Stock market bubbles and monetary policy effectiveness

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Abstract:

In this paper, we provide evidence on the role of conventional monetary policy in the dynamics of stock market bubbles. We analyze the response of stock market returns to monetary policy shocks but condition the analysis on both the direction of monetary policy surprises and business conditions. Following a two-step approach, we first use an structural vector autoregressive (SVAR) model to identify a proxy variable of monetary policy shocks, and then we apply a conditional regression to contemporary stock market returns and these monetary policy shocks to extract the implicit relationship between these variables in different scenarios. Our results show that monetary policy does not impact on stock market returns in a significant form in the scenario defined by positive shocks and expansion periods, i.e. the lower effectiveness of restrictive monetary policy shocks coincides with the phase of the business cycle in which bubbles arise.

JEL Classification: E43, E44, E52, E58, G12.

Keywords: Conditional regressions; exogenous monetary policy shocks; sign-dependent scenarios; state-dependent scenarios, structural autoregressive vector model.

1. Introduction

A debate on how monetary policy should respond to perceived deviations of asset prices from fundamentals persists in the literature since the beginning of the millennium. Some authors, such as Bernanke and Gertler (2001), Kohn (2006) and Bernanke and Gertler (2012), argue that central banks should focus on stabilizing inflation and the output gap, and ignore fluctuations in asset prices and potential bubbles. On the other hand, authors such as Borio and Lowe (2002) and Cecchetti *et al.* (2000) uphold that central banks should pay attention and eventually respond to developments in asset markets. This debate has revived with more intensity after the more recent crisis that led to the emergence of some bubbles.

The *"lean against the wind"* monetary policies are based on the premise that a rise in interest rates will help to deflate a stock market bubble. The wide evidence that monetary policy is one of the macroeconomic variables with the greatest impact on stock markets supports this premise. A robust and significant impact of monetary policy actions on stock market returns has been documented in numerous empirical studies, such as Jensen *et al.* (1996), Patelis (1997), Chen (2007), and Maio (2014a).

Moreover, some of these empirical studies, such as Fair (2002), find that most of the large swings in stock prices have origins in monetary policy shocks, and others, such as Thorbecke (1997), Ehrmann and Fratzscher (2004), Rigobon and Sack (2004), and Bernanke and Kuttner (2005) find a negative contemporaneous correlation between Fed policy tightening and excess market returns.

However, recent works by Galí (2014 and 2020) and Galí and Gambetti (2015) call into question the prevailing dogma among advocates of *"leaning against the wind"* policies. Galí (2014) challenged, on theoretical grounds, the link between interest rates and asset price bubbles underlying the "conventional" view, at least in the case of rational asset price bubbles. However, Miao *et al.* (2019) have found some theoretical solution compatible "with the conventional views". More recently, Galí (2020), also on theoretical grounds, concludes that, "contrary to conventional wisdom, a "leaning against the bubble" policy, even when precisely implemented, does not guarantee the elimination of the bubble or the dampening of its fluctuations." Therefore, we are faced with an open empirical research question.

As Wang and Chen (2019) claim, in contrast to theoretical literature, empirical literature on price bubbles is still poorly developed. In the stock market context, the pioneering work of Galí and Gambetti (2015) is the reference from which current empirical literature has been building. They show evidence that points to protracted episodes in which stock prices increase persistently in response to an exogenous tightening of monetary policy, i.e., contrary to the "conventional" view, the size of the bubble component of stock prices does not necessarily decline in response to an exogenous increase in interest rates. Caraiani and Călin (2018) extend Galí and Gambetti (2015) dataset and use alternatively a shadow interest rate as a measure of the monetary policy stance. Caraiani and Călin (2019) extend Galí and Gambetti (2015) research by considering data of eleven OECD countries where they found mixed evidence. However, no evidence against the positive impact in the bubble component of U.S. stock prices of positive monetary policy shocks is provided.

In this context, the main goal of this paper is to relate the effectiveness of the stock market channel of monetary policy with bubble development. We provide evidence on the response of stock prices to monetary policy shocks but condition the analysis both to the direction of monetary policy surprises and business conditions, because both sign- and state-dependent responses are stylized facts documented in the previous literature. The results permit us to infer the degree of effectiveness of monetary policy in the relevant scenario: the one described by restrictive monetary policy shocks in an expansive phase of the business cycle in which stock market bubbles arise. We show evidence against the ability of monetary policy to control the growth of stock market bubbles.

To obtain these results we follow a two-step approach. Our starting point is to empirically achieve a monthly series of monetary policy shocks. To do so, we estimate a structural vector autoregressive model (SVAR) on monthly US data for industrial production growth, inflation, the monthly federal funds rate, and monthly stock market returns. We use the residuals of the monthly federal funds rate in the SVAR equation as proxies of monetary policy shocks. Then, we regress contemporary stock market returns and monetary policy shocks controlling the expected monetary policy stance. This second step permits us to condition the analysis to achieve our objective.

The remainder of the paper is organized as follows. In Section 2 we use a SVAR model to extract monetary policy shocks from monthly federal fund rates. In Section 3 we analyze the empirical relationship between stock market returns and monetary policy shocks depending on the direction of the shocks and the business conditions. Section 4 performs robustness analyses of the results. In Section 5 we conclude.

