is possible to reject the null hypothesis of the first differenced variables possessing a unit root. It turns out that all tests state that ln(QE) is I(1), since the test statistics fall below the 5% critical values. This means the structural breaks do not seem to matter in hindside on whether QE is a stationary variable or not. Again, the null hypothesis of containing a unit root for ln(IPI) might be rejected at the level.

ARDL Bounds test for cointegration

This section will test whether there is a cointegrating relationship between the variables in the ARDL models. Table 8 shows the results of the bounds test of Pesaran et al. (2001). The optimal lag structure in the models are based on the combination of lags which yields the lowest value of the SIC. The optimal lags in the table are in chronological order for the following variables: ln(P), ln(QE), FFR, ln(IPI), ln(CPI), ln(QE*GFC) and ln(QE*Covid). Since a Mata-based algorithm uses much computational power, the maximum number of lags will be set to 12. This means the algorithm will go over $12*13^6$ or 57.921.708 combinations (the dependent variable starts from lag 1). A maximum lag of 12 with monthly data is intuitive as well, since it allows for every possible month in the past year. Besides, for the unit root tests the optimal lag was determined independently for each variable using the SIC. It turned out that even with a maximum lag of 24 the optimal lags were never higher than three. The ARDL models in table 8 also show a strong indication that such high numbers of lags are not required anyways.

Table 8 Results ARDL bounds test

Dependent variable	Optimal SIC lags	F-statistic	1% critical value I(0)	1% critical value I(1)
$\Delta(\ln(S\&P500_t))$	(1, 1, 0, 0, 0, 4, 0)	11.493	3.27	4.39
$\Delta(\ln(DOW_t))$	(1, 0, 0, 0, 0, 4, 1)	11.940	3.27	4.39
$\Delta(\ln(NASDAQ_t))$	(2, 0, 0, 1, 0, 0, 3)	7.777	3.27	4.39

Note. Lower and upper-bound critical values are taken from Pesaran et al. (2001), Table CI(iv) Case IV.

In the vector error-correction model (VECM) literature and therefore in the bounds test, it is common to distinguish between five different cases of model deterministics:

1. No constant, no trend
2. Restricted constant, no trend
3. Unrestricted constant, no trend
4. Unrestricted constant, restricted trend
5. Unrestricted constant, unrestricted trend

Rewriting the levels equation in first-difference form yields restrictions on the constant term and the linear trend, which are displayed by cases 2 and 4. According to Pesaran et al. (2001) and Luetkepohl (2005), an unrestricted trend in the first-difference equation can generate a quadratic trend in the means of the levels equation. This quadratic trend is implausible for the model of this paper, since the variables are approximately linearized with the help of logarithmic transformations. A constant term in the first-difference equation can generate a linear trend in the mean of the P_t variables in the model, which is plausible. Therefore, case 4, which contains an unrestricted constant and restricted trend, is most suitable for the model. In accordance with this analysis, the lower and upper-bound critical values in table 8 are taken from Pesaran et al. (2001), table CI(iv) Case IV. Table CI(iv) Case IV represents the I(0) and I(1) critical values for a model with an unrestricted intercept and restricted trend.

The results in table 8 clearly state that there is cointegration amongst the variables, since the F-statistics are higher than the upper bound 1% critical value. This implies that the null hypothesis of no long run level relationship among the variables in equation (3) can be rejected. It also implies the ECM (equation (4)) can be estimated in the next step.

ECM regression

Short run

Table 9,10 and 11 represent the short run coefficients in the ARDL model and the corresponding ECT's for the S&P500, DOW and NASDAQ respectively. The values are generated by estimating the ECM of equation (4) in accordance with the chosen lags of the respective model. The variables in table 9 are first differenced, while the lags (see table 8) are based on the levels of the variables. This means that for a variable with zero optimal lags on the level, the ECM regression uses the first lag of that variable.

Beginning with the short run variables in table 9, all variables in the model are significant at the 1% level, except for $\Delta(\ln(IPI))$ and $\Delta((\ln(QE_{t-1} * GFC))$. The interpretation for $\Delta(\ln(QE))$ e.g. is the following: a 1% increase in QE is on average associated with a 0.260% decrease in the S&P500 ceteris paribus at the 1% statistical significance level. The interpretation for the dummies are slightly different: a change in the Covid dummy to 1 is on average associated with a 5.782% decrease in the S&P500 ceteris paribus at the 1% statistical significance level. The interaction terms can be interpreted in the following manner: the effect on the S&P500 of a 1% increase in QE is on average 0.371% higher during Covid than during the period outside of Covid ceteris paribus (significant at the 1% level). The wording of these interpretations can be applied to the other models in table 10 and 11 as well.

It is clear from the respective p-values that there is a significant interaction between QE and the dummies GFC and Covid, except for $\Delta((\ln(QE_{t-1} * GFC))$.

Table 9 ECM regression results for the S&P500

Variable	Coefficient	t-Statistic	P-value
$\Delta(\ln(QE_t))$	-0.260 (0.061)	-4.23	0.000
ΔFFR_t	0.009 (0.003)	2.97	0.003
$\Delta(\ln(IPI_t))$	-0.099 (0.146)	-0.68	0.499
$\Delta(\ln(CPI_t))$	-1.037 (0.256)	-4.05	0.000
$\Delta((\ln(QE_t * GFC))$	0.150 (0.030)	5.03	0.000
$\Delta((\ln(QE_{t-1} * GFC))$	-0.002 (0.002)	-1.12	0.265
$\Delta((\ln(QE_{t-2} * GFC))$	-0.005 (0.002)	-2.81	0.005
$\Delta((\ln(QE_{t-3} * GFC))$	-0.008 (0.002)	-4.84	0.000
$\Delta((\ln(QE_t * Covid))$	0.371 (0.056)	6.66	0.000
ECT_{t-1}	-0.257 (0.044)	-5.84	0.000
Intercept	8.501 (1.219)	6.97	0.000
trend	0.015 (0.002)	6.80	0.000
GFC_t	-2.298 (0.448)	-5.13	0.000
$Covid_t$	-5.782 (0.872)	-6.63	0.000
Adjusted R^2	0.344	-	-

Note. Standards errors are in parentheses; dependent variable is $\Delta(\ln(S\&P500_t))$; the dummies GFC and Covid Represent the values 0 or 1.

This means there exists a synergy effect between these variables – i.e. the combined effect of the variables is more powerful than the sum of their effects. The short run effect of QE on the S&P500 can be calculated with the following equations:

The conditional effect of QE on S&P500 is presented with the following equation:

$$\Delta(ln(S\&P500_t)) = 8.501 - 5.782 * Covid - 2.298 * GFC - 0.260 * QE_t + 0.371 * Covid * QE_t + 0.150 * GFC * QE_t - 0.005 * GFC * QE_{t-2} - 0.008 * GFC * QE_{t-3}$$

The ceteris paribus effect of QE on the S&P500 for the period outside of Covid and the GFC:

$$\mathbf{8.501 - 0.260}\boldsymbol{QE_t}$$

This is in reality the effect on the S&P500 for the period where no QE took place or in other words, where the assets of the Fed stayed relatively flat.
The ceteris paribus effect of QE on the S&P500 during Covid:
$8.501 - 5.782 * 1 - 0.260 * QE_t + 0.371 * 1 * QE_t = \mathbf{2.719 + 0.111}\boldsymbol{QE_t}$

From these equations multiple things becomes clear in the short run:

- The pandemic had a deep negative impact on stock prices, as can be seen by the constant in the second equation.
- A marginal increase in QE during Covid has a positive impact on the S&P500, while a marginal increase in QE for the period outside of Covid and the GFC has a negative impact on the S&P500.
- Covid QE has a larger positive effect than the negative effect of QE in general, meaning the unique marginal effect of Covid is positive (0.111).

The ceteris paribus effect of GFC QE on the S&P500:
$8.501 - 2.298 * 1 - 0.260 * QE_t + 0.150 * 1 * QE_t - 0.005 * 1 * QE_{t-2} - 0.008 * 1 * QE_{t-3} = \mathbf{6.203 - 0.110}\boldsymbol{QE_t} \mathbf{- 0.005}\boldsymbol{QE_{t-2}} \mathbf{- 0.008}\boldsymbol{QE_{t-3}}$

Again, multiple short run conclusions can be derived from the two equations:

- The GFC had a deep negative impact on stock prices, as can be seen by the constant in the second equation. The impact was less severe than during the pandemic.
- A marginal increase in QE during the GFC has a negative impact on the S&P500.
- GFC QE has a smaller positive effect than the negative effect of QE in general, meaning the unique marginal effect of the GFC at time t is still negative (-0.110)
- The lagged QE variables are negligible in size with regards to economic significance.

