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Federica Vassalli and Massimiliano Tancioni

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Shedding lights on Leaning Against the Wind*

Federica Vassalli† Massimiliano Tancioni

Department of Economics and Law
Sapienza University of Rome

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Abstract

The efficacy of monetary policy intervention against stock market bubbles depends on monetary policy shock identification. We estimate a Bayesian VAR identified with mixed zero-sign restriction, where we distinguish a pure monetary policy shock from a central bank information shock. We show that the two shocks affect the asset price components differently, where the asset price is the sum between the fundamental and the bubbly components. A pure tightening monetary policy shock reduces the S&P500 Index but causes the bubble to increase. In contrast, by disclosing information on the economy's future path, a central bank information shock increases the fundamental component causing a drop in the bubble. Ignoring the distinction between the two types of monetary shock helps to explain the ambiguity surrounding the efficacy of leaning against the wind policy in terms of the ability to deflate a bubble.

Keywords: Monetary Policy, Bubbles, LAW, BVAR

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†federica.vassalli@uniroma1.it

1 Introduction

In the aftermath of the Global Financial Crisis, the social-economic costs of the bursting of the housing bubble reopened the debate about leaning against the wind (LAW from now on) (Gambacorta and Signoretti, 2013). The crucial question is whether the central bank should also target financial stability via asset price. Before the crisis, the general consensus belief was that aggressive inflation targeting was enough to ensure macroeconomic stability (Bernanke, 2010). Even if there is not a general agreement on the efficacy of LAW policies, there is an open debate about the financial stability mandate of monetary policy. Recent research suggests (Giglio et al., 2016) that the implications of monetary tightening change dramatically over the theoretical assumptions for theoretical models and bubbles definition in the empirical. In this paper, we establish a connection between these phenomena, showing that the LAW's ambiguous efficacy depends on the definition of monetary policy shock.

Novel to this literature, we apply the methodology by Jarociński and Karadi (2020) (JK from now on) to disentangle a pure monetary policy shock from a central bank information shock. A pure tightening monetary policy shock is an increase in the official interest rate that reduces S&P500 prices. In contrast, an information shock discloses the central bank's expectations about the future growth path of the economy, pushing up stock prices via investors' expectations of future positive returns. The effect of the two shocks on asset price components might differ and affect the LAW's efficacy. In the macroeconomic literature, it is mainstream (Giglio et al., 2016) to define the asset price as the sum between the fundamental component, where the fundamental component is the actualised sum of dividends, and the "non-fundamental" component, i.e. the bubble (Tirole, 1985). In the spirit of Tirole (1985), we will use the "non-fundamental" component and bubbly component as a synonym since we are not interested in classifying it as a positive or negative phenomenon: we consider excessive price movements (Brunnermeier and Schnabel, 2015). In our analysis, we rely on two different methodologies: one is a dividend discount model (Cochrane, 2001), based on the theory of rational bubble. The other one is free of any rationality assumptions and based on a bivariate VAR with price and dividend, where the non-fundamental component is a noisy shock (Forni et al., 2017). By revisiting the model by JK, we directly use the non-fundamental component as a variable in a Constant Coefficient Bayesian VAR. This further novelty allows us to disentangle the effect of the monetary policy shock, in its two components, on asset price compositions, i.e. fundamental component and bubble. We also exploit the monetary surprise identified by JK and by Miranda-Agrippino and Ricco (2021) to estimate local projection models that allow using asset price components. The analysis delivers three main results. First, a pure tightening monetary policy reduces the S&P500 Index through the fundamental component but not the bubble, which grows with an increase in the interest rate by definition (Galì and Gambetti, 2015). Second, a central bank information shock pushes up the S&P500 Index through the fundamental component. Expected future economic growth increased expected future dividend flows, augmenting the fundamental component. Third, the asset price components respond to an interest rate increase without differences to the bubble definitions. Thus, monetary shock identification matters.

Literature review Our work relates to two broad strands of the literature.
The first one examines the bubble definition, which was mainstream during the 80s, gaining new importance after the 2008 financial crisis. The bubble literature is mainly theoretical and based on Overlapping Generations models (OLG from now on) with financial frictions that artificially create bubbles. Pioneers in this field were Samuelson (1957), Diamond (1965) and Tirole (1985). Blanchard and Watson (1982) firstly considered bubbles as stochastic, opening the track to further developments that are largely built on OLG models with infinitely lived agents or two generations agents. Seminal works follow as Farhi and Tirole (2012), Martin and Ventura (2012), Ikeda and Phan (2016), Ikeda and Phan (2019). Several empirical studies have made bubble estimations available via market data. Based on the theory of rational bubble, (Cochrane, 2001) defines a log-linearized linear model to obtain the bubble as the difference between the price and the actualised sum of dividends based on the milestone work by Tirole (1985). It has been recently further developed by Giglio et al. (2016). Bubbles can be seen as a significant deviation from the stock market trend. This is the case of the statistical approach by Jordà et al. (2015) and Phillips et al. (2015). Also, Forni et al. (2017) define the bubble as the residuals of a noise shock affecting both asset price and dividend. Recent strands of the literature investigate real-time bubble detection via implied option price (Jarrow et al. 2011, Jarrow 2015, Greenwood et al. 2019 and Fusari et al. 2020). However, they rely on restricted market data. Our analysis exploits the mainstream technique in macro-financial literature. It suggests that when rational bubbles are augmented with risk premia deliver the same results as non-rational bubbles.