2. Measuring the monetary policy shocks

2.1 The auxiliary SVAR model

In line with Bekaert *et al.* (2013), Nave and Ruiz (2015) and Ruiz (2015) we use the vector autoregressive (VAR) methodology to compute monthly values of a proxy variable of monetary policy shocks. The VAR methodology is a generally accepted way to analyze relationships within a group of variables and is used extensively in the literature on monetary policy. Concretely, we use an SVAR model, a system of simultaneous equations that allows us to analyze the interactions among contemporary and lagged values of the variables that compose the model. Each variable, all considered endogenous, is explained by its own lagged values and by the current and past values for the rest of the variables in the system. We define the proxy of the structural shock in monetary policy as the residual in the monetary policy equation included in the SVAR.

We consider, without losing generality, the following SVAR system representation in matrix form without constants:

$$AX_t = \Phi X_{t-1} + \varepsilon_t \tag{1}$$

where:

A is a matrix containing the parameters of contemporary relationships between the endogenous variables of the model;

X_{t-1} is a matrix of the endogenous variables lagged for one period;

Φ is a matrix of the model parameters; and

ε_t is the vector of structural shocks, i.e., the components of the endogenous variables that are not explained by the model.

To estimate the above SVAR model we formulate it as a reduced VAR rewriting (1) in the following way:

$$X_t = BX_{t-1} + C\varepsilon_t \quad (2)$$

where B is $A^{-1}\cdot\Phi$, and C is A^{-1}.

To correctly identify the structural relationship we need to add restrictions to the SVAR system. As usual, we use the Cholesky decomposition of the estimation of the variance-covariance matrix to do this. This decomposition places restrictions on matrix A that comprises contemporary relationships. Now, the order of variables becomes especially relevant because depending on their position within vector X_t the variable values may or may not be explained by the contemporary values of the other variables.

In the SVAR model we consider four endogenous factors: *(i)* the stance of the monetary policy authority (mp_t); *(ii)* inflation (i_t); *(iii)* the stock market return (mr_t); and *(iv)* the business cycle (bc_t). These factors are collected using vector $X_t = (bc_t, i_t, mp_t, mr_t)$. We order the variables taking into account both the economic logic, confirmed by empirical evidence, and the final objective of our analysis. The order of variables in X_t allows that real activity contemporary affects inflation but not the inverse relationship; that both the real activity and the prices growth contemporarily affect the stance of monetary policy but not the inverse relationship; and that these three variables contemporarily affect stock market prices while stock market prices do have a contemporary impact on any of them. The model also allows monetary policy and macro variables to respond to stock market return structural shocks but not simultaneously. Similarly, macro variable respond to monetary policy shocks but in a lagged form.

2.2 Sample, variables and data for SVAR estimation

The period of analysis considered in this study begins in January 1960 and ends in July 2017. Thus, the entire sample covers 691 observations of monthly data. The factors involved in the SVAR model are measured by proxy variables as follows. To measure the business cycle we use the interannual growth rate of the Industrial Production Index (IPI-IGR).[1] We measure the inflation rate as the monthly interannual variation rate of the Consumption Price Index (CPI-IGR).[2] Using data from the benchmark stock market index S&P500, we compute the stock market return (SMR).[3] Concretely, we use the data for the last day of the month to compute monthly continuous compounding returns. Finally, through the effective monthly Fed funds interest rate (FFR) on the last day of the month we measure the monetary policy stance.[4] The summary statistics of these variables are reported in Table 1.

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1 Board of Governors of the Federal Reserve System (US), Industrial Production Index, retrieved from Federal Reserve Economic Data, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/INDPRO.

2 U.S. Bureau of Labor Statistics, Consumer Price Index: All Items, retrieved from Federal Reserve Economic Data, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL.

3 Data related to the S&P500 index has been retrieved from de CBOE website http://www.cboe.com/

4 Board of Governors of the Federal Reserve System (US), Effective Federal Funds Rate, retrieved from Federal Reserve Economic Data, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FEDFUNDS.

The previous literature has used other monetary policy proxies: *(i)* the change in the implied rate of the Fed funds futures contract as a proxy for the unanticipated change in monetary policy in Kuttner (2001), Faust *et al.* (2004), Bernanke and Kuttner (2005), Gürkaynak *et al.* (2007), Basistha and Kurov (2008) and Hamilton (2009), among others; *(ii)* high-frequency financial data to indirectly identify monetary policy shocks in Cochrane and Piazzesi (2002); Rigobon and Sack (2003) and Rigobon and Sack (2004); *(iii)* the difference between the announcement of the FOMC decision and the average expectation among investors as an estimation of the surprise in Fed policy in Ehrmann and Fratzscher (2004); or *(iv)* the FOMC statements as an indicator of future policy in Gürkaynak *et al.* (2005).