Similar analyses can be performed for the other stock indices as well. The Dow Jones as dependent variable in table 10 shows similar results to table 9, where the S&P500 is the dependent variable. All short run variables in the model are significant at the 5% level, except for $\Delta(\ln(IPI))$ and $\Delta((\ln(QE_{t-1} * GFC))$. Again, there is significant interaction between QE and the dummies GFC and Covid, except for $\Delta((\ln(QE_{t-1} * GFC))$. The conditional effect of QE on the DOW can be calculated with the following equation:

$$\Delta(ln(DOW_t)) = 11.663 - 8.600 * Covid - 1.807 * GFC - 0.108 * QE_t + 0.556 * Covid * QE_t + 0.119 * GFC * QE_t - 0.004 * GFC * QE_{t-2} - 0.008 * GFC * QE_{t-3}$$

The ceteris paribus effect of QE on the DOW for the period outside of Covid and the GFC:

$\mathbf{11.663 - 0.108}\boldsymbol{QE_t}$

The ceteris paribus effect of QE on the DOW during Covid:

$11.663 - 8.600 * 1 - 0.108 * QE_t + 0.556 * 1 * QE_t = \mathbf{3.003 + 0.448}\boldsymbol{QE_t}$

The ceteris paribus effect of GFC QE on the DOW:

$11.663 - 1.807 * 1 - 0.108 * QE_t + 0.119 * 1 * QE_t - 0.004 * 1 * QE_{t-2} - 0.008 * 1 * QE_{t-3} = \mathbf{9.856 + 0.011}\boldsymbol{QE_t}\mathbf{ - 0.005}\boldsymbol{QE_{t-2}}\mathbf{ - 0.008}\boldsymbol{QE_{t-3}}$

Similar to the previous findings, the dummy constants show the pandemic and the GFC were negative events for the Dow Jones. Again, the pandemic had a more severe impact than the GFC on stock prices. A marginal increase in QE during Covid has a positive impact on the DOW, while a marginal increase in QE for the period outside of the GFC and the pandemic has a negative impact on the DOW. The unique marginal effect of Covid on the DOW is positive at 0.448. A marginal increase in QE during the GFC has a negligible unique effect on the DOW. This observation also holds for the lags of QE in the final respective equation.

Table 10 ECM regression results for the DOW

Variable	Coefficient	t-Statistic	P-value
$\Delta(\ln(QE_t))$	-0.108 (0.023)	-4.63	0.000
ΔFFR_t	0.007 (0.003)	2.27	0.024
$\Delta(\ln(IPI_t))$	0.016 (0.146)	0.12	0.902
$\Delta(\ln(CPI_t))$	-1.490 (0.228)	-6.53	0.000
$\Delta((\ln(QE_t * GFC))$	0.119 (0.027)	-4.41	0.000
$\Delta((\ln(QE_{t-1} * GFC))$	-0.003 (0.002)	-1.59	0.114
$\Delta((\ln(QE_{t-2} * GFC))$	-0.004 (0.002)	-2.27	0.024
$\Delta((\ln(QE_{t-3} * GFC))$	-0.008 (0.002)	-5.16	0.000
$\Delta((\ln(QE_t * Covid))$	0.556 (0.080)	6.97	0.000
ECT_{t-1}	-0.279 (0.044)	-6.41	0.000
Intercept	11.663 (1.305)	8.94	0.000
trend	0.018 (0.002)	9.63	0.000
GFC_t	-1.807 (0.404)	-4.48	0.000
$Covid_t$	-8.600 (1.212)	-7.07	0.000
Adjusted R^2	0.335	-	-

Note. Standards errors are in parentheses; dependent variable is $\Delta(\ln(DOW_t))$; the dummies GFC and Covid represent the values 0 or 1.

With regards to the Nasdaq in table 11, the short run results are slightly different than the other two stock indices. In this case, there is only a significant interaction between QE and the Covid dummy and its lags. The conditional effect of QE on the NASDAQ can be calculated with the following equation:

$$\Delta(\ln(NASDAQ_t)) = 10.483 - 6.734 * Covid - 0.058 * QE_t + 0.429 * Covid * QE_t + 0.013 * Covid * QE_{t-1} + 0.015 * Covid * QE_{t-2}$$

The ceteris paribus effect of QE on the NASDAQ for the period outside of the GFC and Covid:

$$\mathbf{10.483 - 0.058}\boldsymbol{QE_t}$$

Table 11 ECM regression results for the NASDAQ

Variable	Coefficient	t-Statistic	P-value
$\Delta(\ln(NASDAQ_{t-1}))$	0.282 (0.064)	4.43	0.000
$\Delta(\ln(QE_t))$	-0.058 (0.022)	-2.62	0.010
ΔFFR_t	0.003 (0.003)	0.76	0.447
$\Delta(\ln(IPI_t))$	1.482 (0.328)	4.52	0.000
$\Delta(\ln(CPI_t))$	-1.892 (0.271)	-6.98	0.000
$\Delta((\ln(QE_t * GFC))$	0.047 (0.030)	1.57	0.118
$\Delta((\ln(QE_t * Covid))$	0.429 (0.126)	3.42	0.001
$\Delta((\ln(QE_{t-1} * Covid))$	0.013 (0.004)	3.39	0.001
$\Delta((\ln(QE_{t-2} * Covid))$	0.015 (0.004)	3.74	0.000
ECT_{t-1}	-0.215 (0.037)	-5.87	0.000
Intercept	10.483 (1.472)	7.12	0.000
trend	0.025 (0.003)	9.22	0.000
GFC_t	-0.680 (0.453)	-1.50	0.135
$Covid_t$	-6.734 (1.912)	-3.52	0.001
Adjusted R^2	0.372	-	-

Note. Standards errors are in parentheses; dependent variable is $\Delta(\ln(NASDAQ_t))$; the dummies GFC and Covid represent the values 0 or 1.

The ceteris paribus effect of QE on the NASDAQ during Covid:

$$10.483 - 6.734 * 1 - 0.058 * QE_t + 0.429 * 1 * QE_t + 0.013 * 1 * QE_{t-1} + 0.015 * 1 * QE_{t-2} = \mathbf{3.749 + 0.371 QE_t + 0.013 QE_{t-1} + 0.015 QE_{t-2}}$$

Since the dummy GFC and the interaction term $\Delta((\ln(QE_t * GFC))$ are not significant at the 5% level, the conditional equation has no GFC terms and the equation for GFC QE cannot be interpreted. The pandemic was once again a significant bearish event for stock prices. A marginal increase in QE for the period outside of the GFC and the pandemic has a negative impact on the NASDAQ. This negative effect of QE is smaller however than for the other stock indices. A marginal increase in QE during Covid has a positive impact on the NASDAQ and although the lagged QE coefficients are clearly smaller in magnitude, the effect is still positive for all lags. The unique marginal effect of Covid QE on the NASDAQ at time t is positive at 0.371. A marginal increase in the lags of Covid QE has a negligible unique effect on the Nasdaq.

It turns out that QE during both the pandemic and the GFC has had a smaller effect on the S&P500 and the Nasdaq than on the Dow Jones. One reason for this could be that the companies in the Dow Jones are more industrial and capital intensive than the other indices. When the economy shut down in the beginning of 2020, these companies were more likely to have a significant part of the business or supply chain shut down. This had a big impact on the financial health of those businesses. Companies in the S&P500 and Nasdaq on the other hand contain more tech companies and other companies that were less impacted due to employees being able to work at home for example. When the central banks launched Covid QE, businesses were more easily able to attract capital and remain solvent. The market priced these improved liquidity positions in and estimated the (share price) recovery to be more significant for companies in the Dow Jones. This argumentation could explain why the constant for Covid in table 10 had a relatively more negative impact on the Dow and why the unique marginal effect on stock prices is larger for the Dow than for the other stock indices.

Another aspect of monetary policy is through the Federal funds rate channel. Except for the Nasdaq, there is statistical evidence in the short run that increases in the FFR have a positive effect on stock prices, although the coefficients in the regression results have lower economic significance than the coefficients of QE and its interaction terms. This positive relationship might seem counterintuitive at first glance. Figure 5 graphs the S&P500 and the FFR over time and supports the positive significant coefficients in the ECM regression tables; the presumable negative relationship between interest rates and stock prices has not been present in the past 20 years. An explanation could be that news about expected interest rate hikes is often publicly known beforehand, which leads the market to price the rate hikes into the market before the event truly takes place. For example, a possible 'large' rate hike in three weeks will lead to a large decline in stock prices at time t_{-3}. When the news is released three weeks later, the market has already anticipated the hike and the market response at time *t* is limited. It might even lead to an increase in stock prices if the rate hike is smaller than expected. This is confirmed by Lobo (2002), who finds that surprises associated with decreases in the Federal funds rate cause stock prices to rise significantly.

Finally, the significance and size of the variables trend, CPI and IPI are worth mentioning as well. As expected, in all models the trend is highly significant at the 1% level, meaning that there seems to be an average monthly increase in the stock indices of 0.015%-0.025% over time. The IPI is only significant for the Nasdaq, but the CPI shows coefficients of at least -1 in combination with significant p-values for all stock indices. This means that a 1% increase in the inflation rate month over month has an average negative impact on the respective stock indices of at least 1% ceteris paribus. Given the central banks' target inflation rate for an entire year is 2%, a 1% CPI increase in one month is concerning to say the least. An explanation for this negative effect on stock prices could be the earlier mentioned argument in the literature review, where extremely high inflation leads to such a big loss in purchasing power that consumers spend less on discretionary items. On the supply side higher (input) costs slash the profits of many companies as well. These chains of events have become strikingly present during the pandemic, where US month over month CPI readings of approximately 1% have occurred frequently and stock markets have dropped simultaneously (US Bureau of Labor Statistics, 2022, July 1).