The second strand studies the monetary policy's role in managing bubbles, i.e. the LAW policy. The focus is on whether monetary policy should respond to the asset price bubble by raising the interest rate to reduce the bubble or not, i.e. to "lean against the wind".
The reason for non-intervention, thus adopting a "wait and see approach", relies on the eventual need to manage the economic fallout due to the crash (Barlevy et al., 2018). If the central bank tries to prevent a rise in asset prices without an overheated economy, it may not be able to further lower interest rates in the fallout phase. Regarding the interventionism of monetary authority, there are different positions also among central bank governors. Bernanke and Gertler (2001) further argues that if the monetary authority acts to stabilise asset prices, this may interfere with its mandate of macroeconomic stability. This is the so-called "Jackson Hole Consensus" approach following the speech of the member of the Federal Reserve System Board of Governors Bernanke (Bernanke and Gertler, 1999) at Jackson Hole, alternatively named known as "mop-up" or "lean against clean" (Mishkin and Serletis, 2011). The "lean against clean" policy contrasts with the LAW,

favouring pure intervention. There is also empirical evidence about the inefficacy of the LAW activism documented by the Riksbank governor, that had unsuccessfully tried to raise the interest rate to calm the strong increase in housing prices (Svensson, 2014). Also, he proves that intervention costs are higher than non-intervention (Svensson, 2017). Provided that the central bank can detect a bubble in real-time, we can distinguish between systematic LAW (S-LAW) and discretionary LAW (D-LAW) (Schularick et al., 2021). The S-LAW implies an "augmented" Taylor rule which considers asset price or credit as target variables in addition to inflation and output gap (Castelnuovo and Nistico 2010, Gambacorta and Signoretti 2013, Ciccarone et al. 2019 among others). At the same time, the D-LAW responds only in the financial booms state (Schularick et al., 2021). In this regard, Castelnuovo and Nistico (2010) previously developed a theoretical model in which the central bank behaves according to an "augmented" Taylor rule. The standard Taylor rule responds to the inflation and output gap; by contrast, the "augmented" also attaches a positive coefficient to the stock price gap, the percentage deviation of the stock price index from its frictionless level. They find evidence of a systematic response of the Fed to stock price cyclical fluctuations driven by the non-fundamental component. Gambacorta and Signoretti (2013) shows that the LAW is desirable when a supply shock hits the economy for a central bank aiming to stabilise the financial markets and the real economy. Galì (2014) introduces the creation of a bubble as a source of economic instability and assesses that a systematic increase in interest rates in response to a growing bubble has a positive effect on bubble growth. Within the debate about the role of monetary policy in economies that experience rational asset bubbles, further contributions come from Ikeda and Phan (2016), who alerts that policy interventions are warranted. Conversely, Martin and Ventura (2016) finds that leaning against the wind policy maximises output and consumption. Later, Martin and Ventura (2018) provides a detailed guide on how rational bubbles can be easily incorporated into standard macroeconomic models and illustrates how they can be used to account for critical macroeconomic phenomena. However, not all the literature agrees on central bank intervention. Provided that the central bank can deflate the bubble, Hirano et al. (2017) shows that it comes at the cost of an economic slowdown. Nevertheless, this is consistent with Caballero and Simsek (2020), who sustain that the central bank should feed the bubble for a fast economic recovery. A more recent study by Ciccarone et al. (2019) points out that, under some circumstances, the central bank behaves according to an "augmented" Taylor rule. Therefore, the monetary authority attaches a positive coefficient to the output and inflation gaps and the "fundamental gap", the difference between the price and the fundamental component, namely a bubble. Ambiguous results about the efficacy of LAW in managing bubbles also come from Caraiani and Călin (2020). Allen et al. (2017) start challenging the milestone work by Galì (2014), showing that small changes in the model parameter lead to very different results, i.e. a dampening in the bubble rather than an increase. They point out that bubbles are dangerous when they arise, not when they burst. Thus, a central bank committed to intervening against bubbles can increase economic well-being. In response to this work, Galí

(2021) develops an OLG New Keynesian model with two different equilibria. He points out that bubbles are suitable for the economy, nor their fluctuations. Thus, the central bank should offset the effect of bubbles on aggregate demand to prevent bubble fluctuations. Furthermore, Allen et al. (2022) using a risk-shift model finds that policy responses are more effective when they discourage risky investment rather than targeting asset price. In this view, macroprudential policy is the correct policy tool to address bubbles (Schularick et al., 2021).

