May 2019

Essays on Monetary Policy and Bitcoin Financial Economics

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ESSAYS ON MONETARY POLICY AND BITCOIN FINANCIAL ECONOMICS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Economics

by
Kyle Rechard
May 2019

Accepted by:
Dr. Gerald P. Dwyer, Jr., Committee Chair
Dr. Robert Tamura
Dr. Michal Jerzmanowki
Dr. Scott Baier
Abstract

This dissertation includes three chapters. The first chapter investigates the impact of the Federal Reserve’s balance sheet normalization using a Bayesian vector autoregression (BVAR) framework. I use counterfactual conditional forecasts to find that a reduction in asset holdings down to a level where the federal funds market is active again will reduce real GDP growth by an average of 0.18 percent per year and core inflation by a non-significant average of 0.07 percent per year under Quantitative Tightening, relative to a scenario where the Federal Reserve maintains a constant dollar amount of assets until 2024.

The second chapter models monetary policy using Taylor’s rule for the nominal interest-rate target and examines the difference between the actual Federal Funds Rate and the Taylor Rule model of behavior for distinct structural changes. Both a simple factor ANOVA and regime switching methods find that there were “tight” or “loose” regimes in U.S. monetary policy over the period 1965 to 2008. However, after accounting for the change in inflation measurement from CPI to PCE and then core PCE after 2004, Alan Greenspan’s tenure from 2003 to 2006 is consistent with his earlier symmetric deviations from the Taylor Rule.

The final chapter examines the volatility of Bitcoin exchange rates which have gained a great deal of attention since the creation of the currency. Standard measures of volatility reflect the dramatic change in the Bitcoin/US dollar exchange rate, from about $0.05 USD in 2010 to the neighborhood of $20,000 USD at the end of 2017, and down to around
$5,000 USD in mid-2019. Characterizing the short-term and long-term volatility gives an impression of the volatility of Bitcoin compared to other assets, as well as implying the viability of Bitcoin as a medium of exchange and alternative asset.
Acknowledgements

This dissertation has been greatly improved by the contributions of many people. First and foremost, I would like to thank my advisor, Dr. Gerald Dwyer, for his constant guidance throughout the entire process. Without his time and dedication, much of this dissertation would not have been possible. I would also like to thank the other members of my committee, Dr. Robert Tamura, Dr. Michal Jerzmanowski, and Dr. Scott Baier, for their helpful comments and suggestions, as well as the participants in the Macro workshop at Clemson. The tips and comments I received while presenting in the workshop were instrumental in shaping my research. I would like to thank Dr. John Deveraux, and Dr. Juan Rubio-Ramirez who were willing to read my work, and provide detailed feedback. I am also extremely grateful to Dr. Sam Standert for his feedback.

Next, I would like to thank my family for their love and support. My parents, Rob and Pat Rechard, have been a constant source of love and encouragement. I would not have accomplished this if it were not for them. Finally, I would like to thank the graduate students at Clemson. My classmates helped shape my love for economics, and the friendships and fun experiences we’ve had are memories I’ll always carry with me. In particular, I am thankful for my officemate, Jacob Walloga, and roommate Ben Harbolt for all the fun conversations. All remaining errors are my own.
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Chapter 1

Quantitative Tightening: What are the macroeconomic consequences of reducing the Federal Reserve Balance Sheet?

1.1 Introduction

What effects will Quantitative Tightening (QT), or Reverse Quantitative Easing have on the United States real economy and financial markets? If the U.S. Federal Reserve’s accumulation of a massive quantity of assets had an expansionary effect on the real economy and financial markets, will the plan to shrink the massive balance sheet have the opposite effect on the real U.S. economy and financial markets?

For the Federal Reserve, the purpose of reducing security holdings is to eventually reduce the reserve holdings of banks and other entities held at the Federal Reserve to a level where overnight borrowings are needed by some entities to meet reserve require-
ments. Once this occurs, the federal funds rate will be the monetary policy instrument of the FOMC, as it was prior to 2008. This balance sheet “normalization” of the conduct of monetary policy will allow the Fed to discontinue the dual policy instrument structure it has operated under since 2008. In the current monetary policy framework, both Interest on Excess Reserves (IOER) and the level of security holdings are used to influence long-term interest rates and (more importantly) portfolio flows from the Treasury market into the private bond and equity markets (Minutes of the FOMC, July 29-30, 2014).

In this paper I create a regime dependent, Bayesian structural vector autoregressive (VAR) model and forecast the differential outcome for real economy until December 2024, conditional on the proposed path of asset reduction or a counterfactual policy of maintaining a $4.2 trillion security holding portfolio. I find that reverse QE will result in an average of 0.18 percent less real GDP growth per year until 2024, comparing the conditional point forecasts for December 2024 to the forecast conditional on the Federal Reserve maintaining a constant dollar value of asset holdings until 2024. However, for both perfect foresight and structural forecasts, the average forecast difference is calculated from forecast variable levels in December 2024. The results are unaffected by shocks to the path of reductions, so long as the Federal Reserve still plans to normalize the balance sheet by the end of 2024.

1.2 Review of the Literature

1.2.1 Quantitative Easing

The Federal Reserve’s response to the 2008-2009 financial crisis included large-scale asset purchases - buying government debt and mortgage backed securities (MBS) as a means to provide continued stimulus after the Federal Funds rate had been reduced near zero in November 2008. There are at least three possible mechanisms for the security purchases
in the bond market to affect the real economy: the portfolio balance channel, the signaling channel, and the management of expectations about future economic outcomes. All of the channels affect real GDP through a wealth effect. The intervention in the market for government debt leads to higher private bond prices, as well as higher equity prices, and those higher prices subsequently cause increased investment and consumption. Real GDP may also be affected through private investment increases if the security purchases result in lower long-term interest rates.

Vayanos and Vila (2009) provide the main theoretical rationale for the portfolio balance channel of QE. Their model is a no-arbitrage pricing framework for securities of various maturities, accounting for the existence of investors, such as pension funds and insurance companies, who have an idiosyncratic demand for securities of specific maturities. Yields on specific maturities depend partly on their relative supply. This implies that the Fed can lower long-term interest rates, and push private investors into riskier asset classes if it reduces the amount of long-term debt held by the private sector. Gorodnichenko and Ray (2018) extend Vayanos and Vila (2009) to determine that QE programs primarily influence interest rates through this portfolio balance channel, and the combined effects of the signaling channel and expectations channel were small. Furthermore, their results suggest that QE programs can be effective in influencing interest rates at specific maturities when financial markets are in crisis, but are less likely to be effective in normal times when the arbitrageurs are more willing to assume risk and can effectively smooth the demand shocks created by the Federal Reserve.

Eggertsson and Woodford (2004) show that in some New Keynesian models, QE can work only through the signaling channel. The signaling channel consists of the Federal Reserve communicating to market participants the Fed’s desire to hold short-term interest rates low for a longer time. An expectation by market participants of lower future short-term interest rates will also result in lower long-term rates, due to the term structure of
There exists a large literature on the effects of unconventional monetary policy on financial markets, but empirical studies of the effect on output and inflation are much more limited due to the difficulty involved. Borio and Zubai (2016) provide an overview of the empirical evidence of unconventional monetary policy’s effect on the real economy and conclude that there is a positive effect on output and inflation from security purchase programs, but the size and stability of the impact are uncertain.

Among the handful of studies using VARs, Baumeister and Benati (2013) provide estimates of positive, significant macroeconomic impact of asset purchases in the United States, United Kingdom, and the euro area due to the decrease in long-term bond spreads following asset purchases. Using a time-varying parameter structural VAR, they find the peak impact of large-scale asset purchases in the U.S. was a 0.9 percent increase in real GDP and a 0.5 percent increase in inflation. Kapetanios et al. (2012) use a VAR counterfactual to find that QE caused GDP in the United Kingdom to increases by 1.4 percent and CPI Inflation to increase by 2.6 percent. Gambacorta et al. (2014) estimate a panel VAR and find that an asset purchase shock increased GDP growth by 2 percent and inflation increased by 2 percent at the maximum. Hausman and Wieland (2014) study QE in Japan and find that the Bank of Japan policy contributed 1 percent to GDP growth in 2013.

The effect of the Fed’s asset purchase program on the U.S. is also covered from a structural modeling perspective in Chung et al. (2011). Simulations from the Fed’s FRB/US macroeconomic model suggest that the first round of QE asset purchases, initiated in 2009, prevented deflation in the United States and reduced the rate of unemployment. The authors conclude that the boost to the level of real GDP was about 3 percent, inflation was 1 percent higher, and the unemployment rate was reduced by 1.5 percentage points.

*Krishnamurthey and Vissing-Jorgensen (2011), Gagnon et al. (2011), and D’Amico et al. (2012) are representative for the studies covering the financial markets in the United States.*
compared with what they would have been in 2011 without QE I. Engen, Laubach, and Reifschneider (2015) also use structural simulations from the FRB/US model to assess the economic stimulus from all three rounds of QE. They conclude that the effect of QE on real GDP growth peaked in 2010, adding 1.2 percent. For inflation, they find the QE impact peaked in 2016, adding 0.5 percent above the counterfactual scenario of no QE.

This paper is most closely related to Weale and Wieladek (2016). The authors use a Bayesian VAR, fit with data from January 2009 to October 2014, to estimate the ex-post effects of QE in the US and UK. They use an announcement series (where the full amount of the QE program is assumed to enter the market at the beginning of each round of QE) as the policy variable in the VAR in order to better estimate the effects of QE in the forward-looking bond and financial markets. They find that QE in the US resulted in an average increase of 0.58 percent in GDP and 0.62 percent in inflation. The Bayesian VAR in their study was fit using a non-informative prior on the autoregressive parameters and identifies a monetary policy shock using four separate identification schemes. The reported impulse effects are the average maximum impact of the QE shock.

1.2.2 Quantitative Tightening

As of July 2017, the security holdings of the Federal Reserve totaled $4.2 trillion dollars, including approximately $3.5 trillion dollars of U.S. Treasury notes/bonds and $800 billion dollars of mortgage-backed securities. Treasury holdings represent 15 percent of all Federal outstanding debt, up from 7 percent of government debt in 2007. When a Treasury security in the portfolio matures, the proceeds from the maturing bond is rolled over, i.e. reinvested in the market for U.S. Treasuries. Rollovers in the System Open Market Account (SOMA) are entered as noncompetitive bids and therefore do not affect the auction of the securities. Noncompetitive bidders receive the stop-out rate, yield or discount margin determined by
the competitive auction process. When the SOMA is awarded securities at auction, the Treasury Department increases the total issue size by the amount of the SOMA’s award, so reducing rollover purchases for the SOMA do not directly impact the price of a Treasury Note or Bond issue.

The Federal Open Market Committee’s (FOMC) statement on July 14, 2017 indicated that it intends to “gradually reduce the Federal Reserve’s security holdings by decreasing the [re]investment of the principal payments it receives from securities held in the System Open Market Account.” The Committee gradually reduced Treasury security holdings to allow $6 billion per month to mature off the balance sheet, increasing maximums in steps of $6 billion in three-month intervals until the max reduction was $30 billion per month. Agency debt and mortgage-backed securities maximum caps were by $4 billion per month initially and then increased in steps of $4 billion per month at three-month intervals until the maximum reduction was $20 billion per month in October 2018 and thereafter. In March 2019, the balance sheet reductions were slowed to $15 billion per month.

The purpose of reducing security holdings is to force reserve holdings of banks and other entities held at the Federal Reserve to reach a level where overnight borrowings are needed by some entities to meet their reserve requirements. Once this occurs, the federal funds rate will be the monetary policy instrument of the FOMC, as it was prior to 2008. This balance sheet “normalization” will allow the Fed to cease operating under a monetary policy stance where interest on excess reserves is the short-term policy rate as opposed to federal funds rate, and long-run interest rates can be influenced by security purchases as well.