Long run

With regards to the long run part of the model, the coefficients of ECT_{t-1} in table 9-11 are significant at the 1% level and have a negative sign, which is in line with the ARDL bounds test. The monthly speed of adjustment to equilibrium after a shock is 0.257 for the S&P500, 0.279 for the Dow and 0.215 for the Nasdaq respectively. Approximately 22-28% of disequilibria from the previous month's shock will converge back to the long run equilibrium in the current month t. It takes 2.33 months for the S&P500 to reduce the disequilibrium by 50% (or half of its lifetime) ceteris paribus ($0.743^n = 0.5$). It takes 2.12 and 2.86 months respectively for the Dow and the Nasdaq to reduce this disequilibrium to 50%.

Table 12 presents the long term coefficients in equation 3 that were captured by the ECT in equation (4). The interpretation of the long run variables are less intuitive than the short run variables, since the long run variables are not in differences. The variable $\ln(QE_{t-1})$ can be interpreted in the following way: an increase of 1 in the lagged natural logarithm of QE is on average associated with a -0.259% decrease in the S&P500 ceteris paribus at the 1% statistical significance level. What is more interesting however is the direction the variables move to in the long run and with what relative magnitude and statistical significance.

Table 12 Long run coefficients ARDL model

	Dependent variable		
Independent variable	$\Delta(\ln(\boldsymbol{S\&P500_t}))$	$\Delta(\ln(\boldsymbol{DOW_t}))$	$\Delta(\ln(\boldsymbol{NASDAQ_t}))$
$\ln(QE_{t-1})$	-0.259***	-0.387***	-0.271***
	(0.084)	(0.074)	(0.098)
FFR_{t-1}	0.037***	0.025**	0.012
	(0.013)	(0.012)	(0.016)
$\ln(IPI_{t-1})$	-0.385	0.059	1.792***
	(0.601)	(0.473)	(0.653)
$\ln(CPI_{t-1})$	-4.040***	-5.342***	-8.822***
	(1.067)	(0.903)	(1.410)
$\ln(QE_{t-1} * GFC)$	0.602***	0.442***	0.221*
	(0.117)	(0.095)	(0.132)
$\ln(QE_{t-1} * Covid)$	1.445***	1.963***	2.015***
	(0.235)	(0.296)	(0.493)

Note. Standard errors between parentheses, significance*: * p < 0.10, ** p < 0.05, ***p < 0.01*

In line with the short run coefficients, the CPI has on average a negative relationship with the stock indices in the long run as well. This is statistically significant at the 1% level. The IPI shows no clear cut associations with the stock market, except for the Nasdaq, which is significant at the 1% level. The federal funds rate has on average a positive effect on the S&P500 and the Dow Jones at the 1% and 5% significance levels respectively. The variables $\ln(QE_{t-1})$ and its corresponding interaction with the dummies GFC and Covid show significant coefficients at the 1% level for all stock indices. In line with the short run dynamics, the general effect of QE is on average negative for stock prices, while the interaction terms are positive. In this case however, the coefficients of the interaction effects are substantially larger than the base variable. This shows first of all that the QE rounds had a positive marginal effect on stock prices. Although the short run and long run coefficients are not directly comparable, the long run effect of quantitative easing on stock prices is relatively larger than for the short run effects. The positive marginal effect on stock prices was substantially bigger for QE during Covid than during the GFC. In addition, the size of the interaction term coefficients of Covid QE compared to the interaction term coefficients of GFC QE is considerably larger than for the short run models. This provides evidence that the proportion of marginal impact on the stock market between Covid QE and GFC QE was larger in the long run than in the short run.

Regarding the economic significance of the QE variables, in the period before QE was implemented and in the period between GFC QE and Covid QE there was a negative relationship with stock prices for both the short run and the long run. Referring to figure 2 and given the strong positive relationships witnessed so far, it is likely the effect is mainly driven by the latter period, where the Fed attempted to reduce the balance sheet. If this shrinkage of the balance sheet indeed caused a decrease in stock prices, it would strenghten the positive relationship between QE and stock prices that has been witnessed so far. Again, when the Fed sells assets and liquidity gets removed from the financial system, there is less currency left to flow to financial markets. In addition, QT increases interest rates, meaning borrowing becomes more expensive and investments are less attractive. This future slowdown in economic growth should be priced into the markets, meaning stock prices decline at time t.

In contrast with these periods, the periods where the Fed practitioned QE and bought financial assets saw significant positive effects on stock prices for both the short run and the long run. In the short run, GFC QE had either a negative or negligible effect on stock prices, while in the long run there is a significant positive effect on stock prices. For the pandemic, both in the short run and the long run there are highly significant coefficients. The discrepancy could be explained by how much QE was done in a short amount of time. For the pandemic, the balance sheet immediately took off and stock prices followed in line, meaning that there was an immediate short run effect of QE on stock prices. During the financial crisis, QE was spread over multiple rounds and there were 'long' times in between the rounds. Although stock prices rose over the entire period after the stock market crash of 2008 and hence the long run coefficients are positive, the short run effects are simply not there. As mentioned before, stock prices declined in the months following the first QE announcement, which is in stark contrast with the immediate price surge after the QE announcement in March of 2020. The difference could be explained by the fact that when QE was first initiated, the market was unfamiliar and hesitant with how stock prices would react. After the first QE round passed by, the market finally recognized that more QE means higher stock prices. Since investors knew this in 2020, stock prices immediately rose explosively. All coefficients point into the same direction however: more QE means higher stock prices and vice versa.

In the short run, the magnitude of the QE coefficients for the pandemic indicates the economic significance. For the DOW a 1% increase in QE is associated with a 0.448% increase in the Dow Jones. Given that the balance sheet of the Fed increased with around 70% between the beginning of March 2020 and the end of May 2020, the ARDL model estimates an increase of around 30% in the Dow Jones. This increase in stock prices is exceptionally large in such a short time span and therefore finding out the Fed likely played a major role in this surge is of high economic significance. The magnitude of the coefficients show the economic significance in the long run as well, given that the interaction terms offsets the general negative QE variable with a large amount. This could mean that QE truly has a lagged effect on stock prices and that it takes some time for the newly created currency to flow through the financial system. This would go against the argument that markets are efficient in the short run and it would mean the effect truly evolves once a long run equilibrium is achieved.

Model diagnostics

Normality

The normal distribution is symmetrical about the mean, so the first thing to do is to check if the distribution of the residuals is symmetrical with a symmetry plot (see figure 6). It turns out there is clear asymmetry in the residuals, since the residuals lie below the reference line in all plots. This indicates that the distributions of residuals are skewed to the left: the residuals with the lowest value are far more negative than the residuals with the highest value are positive. The histograms in figure 7 confirm this observation, since the bulk of the data seems to the right side of the distribution. The p-values for testing whether skewness is present in table 13 are smaller than 5% for the S&P500 and the Dow. The hypothesis of no skewness for the Nasdaq can only be rejected at the 10% significance level though. The p-values for kurtosis indicates we can reject the null hypothesis of no kurtosis for all indices except the Dow at the 5% significance level. The kurtosis is especially visually observable for the Nasdaq histogram in figure 7, where the residuals deep in the tail are more extreme than the tails of the normal distribution. As a final confirmation, the Jarque-Bera normality test in table 14 is performed. The Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. As expected, the p-values of the test clearly state that the residuals of all models do not follow a normal distribution.

In summary, there is clear indication of non-normality in the residuals. One potential explanation for the non-normality could be due to economic shocks like the GFC or the pandemic, which the models have difficulty with to capture. This means the residuals could be very large around such events. This non-normality is tricky to solve, since the variables have already been logarithmically transformed and it is undesirable to transform the variables even more. The only viable solution is to examine whether the residuals are approximately normal with the help of a standardized normal probability plot (see figure 8). With the help of "the fat pencil test", it is fair to say the pencil covers all data points and the data is approximately normally distributed.

Table 13 Skewness and kurtosis test

Model	P-value Skewness	P-value Kurtosis
S&P500	0.000	0.042
DOW	0.007	0.121
NASDAQ	0.062	0.010

Table 14 Jarque-Bera normality test

Model	χ^2 statistic	P-value
S&P500	24.48	0.000
DOW	9.926	0.007
NASDAQ	14.04	0.001

Serial correlation

The presence of autocorrelation will show bias in the OLS estimator, which is why it needs to be tested for. Table 15 presents the Breusch-Godfrey LM test for serial correlation. The Breusch-Godfrey test has an advantage over the classical Durbin Watson D test. The Durbin Watson test relies upon the assumption that the distribution of residuals are normal whereas the Breusch-Godfrey test is less sensitive to this assumption. Since the residuals show signs of non-normality, the Durbin-Watson test might lead to a misleading conclusion. Another advantage of this test is that it allows to test for serial correlation through several lags instead of only one lag. The χ^2 statistics show we cannot reject the null hypothesis of no serial correlation using 12 lags in the residuals at the 5% statistical significance level. The test presents serial correlation using 12 lags, since monthly data is used and there might be serial correlation between the same months. Although not given in the table, all lags between 1 and 4 were tested for as well and provided no p-values that were smaller than 0.05.