However, as Bernanke and Blinder (1992) and Bernanke and Mihov (1998) argue, FFR is a good proxy for Fed policy actions. Moreover, it tends to adjust relatively fast to the Fed funds target rate, as Fama (2013) shows. Therefore, it has also been widely used in the previous literature, as in Patelis (1997), Thorbecke (1997), Goto and Valkanov, (2002), Jensen and Mercer (2002) and Chen (2007), among others. Moreover, as Maio (2014b) notes, in the VAR framework, a regular time-series is needed, so this framework is not compatible with some of the other proxies that are used in an event study context. Additionally, to obtain more precise estimates, we need a sample over as long a period as possible, and the use of FFR as a proxy of monetary policy stance permits us to obtain the longest period.

To select the correct VAR order we use the Akaike (AIC), the Hannan-Quinn (HQ), and the Schwarz Bayesian (SB) information criteria as well as the final prediction error (FPE) and the likelihood ratio (LR) statistic. To better avoid serial correlation, we perform our analysis using the greatest number of lags among those reported by the five criteria applied. Concretely, as Table 2 shows, we use the number of lags reported by the LR criterion, sixteen lags. Table 3 shows that this VAR order removes residual serial correlation except at lag twelve where serial autocorrelation induced by the definition of interannual change variables are captured. As Table 4 shows, all roots of the system of characteristic polynomials lie in the unit circle, so the system with sixteen lags remains stable and thus stationary.

We estimate this four-factor SVAR auxiliary model with sixteen lags and extract the residuals' series of the monetary policy stance equation that we use as monetary policy shocks in the further empirical analysis. As we lose sixteen degrees of freedom in the SVAR estimation this series only counts 675 observations, from May 1961 to July 2017.

3. Empirical analysis

3.1. Empirical models

To examine the average effect of monetary policy stance on stock market returns, we start from the following empirical simple model that lineally relates the stock market returns for the period t (SMR_t) with the variable that measures the monetary policy at period t,

$$SMR_t = a + b \cdot FFR_t + \varepsilon_t \tag{3}$$

Then, we define the monetary policy shock at month t by the residual of the monetary policy stance equation in the auxiliary SVAR model implemented in Section 2 at month

t. This allows us to decompose the monthly values of the proxy variable that measure the monetary policy stance (FFR_t) into expected and unexpected values such that:

$$FFR_t = EFFR_t + UFFR_t \tag{4}$$

where:

$EFFR_t$ denotes the expected FFR at the end of month t; and

$UFFR_t$ denotes the shock or unexpected FFR at t month-end.

Decomposition in (4) permits us to compute $EFFR_t$, from the know values of FFR_t and $UFFR_t$. The main statistics of these variables are also reported in Table 1. Additionally, this decomposition permits us to reformulate the empirical model in equation (3), allowing for differentiated effects on the stock market returns from the expected monetary policy actions and from monetary policy shocks, which becomes:

$$SMR_t = a + b \cdot EFFR_t + c \cdot UFFR_t + \varepsilon_t \tag{5}$$

Evidence in previous literature supports that studies that do not account for the economic state find that stocks weakly react to macroeconomic news, suggesting that stock investors do not process the information efficiently. Thus, as the literature shows since the McQueen and Roley's (1993) pioneering work, the effect of business conditions must be incorporated into the empirical models to capture the real impact of news on the stock market. In this context, Basistha and Kurov (2008) find a much stronger response of stock returns to unexpected changes in the Fed funds target rate in recession. Additionally, as Lobo (2000) and Chulia *et al.* (2010) have reported, asymmetric stock price reactions to monetary policy may exist depending on the direction of the shock (expansive or restrictive). In this context, since we are particularly interested in bubble formation, we focus on the expansion period of the business cycle and capture the effects that, in those periods, have restrictive monetary shocks on stock market returns.

To do this, we introduce two dummy variables in our empirical model: the first one ($D1_t$), with value one when the month t belongs to an expansive period of the business cycle as defined by the NBER[5] and zero otherwise, to isolate the specific (differential) effects of monetary policy stance on stock market returns in the US business cycle expansions; and the second ($D2_t$), with the value one when the t-month monetary shock is positive and zero otherwise, that isolates the specific (differential) effects of restrictive monetary policy shocks on stock market returns. Their combination ($D1_t \cdot D2_t$) captures the specific (differential) effects of those restrictive monetary policy shocks in the expansive periods of the business cycle. Table 1 shows the descriptive statistics of these dummy variables where we can observe that *D1* takes the value one in 87,5% of the total observations, i.e., in 591 observations; *D2* in 332 observations, 49,2% of total observations; and *D1·D2* in 297 of the 675 observations that compose the sample. Thus our enlarged empirical model becomes:

$$EMR_t = a + b \cdot EFFR_t + c \cdot UFFR_t + D1_t \cdot (d + e \cdot EFFR_t + f \cdot UFFR_t) +$$
$$+ D1_t \cdot D2_t \cdot (g + h \cdot EFFR_t + i \cdot UFFR_t) + \varepsilon_t \qquad (6)$$

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5 "The NBER does not define a recession in terms of two consecutive quarters of decline in real GDP. Rather, a recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. For more information, see the latest announcement from the NBER's Business Cycle Dating Committee, dated 9/20/10."