In an addendum to the July 2017 meeting of the FOMC, the committee projected the range of reserve balances where the federal funds market will be active again (i.e. the Federal Funds rate will be the primary monetary policy tool) to be between $600 billion and $100 billion. Security holdings are to be reduced until the level of reserves is sufficiently
low that some banks have a shortage of reserves and reserve trading on the Federal Funds market will resume. Asset holdings will begin to rise again at the same rate of currency in circulation (Figure 1.1). The projected security holdings paths to the upper and lower bounds of the range were published along with the addendum, providing the necessary future policy to condition forecasts upon.

The path represents the maximum rate at which the balance sheet will be reduced. Events such as the March 2019 announcement that the balance sheet reduction would be put on hold in September 2019 can be interpreted as a shock to expectations, increasing the relevance of the structural forecast inference prior to December 2024. However, the forecast differences of primary interest in this paper only depend on the Federal Reserve’s commitment to a level of assets in December 2024, and not on the particular path of security holdings.

**Figure 1.1: Federal Reserve Balance Sheet Trends**

Notes: The figure shows the paths of select U.S. Federal Reserve balance sheet components since January 2006, along with the proposed maximum security holding reduction paths and the future path currency in circulation implied by a 7 percent annual growth rate. The goal of the reduction in security holdings is a balance sheet where between $600 Billion and $100 Billion in reserves (Reverse QE I and Reverse QE II) are held at the Fed. This is the reserve balance range where it is believed that an overnight market for reserves will exist as it did before the financial crisis. The predicted growth in currency in circulation will allow security holdings to begin increasing again sometime after 2021 while reserve balances remain within the desired range.
While there is a lack of any similar historical experience to reverse QE, Gorodnichenko and Ray (2018) suggest that the effect of demand shocks on the bond market are diminished during “normal” circumstances due to the decreased risk aversion of arbitrageurs. In addition, the Treasury has attempted to allocate its rollover purchases in equal proportions across the yield curve as opposed to purchasing one specific maturity - a strategy which the authors find further diminishes the impact of demand shock on preferred habit investors. Their results suggest that reverse QE can have less impact on the real economy than the original rounds of large-scale asset purchases, although the negative impact could still be substantial. This result seems at odds with the long-run neutrality of money, as it suggests QE resulted in a permanent increase in real GDP and the price level.

This paper goes beyond the current literature by conditionally forecasting the relative effect of the real economy of Reverse QE (Quantitative Tightening). I use an asymmetric extension of the Weale and Wieladek (2016) VAR in order to take advantage of data available outside of the period from 2009 to October 2014 to create counterfactual, conditional forecasts for the real economy from January 2018 to December 2024. Federal Reserve security holdings is used as the QE variable, as suggested by Bhattari et al. (2015). Since security holdings, as a percentage of nominal GDP, have actually been declining since October 2014, I have some information on the effects of security holdings after the reversal of their upward trend if I use security holdings as a proportion of nominal GDP as my QE variable. The interest rate on excess reserves (IOER) is also included as a variable in my model, due to its increasing relevance as the short term policy interest rate. Focusing on the counterfactual difference in the forecast allows for the use of long-term structural time series forecasting methods without additional information on future trade or fiscal policy needing to be being included in the model.

Using security holdings as the QE policy variable explicitly recognizes that the primary influence of security holding changes on the real economy comes through the
private capital flows it causes to come out of the Treasury and MBS markets and into the private bonds and equity markets (the Portfolio Balance Channel) rather than an interest rate channel. If forecasting reverse QE’s effect forward-looking variables such as Treasury yields and equity prices were the primary concern of this paper, an announcement series as the policy variable would be more useful.

Since I use counterfactual forecasts and focusing on the difference in effect Quantitative Tightening has on the level of real GDP and core PCE, I am not concerned with including variables other than those in the structural model for forecasting since their impact is differenced away.

The rest of the paper is organized as follows. Section 3 describes the state-dependent VAR and identification strategies. Section 4 describes the VAR parameter estimation, as well as the conditional forecast methodology. Section 5 analyses the results of the conditional forecasts under the different parameter and identification combinations and Section 6 concludes.

1.3 Empirical Approach

Given that reverse QE implies a break in the trend of security holdings that will not be opposite in scale of the original large-scale asset purchase program, it necessary to use a VAR that is dependent on the state of unconventional monetary policy. Only using data from the post-QE period would both likely result in very imprecise effect estimates, given the small sample size. A VAR dependent on policy state of QE (when QE is occurring vs. not occurring) allows the use of data from the period of the financial crisis until December 2017. I specify the model as

\[ A_0 Y_t = \alpha_c + \sum_{i=1}^{p} A_i Y_{t-i} + \sum_{i=1}^{p} \gamma_i (Y_{sec,t-i} \ast I_{t-i}) + \gamma_I X_{IOER,t} + e_t, \quad e_t \sim N(0, \Sigma) \]  

(1.1)
where

\[ I_t = \begin{cases} 
1 & \text{if } t \in \text{QE period} \\
0 & \text{if } t \in \text{Non-QE period}.
\end{cases} \tag{1.2} \]

In Equation (1.1), the vector \( Y_t = [\text{Real GDP} (y_t), \text{Personal Consumption Expenditure less food and energy} (\pi_t), \text{Fed Securities/Nominal GDP} (sec_t), \text{U.S. 10-year Treasury yield} (i_t), \text{and the real S&P 500 index} (sp_t)] \). All variables, except for the Federal Reserve security holdings as a percentage of the nominal economy (sec_t) and the 10-year Treasury Yield (i_t), are in log levels†. The data are monthly observations beginning in January 2007 (the beginning of the financial crisis) and ending in December 2017 (T=132). All macroeconomic variables, except monthly real and nominal GDP were taken from the St. Louis Federal Reserve’s FRED database. Monthly real and nominal GDP come from the Macroeconomic Advisors approximation method. A summary of the data sources can be found in the Appendix.

The second policy instrument, IOER (\( X_{IOER} \)), enters the model contemporaneously as an exogenous variable due to the lack of variation in the administratively set rate. To extend the IOER variable back to 2007, it is necessary to concatenate IOER with the Federal Funds rate for the period from January 2007 to October 2008, when the Fed began paying interest on excess reserves. The peak of the financial crisis occurred during those 21 months from January 2007 to October 2008, and the Federal Reserve rapidly decreased the Fed Funds rate toward zero from 5.25 percent (Figure 1.2). I find no statistical justification to include lagged values of the interest rate in the VAR, even when I include the 21

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†Sims, Stock and Watson (1990) point out that attempting to transform models to stationary form by difference or cointegration is often unnecessary. Differencing or including a deterministic time trend is particularly undesirable when using a multivariate time series model for long-run forecasting.
Notes: The figure shows the path of Interest on Excess Reserves (IOER), as well as the Federal Reserve’s communicated path of the policy interest rate from 2018 - 2024. Prior to October 2008, the policy rate is the Federal Funds rate.

observations prior to October 2008 in the sample, due to the lack of monthly variation ‡. Including other exogenous variables that might be useful for making a long term GDP or inflation forecast is undesirable since the focus of this analysis is a counterfactual forecast with a structural model of monetary policy. I make no attempt to make a long-term forecast of the level of GDP in 2024.

Simply using the absolute level of asset holdings as the policy variable in the VAR overstates the negative impact and relative importance of security holdings since, until December 2017, Federal Reserve security holdings had only ever risen or stayed constant. Also Treasury asset holdings, as a percentage of contemporaneous nominal output, have actually been declining since October 2014 (Figure 1.3). This period of “Post-QE” created 38 monthly observations, from October 2014 to December 2017, where the U.S. economic conditions should be similar to the economic environment during the future period of re-

‡The optimal lag length of Equation (1.1) is determined by a majority vote of the Akaike Information Criterion (AIC), Hannan-Quinn (HQ) criterion, Bayes-Schwartz Information Criterion (BIC). Using the OLS/MLE estimates of Equation (1.1), two lags \( p = 2 \) is considered the optimal model by the majority of information criterion for the sample of 2007-2017. The HQ and BIC criterion both select two lags. The HQ criterion selects a two lag VAR if the sample is truncated to begin 2009 or 2010, as does the AIC criterion.
verse QE. The QE period, delineated by the indicator function in Equation (2), lasts from January 2009 to October 2014.

**Figure 1.3:** Securities Held Outright as a proportion of nominal GDP

Notes: The figure shows the proposed paths of the U.S. Federal Reserve’s asset holdings since January 2007 as a percentage of nominal GDP. As a percentage of nominal GDP, asset holdings begin declining in November 2014 as soon as asset purchases ceased, providing a 38-month period of observations useful in forecasting the macroeconomic impact of further reductions in Federal Reserve asset holdings.

Evidence in favor of the state-dependent VAR comes from the approach to testing for symmetry described in Cover (1992), which involves testing whether the OLS coefficients $\gamma_1, \gamma_2$ in Equation (1.1) are jointly significant. Table 1 shows that the null hypothesis of symmetry is rejected at the 95 percent level regardless of whether the standard likelihood ratio test statistic or the test statistic correct for small sample bias was used.

The state-dependent autoregressive terms for asset holdings appear to have minimal impact on the calculated impulse responses, as can be seen by fitting the model with as Minnesota prior in Figure 1.7 §. Although there is little difference in the impulse responses in the QE vs. non-QE state, the trend in security holdings as a percentage of nominal GDP clearly shifts after October 2014, and asymmetric coefficients are required.

---

§ In Equation (1.1), the coefficient on the interaction variable, $\gamma$, captures the asymmetric response of Fed asset holding increases.
1.3.1 Identification

When forecasting with the assumption that constant monetary policy shocks are affecting the economy, it is necessary to be able identify the individual shocks $\epsilon_{j,t}$ from the reduced form residuals $e_{j,t}$. This requires either imposing structural restrictions on $A_0$ in Equation (1.1) directly, where $A_0^{-1}e_{j,t} = \epsilon_{j,t}$, or inferring restrictions on $A_0$ from sign restrictions.