Table 15 Breusch-Godfrey LM test for serial correlation

Model	χ^2 statistic	P-value
S&P500	19.462	0.078
DOW	11.505	0.486
NASDAQ	19.999	0.067

Note. 12 lags for all models

Model stability

To assess the parameter stability of the model, the cumulative sum of recursive residuals (CUSUM) and the CUSUM of squares tests of Brown et al. (1975) are applied. To measure stability of the model, an upper and lower control limit is presented as well. If the CUSUM line goes above or below the control limits of the 95% confidence interval, it is with high degree of certainty that the model contains a structural change and the null hypothesis of no stability over time can be rejected.

The CUSUM plots in figure 9 indicate the absence of any instability of the coefficients because the plot of the CUSUM statistic falls inside the control limits of the 95% confidence interval of parameter stability. The CUSUM of squares plots in figure 10 indicate the coefficients are stable up to around the global financial crisis in 2008, then the model restabilizes up to around 2017/2018. This is the point where especially the model coefficients for the Nasdaq become unstable. The model suddenly jumps at the beginning of the pandemic and quickly reaches stability again. The instability around the GFC and the pandemic are in line with previous structural break analysis. The fact that significance is achieved by the CUSUM of squares plot but not by the CUSUM plot suggests that instability may be due to a shift in residual variance than to shifts in values of regression coefficients. However, examination of coefficients and residuals over time with the help of rolling regressions clearly show the instability is caused by changes in the coefficients.

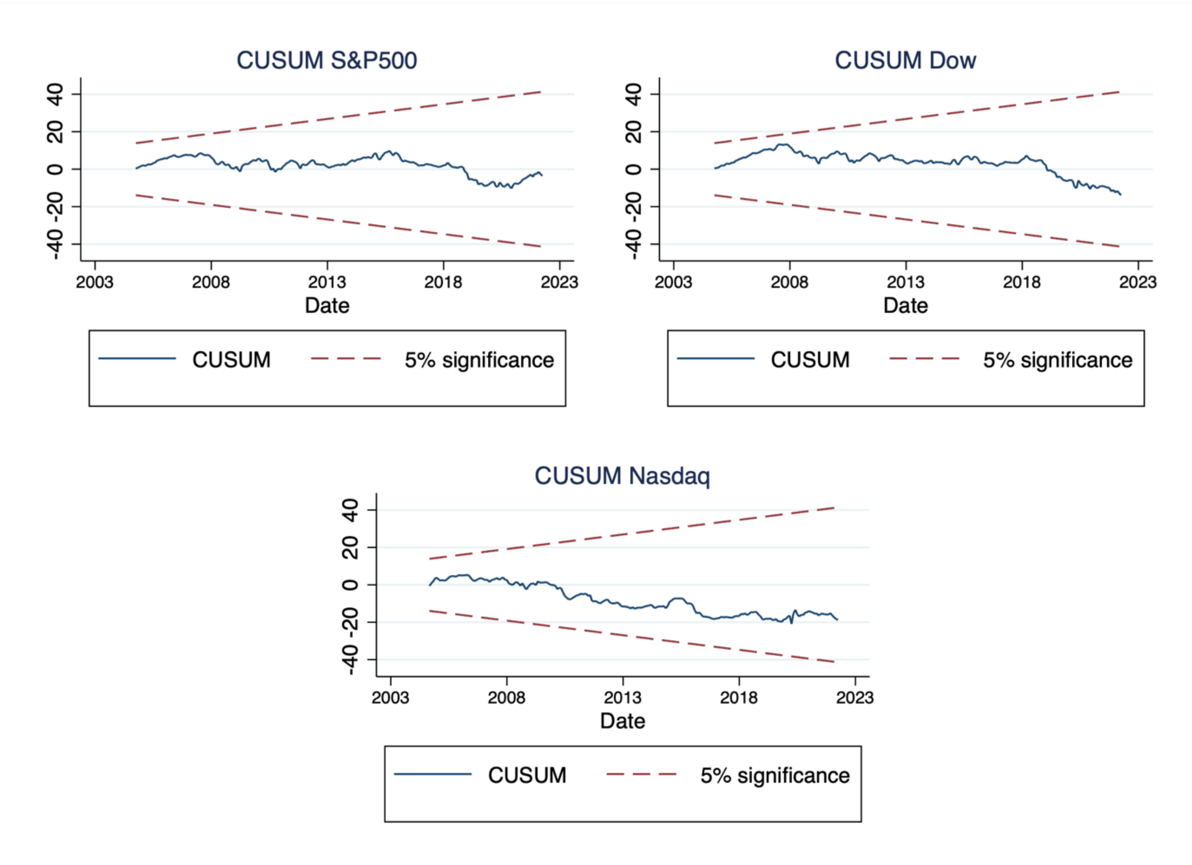

Figure 9 CUSUM plots for the S&P500, Dow and the Nasdaq (2003-2022)

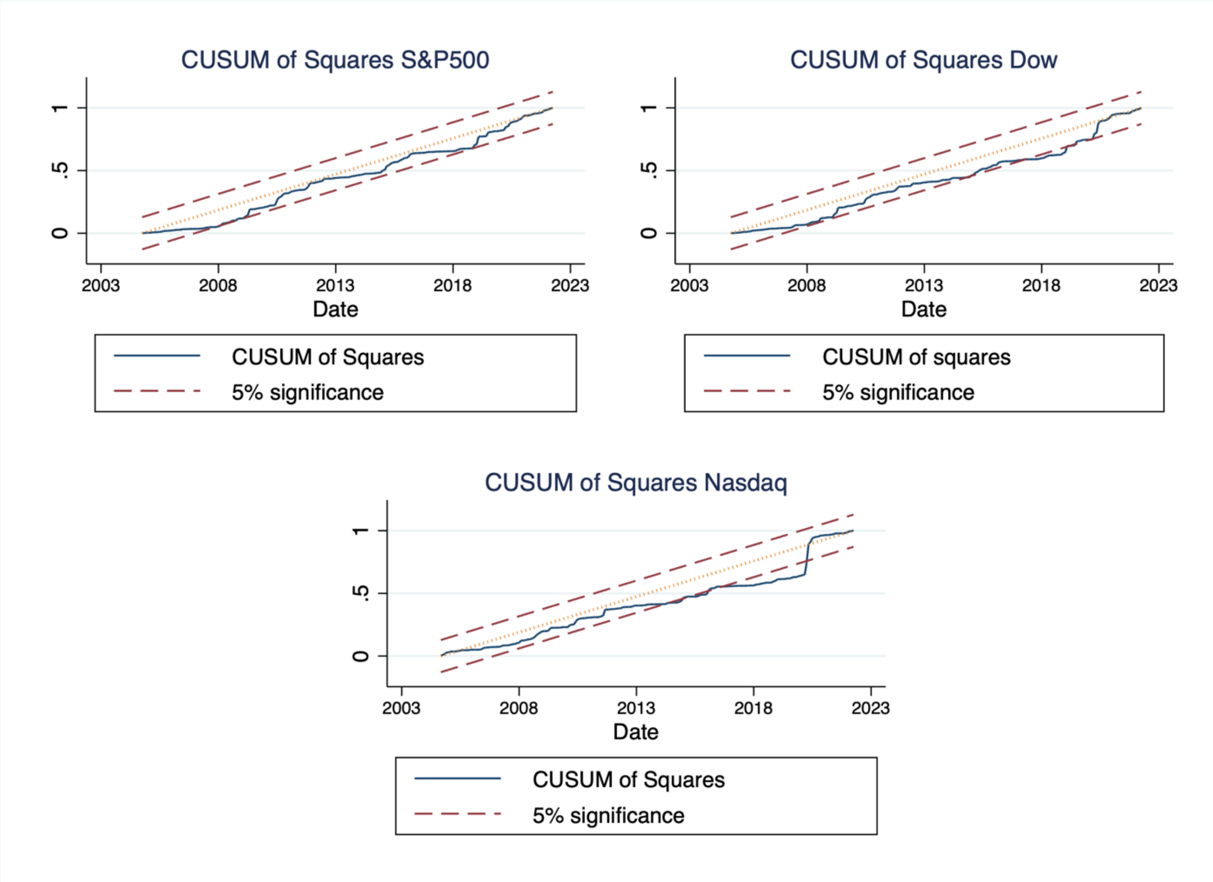

Figure 10 CUSUM of Squares plots for the S&P500, Dow and the Nasdaq (2003-2022)

Homoskedasticity

Table 16 White test for heteroskedasticity

Model	χ^2 statistic	P-value
S&P500	100.869	0.067
DOW	73.799	0.452
NASDAQ	116.923	0.003

At last, table 16 presents the White test for heteroskedasticity. The white test tests whether the variance of the residuals is constant over time. Except for the Nasdaq, the p-values indicate we cannot reject the null hypothesis of homoskedasticity. It looks like the reason why the NASDAQ residuals are heteroskedastic is because there seems to be a large shift in the Cusum of squares graph at the beginning of Covid in figure 10. This also strengthens the point that the pandemic was a structural break. The OLS estimators for the NASDAQ model are no longer 'BLUE' (Best Linear Unbiased Estimators), meaning the regression predictions are inefficient and the standard errors are no longer valid. To solve these problems, either Generalized Least Squares (GLS) or Huber-White robust standard errors are used. For GLS, a new estimator $\widehat{\omega}$ for the variance is estimated by regressing the variance of the model in table 11 on the regressors in the same table. Subsequently all variables in the new OLS regression will be divided by the square root of $\widehat{\omega}$. Since the GLS model showed higher standard errors than the model with White standard errors and the GLS model still indicated heteroskedasticity, the model with White standard errors is used (see table 17). The benefit of this model is that OLS is unbiased due to the coefficients remaining the same. Table 17 shows that the standard errors slightly increased and that the t-statistics shrunk slightly in magnitude compared to table 11, but the coefficients remain their same statistical significance. This means the interpretations for the NASDAQ remains the same.