The fifth right-hand side term in (6) isolates the differential effect of restrictive monetary policy shocks in the expansive periods of the business cycle over the average differential effect of all monetary policy shocks in the expansive periods of the business cycle, captured by the fourth right-hand side term, and over the average base effect of all monetary policy shocks throughout the analyzed period when the asymmetric effects due to the business cycle and the sign of monetary policy shocks are taken into account. Restrictions in the enlarged empirical model (6) allow us to conduct alternative analyses of the total effects in different scenarios.

3.2. Empirical Results

To examine the average effect of the monetary policy on stocks, we conduct the OLS regression for equation (5) that we have labeled as Model 1 in Table 5 that shows the estimation results. As we expect, shocks in the monetary policy stance have a significant, near at the 1% level, average effect on stock market returns while the expected changes of FFR do not. Similarly, the sign of this effect is negative, showing the desirable countercyclical efficacy of monetary policy. In the case of unexpected monetary policy actions, the slope estimate is -12,08.

Despite the different monetary policy proxies and different samples used, this result is in line with those shown in Bernanke and Kuttner (2005) and in Maio (2014b). In Bernanke and Kuttner (2005), where the effects of both expected and unexpected changes in the monetary policy stance are jointly estimated, the estimated response of stock market returns to monetary policy shocks is -11,43. In contrast, Maio (2014b) separately regress the effects of both expected and unexpected monetary policy actions on stock market returns and estimate a slope for monetary policy shocks of -10,08 on an annual basis, which is also significant at the 1% level.

However, as we mentioned above, we are interested in testing whether the countercyclical efficacy of monetary policy remains, on average, in all the scenarios including different business cycle phases and signs of monetary policy shocks. More concretely, we are interested in the positive monetary shocks in the expansion phase of the business cycle because the ability of monetary policy to control stock market bubbles depends on their effectiveness.

Model 2 in Table 5 introduces the dummy variable that accounts for the expansive phase of the business cycle, *D1*, and permits us to corroborate that in that phase of the business cycle, the effectiveness of monetary shocks is reduced by more than half due to the differential effect. This differential effect, despite being less significant, is positive and important enough with respect to the estimated base effect that becomes more significant and intense than the average effect in Model 1, reflecting a more intense and significant negative effect during the recession phase of the business cycle. This result is consistent with the previous evidence shown by Basistha and Kurov (2008), who find a stronger response of stock returns to monetary policy shocks in recessions.

Table 5 also shows the results of regressing the labeled as Model 3 that combines both the dummy variable that permits us to differentiate the expansion phase of the business cycle, *D1*, and the dummy variable that isolates the positive monetary shocks, *D2*. The results of the OLS regression of this model show an important and significant differential effect of unexpected monetary policy changes in this scenario of a positive monetary shock in the expansion phases of the business cycle. However, the sign of this differential effect is positive and similar to the negative base effect, so its sum, the total effect of positive monetary shocks in expansions, contrary to the expected, is positive but very small.

To test the significance of the total effect of positive monetary shocks in expansions, we regress Model 4, where only that scenario is taken into account. The results in Table 5 show an undesirable slightly positive effect but not significant, confirming that the effect of positive monetary shocks in expansions becomes statistically null. These results imply that in the expansive phase of the business cycle, positive monetary policy shocks have no ability to stop the formation of bubbles in the stock market, while negative monetary policy shocks retain the ability to inflate them.

These results reinforce the evidence shown in Galí and Gambetti (2015) and complement it. If they found evidence of protracted episodes in which stock prices increase persistently in response to an exogenous tightening of monetary policy, now our results circumscribe them to the expansion phase of the business cycle when bubbles arise. These results caution against using the *"lean against the wind"* monetary policies to deal with the bubbles as Svensson (2014) does.

4. Robustness of results

To check the robustness of the results we conduct a set of analyses concerning three issues: (1) the effect of the lag order selection for the four-factor SVAR model, (2) the effect of the four-factor SVAR model identification scheme used, and (3) the effect of the sample period. We discuss the main qualitative results from these robustness analyses in the next subsections.

4.1. Alternative order of the four-factor SVAR auxiliary model

As we argue in Subsection 2.2, we select the VAR order of sixteen because it is the highest order report by the five criteria used as the optimal value as Table 2 shows. This order has the advantage of better remove serial residual autocorrelation in general, and especially that generated up to the order of twelve lags due to the use of monthly data. However, while the final prediction error statistic (FPE) and the Akaike (AIC) and the Hannan-Quinn (HQ) information criteria report lag orders near to the sixteen reported by the sequential modified the likelihood ratio statistic (LR), the Schwarz Bayesian information criterion (SB) reports an ostensibly smaller optimal lag order value that induce to reflect on the possibility of overspecification errors when a lag order of sixteen is used.