To estimate the impulse responses of an asset purchase the shock in a quantitative easing regime, the $A_i$ endogenous coefficient matrix must include $A_{S/GDP,i} + \gamma_i$, (adding the coefficients of the together), for $i = 1, 2$. For a single lag ($p = 1$) version of Equation (1.1), write the model as

$$A_0Y_t = \alpha_c + A_1Y_{t-1} + \gamma_1Y_{t-1}I_{t-1} + e_t$$  \hspace{1cm} (1.3)

$$Y_t = A_0^{-1}\alpha_c + A_0^{-1}(A_1 + \gamma_1I_{t-1})Y_{t-1} + A_0^{-1}e_t$$  \hspace{1cm} (1.4)

where $y$ and $e$ are $p \times 1$ vectors. The impulse response at horizon $h$ of the variables to an exogenous shock

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Table 1.1: OLS Estimation: Non-Linear Coefficients

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<td>Securities/GDP</td>
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<td>0.0055</td>
<td>0.0144</td>
</tr>
<tr>
<td>$t-1 \times I_1$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Securities/GDP</td>
<td>0.5207</td>
<td>-0.0038</td>
<td>-0.8639</td>
</tr>
<tr>
<td>Securities/GDP</td>
<td>-0.0019</td>
<td>-0.0020</td>
<td>0.0008</td>
</tr>
<tr>
<td>$t-2$</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Securities/GDP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t-2 \times I_2$</td>
<td></td>
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<td></td>
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<tr>
<td>Securities/GDP</td>
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<td>-0.0523</td>
<td>-0.7101</td>
</tr>
<tr>
<td>Securities/GDP</td>
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<td>-0.0017</td>
<td>0.0042</td>
</tr>
<tr>
<td>$LR = 19.118$</td>
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<td></td>
<td></td>
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<tr>
<td>Securities/GDP</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$t-2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Securities/GDP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t-2 \times I_2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Securities/GDP</td>
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<td>-0.025</td>
<td>1.7254</td>
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<tr>
<td>Securities/GDP</td>
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<td>0.0101</td>
<td>0.0063</td>
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<tr>
<td>$LR = 26.036$</td>
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<tr>
<td>Securities/GDP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t-2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Securities/GDP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t-2 \times I_2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Securities/GDP</td>
<td>-0.0016</td>
<td>-0.0017</td>
<td>0.0022</td>
</tr>
<tr>
<td>$LR = 22.297$</td>
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</table>

To estimate the impulse responses of an asset purchase the shock in a quantitative easing regime, the $A_i$ endogenous coefficient matrix must include $A_{S/GDP,i} + \gamma_i$, (adding the coefficients of the together), for $i = 1, 2$. For a single lag ($p = 1$) version of Equation (1.1), write the model as
placed on the impulse responses, as in Uhlig (2005) or Rubio-Ramirez, Waggoner and Zha (2010). The simplest approach of imposing restrictions on $A_0$ directly is to use the Cholesky decomposition of $\hat{\Sigma}$, to find $A_0$, since $A_0^{-1}(A_0^{-1})' = \hat{\Sigma}$. This is equivalent to imposing recursive restrictions on $A_0$. A non-recursive identification for a system would potentially be useful, but since Waggoner and Zha (1999) show that structural VAR forecasts are equivalent for any just-identified $A_0$ and forecasts from the VAR are my primary interest, I do not entertain other non-Cholesky short-run identification strategies or alternative orderings. Reversing the order of the fast-moving variables, equities and long-term interest rates, did not affect the results for the structural forecasts. For the 2007-2017 sample,

$$A_0 Y_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.018 & 1 & 0 & 0 & 0 \\ -0.158 & -0.018 & 1 & 0 & 0 \\ 0.094 & -0.405 & 0.198 & 1 & 0 \\ 2.360 & -3.359 & 1.585 & 4.618 & 1 \end{bmatrix} \begin{bmatrix} y_t \\ \pi_t \\ sec_t \\ i_t \\ sp_t \end{bmatrix}.$$  

The recursive ordering implies that output and prices react with a lag to any asset purchases shock, while asset purchases can impact bond yields and equity prices contemporaneously. The structure also implies that shocks from the market for 10-year Treasury bonds can affect the equity market contemporaneously, but shocks from the equity market to variable $j$ is then

$$\frac{\partial Y_{t+h}}{\partial e_{j,t}} = \frac{\partial}{\partial e_{j,t}} \left\{ A_0^{-1} \alpha_c + A_0^{-1}(A_1 + \gamma_1 I_1)Y_{t+h-1} + A_0^{-1}e_{t+h-1} \right\} = \ldots$$  \hspace{1cm} (1.5)

$$= \frac{\partial}{\partial e_{j,t}} \left\{ (A_0^{-1}A_1 + A_0^{-1}\gamma_1 I_1)^h Y_t + A_0^{-1} \sum_{i=0}^{h} (A_0^{-1}A_1 + A_0^{-1}\gamma_1 I_1)^i e_{t+h-i} \right\}$$  \hspace{1cm} (1.6)

$$= \frac{\partial}{\partial e_{j,t}} \left\{ (A_0^{-1}A_1 + A_0^{-1}\gamma_1 I_1)^h A_0^{-1} \alpha_c \right\}$$  \hspace{1cm} (1.7)

$$= (A_0^{-1}A_1 + A_0^{-1}\gamma_1 I_1)^h A_0^{-1} e_j$$  \hspace{1cm} (1.8)

where $e_j$ is the $j$th row of the $p$ identity matrix. That is, the response of all $p$ variables at horizon $h$ to a shock to variable $j$ is the $j$th column of $(A_0^{-1}A_1 + A_0^{-1}\gamma_1 I_1)^h$. 


cannot affect the bond market within the same month. While it obviously would be ideal for both “fast-moving” variables to transmit shocks to one another, this ordering represents the causal structure of the portfolio balance channel, and real equity shocks are not of primary interest.

Alternatively, Faust (1998), Canova and De Nicolo (2002), Uhlig (2005), and Rubio-Ramirez, Waggoner and Zha (2010), show that identification of structural shocks in VAR models can be based on prior beliefs about the signs of the impact of a certain shock. As Uhlig (2017) explains, sign identification is achieved through restrictions on $A_0^{-1}$, as opposed to $A_0$ in traditional identification. The restrictions impose prior beliefs on impulse responses, in the form of “a shock to variable x results in a decrease in variable y for at least 5 months”. An advantage of sign identification is that, for VARs that include multiple fast-moving financial variables, the financial variables can transmit shocks to one another within the time unit of observation. Partial identification by sign restriction eliminates the assumption in the recursive ordering that stock prices cannot impact bond yields within the same month, as well the always controversial restriction on the policy variable being unable to affect contemporaneous prices.

While a VAR identified by sign restriction relaxes the exclusion restrictions in the recursively identified model, previously unrestricted parameters in $A_0^{-1}$ are restricted instead, so the recursive model is not nested within the sign-identified model. The two approaches represent alternatives, as it is not possible to validate or invalidate the implications of a recursively identified VAR with a sign-identified VAR model.

In this paper only a single structural shock, the security reduction shock, is of interest. For the five-variable model here, the shock is defined by a restriction that a decline in Federal Reserve Assets for one quarter results in a contemporaneous decline in equity prices, as well being unable to affect real GDP or prices for the first month. Table 3.1 summarizes this combination of sign and zero restrictions over the three-month time hori-
zon. In this case, the set of sign restrictions impose weaker identification restrictions than

| Table 1.2: Security Purchase Shock Sign Restrictions |
|---|---|---|---|---|
| Variable | $K=t+0$ | $K=t+1$ | $K=t+2$ | $K=t+3$ |
| Real GDP | 0 | . | . | . |
| Core PCE | 0 | . | . | . |
| Securities/GDP | $<0$ | $<0$ | $<0$ | $<0$ |
| 10-year yield | . | . | . | . |
| S&P 500 | $<0$ | $<0$ | $<0$ | $<0$ |

the baseline Cholesky ordering. This results in less precise posterior inference for the impulse responses and the structural forecasts with the asset reduction shocks identified in this manner, although the median forecasts are similar to structural forecasts using a Cholesky ordering.

1.4 Estimation and Inference

The stacked system linear system for Equation (1.1) is

$$Y = XB + A_{-1}^{-1}e,$$

(1.10)

where

$$X = [Y_{t-1}, Y_{t-2}, Y_{s,t-1} * I_{t-1}, Y_{s,t-2} * I_{t-2}, X_{IOER,t}, 1],$$

and

$$B = [A_{-1}^{-1}A_{t-1}, A_{-1}^{-1}A_{t-2}, A_{-1}^{-1}\gamma_1, A_{-1}^{-1}\gamma_2, A_{-1}^{-1}\gamma_{IOER,t}, A_{-1}^{-1}\alpha_c]' .$$

The parameters of the VAR are estimated using the Bayesian approach with either a non-informative prior, or a with Minnesota-type prior\(^\dagger\). Using a non-informative prior\(^\ddagger\) In the VAR forecasting literature, it is generally more common to use models with parameters estimated

\(^\dagger\)In the VAR forecasting literature, it is generally more common to use models with parameters estimated
allows for Bayesian inference, but produces median posterior parameter estimates similar to OLS.

The critical advantage of the Bayesian approach is that it is possible to formally and transparently bring to bear information on what constitutes reasonable estimates for model parameters. For such an information-bearing prior on the autoregressive parameters, I use a version of the Minnesota prior, as described in the Online Appendix G. The original Minnesota prior from Doan, Litterman, and Sims (1984), or Litterman (1986) shrinks the VAR parameter estimates toward multivariate random walks since it specifies the prior mean of the first lag of the dependent variable to one, and sets the prior mean of all other slope coefficients to zero. So, if the prior means were the true parameter values, each variable would follow a random walk (a no-change forecast).

A reasonable prior belief is that the impulse response of real GDP to a monetary policy shock should be hump-shaped, with a maximum impulse similar in magnitude to the range outlined in the QE literature (i.e. the range from Borio and Zubai, 2016), and so the hyperparameters are set to be $\lambda = 2.75$ and $\mu = 0.001$ (using the Minnesota/dummy variable prior parameterization outlined in Lubik and Schorfheide, 2005)) in order to replicate a 0.58 percent maximum impact of a 1 percent asset purchase shock on real GDP. This results in a forecast for the effects of the reduction in the balance sheet on real GDP and inflation that is calibrated by the literature estimates for the effects of QE I-III.

by an informative (usually a Minnesota type) prior, since studies such as Banbura, Giannone, and Reichlin (2010) and Wright (2012) have shown forecasts are often more accurate than using an OLS-estimated VAR. These forecasting accuracy gains increase as the model grows larger. However, Baumeister and Kilian (2012) do provide an example of OLS-estimated VAR forecasts having smaller prediction errors than a Bayesian VAR, so it useful to forecast with both non-informative and informative priors.
1.4.1 Counterfactual Forecasting

The VAR in Equation (1.1) is intended to estimate the impact of shocks to the level of Federal Reserve asset holdings have on real GDP and inflation. Counterfactual conditional forecasts illuminate the relative difference in the outcome from different paths of policy variables. I compare the difference in the forecasts for the U.S. real economy conditional on the proposed reduction in the level of the Federal Reserve security holdings from January 2018 to December 2024, and the forecasts conditional on a policy of maintaining Federal Reserve security holdings at 4.2 trillion dollars for the same period. There are also two distinct conditional forecasting methods, one where the Federal Reserve’s proposed security holding estimates as a proportion of nominal GDP are assumed to be credible at all future dates, and one where it is not. In all cases, the path of Federal Reserve short interest rates ($X_{IOER,t+K}$) is assumed to be exogenous and known, since the Federal Reserve has been consistent in signaling the future path of the short rates and has published the expected path of short rates (Figure 1.2). The conditional forecasts also require knowledge of future U.S. nominal GDP (since the conditioning variable is the path of security holdings as a proportion of nominal GDP). I approximate nominal GDP by using the nominal GDP implied by the real GDP and core PCE forecasts from the previous iteration of Gibbs sampler.

Conditioning-on-observables (Antolin-Diaz, Petrella, and Rubio-Ramirez, 2018) forecasting assumes no structural shocks affect the economic forecasts. This is equivalent to assuming that the Fed’s proposed path of security holdings is considered completely credible by economic agents in the U.S. and no monthly reduction will constitute a policy surprise, similar to a perfect foresight assumption in a recursive model representative agent model. This assumption substantially narrows the bounds on the conditional forecasts, as the only source future uncertainty comes from the estimated VAR parameters. Conditional forecasts for a credible Federal Reserve are calculated where $Y_{sec,t+K}, Y_{sec,t+K-1}$ known
for all $K$. Bayesian credible regions constructed as in Banbura et al. (2015). Assuming the proposed future path of security holdings is completely credible substantially narrows the bounds on the conditional forecasts.