The heteroskedasticity problem is still inherent in the model however. Using White standard errors is essentially 'shoving the problem under the rug', which is why a different model will be used by choosing the lag order based on the AIC instead of the BIC. Since the AIC tends to prefer more lags than the BIC, the maximum number of lags will be set to 12. The generated lag order in the same chronological order as before is (9, 2, 8, 1, 9, 7, 7). The bounds test indicates there is cointegration amongst the variables with a F-statistic of 7.722. The model cannot reject the null hypothesis of homoskedasticity in the White test. The model passes all other previous diagnostic tests as well except for the normality tests. Again, the fat pencil test indicates approximation of normality. The short run and long run coefficients of the regression do change however. The most noticeable differences are presented in table 18 and discussed in the next paragraphs.

The reason only the first difference at time t is given in table 18 for the interaction term QE GFC is because all the lags were negligible in size from an economic point of view, although most were statistically significant at the 5% level. In line with table 11, the interaction term of QE Covid shows positive and statistically significant coefficients up till the second differenced lag. The other lags were not statistically significant anymore. An important difference is found in the ECT. The ECT is once again significant at the 1% level but decreased to -0.435. This means the monthly speed of adjustment to equilibrium after a shock is almost twice as fast as in the previous models.

For the short run coefficients, $\Delta(\ln(QE_t))$ is not significant anymore, while $\Delta(\ln(QE_{t-1}))$ is positive at the 1% significance level. This indicates that in general there is a significant positive lagged effect of QE on the Nasdaq, which is contrary to the significant negative coefficients that were witnessed so far. The coefficient of the FFR at time t is not significant anymore, while the coefficients of the third and fourth lag of the FFR are negative and significant at the 1% level. This is contrary to the FFR coefficients in the other models, since those coefficients were positive at time t and smaller in size. Intuitively, the results are in line with the earlier interpretation. The FFR might be fully priced in already at time t and therefore be positive for stocks, while the whispers of the market in earlier months about future rate hikes cause stock prices to go down. Again, the GFC dummy is not significant at the 5% level, which is why this variable and the interaction term with QE will not be interpreted. The coefficient of the interaction term $\Delta((\ln(QE_t * Covid))$ is almost twice as large as in table 11. The coefficients with regards to QE during Covid indicate that the unique marginal effect of Covid QE on the NASDAQ at time t is 0.846. At time t-1 the unique marginal effect is 0.248 (0.230 + 0.018). These effects are not only larger than for the original model, but also for the S&P500 and DOW models.

The long run coefficients are similar with regards to the NASDAQ coefficients of table 12, except for the FFR_{t-1} and $(\ln(QE_{t-1}))$. The coefficient of the FFR is positive and significant at the 1% level, in line with the other models. The coefficient of QE is not significant anymore. The other coefficients can be interpreted in the same way as the long term coefficients in table 12.

Table 18 SR and LR regression results for the NASDAQ

Variable	Coefficient	t-Statistic	P-value
Short run			
$\Delta(\ln(NASDAQ_{t-1}))$	0.367 (0.080)	4.59	0.000
$\Delta(\ln(NASDAQ_{t-5}))$	0.139 (0.068)	2.04	0.043
$\Delta(\ln(NASDAQ_{t-8}))$	0.172 (0.063)	2.71	0.007
$\Delta(\ln(QE_t))$	-0.137 (0.100)	-1.37	0.174
$\Delta(\ln(QE_{t-1}))$	0.230 (0.106)	2.17	0.031
ΔFFR_t	0.014 (0.015)	0.93	0.352
ΔFFR_{t-3}	-0.047 (0.016)	-2.89	0.004
ΔFFR_{t-4}	-0.051 (0.017)	-2.95	0.004
$\Delta(\ln(IPI_t))$	1.515 (0.386)	3.92	0.000
$\Delta(\ln(CPI_t))$	-1.058 (1.103)	-0.96	0.339
$\Delta(\ln(CPI_{t-1}))$	2.719 (1.289)	2.11	0.036

$\Delta((\ln(QE_t * GFC))$	0.076 (0.040)	1.90	0.059
$\Delta((\ln(QE_t * Covid))$	0.846 (0.187)	4.52	0.000
$\Delta((\ln(QE_{t-1} * Covid))$	0.018 (0.004)	4.23	0.000
$\Delta((\ln(QE_{t-2} * Covid))$	0.015 (0.005)	3.40	0.001
ECT_{t-1}	-0.435 (0.070)	-6.26	0.000
Intercept	22.909 (3.061)	7.48	0.000
trend	0.024 (0.002)	12.18	0.000
GFC_t	-1.156 (0.613)	-1.89	0.061
$Covid_t$	-13.090 (2.852)	-4.59	0.000
Long run			
$\ln(QE_{t-1})$	-0.068 (0.067)	-1.01	0.312
FFR_{t-1}	0.049 (0.014)	3.63	0.000
$\ln(IPI_{t-1})$	1.500 (0.511)	2.94	0.004
$\ln(CPI_{t-1})$	-9.844 (1.337)	-7.36	0.000
$\ln(QE_{t-1} * GFC)$	0.186 (0.092)	2.02	0.045
$\ln(QE_{t-1} * Covid)$	1.927 (0.327)	5.90	0.000
Adjusted R^2	0.489	-	-

Note. Standards errors are in parentheses; dependent variable is $\Delta(\ln(NASDAQ_t))$; the dummies GFC and Covid represent the values 0 or 1; Lags are based on the AIC.

Granger Causality

Short run Granger Causality

So far robust evidence has been found for a cointegrating relationship among the variables of interest. This section will present the results of the short run and long run Granger causality results. The models for equation 6 reject the null hypothesis of no cointegration in the bounds test with F-statistics for the S&P500, Dow and Nasdaq (as independent variables) of 6.907, 5.962 and 6.263 respectively. The models used the AIC with a maximum of 12 lags to get the following lag order for the S&P500, Dow and Nasdaq respectively: (12, 3, 11, 11, 12, 11, 12), (12, 4, 11, 12, 12, 0, 8) and (11, 12, 11, 11, 12, 12, 9).

The AIC was used over the SIC in choosing the optimal lags, since the models chosen by the SIC failed all previously mentioned residual diagnostics tests. The models using the lags based on the AIC only failed for serial correlation in the residuals. To solve this issue, Newey-West standard errors are used. The Jarque-Bera test indicates non-normality and the kurtosis test indicates kurtosis for both the S&P500 and the DOW. The histogram residual plots also show the tails are larger than for a normal distribution and the center of the distribution is more peaked. Again, according to the fat pencil test the distribution is approximately normal. The Residual versus fitted plot shows significant outliers, but it is undesirable to remove the datapoints, since they are not errors but part of the model. Nearly all the 'outliers' fall in the period September till November of 2008 in all the plots, meaning it is more likely the models were simply poorly able to capture volatile events like the GFC and the first QE round in November of 2008.

The direct short run causality results of the Wald test are given in table 19 and 20. Table 21 summarizes the results from 19 and table 20. It turns out there is solely unidirectional Granger causality running from the independent variables to the dependent variables, except for the NASDAQ and QE during Covid where there is bi-directional causality. GFC QE Granger causes the S&P500 and the DOW, while Covid QE Granger causes the NASDAQ. The NASDAQ Granger causes QE and the FFR Granger causes QE in all models. Taking a closer look at the lagged FFR coefficients in the models where QE is the dependent variable, the coefficients are not unanimous in terms of the sign, although it looks like the significant lags are negative for the first and last few lags and positive for the lags in the middle. An explanation for the negative coefficients of the first few lags could be that in a tightening cycle an increase in the FFR precedes quantitative tightening (meaning the Assets of the Fed go down) and vice versa in a loosening cycle. Some empirical evidence: the former is what has occurred since 2022 and the latter has occurred in the beginning of the pandemic. The IPI granger causes QE for the models where the DOW and NASDAQ are independent variables, which indicates that the Fed indeed reacts to economic conditions.

Regarding the stock indices, all the stock indices during the pandemic Granger cause QE, which indicates that the Fed responded to the stock market during the pandemic. The Nasdaq during the GFC Granger causes QE, although this is not the case for the model with the S&P500 and DOW as independent variables. Interestingly, the assets of the Fed in general do not seem to

Granger cause stock prices. The results provide strong evidence this is unidirectionally the case for the GFC and the pandemic, although there is less evidence for the pandemic.