To check this possibility we have redone the analysis using as a proxy of the monetary shocks the residuals of the monetary policy equation of the four-factor SVAR model but now using a lag order of two. Table 6 shows the results that are qualitative, and even quantitative, similar to those shown in Table 5.[6]

4.2. Alternative four-factor SVAR auxiliary model identification scheme

As usual, we use the Cholesky decomposition of the estimation of the variance-covariance matrix to correctly identify the structural relationship in the SVAR system,

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[6] We also redone our analysis using fourteen and thirteen lags as the final prediction error statistic (FPE) and the Akaike (AIC) and the Hannan-Quinn (HQ) information criteria suggest and again the results are in line to those reported in Table 5 and both qualitatively and quantitatively.

restricting the contemporaneous relations between factors. As we argue in Subsection 2.1, this identification scheme does not permit the simultaneous interdependence between domestic stock market prices and domestic monetary policy contemporarily as literature supports (Rigobon and Sack, 2003). To analyze the impact of this fact on the results we follow Nave and Ruiz (2015) and use an alternative identification scheme that permits this simultaneity in the contemporary relations.

We remove the restriction in the matrix of the SVAR coefficients of simultaneous relationships that prevents this relationship, i.e., now domestic stock market prices influence domestic monetary policy contemporarily, and vice versa. To complete the number of restrictions that globally identifies the SVAR system we add a restriction on the long-run properties of the accumulated impulse responses using the Blanchard and Quah (1989) approach. Based on the long-run monetary policy neutrality proposition and following Bjørnland and Leitemo (2009), we assume that monetary policy does not have a long-run effect on stock market returns and we introduce the corresponding restriction in the SVAR.

In Table 7, we show the results of our analysis when we use as proxies of monetary policy shocks the residuals of the monetary policy equation in the four-factor SVAR model with sixteen lags that uses the alternative identification scheme that include one long-run restriction. Again, the results are in line with those shown in Table 5 when we draw on Cholesky decomposition of the estimated covariance matrix to identify the structural model.

4.3. Alternative sample

To achieve greater stability in our four-factor SVAR model, we work with a wide sample that covers the period from January 1960 to July 2107. This sample includes the global crisis period that may distort the results to the extent that monetary authorities conduct unconventional monetary policy interventions more frequently in that period, especially from mid-December 2008 when the Federal funds rate had reached nearly zero percent and could go no lower. Whether we remove the data for the crisis period from the sample, we will limit this effect on the results. Because the postcrisis data are insufficient to carry out a separate analysis, we only use a precrisis sample for a robustness analysis of the whole sample results discussed in Section 3. In this way, we also avoid the effect in results of unconventional monetary policy whose measurement is not straightforward.

Table 8 shows the results of the regression analysis when the sample was shortened until November 2008 and only 573 monthly observations are included. The SVAR auxiliary model is now estimated with fourteen lags. Following the same criteria than in Subsection 2.2 we use the greatest number of lags among those reported by the five criteria selection applied. The results show a similar pattern, not only quantitatively but qualitatively, to those shown in Table 5 when the whole sample is used: the order of magnitude, the signs and the significance of the slope parameters are reproduced in both tables.

5. Concluding remarks

In this paper, we provide evidence on the response of stock market returns to monetary policy shocks in the scenarios defined by the interaction of the direction of monetary policy surprises (good news or bad news) and business conditions (contraction or expansion). To do so, we follow a two-step approach that permits us to condition the analysis to achieve our objective. In the first step, we conduct an estimation of an SVAR model to obtain a monthly monetary policy shocks series, while in the second step, we use regression analyses in order to capture the contemporaneous relationship between stock market returns and these shocks.

Our main result shows that when we jointly consider the sign of the monetary policy shocks and the phase of the business cycle, the monetary policy does not impact on stock market returns in a significant form in the scenario defined by positive shocks of the monetary policy and an expansion period. We found that in this phase of the business cycle, the stock market channel does not transmit effectively the bad news from monetary authorities. This result is in line with Galí and Gambetti's (2015) results. However, we observe that the effects of positive monetary shocks on stock market returns are not significant only in the expansion periods. This fact heightens the relation of these results with the development of stock price bubbles because the poor effectiveness of contractionary monetary policy transmission is now concretely located in the phase of the business cycle in which these bubbles arise.

On the other hand, the effect on the stock market returns of negative monetary policy shocks in expansion periods remains negative and significant as expected. So in expansion periods, negative monetary policy shocks help to inflate bubbles, while positive monetary policy shocks do not have a significant effect on them. This asymmetrical behavior of the stock market channel of monetary policy transmission places monetary policy driven by short-term interest rates at the epicenter of the stock market bubble generation. All the robustness analyses performed corroborate the initial evidence and therefore support our conclusions, which could make macroprudencial monetary policies tools more appropriate to deal with stock market bubbles than "conventional" monetary policy tools.

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Table 1. Data Summary Statistics

	Obs.	Mean	Median	Max.	Min.	Std. Dev.	Skew.	Kurtosis
IPI-IGR	691	2.736	2.924	13.381	-15.397	4.699	-0.878	4.611
CPI-IGR	691	3.790	3.061	14.592	-1.958	2.868	1.534	5.383
FFR	691	5.125	5.000	19.100	0.070	3.683	0.886	4.249
SMR	691	6.459	10.860	181.251	-294.51	50.993	-0.678	5.580
EFFR	675	5.179	5.097	19.130	-0.513	3.684	0.842	4.195
UFFR	675	0,000	-0.005	2.715	-5.293	0.415	-2.317	46.515
D1	675	0.875	1.000	1.000	0.000	0.330	-2.275	6.178
D2	675	0.492	0.000	1.000	0.000	0.500	0.033	1.001
D1·D2	675	0.440	0.000	1.000	0.000	0.497	0.242	1.058