The second type of conditional forecasting method allows for structural shocks to affect the conditional forecasts, so $e_{sec,t+K}$ is now constrained, rather than assuming $Y_{sec,t+K}, Y_{sec,t+K-1}$ is known for all future periods. The difference between the unconditional forecast of Fed security holdings and the proposed path of security holdings at time $t + K$ constitutes a constraint, $r$, on the innovations, $e_{sec,t+K}$. This can be expressed as

$$ R e_{sec} = r, \quad (1.11) $$

where $r$ is a $(M \times K) \times 1$ vector. $M = 1$ is the number of constrained variables (Federal Reserve securities as a percentage of nominal GDP) and $K = 84$ denotes the number of periods the constraint is applied. The elements of the vector $r$ consist of the known future path for securities minus the unconditional forecast of security holdings at time $t + K$. $R$ is a matrix of dimensions $(M \times K) \times (N \times K)$. The elements of this matrix are the impulse responses of the constrained variables to the structural shocks at horizon $1, 2, \ldots, K$. The $(N \times K) \times 1$ vector $e$ contains the constrained future shocks. Doan et al. (1983) shows that the least squares solution for the constrained innovations is given as

$$ e_{sec}^* = R'(R'R)^{-1}r. \quad (1.12) $$

With these constrained shocks $e_{sec}^*$ in hand, the conditional forecasts can be calculated.

---

1Doan et al. (1984) arrives at this result under the assumption that model in 1.1 is stationary, but the stationarity assumption is not required for the distributional result in Waggoner and Zha (1999).
Waggoner and Zha (1999) find that the restricted future shocks \( e \) are distributed as

\[
e^\text{sec} \sim N(R'(R'R)^{-1}r, I - R'(R'R)^{-1}R),
\]

allowing for the creation of posterior density regions around the conditional forecasts. Waggoner and Zha’s (1999) Gibbs sampling algorithm is used to generate the forecast credible distribution**.

This second type of conditional forecast is equivalent to assuming that the Fed’s proposed path of security holdings is non-credible for economic agents, and every monthly reduction will constitute a policy surprise. This substantially increases the imprecision of the conditional forecasts. I consider the two conditional forecasting methods to provide the lower and upper bounds, respectively, on the width of the credible intervals around the conditional forecasts. Antolin-Diaz, Petrella, and Rubio-Ramirez (2018) extends Waggoner and Zha (1999) to allow for the possibility of conducting inference when only one of the structural shocks (in this case Fed security holdings) is identified using sign restriction. Partial identification of \( A_0 \) is an attractive procedure, since I am only interested in an asset purchase shock, but it comes at the cost of wider forecast posterior density intervals due to the wider range of shocks which are allowed to affect the forecast. The algorithm is described in the Appendix.

1.5 Results

Table 1.3 shows the forecast differences in the annualized growth rates for the VAR endogenous variables between the Federal Reserve counterfactual security holding paths, i.e.

**Waggoner and Zha (1999) show that the conditional forecasts when the Fed is considered non-credible are the same regardless of \( A_0 \) being just-identified using a recursive Cholesky ordering, or just-identified using a non-recursive ordering.
Table 1.3: Reverse QE I 2018-2024 Annualized Median Differential Effects: 2007-2017 sample

<table>
<thead>
<tr>
<th>Parameter Prior &amp; identification</th>
<th>Real GDP</th>
<th>Core PCE</th>
<th>10YR</th>
<th>S&amp;P 500</th>
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<tr>
<td><strong>Perfect Foresight</strong></td>
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<td></td>
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<tr>
<td>Minnesota Prior</td>
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<td>-0.07</td>
<td>0.26</td>
<td>-2.33</td>
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<td></td>
<td>[-0.25, -0.19]</td>
<td>[-0.10, -0.05]</td>
<td>[0.17, 0.37]</td>
<td>[-2.53, -2.10]</td>
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<td>Jeffrey’s Non-Informative Prior</td>
<td>-0.40</td>
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<td>0.21</td>
<td>-3.11</td>
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<td>[-0.42, -0.38]</td>
<td>[-0.25, -0.23]</td>
<td>[0.14, 0.29]</td>
<td>[-3.27, -2.92]</td>
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</tr>
<tr>
<td>Minnesota Prior, recursive</td>
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<td>-0.06</td>
<td>-0.04</td>
<td>-1.73</td>
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<td>[-0.62, 0.32]</td>
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<td>[-1.18, 1.08]</td>
<td>[-5.05, 0.99]</td>
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<tr>
<td>Jeffrey’s Prior, recursive</td>
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<td>-0.28</td>
<td>0.26</td>
<td>-2.96</td>
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<td>[-0.85, -0.01]</td>
<td>[-0.63, 0.05]</td>
<td>[-0.88, 1.47]</td>
<td>[-6.32, -0.03]</td>
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<tr>
<td>Jeffrey’s Prior, Sign identification</td>
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<td>-2.79</td>
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<td>[-1.01, 0.04]</td>
<td>[-0.82, 0.17]</td>
<td>[-0.96, 1.68]</td>
<td>[-8.10, 1.36]</td>
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<tr>
<td><strong>Minnesota Prior Mean Difference</strong></td>
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<td><strong>-0.06</strong></td>
<td><strong>0.11</strong></td>
<td><strong>-2.03</strong></td>
</tr>
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<td></td>
<td>[-0.44, 0.06]</td>
<td>[-0.27, 0.13]</td>
<td>[-0.51, 0.73]</td>
<td>[-3.79, 0.56]</td>
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</table>

Notes: The first value represents the differential in the compound annual percent growth rate between the forecast with a constant asset policy and Reverse QE I implied by the median forecasts for December 2024. The bracketed values are the 90 percent posterior for the annualized forecast differential. The first two models conditionally forecast the four variables of interest with the assumption that the future Securities Held Outright levels are a fixed commitment by the Federal Reserve. The last three models conduct conditional forecast inference using structural forecast error restriction, which in this application is equivalent to assuming the Federal Reserve’s projected path of Quantitative Tightening is non-credible.

a constant 4.2 trillion dollar security level and the proposed path of security holding reduction resulting in approximately 600 billion dollars of reserve balances (the more optimistic level of reserves which results in a functioning Federal Funds market). Table 1.4 in the Appendix shows the forecast differences in the annualized growth rates between the constant 4.2 trillion dollar security level and the proposed path of security holding reduction resulting in ~ 100 billion dollars of reserve balances (Reverse QE II) for each forecasting method.
Figure 1.4: Perfect Foresight Conditional Forecasts: 2007-2017 sample

Notes: The figure shows, for each of the endogenous variables in the model, the median forecast and 90 percent Bayesian credible set from January 2018 - December 2024 for a constant asset level policy (blue) and Reverse QE I (red) under four combinations of parameter priors and forecast error assumptions. The forecasts are conditional on both the Federal Reserve forecast of Interest Rate on Excess Reserves and the potential paths of the series starting points.
Though future nominal GDP was approximated in each Gibbs sampler iteration by the prior iteration’s forecasts for real GDP and core PCE, there is little fluctuation the path of nominal GDP (and thus little uncertainty in the conditional variable of Fed Assets as a percentage of nominal GDP) due to the inflation-output tradeoff that is present in the forecasts (Figure 1.4).

The credibility of the Federal Reserve’s commitment to the eventual conclusion of security reductions in 2024 and the momentum of economic growth play a large role in the level of certainty attached to the differential growth estimates as the results in Table 1.3 show. The main results are illustrated in Figures 1.4 and 1.5. Figure 1.4 shows the raw conditional forecast paths of real GDP, core PCE, U.S. 10-year Treasury yield and the real S&P 500 index for Reverse QE I and the alternative constant security level policy the various forecast methods.

The prior calibrated for the level of QE impact finds a small effect for the Quantitative Tightening. The forecast differences using the calibrated prior constitute the main result. These estimates are contrasted with growth difference estimates using a non-informative prior in Table 1.3. The average difference in real GDP and inflation are invariably larger when using a non-informative parameter prior. In general, forecast uncertainty increases substantially when asset purchase shocks are assumed to affect the forecast (the security holding reductions are a constant surprise) by design in structural forecasting, but the median forecast differences are similar to those to conditioning-on-observable forecasts. Figure 1.5 displays the counterfactual forecasts of real GDP and core PCE, along with the posterior density for the differences in real GDP and core PCE.

Despite the obvious divergence in precision across the perfect foresight and conditional forecasts, there is consistency in the median differences across the perfect foresight and structural methods using the same parameter prior, as Table 1.3 and Figure 1.5 show. December 2024 real GDP has a high probability (greater than 85 percent) of being less than
the counterfactual based on the posterior forecast density.

The forecasts with partial shock identification produce median counterfactual differences similar to the recursively identified shocks with non-informative parameter priors††. Figures 1.4 and 1.5 display the structural forecasts using sign restriction.

1.5.1 Robustness

I examine sample robustness by truncating the sample to begin in either 2009 or 2010 (at the beginning of QE and after the first round of QE). Although the forecast difference uncertainty increases with smaller sample sizes, the model average difference between the counterfactuals remains similar for real GDP and core PCE. The results from the truncated samples are found in the Online Appendix.

†† As Baumeister and Hamilton (2015), sign-identified VARs can only use a non-informative parameter prior distribution.
The first two panels of each row the figure shows the median forecast and 90 percent Bayesian credible set for output and inflation from January 2018 - December 2024 using either a Minnesota Prior or Jeffrey’s non-informative prior for the autoregressive parameters under the constant asset policy (blue) or Reverse QE I (red). The right two panels show the percent difference in the forecast levels of real GDP and PCE-X between a Federal Reserve constant asset policy and Reverse QE I, calculated from the point forecasts in the first two panels. The bands in the right two panels show the 90 percent credible set for the forecast differences.
1.6 Conclusion

The results in this paper are the first to imply that the policy of reducing the security holdings of the Federal Reserve will contribute an additional source of fluctuation in the real GDP level from 2018-2024. Across Minnesota and non-informative prior using perfect foresight forecast, I find that actively reducing the security holdings the Federal Reserve will result in a median 1.35 percent decline in real GDP by 2024, an average of 0.18 percent less real GDP growth per year, relative to a constant balance sheet policy. This is the combined posterior of the calibrated prior across the perfect foresight and structural difference distributions. Core PCE only declines 0.07 percent per year on average, and there is more uncertainty in the estimate to the extent that the true effect is likely close to zero. This small effect on inflation is possibly a reflection of the lack of loan growth (broad money growth) promoted by QE. The counterfactual real GDP difference is somewhat less uncertain than the core PCE difference across the possible future asset holding scenarios.

For the less optimistic path of security holdings, where the Federal Funds market becomes active again when there are approximately 100 billion dollars of reserves (Reverse QE II), I find that reducing security holdings of the Federal Reserve will result in a level of real GDP in 2024 that implies 0.26 percent less real GDP growth per year from on average until 2024 (Table 1.4), if the Federal Reserve reduces assets to $100 billion in reserves. Again, this is relative to the real GDP growth forecast to occur under a policy of maintaining a constant level of assets and allowing security holdings to decline only as a percentage of U.S. nominal GDP. Core PCE is forecast to grow 0.09 percent less per year than under the counterfactual with the calibrated Minnesota Prior. There is also a higher degree of uncertainty under the larger asset reduction scenario, as Table 1.4 shows.

No scenario for the reduction in security holdings results in a permanent reduction in real GDP - if the trend of security holdings seen in figure 1.2 is extended past December...
2024 to allow for a longer conditional forecast. For any forecasting procedure, the forecast level of real GDP is, eventually, not significantly different from the counterfactual level of real GDP. However, I do not attempt to forecast the date of re-convergence of the real GDP level between the two policy alternatives.

The results have obvious implications for Federal Reserve balance sheet actions. Normalizing the balance sheet over a longer time horizon will decrease the average yearly effect on real GDP, and vis-versa. The effect of balance sheet normalization on the price level is more uncertain, but there is a lower probability that it will result in a noticeable effect on inflation. The balance sheet will continue to be monetary policy instrument for the foreseeable future.
1.7 Appendix

Figure 1.6: The Data

Notes: The figure shows the data series used in the VAR model of the U.S.
Algorithm for Conditional Forecasting with a Sign-identified SVAR

(Antolin, Petrella, and Rubio-Ramirez 2018)

Initialize $y_{T+h}^{(0)} = [y_T^T, y_{T+1}^{(0)}]$.  