Maziarz (2015) warns about Granger causality fallacies and more specific to this paper's methodology in the form of the common cause fallacy. Common cause fallacy implies the existence of a third variable Z(t) that Granger causes both X(t+1) and Y(t+2). The conclusion that is observed is that X(t+1) Granger causes Y(t+2), while in reality there is a spurious causality. The severity of the problem for this paper depends again on how exogenous the assets of the Fed are, since this is the main variable of interest. This endogeneity issue has been comprehensively discussed before. Maziarz adds that common cause fallacy should be suspected when the causality tests indicate bi-directional Granger-causality. Table 21 presents weak evidence for this suspicion.

Table 19 Short run Granger causality tests with stock index as dependent variable

	Dependent variable		
Independent variable	$\Delta(\boldsymbol{ln}(\boldsymbol{S\&P500_t}))$	$\Delta(\boldsymbol{ln}(\boldsymbol{DOW_t}))$	$\Delta(\boldsymbol{ln}(\boldsymbol{NASDAQ_t}))$
$\Delta(\ln(QE))$	-	-	-
$\Delta(\text{FFR})$	-	-	-
$\Delta(\ln(IPI))$	-	-	-
$\Delta(\ln(CPI))$	-	-	-
$\Delta(\ln(QE * GFC))$	10.17***	10.68***	-
$\Delta(\ln(QE * Covid))$	-	-	9.33***

Note: - indicates zero lags, significance: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 20 Short run Granger causality tests with QE as dependent variable

	Dependent variable		
Independent variable	$\Delta(\boldsymbol{ln}(\boldsymbol{QE_t}))_{S\&P500}$	$\Delta(\boldsymbol{ln}(\boldsymbol{QE_t}))_{DOW}$	$\Delta(\boldsymbol{ln}(\boldsymbol{QE_t}))_{NASDAQ}$
$\Delta(\ln(S\&P500))$	1.42	x	x
$\Delta(\ln(DOW))$	x	1.65	x
$\Delta(\ln(NASDAQ))$	x	x	1.79*
$\Delta(\text{FFR})$	8.87***	8.20***	7.19***
$\Delta(\ln(IPI))$	1.22	2.55***	2.83***
$\Delta(\ln(CPI))$	0.57	0.75	0.89
$\Delta(\ln(S\&P500 * GFC))$	0.96	x	x
$\Delta(\ln(S\&P500 * Covid))$	4.23***	x	x
$\Delta(\ln(DOW * GFC))$[a]	x	-	x
$\Delta(\ln(DOW * Covid))$	x	4.33***	x
$\Delta(\ln(NASDAQ * GFC))$	x	x	2.15**
$\Delta(\ln(NASDAQ * Covid))$	-	-	7.77***

Note: x means not part of the model; [a]$\Delta(\ln(DOW * GFC))$ has zero lags; significance: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 21 Direction short run Granger causality

Direction of causality		
$\Delta(\ln(QE * GFC))$	$\longrightarrow$	$\Delta(ln(S\&P500_t))$; $\Delta(ln(DOW_t))$
$\Delta(\ln(QE * Covid))$	$\longrightarrow$	$\Delta(ln(NASDAQ_t))$
$\Delta(\ln(NASDAQ))$	$\longrightarrow$	$\Delta(ln(QE_t))_{NASDAQ}$
$\Delta(\text{FFR})$	$\longrightarrow$	$\Delta(ln(QE_t))_{S\&P500}$; $\Delta(ln(QE_t))_{DOW}$; $\Delta(ln(QE_t))_{NASDAQ}$
$\Delta(\ln(IPI))$	$\longrightarrow$	$\Delta(ln(QE_t))_{DOW}$; $\Delta(ln(QE_t))_{NASDAQ}$
$\Delta(\ln(S\&P500 * Covid))$	$\longrightarrow$	$\Delta(ln(QE_t))_{S\&P500}$
$\Delta(\ln(DOW * Covid))$	$\longrightarrow$	$\Delta(ln(QE_t))_{DOW}$
$\Delta(\ln(NASDAQ * GFC))$	$\longrightarrow$	$\Delta(ln(QE_t))_{NASDAQ}$
$\Delta(\ln(NASDAQ * Covid))$	$\longrightarrow$	$\Delta(ln(QE_t))_{NASDAQ}$

Note: Arrows indicate which way the causality runs

Long run Granger causality

Table 22 visualizes the ECT's of the models where P is the dependent variable and where QE is the dependent variable. The ECT's of the stock indices as the dependent variable are copied from tables 9, 10 and 18. The significant results provide evidence we can reject the null hypothesis of no long run granger causality: there is long run granger causality running from the independent variables to the dependent variable in every model. Since all the terms are at least significant at the 5% level, there is bi-directional long run granger causality between the stock indices and QE. It turns out that in the long run there is a dynamic interaction between the two variables. While the prices of the major stock indices affect monetary policy in the form of QE, QE influences the prices of stock indices. Again, this provides evidence that the FED reacts to the stock market. More importantly, it provides evidence that the long run coefficients that were found indeed have a significant influence on the stock market.

Table 22 Long run Granger causality

Dependent variable	$\boldsymbol{ECT_{t-1}}$
$\Delta(ln(S\&P500_t))$	-0.257***
$\Delta(ln(DOW_t))$	-0.279***
$\Delta(ln(NASDAQ_t))$	-0.435***
$\Delta(ln(QE_t))_{S\&P500}$	-0.095***
$\Delta(ln(QE_t))_{DOW}$	-0.079***
$\Delta(ln(QE_t))_{NASDAQ}$	-0.072**

significance*: * p < 0.10, ** p < 0.05, ***p < 0.01*

Conclusion

First, this paper has distinguished between both the short run and long run effects of quantitative easing on stock prices. Second, this paper has examined the effects on stock prices between periods where QE took place and where it did not. Third, granger causal relationships between QE and stock prices have been researched to discover the causal dynamics between the respective variables.

The ARDL bounds test of Pesaran et al. (2001) provided evidence of a cointegrating relationship amongst the variables in question for all three stock index models.

In the short run shocks and deviations from equilibrium occur. Except for the Nasdaq, a marginal increase in the assets of the Fed in a period where no QE takes place has a negative impact on stock prices. A marginal increase in QE during Covid has a positive impact on the S&P500 in the short run. A marginal increase in QE during the GFC has a negative impact on the S&P500. These interpretations are consistent for the Dow Jones as well, except that a marginal increase in QE during the GFC has a negligible unique effect on the DOW. This shows that the effect of QE during the financial crisis on the stock market was either negative or negligible in the short run. For the Nasdaq a more robust model was implemented, which showed that the unique marginal effect of Covid QE on the NASDAQ at time t is 0.846 and 0.248 at time t-1. These effects were the largest out of all the previous models. Finally, there is a substantially larger effect of QE during the pandemic on stock prices than the effect of QE during the GFC on stock prices. These findings providence evidence that only the first null hypothesis that was proposed cannot be rejected. The second and third null hypothesis can be rejected, which answers the research question for the short run.

Once returned in long run equilibrium, different relationships are observed. QE during both the pandemic and the GFC has a positive marginal effect on stock prices. The positive marginal effect on stock prices was substantially bigger during Covid than during the GFC. The long run effect of quantitative easing on stock prices is relatively larger than for the short run effects. In addition, the difference in effect on the stock market between Covid QE and GFC QE was larger in the long run than in the short run. These findings show we can reject the three null hypotheses and answer the research question for the long run.

Additional analysis was done on short run and long run Granger causality with the focus on QE and the stock market. In the short run, QE regarding the GFC unidirectionally Granger causes the S&P500 and the DOW, while QE regarding Covid bi-directionally Granger causes the NASDAQ. All the stock indices during the pandemic granger cause QE, indicating that the Fed responded to the stock market during the pandemic. In the long run, there is bi-directional Granger causality between the stock indices and QE. This provides robust evidence that the long run coefficients have a significant influence on the stock market.

Discussion

In summary and in line with expectations, the events of the global financial crisis and especially the pandemic were significantly negative for stock prices. The reaction by the central banks however in the form of quantitative easing boosted stock prices with a significant economic magnitude. The results of this paper are in line with the findings of Florackis et al. (2014) and Mendonca et al. (2016). The former explain there is a strong correlation between a lack of market liquidity and a fall in the stock market. The latter find similar long run results with regards to the effect of QE on the stock market during the financial crisis.

The results of this paper reach out to policymakers, regulators or central bankers that are interested in the effect of monetary policy on the stock market. Understanding the relationship of QE and the Federal funds rate, but also other macro-economic variables on asset markets is essential for implementing effective policy. In addition, since the wealth effect is a trusted concept for governmental bodies, understanding the effects of monetary policy tools on equities and therefore subsequent wealth inequality is of crucial importance.

The results that were found also have implications for banks, pension funds, mutual funds and other financial institutions that manage large investments in equities. Adding monetary policy tools into account when investing in certain asset classes or sectors is recommended, since the results in this paper clearly show there are Granger causal dynamics between QE and stock prices. An understanding of monetary policy and macro-economic indicators complements risk analysis and could help in improving risk management. For academics, incorporating QE as a factor into asset pricing models has potential to improve the already existing models.

In advance, expectations were made with regards to the coefficients of the models. The long run and short run coefficients of the NASDAQ models displayed positive significant coefficients, which was against expectations. The FFR coefficients have been discussed extensively in the results. The predictions for the IPI was not fully in line with expectations, since the coefficients were only positive and highly significant for the NASDAQ models. One would expect the opposite to occur, given the other stock indices are plausibly a better representation of the US economy. As expected, the CPI was strongly negatively associated with the stock market indices. The predictions with regards to QE were quite accurate, except for the general effect of the assets of the Fed, which was negative. QE following the GFC most of the times had a positive effect on stock prices, with Covid QE having an even larger effect.