IPI-IGR: Monthly inter-annual growth rate of the Industrial Production Index. **CPI-IGR**: Monthly inter-annual growth rate of the Consumption Price Index. **SMR**: Monthly continuous compounding stock market returns computed from S&P 500 Index data. **FFR**: Effective monthly Fed funds interest rate on the last day of the month. **UFFR**: unexpected FFR at the end of the month computed from US four-factor SVAR model with sixteen lags. **EFFR**: expected FFR computed as the difference between FFR and UFFR. **D1**: Dummy variable with value one in months belonging expansive periods of the business cycle as defined by the NBER and zero otherwise. **D2**: Dummy variable with value one in months where monetary shock is positive and zero otherwise. **Sample period:** from January 1960 to July 2017, 691 monthly observations; 16 less monthly observations in the regression analysis lost in the SVAR estimate.

Table 2. Four-factor SVAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
1	-2230.218	6761.353	0.010009	6.747280	6.882296	6.799587
2	-2086.358	283.8366	0.006822	6.363893	**6.606922***	6.458047
3	-2049.336	72.60183	0.006405	6.300857	6.651899	6.436857
4	-2029.709	38.25255	0.006336	6.289983	6.749038	6.467829
5	-2002.479	52.74616	0.006127	6.256308	6.823376	6.476001
6	-1989.305	25.36055	0.006179	6.264782	6.939863	6.526321
7	-1977.985	21.65606	0.006267	6.278814	7.061908	6.582199
8	-1959.557	35.03241	0.006222	6.271534	7.162641	6.616765
9	-1940.849	35.34024	0.006173	6.263415	7.262534	6.650492
10	-1922.274	34.86644	0.006126	6.255693	7.362826	6.684617
11	-1901.025	39.63126	0.006032	6.239954	7.455099	6.710723
12	-1888.429	23.33953	0.006095	6.250163	7.573322	6.762779
13	-1737.373	278.1071	0.004067	5.845196	7.276368	**6.399658***
14	-1707.817	54.05964	**0.003906***	**5.804550***	7.343734	6.400858
15	-1697.450	18.83773	0.003974	5.821440	7.468638	6.459595
16	-1680.848	**29.96915***	0.003968	5.819634	7.574844	6.499634
17	-1667.729	23.52305	0.004005	5.828274	7.691497	6.550120
18	-1655.329	22.08687	0.004050	5.839066	7.810303	6.602759

LR: sequential modified LR test statistic (each test at 5% level). **FPE**: Final prediction error. **AIC**: Akaike information criterion. **SC**: Schwarz information criterion. **HQ**: Hannan-Quinn information criterion. * Indicates the lag order selected by each criterion for the US four-factor SVAR model estimated using the variables: **IPI-IGR** (Inter-annual growth rate of the Industrial Production Index), **CPI-IGR** (Inter-annual growth rate of the Consumption Price Index), **FFR** (Effective monthly Fed funds interest rate on the last day of the month) and **SMR** (Monthly continuous compounding stock market returns computed from S&P 500 Index data), in this order. Sample period: from January 1960 to July 2017. Monthly observations included: 691.

Table 3. LM tests for the four-factor SVAR with sixteen lags.

Lags	LM-Stat	Prob	Lags	LM-Stat	Prob
1	17.91025	0.3292	10	33.25358	0.0068
2	28.71698	0.0259	11	44.55366	0.0002
3	25.28198	0.0650	12	150.9921	0.0000
4	21.00614	0.1783	13	27.53511	0.0359
5	28.60268	0.0268	14	29.14363	0.0230
6	14.07605	0.5930	15	18.32013	0.3055
7	12.47848	0.7104	16	9.641020	0.8847
8	15.83134	0.4648	17	22.42197	0.1301
9	29.07189	0.0235	18	11.88966	0.7515

The null hypothesis is no serial correlation at each lag order. **Prob**: Probability from Chi-Square with 16 degrees of freedom. US four-factor SVAR model estimated using the variables: **IPI-IGR** (Inter-annual growth rate of the Industrial Production Index), **CPI-IGR** (Inter-annual variation rate of the Consumption Price Index), **FFR** (Effective monthly Fed funds interest rate on the last day of the month) and **SMR** (Monthly continuous compounding stock market returns computed from S&P 500 Index data), in this order. Sample period: from January 1960 to July 2017. Monthly observations included: 691.