1. Conditioning on $y^{T+,(i-1)} = [y_T^T, y_{T+1,T+h}^{(i-1)}]$, draw $(B^{(i)}, \Sigma^{(i)})$.  

2. Make $M$ draws of the impulse vector, $Q^{(i)}$.  

3. Keep a triplet of $(B^{(i)}, \Sigma^{(i)}, Q^{(i,m)})$ which satisfies the sign and zero restrictions.  
   Call it $(B^{(i)}, \Sigma^{(i)}, Q^{(i)})$.  

4. Conditioning on $(B^{(i)}, \Sigma^{(i)}, Q^{(i)})$ and $y_T^T$, draw $y_{T+1,T+h}^{(i)}$.  

5. Return to Step 1 until the required number of draws has been obtained.  

-In this application, since nominal GDP necessary to find the ratio of Federal Reserve assets to nominal GDP (the conditioning variable), nominal GDP is estimated based on the forecasts of real GDP and core PCE. An initial estimate of the nominal GDP series is used to initialize $y_{T+1,T+h}^{(0)}$.  
Then in Step 4, $y_{T+1,T+h}^{(i)}$ is made conditional on the estimate of nominal GDP based on the real GDP and core PCE from $y_{T+1,T+h}^{(i-1)}$.  

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<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
<th>Transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real GDP</td>
<td>Monthly U.S. GDP from Macroeconomic Advisers.</td>
<td>( \log(GDP_t) \times 100 )</td>
</tr>
<tr>
<td>Core PCE</td>
<td>Monthly Personal Consumption Expenditure excluding food and energy index from FRED (PCEPILFE).</td>
<td>( \log(PCEX_t) \times 100 )</td>
</tr>
<tr>
<td>Asset Purchases</td>
<td>Ratio of Securities Held Outright by the Federal Reserve from FRED (WSECOUT) to Nominal GDP from Macroeconomic Advisors.</td>
<td>( (Assets_t/NGDP_t) \times 100 )</td>
</tr>
<tr>
<td>Asset Levels 2018-2024</td>
<td>Ratio of Federal Reserve forecasted Security Open Market Account levels (SOMA1 and SOMA2) to trend Nominal GDP (trend between January 2015 and December 2017).</td>
<td>( (Assets_t/NGDP_t) \times 100 )</td>
</tr>
<tr>
<td>10-year yield</td>
<td>Constant maturity yield on 10-year U.S. Treasury Bonds from FRED (WGS10YR).</td>
<td>None</td>
</tr>
<tr>
<td>Real S&amp;P 500</td>
<td>Last monthly S&amp;P 500 index value from Yahoo Finance (GSPC).</td>
<td>( \log(SP500_t/PCEX_t) \times 100 )</td>
</tr>
<tr>
<td>Opportunity Cost of Reserves</td>
<td>Interest on Excess Reserves from FRED (IOER). Federal Funds rate prior to October 2008 (FEDFUNDS).</td>
<td>None</td>
</tr>
<tr>
<td>Future IOER</td>
<td>Congressional Budget Office (CBO) forecast of future IOER.</td>
<td>None</td>
</tr>
</tbody>
</table>
Figure 1.7: Asymmetric Impact of 1% Decline in Assets/GDP Ratio

Notes: This figure shows, for each of the variables in the model, the median impulse responses in response to an unexpected 1% asset purchase announcement as a fraction of contemporaneous Nominal GDP, together with 90% Bayesian credible sets. I show results for all three data starting points for the United States, each with the same Minnesota Prior hyperparameters. 10,000 Monte Carlo draws were used to generate the responses. The horizontal axis indicates the number of monthly time periods since the announcement. The prior hyperparameters were chosen to replicate a 0.58% maximum impact on Real GDP of the 1% asset purchases announcement for the dataset starting in 2009.
Table 1.4: Reverse QE II 2018-2024 Annualized Differential Effects: 2007-2017 sample

<table>
<thead>
<tr>
<th>Parameter Prior &amp; Identification</th>
<th>Real GDP</th>
<th>Core PCE</th>
<th>10YR</th>
<th>S&amp;P 500</th>
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<tr>
<td><strong>Perfect Foresight</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minnesota Prior</td>
<td>-0.31</td>
<td>-0.10</td>
<td>0.35</td>
<td>-3.42</td>
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<tr>
<td></td>
<td>[-0.34, -0.27]</td>
<td>[-0.12, -0.06]</td>
<td>[0.27, 0.43]</td>
<td>[-3.62, -3.20]</td>
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<tr>
<td>Jeffrey’s Non-Informative Prior</td>
<td>-0.53</td>
<td>-0.31</td>
<td>0.29</td>
<td>-4.59</td>
</tr>
<tr>
<td></td>
<td>[-0.55, -0.51]</td>
<td>[-0.33, -0.29]</td>
<td>[0.22, 0.37]</td>
<td>[-4.77, -4.37]</td>
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<tr>
<td><strong>Structural</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minnesota Prior, recursive</td>
<td>-0.21</td>
<td>-0.08</td>
<td>-0.06</td>
<td>-2.56</td>
</tr>
<tr>
<td></td>
<td>[-0.68, 0.26]</td>
<td>[-0.45, 0.31]</td>
<td>[-1.18, 1.13]</td>
<td>[-6.05, 0.41]</td>
</tr>
<tr>
<td>Jeffrey’s Prior, recursive</td>
<td>-0.54</td>
<td>-0.35</td>
<td>0.32</td>
<td>-4.19</td>
</tr>
<tr>
<td></td>
<td>[-0.98, -0.12]</td>
<td>[-0.70, -0.01]</td>
<td>[-0.84, 1.48]</td>
<td>[-8.08, -1.03]</td>
</tr>
<tr>
<td>Jeffrey’s Prior, Sign identification</td>
<td>-0.52</td>
<td>-0.29</td>
<td>-0.00</td>
<td>-4.07</td>
</tr>
<tr>
<td></td>
<td>[-1.75, 0.52]</td>
<td>[-1.29, 0.59]</td>
<td>[-1.56, 1.68]</td>
<td>[-14.21, 1.72]</td>
</tr>
<tr>
<td><strong>Minnesota Prior Mean Difference</strong></td>
<td><strong>-0.26</strong></td>
<td><strong>-0.09</strong></td>
<td><strong>0.15</strong></td>
<td><strong>-2.99</strong></td>
</tr>
<tr>
<td></td>
<td>[-0.51, -0.01]</td>
<td>[-0.29, 0.13]</td>
<td>[-0.46, 0.78]</td>
<td>[-4.84, 1.40]</td>
</tr>
</tbody>
</table>

Note: The first value represents the differential in the compound annual percent growth rate between the forecast with a constant asset policy and Reverse QE II implied by the median forecasts for December 2024. The bracketed values are the 90 percent posterior for the annualized forecast differential. The first two models conditionally forecast the four variable of interest with the assumption that the future Securities Held Outright levels are a fixed commitment by the Federal Reserve. The last three models conduct conditional forecast inference using Waggoner and Zha (1999) forecast error restriction, which assumes the Federal Reserve projected path of Reverse QE is non-credible. Each month, the path restricted level of security holdings constitutes a shock (identified recursively or with sign restrictions) relative to the level implied by the unconditional forecast level of security holdings for that month.
Chapter 2

Greenspan didn’t cause the Great Recession: Examining Federal Reserve Chairmen Deviations from the Taylor Rule

2.1 Introduction

Since the end of the inflationary episode in the 1970s, the U.S. has experienced a significant reduction in the volatility of GDP growth (with the exception of the 2008 recession) and only a moderate amount of yearly inflation. There has, unsurprisingly, been a large amount of empirical research to assess why economic conditions have changed so dramatically. A possible explanation is that the U.S. Federal Reserve has changed the decision-making process that decides the federal funds rate. Consequently, there is a large amount of interest in modeling the process by which this decision is made and knowing whether this process has changed over time.

The clear winner of various efforts to model the decision-making process of the Federal Reserve on the question of the federal funds rate is the 'Taylor Rule'. Presented initially by Taylor at the 1992 Carnegie-Rochester Conference as an empirical regularity rather than a theoretical conjecture, the
descriptive power of the simple rule gradually has transformed the formula into a policy prescription, particularly by Taylor himself. The original rule from Taylor (1993) stipulates that the federal funds rate, $r_t$, should be set in response to the output gap (the difference between nominal output, $Y_t$, and potential output, $Y_t^*$), the target federal funds rate, $r^*$, and the inflation gap (the difference between the observed inflation, $\pi_t$, the estimated equilibrium real interest rate, $\pi^*$) according to

$$i_t = r^* + \pi_t + \lambda_1(Y_t - Y_t^*) + \lambda_2(\pi_t - \pi^*).$$

(2.1)

Including Taylor’s suggestion for the parameter values and targets the rule becomes

$$i_t = 2 + \pi_t + 0.5(Y_t - Y_t^*) + 0.5(\pi_t - 2).$$

(2.2)

Taylor (2007, 2009) used his rule to argue that monetary policy was “too loose” from 2003 to 2006 compared to the experience of the previous few decades and played a role in the formation of the housing bubble by making housing finance cheap and attractive and contributing to a boom-bust in housing starts. Orphanides and Wieland (2008), however, conclude that policy actions from 1988 to 2007 (Greenspan’s tenure) have been consistent with a stable Taylor rule. Mehra and Sawhney (2010) also find the gap between the federal funds rate and the Taylor rule recommendation in 2003-2006 disappears when a forward-looking Taylor rule using real-time inflation and unemployment data is applied.

The paper identifies regime changes in U.S. monetary policy over the 40 year period 1965-2008, based on the consistency of the federal funds rate with the Taylor Rule. This also answers the question of whether the Greenspan era was unusually “loose” relative to the historical deviance of monetary policy from the Taylor Rule.

I perform a data-based determination of regime changes in U.S. monetary policy, relying on only the statistical properties of the deviation series to determine if the deviations from the Taylor Rule are systematic over certain periods. I employ a standard non-forward-looking version of Taylor’s (Taylor, 1993, 1999) decision model of the federal funds rate, the version of the Taylor Rule suggested by the St. Louis Federal Reserve (equation 2), where the potential GDP series comes from the Congressional Budget Office (CBO) model potential GDP in the U.S. I focus on the issue of whether there have been regime changes in U.S. monetary policy over the 50 year period.
The rest of the paper is organized as follows. Section 2 discusses previous regime identification literature. Section 3 reviews the Taylor Rule and the construction of deviation series with the data available to the Fed at the time of their decisions. Section 4 discusses the empirical regime detection methodology, Section 5 presents the empirical results, and Section 6 concludes.

2.2 Previous Literature

The standard approach to studying regime changes is to examine various different regimes separately; for example, Fair (2001) treats the period of October 1979-July 1982, when the Fed experimented with targeting money growth rates, as one regime and the periods before and after as separate regimes. A difficulty with this approach is that the various policy regimes have to be alternatively, one might consider the terms of Fed chairmen as defining different regimes (e.g., Judd and Rudebusch, 1998, Clarida, Gali, and Gertler, 1998, 2000, Taylor, 1999).