With regards to QE during the pandemic, the coefficients might be less reliable due to a lack of data. Although the bounds test approach of Pesaran et al. (2001) has more robust small sample properties than other popular methods, it is possible that the short run is too short to say anything logical about it. The CUSUM of squares plots in figure 10 show the long run equilibrium is reached extremely fast during the pandemic. This cannot be said with certainty however, since it depends on how the ARDL model distinguishes between data that match the short run and the long run. If the pandemic is still going on in a few years, there will be a better possibility to differentiate between the short run and the long run effects.

The residual diagnostic tests indicated the residuals were not normally distributed. Although the paper assumes the residuals are approximately normal with the help of multiple visual figures like the fat pencil test, the statistical normality tests showed the null hypothesis of normality had to be rejected. This means there could be a violation of the normality assumption of OLS, which could lead to the standard errors and p-values of t-tests being less reliable. It could also influence the validity of the bounds test, although this would likely be less of a problem given the magnitude of the F-statistics.

The simultaneity bias mentioned in the endogeneity section is less of a mystery with the help of the Granger causality results. It turns out that QE regarding the GFC Granger causes the S&P500 and the DOW. QE during Covid Granger causes the NASDAQ, but at the same time the NASDAQ during covid causes QE, which means the coefficients of the respective variables could suffer from simultaneity bias, since there is direct bi-directional Granger causality between the two. This bias might also be present in the error correction terms, although it is more difficult to say in which variables the bias would be present. The ECT is simply the OLS residuals that are influenced by multiple variables at the same time, unlike the direct short run causality in tables 19-21.

Since the SIC tends to prefer a smaller number of lags than the AIC, the results are limited for the models that use the SIC for determination of the optimal number of lags. Many variables in the models have zero lags as the optimal number according to the SIC. Since no lags are used for certain variables, those variables automatically imply that they do not Granger cause stock prices. The AIC would likely give a higher number of lags and therefore yields the possibility to examine nearly every variable. Thus, if theoretically justified, it is recommended to use different lag order selection criteria to investigate the granger causality dynamics more extensively.

A recommendation for future research is to examine the effect of QE on the stock market in other countries. For example, the effect of QE implemented by the ECB, the BOJ or BOE on their respective stock markets. Another option could be spillover effects to the stock markets of the major economies. For example, spillover effects of QE in the US on European, Chinese or Japanese stock markets and vice versa. Much literature has already been focused on spillover effects to emerging market economies (see Lavigne et al. (2014) and previously mentioned literature), but additions to the existing literature are always recommended.

This paper has briefly discussed the effect of the FFR on stock prices and thus made a distinction between conventional and unconventional monetary policy instruments. Conventional monetary policy tools were not the focus of this paper however. A second recommendation for researchers is to investigate the different effect conventional policy and QE has on stock prices or other macro-economic variables. Research of Curcuru et al. (2018) addresses both recommendations and shows that quantitative easing does not have greater international spillovers than conventional monetary policies.

Appendix

Tables

Table 4 Linear regression results and correlation coefficients between stock price indices and time (2003-2022)

Regressand	Regressor	T-statistic	1% Critical value	Correlation coefficient
Ln(S&P500)	t	33.83	2.58	0.913
Ln(DOW)	t	37.17	2.58	0.926
Ln(NASDAQ)	t	44.47	2.58	0.947

Table 17 ECM regression results for the NASDAQ (White SE's)

Variable	Coefficient	t-Statistic	P-value
$\Delta(\ln(NASDAQ_{t-1}))$	0.282 (0.068)	4.11	0.000
$\Delta(\ln(QE_t))$	-0.058 (0.024)	-2.39	0.018
ΔFFR_t	0.003 (0.004)	0.68	0.497
$\Delta(\ln(IPI_t))$	1.482 (0.554)	2.68	0.008
$\Delta(\ln(CPI_t))$	-1.892 (0.442)	-4.28	0.000
$\Delta((\ln(QE_t * GFC))$	0.047 (0.032)	1.49	0.137
$\Delta((\ln(QE_t * Covid))$	0.429 (0.138)	3.11	0.002
$\Delta((\ln(QE_{t-1} * Covid))$	0.013 (0.004)	3.57	0.000
$\Delta((\ln(QE_{t-2} * Covid))$	0.015 (0.005)	2.80	0.006
ECT_{t-1}	-0.215 (0.044)	-4.90	0.000
Intercept	10.483 (1.976)	5.31	0.000
trend	0.025 (0.001)	5.30	0.000
GFC_t	-0.680 (0.480)	-1.42	0.158
$Covid_t$	-6.734 (2.100)	-3.21	0.002
Adjusted R^2	0.372	-	-

Note. Robust Standards errors are in parentheses; dependent variable is $\Delta(\ln(NASDAQ_t))$; the dummies GFC and Covid represent the values 0 or 1.