Table 4. Roots of the characteristic polynomial SVAR system with sixteen lags

Root	Modulus	Root	Modulus
0.980901 - 0.017098i	0.981050	-0.863614 + 0.203770i	0.887328
0.980901 + 0.017098i	0.981050	-0.863614 - 0.203770i	0.887328
0.292771 - 0.921846i	0.967220	0.864071 - 0.079825i	0.867751
0.292771 + 0.921846i	0.967220	0.864071 + 0.079825i	0.867751
-0.932354 + 0.242167i	0.963290	0.367972 + 0.779702i	0.862171
-0.932354 - 0.242167i	0.963290	0.367972 - 0.779702i	0.862171
0.696262 + 0.653389i	0.954829	-0.390669 - 0.761280i	0.855669
0.696262 - 0.653389i	0.954829	-0.390669 + 0.761280i	0.855669
-0.911309 + 0.256032i	0.946592	-0.582991 + 0.625328i	0.854935
-0.911309 - 0.256032i	0.946592	-0.582991 - 0.625328i	0.854935
0.215610 + 0.912466i	0.937593	0.000727 + 0.851868i	0.851868
0.215610 - 0.912466i	0.937593	0.000727 - 0.851868i	0.851868
-0.197750 + 0.914220i	0.935363	-0.317699 - 0.789070i	0.850625
-0.197750 - 0.914220i	0.935363	-0.317699 + 0.789070i	0.850625
0.929942 + 0.100332i	0.935339	-0.695760 - 0.474321i	0.842058
0.929942 - 0.100332i	0.935339	-0.695760 + 0.474321i	0.842058
0.654549 - 0.661022i	0.930261	0.655675 - 0.458240i	0.799933
0.654549 + 0.661022i	0.930261	0.655675 + 0.458240i	0.799933
-0.689219 - 0.622119i	0.928469	0.711503 + 0.329740i	0.784197
-0.689219 + 0.622119i	0.928469	0.711503 - 0.329740i	0.784197
0.886077 + 0.266375i	0.925250	-0.769088 - 0.133784i	0.780637
0.886077 - 0.266375i	0.925250	-0.769088 + 0.133784i	0.780637
-0.656527 - 0.646589i	0.921469	-0.485335 - 0.608559i	0.778392
-0.656527 + 0.646589i	0.921469	-0.485335 + 0.608559i	0.778392
0.178031 - 0.902907i	0.920291	0.753922 - 0.184210i	0.776100
0.178031 + 0.902907i	0.920291	0.753922 + 0.184210i	0.776100
-0.231357 + 0.881473i	0.911329	0.102974 - 0.691884i	0.699505
-0.231357 - 0.881473i	0.911329	0.102974 + 0.691884i	0.699505
0.624410 + 0.659905i	0.908495	-0.219799 - 0.630480i	0.667695
0.624410 - 0.659905i	0.908495	-0.219799 + 0.630480i	0.667695
0.814771 - 0.385702i	0.901454	0.643207	0.643207
0.814771 + 0.385702i	0.901454	-0.419990	0.419990

No root lies outside the unit circle so the SVAR satisfies the stability condition. US four-factor SVAR model estimated using the variables: **IPI-IGR** (Inter-annual growth rate of the Industrial Production Index), **CPI-IGR** (Inter-annual variation rate of the Consumption Price Index), **FFR** (Effective monthly Fed funds interest rate on the last day of the month) and **SMR** (Monthly continuous compounding stock market returns computed from S&P 500 Index data), in this order. Period: from January 1960 to July 2017. Monthly observations: 691.

Table 5. Effects of monetary policy on stock market returns.

	Model 1	Model 2	Model 3	Model 4
Const.	9.083672***	-4.698431	8.288521*	5.636655**
	(0.0075)	(0.6522)	(0.0585)	(0.0329)
$EFFR_t$	-0.506879	-0.639202	-1.345990*	
	(0.3418)	(0.5821)	(0.0516)	
$UFFR_t$	-12.07921**	-22.03433***	-24.84876***	
	(0.0108)	(0.0013)	(0.0001)	
D1 · Const.		14.04246		
		(0.2045)		
D1 · $EFFR_t$		0.459902		
		(0.7285)		
D1 · $UFFR_t$		16.67118*		
		(0.0846)		
D1 · D2 · Const.			-0.807667	1.844199
			(0.9072)	(0.7599)
D1 · D2 · $EFFR_t$			1.316400	-0.029590
			(0.2542)	(0.9748)
D1 · D2 · $UFFR_t$			25.66335*	0.814589
			(0.0521)	(0.9447)

This table shows by column the estimated slopes in models nested in equation (6) where the dependent variable is **SMR**: Monthly continuous compounding stock market returns computed from S&P 500 Index month-end daily data. **FFR** is the effective month-end Fed funds interest rate. **UFFR** is the month-end unexpected FFR computed from US four-factor SVAR model with sixteen lags. **EFFR** is the month-end expected FFR computed as the difference between FFR and UFFR. **D1** is a dummy variable with value 1 when the month belongs to an expansive period of the business cycle as defined by the NBER and zero otherwise. **D2** is a dummy variable with value one when the month-end monetary shock is positive and zero otherwise. P-values in brackets: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample period: from May 1961 to July 2017. Monthly observations included: 675.

Table 6. Effects of monetary policy on stock market returns: Robustness analysis using an alternative order of the four-factor SVAR auxiliary model.