A typical method is to choose regime dates based on some known features and history of the available data and then use tests of parameter constancy, e.g., Chow tests, to justify the dates chosen. However, as Hansen (2001) observes, if the breakpoints are not known a priori, then the Chi-squared critical values for the Chow test are inappropriate. Using known features of the data (e.g., the Volker policy experiment of 1979-82) to determine breakpoints can make these candidate break dates endogenously correlated with the actual data-leading to incorrect inferences about the significance of those candidate break dates. Furthermore, not all of the parameters or targets necessarily change at the same date. Fitting values to the policy parameters on the output and inflation gap, $\lambda_1$ and $\lambda_2$ in equation (1), with an OLS model, such as

$$i_t = \alpha + \beta_1(Y_t - Y^*) + \beta_2(\pi_t - \pi^*) + \epsilon_t,$$

provides less than reliable parameter estimates if the regime include little data, as in the case with potential Volker policy experiment.

Boivin (2006) deals with some of these issues by using a Time-Varying Parameter model that assumes that the policy parameters are time series which follow drift-less random walks. This
is the Kalman filter model of Cooley and Prescott (1976), and all of the parameters in the model can be estimated jointly by maximum likelihood estimation. However, when the variance of the policy parameter time series is found to be small, the parameters can only change slowly over time and policy regime shifts are not visible. Boivin (2006) deals with this problem in an *ad hoc* manner, but still does not identify discrete regimes that agree with the terms of particular Federal Reserve Chairmen. He finds only a gradual shift in the Taylor rule policy parameters until around 1982, the start of the Great Moderation.

### 2.3 Data

The federal funds rate, inflation, unemployment, and output time series come from the U.S. Federal Reserve Bank of St. Louis’ FRED database. The potential output series in the initial Taylor rule comes from the Congressional Budget Office and is imported by the St. Louis Federal Reserve. The series run from quarterly for 54 years from 1954:Q3-2008:Q4.

**Figure 2.1: St. Louis Fed Taylor rule**

![St. Louis Fed Taylor rule](image)

Notes: The figure shows the federal funds rate (red), along with the implied federal funds rate from the original formulation of the Taylor Rule (blue), as calculated by The St. Louis Federal Reserve. The vertical bars denote recessions as defined by the NBER. Both series are based on quarterly data, with the federal funds rate data points representing the quarterly average of the effective federal funds rate.

Plotting the difference between the federal funds rate and the rate from the St. Louis Taylor
Rule, $i_{FedFund,t} - i_{St.Louis,t}$, in Figure 2, it is clear the difference series is not stationary (we cannot reject the null hypothesis of non-stationarity using a unit root test), and is negatively biased (mean = -0.93 %), so even though the Taylor rule visually fits the actual federal funds rate series well, the federal funds rate is not completely consistent with the single Taylor rule over the entire period.

**Figure 2.2: $i_{FedFund,t} - i_{Taylor,t}$: 1954-2008**

Notes: The figure shows the difference between the quarterly average federal funds rate, $i_{FedFund}$ and the federal funds rate implied by the Taylor rule, $i_{Taylor}$. The series is quarterly from 1954:Q3 to 2008:Q1.

Since the difference series is both biased and non-stationary, it follows that there is a non-random effect from the particular policymaker on the deviation of federal funds rate from the Taylor rule.

### 2.3.1 Real Time Taylor Rule

The Taylor Rule assumes that policymakers know, and can agree on, the size of the output gap. In fact, measuring the output gap is very difficult and FOMC members typically have different judgments. In addition, the FOMC meets eight times per year, so assessing the Taylor rule consistency of the FOMC using quarterly data could be misleading. It is fairer to assess the consistency of the federal funds rate with Taylor rule using monthly data that was available to the committee at the
time of their meeting. Instead of attempting to interpolate quarterly output and potential output data with a method similar to Sims (1980), I choose to approximate the output gap using Okun’s law,

\[ Y_t - Y^*_t = -c(U_t - U^*_t). \]  

Equation (4) is the gap version of Okun’s 'rule of thumb' as presented in Abel and Bernanke (2005). For the period of 1954-2008, the slope of the line is -1.4 (Figure 3). This suggests that the Taylor rule on a monthly frequency is

\[ i_t = 2 + \pi_t + 0.5(-1.26(U_t - U^*_t)) + 0.5(\pi_t - 2). \]  

This version of the Taylor rule also has the advantage of being able to use the historical values of inflation and unemployment values that were the estimates at the time of the FOMC meeting, rather than the revised series. This data is available from the Federal Reserve Bank of Philadelphia’s Real-Time Data Set from 1965 onward.

Assuming a natural unemployment rate, \( U^* \) of 5.5%, the implied “real-time” Taylor rule is

\[ i_t = 2 + \pi_t - 0.63(U_t - 5.5) + 0.5(\pi_t - 2). \]  

38
Figure 2.3: Gap Version of Okun’s Law 1954-2008

Notes: The figure shows the results regression based on equation 2.4, regressing the Output gap on the Unemployment gap using quarterly Output and Unemployment. The estimated slope for the period is -1.26, rather that the -2 estimated from Okun’s original data.

Figure 2.4: Real-Time $i_{FedFund,t} - i_{St.Louis,t}$, 1965-2008

Notes: The figure shows the difference between the monthly average federal funds rate, $i_{FedFund}$ and the federal funds rate implied by the monthly version of the Taylor rule, $i_{TaylorMonthly}$, in equation 2.6. The inflation and unemployment estimates are the initial series available at the time of the Federal Reserve meeting, acquired from the Federal Reserve Bank of Philadelphia’s Real-Time Data Set, rather than the revised series published by St. Louis Federal Reserve. The series runs from February 1965 to December 2007.
This use of this Taylor rule leads to the data series in Figure 4, 507 monthly data points from 1965-2008. The Taylor rule residual series is still biased (mean = -1.25 \%) toward a higher interest rate than the Taylor rule suggests (i.e. a bias toward less permissive monetary policy). The 'Real-Time' series is obviously much closer to being stationary but is still not consistent with the single Taylor rule over the entire period.

In February 2000, the CPI was replaced by the personal consumption expenditures (PCE) deflator measure of inflation and from July 2004 onward inflation forecasts employed the core PCE deflator that excludes food and energy prices. As Mehra and Sawhney (2010) point out, this reduces much of the apparent Greenspan deviation from the Taylor Rule from 2003 to 2006.

### 2.4 Empirical Methodology

The Tukey Honest Significant Difference Test is a single-step multiple comparison procedure to find if sample means are significantly different from each other simultaneously. The test assumes that the observations are independent within and among the groups and there is homogeneous within-group variance across the groups. Since I first wish to first test whether Greenspan’s tenure is distinguishable from the other Fed Chairmen on an aggregate basis, this is a suitable procedure to perform before attempting to identify regimes with an agnostic statistical procedure.

The CUSUM test of Brown, Durbin, and Evans (1975) is based on recursive residuals from a simple AR(1) fitted model finds evidence of structural breaks. It is easiest to judge the break points, however, using the multiple mean model, even though there is autocorrelation in the federal funds rate -Taylor rule difference series. It is also perhaps most useful to think of the FOMC monetary policy having an unbiased error in relation to the Taylor rule in each regime. Using this assumption and using the methodology of Bai and Perron (1998), if I fit multiple mean equations to the series and choose the points in time that minimize the residual sum of squares for the chosen number of breakpoints. The optimal number of breakpoints is three, based on the Schwartz Information Criterion (SIC).

Another useful way to find the hidden regimes in monetary policy is with the Markov switching model of Hamilton (1989), one of the most popular nonlinear time series models in the literature. This model involves multiple structures (equations) that can characterize the time series behaviors
in different regimes. By permitting switching between these structures, this model is able to capture more complex dynamic patterns. A novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable that follows a first-order Markov chain. In particular, the Markovian property regulates that the current value of the state variable depends on its immediate past value. As such, a structure may prevail for a random period of time, and it will be replaced by another structure when a switching takes place. This is in sharp contrast with the random switching model of Quandt (1972) in which the events of switching are independent over time. The original Markov switching model focuses on the mean behavior of variables. This model and its variants have been widely applied to analyze economic and financial time series; see e.g., Hamilton (1988, 1989), Engel and Hamilton (1990), Lam (1990), Garcia and Perron (1996), Goodwin (1993), Diebold, Lee and Weinbach (1994), Engel (1994), Filardo (1994), Ghysels (1994), Sola and Drifill (1994), Kim and Yoo (1995), Schaller and van Norden (1997), and Kim and Nelson (1998), among many others.

Let $s_t$ denote the unobservable state variable. The switching model for the Taylor Rule deviation ($i_{Taylor}$) series I consider involves three regimes.

$$i_{Taylor} = \begin{cases} 
\alpha_0 + \epsilon_t, & \epsilon_t \sim N(0, \sigma_1^2), \quad s_t = 0 \\
\alpha_1 + \epsilon_t, & \epsilon_t \sim N(0, \sigma_2^2), \quad s_t = 1 \\
\alpha_2 + \epsilon_t, & \epsilon_t \sim N(0, \sigma_3^2), \quad s_t = 2.
\end{cases}$$  \hspace{1cm} (2.7)

This model could be thought of a representing three states of monetary policy relative to the Taylor Rule, where “tight”, “loose”, and “other” are three hidden states which each $s_t$ might represent. This formulation allows for the presence of different conditional variances across regimes, and so is a less restrictive version of the methodology of Bai and Peron.

When $s_t$ are independent Bernoulli random variables, it is the random switching model of Quandt (1972). In the random switching model, the realization of $s_t$ is independent of the previous and future states. This would imply that the deviation from the Taylor rule would belong to one of several regimes randomly, which is not consistent with the concept of the hidden state being the particular Fed chairman, who is likely not changing policy stances from month to month randomly. Suppose instead that $s_t$ follows a first-order Markov chain with the following transition
matrix:
\[
P = \begin{bmatrix}
  p_{00}(s_t = 0|s_{t-1} = 0) & p_{01}(s_t = 1|s_{t-1} = 0) & p_{02}(s_t = 2|s_{t-1} = 0) \\
  p_{10}(s_t = 0|s_{t-1} = 1) & p_{11}(s_t = 1|s_{t-1} = 1) & p_{12}(s_t = 2|s_{t-1} = 1) \\
  p_{20}(s_t = 0|s_{t-1} = 2) & p_{21}(s_t = 0|s_{t-1} = 2) & p_{22}(s_t = 2|s_{t-1} = 2)
\end{bmatrix}
\]  

(2.8)

where \( p_{ij} \) (i,j = 0,1,2) denote the transition probabilities of \( s_t = j \) given that \( s_{t-1} = i \) so that the transition probabilities satisfy \( p_{i0} + p_{i1} + p_{i2} = 1 \). The transition probabilities determine the persistence of each regime.

2.5 Results

Table 2.1 and Table 2.2 show that regardless of what form of the Taylor Rule is used, Greenspan’s Federal Reserve Chairmanship is significantly closer to the Taylor Rule in aggregate than any other chairman before him. Only Bernanke from 2005-2008 is indistinguishable from Greenspan.

Figure 2.5: Fitted Regimes with Fed Chairman tenure periods, 1965-2008

Notes: The figure shows the monthly series representing the monthly deviation from the Taylor Rule (green), along with the condition means from the Bai and Perron structural break methodology. The tenure of each Federal reserve chairman are represented by the shaded background regions. Martin (pink), Burns (salmon), Volker (yellow), Greenspan (tan), Bernanke (light blue), and Yellen (dark blue) are denoted. Vertical grey bars represent the NBER recession periods.
The federal funds rate-Taylor Rule difference series with separate means fit for each regime is shown in Figure 2.5. The first regime of the Bai and Peron’s statistical procedure identifies covers the chairmanship tenures of William Martin (1951-1970) and Arthur Burns (1970-1978), from the start of series until 1973. This is a period of very loose monetary policy, perhaps influenced by President Nixon’s threats of taking away Federal Reserve independence. Burns’ monetary policy under the Ford presidency after the breakpoint in 1973 was even looser and less consistent with the Taylor rule. The second breakpoint in 1980 is somewhat expected -it agrees with the drifting output and inflation gap evidence from Boivin (2006). The chairmanship of Paul Volker (1979-1987) shows a clear breakpoint in Taylor rule consistency to a regime of tight monetary policy in November of 1980 until the end of tenure, an unsurprising result given that 1979-1982, the Federal Reserve targeted non-borrowed reserve levels rather than the federal funds rate. The high interest rate period continued until the end of Volker’s tenure in 1987, as the Fed continued to battle stagflation with by first taming inflation (an emphasis on the inflation gap over the output gap in the standard Taylor rule).