Figures

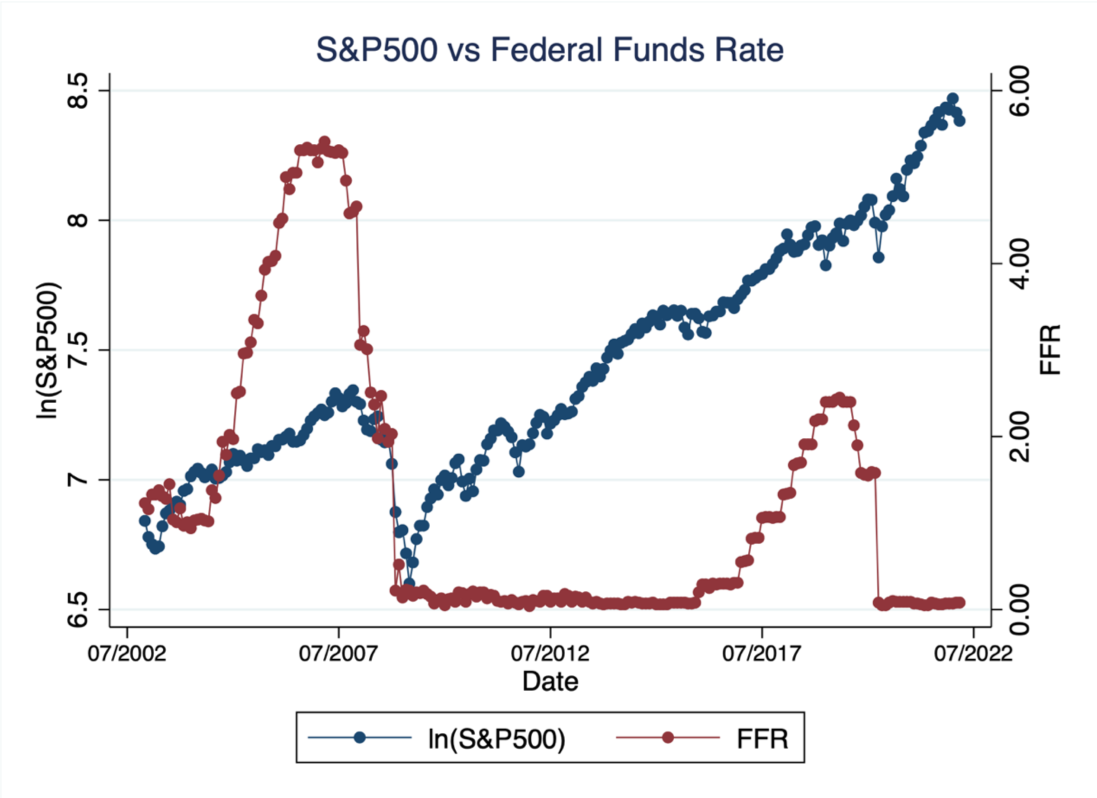

Figure 5 S&P500 and Federal Funds Rate over the period 2003-2022

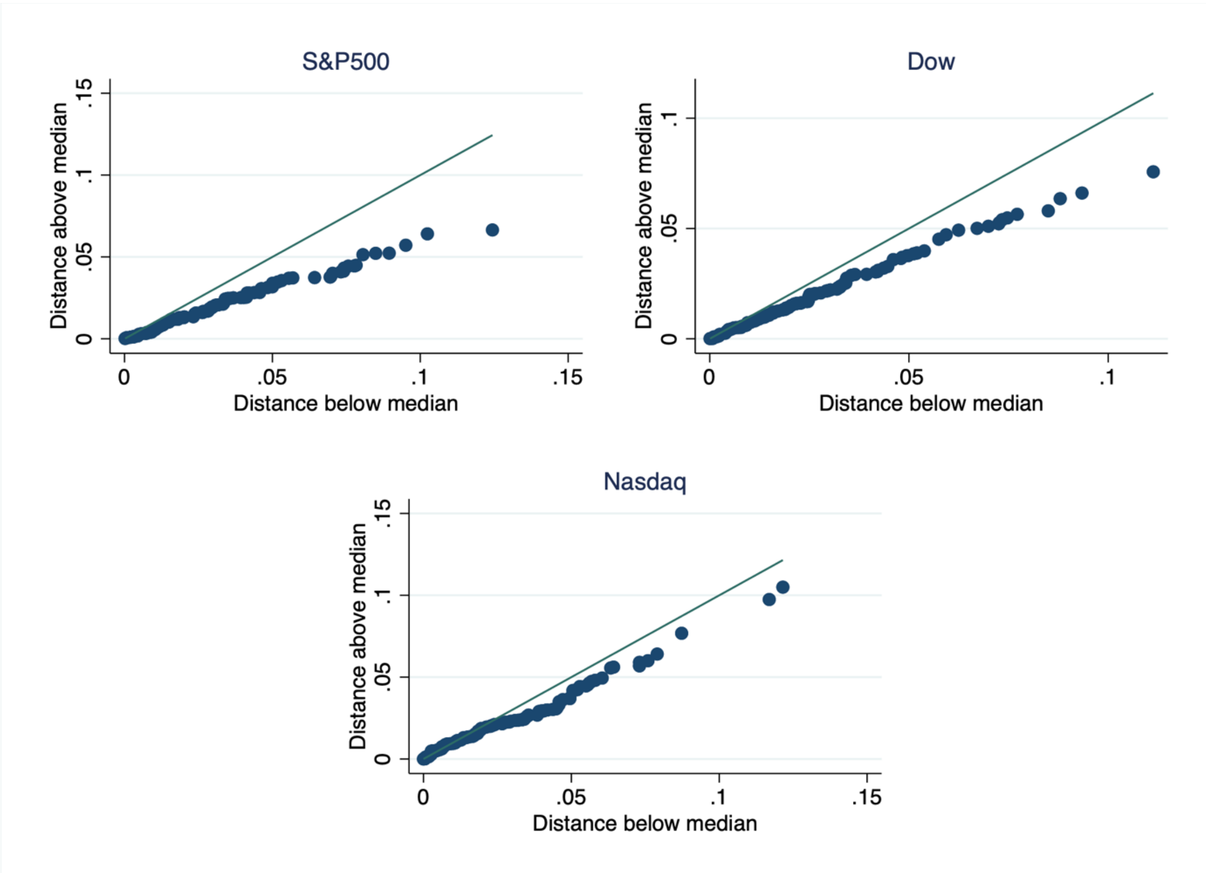

Figure 6 Residual symmetry plots of S&P500, Dow and Nasdaq

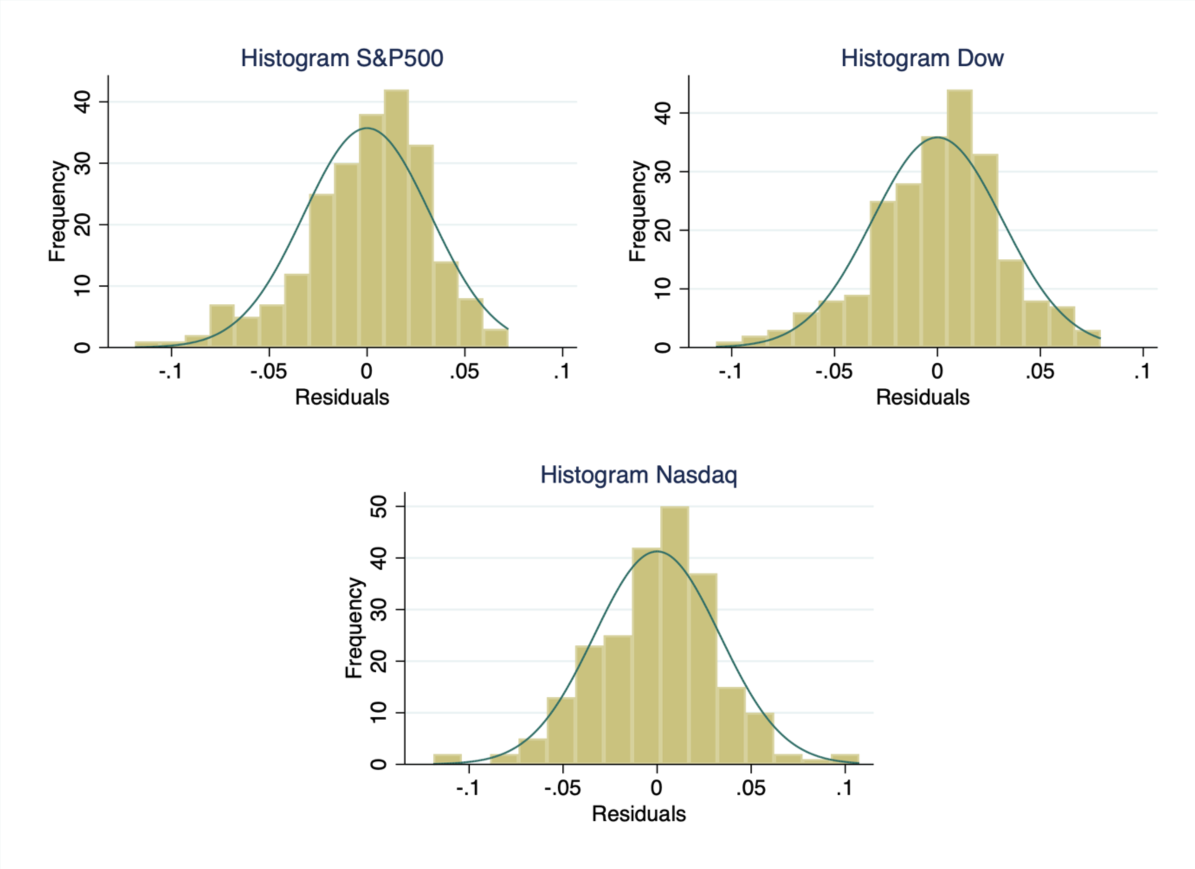

Figure 7 Histograms of residuals S&P500, Dow and Nasdaq

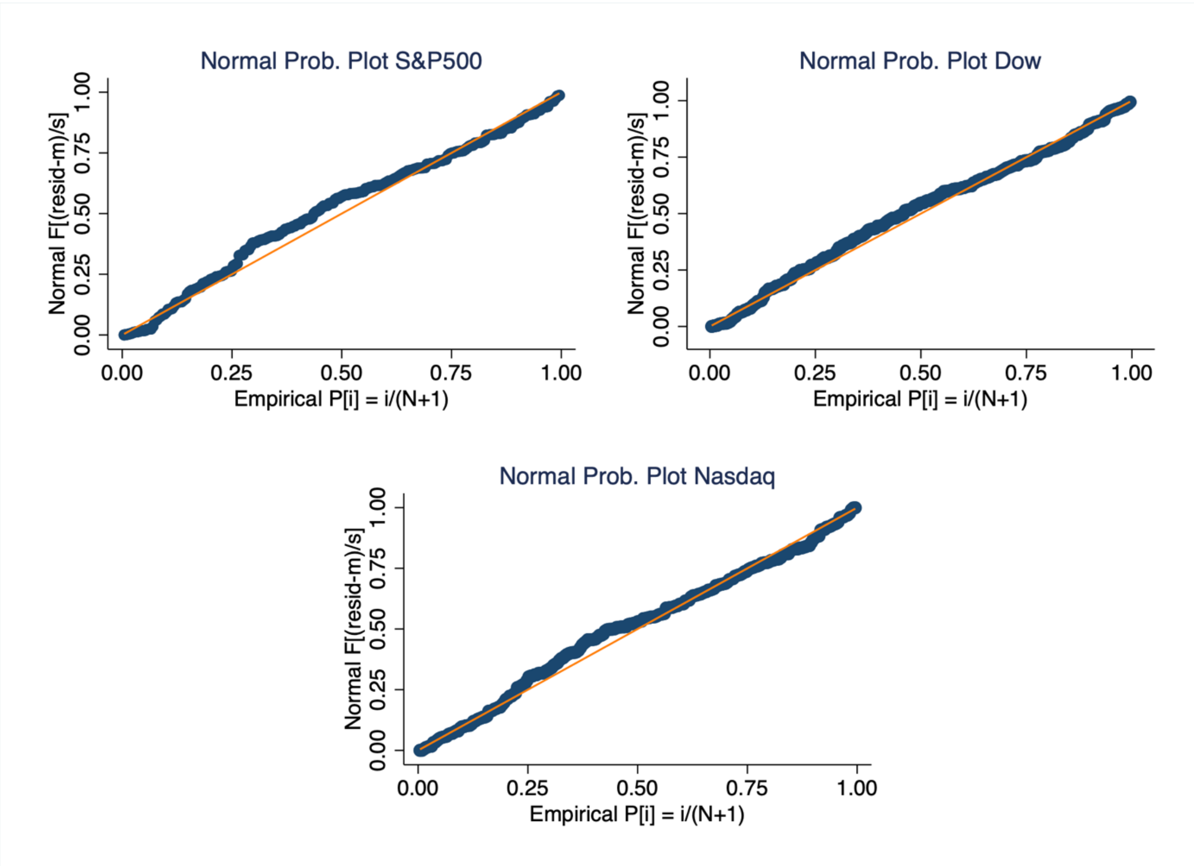

Figure 8 Normal Probability Plots of residuals S&P500, Dow and Nasdaq

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