	Model 1	Model 2	Model 3	Model 4
Const.	9.388800***	-1.213133	10.02752**	6.831071***
	(0.0050)	(0.8970)	(0.0121)	(0.0073)
$EFFR_t$	-0.545390	-1.037241	-1.191792*	
	(0.3032)	(0.3439)	(0.0633)	
$UFFR_t$	-9.324120**	-17.47047***	-17.18171***	
	(0.0241)	(0.0027)	(0.0012)	
D1 · Const.		8.259230		
		(0.4120)		
$D1 \cdot EFFR_t$		0.810230		
		(0.5227)		
$D1 \cdot UFFR_t$		14.48562*		
		(0.0861)		
D1 · D2 · Const.			-3.259453	-0.063005
			(0.6585)	(0.9925)
$D1 \cdot D2 \cdot EFFR_t$			0.942340	-0.249452
			(0.4734)	(0.8291)
$D1 \cdot D2 \cdot UFFR_t$			20.94937*	3.767660
			(0.0755)	(0.7223)

This table shows by column the estimated slopes in models nested in equation (6) where the dependent variable is **SMR**: Monthly continuous compounding stock market returns computed from S&P 500 Index month-end daily data. **FFR** is the effective month-end Fed funds interest rate. **UFFR** is the month-end unexpected FFR computed from US four-factor SVAR model with two lags. **EFFR** is the month-end expected FFR computed as the difference between FFR and UFFR. **D1** is a dummy variable with value 1 when the month belongs to an expansive period of the business cycle as defined by the NBER and zero otherwise. **D2** is a dummy variable with value one when the month-end monetary shock is positive and zero otherwise. P-values in brackets: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample period: from May 1961 to July 2017. Monthly observations included: 675.

Table 7. Effects of monetary policy on stock market returns: Robustness analysis using an alternative four-factor SVAR auxiliary model identification scheme.

	Model 1	Model 2	Model 3	Model 4
Const.	8.746972***	-4.810823	12.28981***	8.951422***
	(0.0093)	(0.6424)	(0.0050)	(0.0006)
$EFFR_t$	-0.436460	-0.622552	-1.540744**	
	(0.4091)	(0.5873)	(0.0260)	
$UFFR_t$	-17.72195***	-23.67983***	-27.55961***	
	(0.0001)	(0.0004)	(0.0000)	
D1 · Const.		13.22740		
		(0.2289)		
$D1 \cdot EFFR_t$		0.673881		
		(0.6085)		
$D1 \cdot UFFR_t$		8.602015		
		(0.3638)		
D1 · D2 · Const.			-11.04956	-7.711880
			(0.1066)	(0.1952)
$D1 \cdot D2 \cdot EFFR_t$			1.857489	0.316745
			(0.1037)	(0.7330)
$D1 \cdot D2 \cdot UFFR_t$			29.03175**	1.472136
			(0.0287)	(0.9022)

This table shows by column the estimated slopes in models nested in equation (6) where the dependent variable is **SMR**: Monthly continuous compounding stock market returns computed from S&P 500 Index month-end daily data. **FFR** is the effective month-end Fed funds interest rate. **UFFR** is the month-end unexpected FFR computed from US four-factor SVAR model with fourteen lags and one long-run restriction in the specification scheme. **EFFR** is the month-end expected FFR computed as the difference between FFR and UFFR. **D1** is a dummy variable with value 1 when the month belongs to an expansive period of the business cycle as defined by the NBER and zero otherwise. **D2** is a dummy variable with value one when the month-end monetary shock is positive and zero otherwise. P-values in brackets: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample period: from May 1961 to July 2017. Monthly observations included: 675.

Table 8. Effects of monetary policy on stock market returns: Robustness analysis using an alternative sample period.

	Model 1	Model 2	Model 3	Model 4
Const.	7.023670	-11.07637	9.919703	5.280889*
	(0.1219)	(0.3761)	(0.1050)	(0.0679)
$EFFR_t$	-0.243522	0.036666	-1.533656*	
	(0.7112)	(0.9780)	(0.0788)	
$UFFR_t$	-12.80441***	-22.69149***	-25.18295***	
	(0.0086)	(0.0013)	(0.0001)	
$D1 \cdot Const.$		17.93121		
		(0.1850)		
$D1 \cdot EFFR_t$		0.126891		
		(0.9349)		
$D1 \cdot UFFR_t$		16.60455*		
		(0.0910)		
$D1 \cdot D2 \cdot Const.$			-9.283685	-4.644871
			(0.3083)	(0.5318)
$D1 \cdot D2 \cdot EFFR_t$			2.455097*	0.921441
			(0.0775)	(0.4006)
$D1 \cdot D2 \cdot UFFR_t$			24.57729*	-0.605655
			(0.0818)	(0.9621)

This table shows by column the estimated slopes in models nested in equation (6) where the dependent variable is **SMR**: Monthly continuous compounding stock market returns computed from S&P 500 Index month-end daily data. **FFR** is the effective month-end Fed funds interest rate. **UFFR** is the month-end unexpected FFR computed from US four-factor SVAR model with fourteen lags. **EFFR** is the month-end expected FFR computed as the difference between FFR and UFFR. **D1** is a dummy variable with value 1 when the month belongs to an expansive period of the business cycle as defined by the NBER and zero otherwise. **D2** is a dummy variable with value one when the month-end monetary shock is positive and zero otherwise. P-values in brackets: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample period: from March 1961 to November 2008. Monthly observations included: 573.