Alan Greenspan’s tenure from 1987-2006 was remarkably consistent with the Taylor Rule, regardless of if the shift from targeting core CPI to core PCE in 2000 is reflected in the Taylor Rule. The conditional mean deviation of Greenspan’s tenure is approximately zero, in either case, as Figures 2.5 and 2.6 show.

The less restrictive Markov-Switching regime structure finds periods of more and less adherence to the Taylor Rule. In some periods, he is indeed classified in the “loose” regime, as shown in Figure 2.9, the rest of his regime has a conditional mean greater than zero (“tight”). However, it is important to note that the conditional standard deviation of both the “tight” (conditional deviation mean greater than zero) and “loose” (conditional deviation mean less than zero) periods is that the conditional standard deviation in both regimes is similar (0.722 vs. 0.764). This shows that Greenspan was symmetric in his deviations from the Taylor Rule, in addition to being cyclical.

The Markov-Switching model classifies Volker and Burns in the same regime, despite their obviously different mean deviations from the Taylor Rule (Figure 2.8). The conditional variance of this regime is quite high, however, so Regime 2 in the Markov-Switching model can be interpreted as monetary policy regime inconsistent with the Taylor Rule, either very tight or very loose.
**Figure 2.6**: Fitted Regimes using PCE rather than CPI inflation target from 2000 to 2008

Notes: The figure shows the monthly series representing the monthly deviation from the Taylor Rule (green) corrected for the use of PCE as the preferred measure of inflation beginning in 2000, along with the condition means from the Bai and Perron structural break methodology (brown). The tenure of each Federal Reserve chairmen are represented by the shaded background regions. Martin (pink), Burns (salmon), Volker (yellow), Greenspan (tan), Bernanke (light blue), and Yellen (dark blue) are denoted. Vertical grey bars represent the NBER recession periods.

**Figure 2.7**: Markov Switching: Regime 1

Notes: The figure shows the periods corresponding to the first Markov switching regime conditional mean and variance for the deviations from the Taylor Rule. The fitted conditional mean and standard deviation are 0.358 and 0.722, respectively. This regime can be interpreted as “tight” regime, where the federal funds rate is higher than the recommendation from the Taylor Rule.
Figure 2.8: Markov Switching: Regime 2

Notes: The figure shows the periods corresponding to the second Markov switching regime conditional mean and variance for the deviations from the Taylor Rule. The fitted conditional mean and standard deviation are -1.546 and 4.930, respectively. This regime can be interpreted as a non-standard regime, periods where monetary policy substantially deviates from the Taylor rule. The period covers the Burns chairmanship keeping monetary policy loose at Nixon’s behest, and the Volker chairmanship keeping monetary policy tighter than recommended due to the emphasis on fighting inflation over boosting output during his tenure.
Notes: The figure shows the periods corresponding to the third Markov switching regime conditional mean and variance for the deviations from the Taylor Rule. The fitted conditional mean and variance are -1.856 and 0.764, respectively. This regime can be interpreted as “loose” regime, where the federal funds rate is lower than the recommendation from the Taylor Rule.

For estimated conditional means and variance for the model in equation 2.7 are

\[
i_{Taylor} = \begin{cases} 
0.358 + \epsilon_t, & \epsilon_t \sim N(0, 0.722), \quad s_t = 0 \\
-1.546 + \epsilon_t, & \epsilon_t \sim N(0, 4.930), \quad s_t = 1 \\
-1.856 + \epsilon_t, & \epsilon_t \sim N(0, 0.764), \quad s_t = 2.
\end{cases}
\]  

and the estimated transition matrix is

\[
P = \begin{bmatrix} 
0.968 & 0.007 & 0.025 \\
0.014 & 0.981 & 0.007 \\
0.019 & 0.012 & 0.969
\end{bmatrix}
\]  

2.6 Conclusion

The first part of Alan Greenspan’s tenure, from 1988 to the end of 2000 is exceptionally consistent with real-time Taylor Rule(series mean of zero), with the federal fund rate in a low variance
oscillation about the prescription of the Taylor rule in any given month. While the second part of Greenspan’s Federal Reserve leadership was characterized by a policy that appeared to be looser than that suggested by the Taylor rule, the conditional mean found by the Bai and Peron structural break process is still consistent across his tenure. The Markov switching regime classified the contentious 2003 as “loose” regime, but also not recognizably different than the two earlier “loose” periods during his tenure, or most of Martin’s chairmanship during the late 1960s. In fact, based on the ANOVA regression in Table 2.1, Greenspan had a tighter adherence to the Taylor Rule than Martin overall.

It is difficult to conclude that the interest rate policies under Ben Bernanke (2005-2008) were inconsistent at all with the Taylor rule for the three years which the federal funds rate was the primary monetary policy tool during his tenure. The federal funds rate was at zero for most of Bernanke’s tenure and could not go any lower even if the Taylor rule suggested a negative interest rate policy. Unconventional Monetary Policy in the form of Quantitative Easing makes arguments about Taylor rule consistency irrelevant past 2008. Bernanke himself suggested that he placed a larger emphasis on output rather than inflation than the traditional Taylor Rule. Regardless, his interest rate policies were broadly consistent with the Taylor Rule.

The contention by Taylor (2007,2009) that Greenspan inflated the housing bubble is inconsistent with a historical inspection of Federal Reserve deviations from the Taylor Rule. Greenspan had a condition mean deviation of zero throughout his tenure, assuming a constant level of variance with the Bai and Peron (2003) A less restrictive Markov-Switching model finds that some periods of Greenspan’s tenure corresponded to “loose” monetary policy, but the conditional variance was extremely close for both the “loose” and “tight” Markov-switching regimes as Equation 2.9 shows. To the extent that Greenspan deviated from the Taylor Rule, he deviated in a cyclical, symmetric manner. Negative deviations were offset by positive deviations from the Taylor Rule, which is inconsistent with Taylor’s argument that the period of 2003-2006 differed from what economic agents had come to expect of monetary policy, and thus fueled the housing bubble. Greenspan was never classified in the same regime as the notoriously low interest rate tenure of Arthur Burns regardless of methodology.
### Table 2.1: Tukey HSD: St. Louis Rule

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<th>Upper</th>
<th>P-value</th>
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<td>-3.861</td>
<td>-2.118</td>
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</tr>
<tr>
<td>Martin-Greenspan</td>
<td>-1.218</td>
<td>-2.309</td>
<td>-0.127</td>
<td>0.017</td>
</tr>
<tr>
<td>Miller-Greenspan</td>
<td>-4.450</td>
<td>-6.198</td>
<td>-2.701</td>
<td>0</td>
</tr>
<tr>
<td>Volker-Greenspan</td>
<td>2.568</td>
<td>1.696</td>
<td>3.439</td>
<td>0</td>
</tr>
<tr>
<td>Burns-Bernanke</td>
<td>-2.155</td>
<td>-3.182</td>
<td>-1.128</td>
<td>0.00000</td>
</tr>
<tr>
<td>Martin-Bernanke</td>
<td>-0.383</td>
<td>-1.602</td>
<td>0.835</td>
<td>0.968</td>
</tr>
<tr>
<td>Miller-Bernanke</td>
<td>-3.615</td>
<td>-5.446</td>
<td>-1.785</td>
<td>0.00000</td>
</tr>
<tr>
<td>Volker-Bernanke</td>
<td>3.402</td>
<td>2.375</td>
<td>4.429</td>
<td>0</td>
</tr>
<tr>
<td>Martin-Burns</td>
<td>1.772</td>
<td>0.551</td>
<td>2.992</td>
<td>0.0004</td>
</tr>
<tr>
<td>Miller-Burns</td>
<td>-1.460</td>
<td>-3.292</td>
<td>0.372</td>
<td>0.219</td>
</tr>
<tr>
<td>Volker-Burns</td>
<td>5.557</td>
<td>4.528</td>
<td>6.587</td>
<td>0</td>
</tr>
<tr>
<td>Miller-Martin</td>
<td>-3.232</td>
<td>-5.178</td>
<td>-1.286</td>
<td>0.00002</td>
</tr>
<tr>
<td>Volker-Martin</td>
<td>3.785</td>
<td>2.565</td>
<td>5.006</td>
<td>0</td>
</tr>
<tr>
<td>Volker-Miller</td>
<td>7.017</td>
<td>5.185</td>
<td>8.849</td>
<td>0</td>
</tr>
</tbody>
</table>

**Notes:** The table shows the results of the Tukey Honest Significant Difference multiple comparison procedure for testing the difference in mean Federal Reserve Chairman deviance from the original version of the Taylor Rule. Greenspan has a significantly tighter adherence to the Taylor Rule than every former Chairman other than Bernanke.
### Table 2.2: Tukey HSD: Bernanke Rule

<table>
<thead>
<tr>
<th>Difference</th>
<th>Lower</th>
<th>Upper</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bernanke-Greenspan</td>
<td>0.297</td>
<td>1.231</td>
<td>0.965</td>
</tr>
<tr>
<td>Burns-Greenspan</td>
<td>-2.475</td>
<td>-1.538</td>
<td>0</td>
</tr>
<tr>
<td>Martin-Greenspan</td>
<td>-2.341</td>
<td>-1.168</td>
<td>0.0000</td>
</tr>
<tr>
<td>Miller-Greenspan</td>
<td>-4.222</td>
<td>-2.342</td>
<td>0</td>
</tr>
<tr>
<td>Volker-Greenspan</td>
<td>3.974</td>
<td>4.911</td>
<td>0</td>
</tr>
<tr>
<td>Burns-Bernanke</td>
<td>-2.773</td>
<td>-1.669</td>
<td>0</td>
</tr>
<tr>
<td>Martin-Bernanke</td>
<td>-2.638</td>
<td>-1.328</td>
<td>0.0000</td>
</tr>
<tr>
<td>Miller-Bernanke</td>
<td>-4.519</td>
<td>-2.551</td>
<td>0</td>
</tr>
<tr>
<td>Volker-Bernanke</td>
<td>3.676</td>
<td>4.780</td>
<td>0</td>
</tr>
<tr>
<td>Martin-Burns</td>
<td>0.135</td>
<td>1.447</td>
<td>1.000</td>
</tr>
<tr>
<td>Miller-Burns</td>
<td>-1.747</td>
<td>0.223</td>
<td>0.121</td>
</tr>
<tr>
<td>Volker-Burns</td>
<td>6.449</td>
<td>7.556</td>
<td>0</td>
</tr>
<tr>
<td>Miller-Martin</td>
<td>-1.881</td>
<td>0.211</td>
<td>0.110</td>
</tr>
<tr>
<td>Volker-Martin</td>
<td>6.314</td>
<td>7.627</td>
<td>0</td>
</tr>
<tr>
<td>Volker-Miller</td>
<td>8.196</td>
<td>10.165</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: The table shows the results of the Tukey Honest Significant Difference multiple comparison procedure for testing the difference in mean Federal Reserve Chairman deviance from the Bernanke version of the Taylor Rule. Greenspan has a significantly tighter adherence to the rule than every former Chairman besides Bernanke.
Chapter 3

Long-run and Short-run Volatility in Bitcoin’s Price

3.1 Introduction

Bitcoin is a digital currency introduced by Satoshi Nakamoto (possibly a pseudonym) which became fully operational in January 2009. The volatility of Bitcoin exchange rates has gained a great deal of attention since its creation. One of the reasons for Bitcoin’s volatility may be its short existence and the fact that only a portion of bitcoins have been mined so far. Consequently, the price of bitcoin can be influenced even by a comparatively small amount of activity by speculators or noise traders. Events like bankruptcy of Mt. Gox, shutdown of Silk Road or negative statements about Bitcoin from representatives of the People’s Bank of China also play a very important role. The increase in the price since 2010 level, if it is not a transitory increase, reflects Bitcoin’s actual or expected success and is a good thing.

Analyzing the volatility of BTC/USD exchange rate is also interesting due to the fact that Bitcoin exchanges operate 24 hours a day, 7 days a week. That differentiates Bitcoin market from other global financial exchanges such as NASDAQ or NYSE, which are open only within stated time frame (Waring 2014). It seems best to separate short-term and long-term volatility to get an impression of the volatility of Bitcoin compared to other assets.

Figure 3.1 shows the log price of Bitcoin in the Coinbase exchange compared to other currencies
and assets. The data underlying this figure are all the prices at which bitcoins were exchanged at Coinbase. Here, there is variation at a lower frequency than daily and this variation and some variation above the daily frequency is likely to be more of a concern as excessive volatility.

**Figure 3.1: Log Scale Price Level**

Notes: The figure shows the daily log price level for various currency pairs and assets. Bitcoin/Currency pairs have a high appreciation in general.

The rest of the paper is organized as follows. Section 2 compares the volatility of Bitcoin to other currencies and assets. Section 3 summarizes possible volatility decompositions. Section 4 decomposes the volatility of Bitcoin into long and short-run components. Section 5 concludes.

### 3.2 Volatility of Bitcoin

It is natural to compare Bitcoin volatility to some currencies which are thought of as safe-haven currencies, namely the U.S. Dollar (USD), Japanese Yen (JPY), and Swiss Franc (CHF). Conversely, it is informative to compare these relatively stable currencies to currencies which have recently undergone some high inflation episodes, namely the Venezuelan Bolivar (VEB), and the Argentine
peso (ARS). All rates are relative to the U.S. Dollar, except for the dollar, which is relative to the Euro (EUR).

Since the official Venezuelan Bolivar exchange rates and the black market exchange rates differ by a wide degree, we use the parallel black market exchange rate for VEB/USD reported on the website DolarToday*. The website is headquartered in Miami, Florida and run by expatriate Venezuelan citizens. The prices are based on operations in the city of Cucuta, on the Venezuelan border†. The Argentine peso (ARS) exchange rate comes from Investing.com.

Bitcoin and gold have some key similarities, both are speculative investments that have been thought of as “safe-haven” assets. Gold has been thought of as a safe haven asset for a long time, but Bitcoin can possibly be seen as a safe-haven financial asset as well, since the price has reacted in positively in relation to negative geo-political news‡. We use the daily 3pm (London time) fixing price of gold in U.S. Dollars from the FRED database (GOLDPMGBD228NLBM).

### 3.2.1 Volatility Calculation

Monthly realized variance is calculated as the sum of the squared daily returns for a given month, and realized volatility is calculated as the square root of the realized variance, i.e.

\[
RV_t = \sqrt{\sum_{i=1}^{d} r_i^2},
\]  

(3.1)

where \(d\) is the number of days in a month. Linearly detrended realized volatility is calculated by linearly de-trending the log price and then computing the variance of that detrended price as well as the variance of original series.

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*http://dolartoday.com  
‡https://www.thestreet.com/story/14285619/1/is-bitcoin-stealing-gold-s-safe-haven-status.html
3.3 Short-run and Long-run Variance Decompositions

3.3.1 Changes in Mean Over Time

Computing realized volatility with a changing mean each month is a way of allowing for changes in the mean return and its effect on volatility. Represent the series as a random walk with a
time-varying drift

\[ y_t = \mu_t + y_{t-1} + \epsilon_t \]  \hspace{1cm} (3.2)

We have not specified a process of \( \mu_t \). If \( y_t \) is the logarithm of the price, the log return \( r_t = y_t - y_{t-1} \) can be represented as

\[ r_t = \mu_t + \epsilon_t \]  \hspace{1cm} (3.3)

Realized volatility is computed using daily data for each month. Let \( t \) represent the month and add a subscript \( i \) for each day of the month, with \( i = 1, \ldots, T_i \). Then

\[ m_t = \frac{\sum_{i=1}^{T_i} r_{t,i}}{T_i} \]  \hspace{1cm} (3.4)

where \( m_t \) is the mean for the month. Given the computation, \( E m_t = \mu_t \) is the parameter for which \( m_t \) is an estimator. Realized variance for month \( t \) is

\[ s_t^2 = \frac{\sum_{i=1}^{T_i} (r_{t,i} - m_t)^2}{T_i - 1} \]  \hspace{1cm} (3.5)

where \( s_t^2 \) is the realized variance for the month. Given the computation, \( E s_t^2 = \sigma_t^2 \) if \( \sigma_t^2 \) is the parameter for which \( s_t^2 \) is an estimator.

It is possible to decompose the overall variance into components based on deviations of the mean over time and deviation from the monthly means\(^8\). Let

\[ TSS_i = \sum_{i=1}^{T_i} (r_{t,i} - m_t)^2. \]  \hspace{1cm} (3.6)

Also let

\[ TSS = \sum_{t=1}^{T} \sum_{i=1}^{T_i} (r_{t,i} - m_t)^2. \]  \hspace{1cm} (3.7)

\( TSS \) has deviations for the overall mean \( m \) and \( TSS_i \) has deviations from the mean each period \( m_t \). \( TSS \) can be rewritten

\[^8\text{This is basically an analysis of variance computation}\]
The term \((r_{t,i} - m_t + m_t - m)^2\) can be rewritten
\[
(r_{t,i} - m_t + m_t - m)^2 = (r_{t,i} - m_t)^2 + (m_t - m)^2 + 2(r_{t,i} - m_t)(m_t - m).
\] (3.8)

The last term summed (with the 2 suppressed) is
\[
TSS = \sum_{t=1}^{T} \sum_{i=1}^{T_i} (r_{t,i} - m_t)(m_t - m)
\]
\[
= \sum_{t=1}^{T} (m_t - m) \sum_{i=1}^{T_i} (r_{t,i} - m_t)
\]

because \(\sum_{i=1}^{T_i} (r_{t,i} - m_t) = 0\) for all \(i\) which follows from
\[
\sum_{i=1}^{T_i} (r_{t,i} - m_t)
\]
\[
= \sum_{i=1}^{T_i} r_{t,i} - \sum_{i=1}^{T_i} m_t
\]
\[
=T_i m_t - T_i m_t
\]
\[
=0.
\]

The bottom line is that it is possible to decompose the variance into variation around the monthly means and variation in the monthly means over time. A month is an arbitrary period, but it is neither too long nor too short to be interesting as for computing short-run variation. This can be seen because equation (3.7) becomes
\[ TSS = \sum_{t=1}^{T} (m_t - m) + TSS_i \]  
\[ = TSS_m + TSS_i \]

where \( TSS_m \) is the total squared deviation for the monthly means around the overall mean.

### 3.3.2 The Local Linear Trend Model

Again, if \( y_t \) is the logarithm of the price, and \( r_t = y_t - y_{t-1} \), the realized volatility in a given month is

\[ RV_t = \sqrt{\sum_{i=1}^{d} r_i}. \]  
\[ (3.11) \]

Suppose we use the following model for the monthly realized volatility. This model is called the “local linear trend” (Durbin and Koopman, 2012). It is given by

\[ RV_t = \mu_t + \epsilon_t, \quad \epsilon \sim N(0, \sigma^2_\epsilon) \]  
\[ (3.12) \]

\[ \mu_{t+1} = \beta_t + \mu_t + \eta_t, \quad \eta \sim N(0, \sigma^2_\eta). \]  
\[ (3.13) \]

\[ \beta_{t+1} = \beta_t + \zeta_t, \quad \zeta \sim N(0, \sigma^2_\zeta). \]  
\[ (3.14) \]

The state \( \beta_{t+1} \) represents the trend in short-run realized volatility, while \( \mu_{t+1} \) represents latent level of short-run realized volatility. All the disturbances in the model are independent at all lags and leads. If \( \sigma^2_\zeta = 0 \), the trend is a random walk with constant drift \( \beta_1 \). If \( \beta_1 = 0 \) the model reduces to local level model. If \( \sigma^2_\zeta > 0 \), but \( \sigma^2_\eta = 0 \), then the trend is a smooth curve, or and integrated random walk. Given a vector of realized volatility \( RV_t = (RV_1, ..., RV_T)' \), we want to estimate the \( \beta \)'s and \( \mu \)'s and the variances of the innovations of the three components of the series. When filtering, the purpose is to update the estimate of the state as each new observation arrives. This generates the Kalman filtering updating equation.
3.4 Variance Decompositions of Bitcoin

Table 3.1: Changes in Mean Decomposition

<table>
<thead>
<tr>
<th>Asset</th>
<th>$TSS_m/TSS x 100$</th>
<th>$TSS_{1:t}/TSS x 100$</th>
<th>$TSS_m$</th>
<th>$TSS$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gold</td>
<td>0.270%</td>
<td>99.730%</td>
<td>0.0005</td>
<td>0.1963</td>
</tr>
<tr>
<td>USD/EUR</td>
<td>0.207%</td>
<td>94.793%</td>
<td>0.0001</td>
<td>0.577</td>
</tr>
<tr>
<td>JPY/USD</td>
<td>0.022%</td>
<td>99.978%</td>
<td>0.162</td>
<td>726.039</td>
</tr>
<tr>
<td>CHF/USD</td>
<td>0.177%</td>
<td>99.823%</td>
<td>0.046</td>
<td>25.834</td>
</tr>
<tr>
<td>VEB/USD</td>
<td>0.236%</td>
<td>99.764%</td>
<td>0.004</td>
<td>1.557</td>
</tr>
<tr>
<td>ARS/USD</td>
<td>0.221%</td>
<td>99.779%</td>
<td>0.0003</td>
<td>0.1363</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>0.124%</td>
<td>99.876%</td>
<td>0.0002</td>
<td>0.1411</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>0.158%</td>
<td>99.842%</td>
<td>0.0124</td>
<td>7.7878</td>
</tr>
<tr>
<td>BTC/JPY</td>
<td>0.064%</td>
<td>99.936%</td>
<td>0.0121</td>
<td>8.860</td>
</tr>
</tbody>
</table>
Figure 3.3: Change-in-Mean Volatility Decomposition

Notes: The figure shows the realized volatility calculated monthly for various currency pairs and assets. Bitcoin/Currency pairs have high monthly volatility in general.
3.5 Conclusion

Bitcoin is a volatile asset, both relative to other currencies and traditional “safe-haven” assets such as gold. Like most currencies and assets in Table 3.1, the overwhelming majority of volatility in Bitcoin is short-run volatility. Currently, Bitcoin prices remain highly volatile. However, as Figure 3.4 shows, the average level of short-run price volatility in Bitcoin has been declining since trading began in 2011 on the Mt. Gox Bitcoin Exchange. This trend has important implications for the usefulness of Bitcoin as a medium of exchange. Less price volatility would be better if Bitcoin is going to be used as a medium in a significant share of transactions. However, much of the interest in Bitcoin as an alternative asset to date is due to the high level of volatility, and thus the possibility of large investment returns.
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