On the empirical side of literature, the investigation is not very large, and it mainly depends on the work by Galì and Gambetti (2015). They focus on US monetary policy and the US stock market, finding the inefficacy of a tightening monetary policy in deflating bubbles using a Time-Varying SVAR. The results of Jordà et al. (2015) agree with Galì and Gambetti (2015), but they emphasise the role of leveraged bubbles. Also, a working paper by Aastveit et al. (2017) finds that the Federal Reserve has reacted to fluctuations in house prices, which feeds the stock market's non-fundamental component. However, Allen et al. (2018) prove that these results are model dependent. In this regard, we want to shed some light on the efficacy of LAW. We study this issue in a novel empirical setup à la JK to avoid any confusion between the actual policy interventions and the information disclosed by the Fed actions. By construction, these two shocks affect S&P500 Index differently. Therefore, by focusing on the asset price composition, we can affirm that the ambiguity about the efficacy of the LAW in managing the asset price bubble relies on the identification of the monetary policy shock. The remainder of this paper is organised as follows: Section 2 describes the variables, the empirical methodology, and the identification strategy, and Section 3 presents the results. Section 4 shows some robustness exercises while Section 5 concludes.

2 Dataset and methodology

The dataset covers the period from February 1991 to June 2019, including 11 episodes of financial turmoils. However, we exclude the Covid-19 period to avoid the extra loosening monetary policy measures following the pandemic restrictions.

2.1 The non-fundamental components

There is no unique definition of a bubble or non-fundamental component, and there are also strands of literature sceptic about the existence[1]. In the macro-financial literature, there are seminal works by Jordà et al. (2015) and Phillips et al. (2015) that statistically test for their existence, finding consistent positive results. Also, studies in pure financial

[1]We will use bubble and non-fundamental components as a synonym since we are not interested in classifying the bubbles as a positive or negative phenomenon (Brunnermeier and Schnabel, 2015).

literature prove the existence of bubbles based on options data (Jarrow et al. 2011, Jarrow 2015, Greenwood et al. 2019, and Fusari et al. 2020). Given the lack of consensus on bubble definition, we rely on the theory of rational bubbles and on no rational assumptions. The theory of rational bubbles is mainstream in macroeconomic and macro-financial literature (Giglio et al., 2016), and we estimate non-fundamental components for the S&P500 Index starting from there.

Rational bubbles The theory of rational bubbles affirms that when the transversality condition does not hold, a rational bubble grows at the same pace as the real interest rate. Thus, the present value of a bubble is a function of the real interest rate:

$$B_t = E_t\left(\frac{B_{t+1}}{R}\right) \tag{1}$$

Tirole (1985) defines bubbles as the difference between the price and the fundamental component:

$$B_t = E_t\left[\frac{P_t}{R^{T-t}}\right] - E_t\left[\frac{\sum_{k=1}^{T-t} D_{t+k}}{R^k}\right] \tag{2}$$

whit D_t dividends and $R_t = 1 + r_t$, where r_t is the real interest rate. Given this definition, we use the formula by Cochrane (2001) for deriving the fundamental component that, in log-linearised terms, is

$$q_t^F = K + \sum_{j=0}^{\infty} \Lambda^j [(1-\Lambda)d_{t+j} - r_{t+j}] \tag{3}$$

where K is a constant equal to $\log(1+P/D) - \frac{P/D}{1+P/D}$ and P/D is the price to dividend ratio in level. Λ represents the ratio between the growth rate of dividend g and the real interest rate R, d_{t+j} is the dividend series in logs and r_{t+j} is the approximate one-year return in logs, in our case the real interest rate. Hence, we derive the bubble as the difference between the price and the fundamental component:

$$q_{i,t}^B = p_t - q_{i,t}^F \quad \text{with} \quad i = 1, 2 \tag{4}$$

with p_t the log of S&P500 Price Index and q_t^F obtained from Equation 3. For more accuracy, we regress the price, dividends, and real interest rate series on their mean and apply Equation 3 to the dividend residuals. From Equation 4, we derive the two rational bubbles: when $i = 1$ the discount rate Λ_1 is estimated as defined in Equation 3, which is $\Lambda_1 = 0.94$[2]. When $i = 2$, we augment the real interest rate with the risk premium (Blanchard and Watson, 1982) to remove asset price fluctuations due to variations in

[2] Λ_1 is obtained from observed data and the sample size is long enough to assume the estimated parameter converges to its true value.

investors' risk attitude[3]. The discount rate becomes $\Lambda_2 = 0.76$. We will use the bubble augmented with risk premium to control for the generic changes in financial conditions. Indeed, the novelty of our paper is that we directly estimate the bubbly component of the S&P500 Index to use it as a variable.

Non-rational bubble The methodology from Forni et al. (2017) identify three sources of stock price volatility: the dividend shock, the interest rate shock, and the noise shock. The non-fundamental component arises from the noise shock. Also, bubbles are considered a measure of the percentage deviation (positive or negative) of prices from their fundamental values. The theoretical representation of asset price is:

$$\Delta p_t = \frac{\sigma_a^2}{\sigma_s^2}\big(a_t + \frac{\sigma_e^2}{\sigma_a^2}a_{t-1}\big) + \frac{\sigma_a^2}{\sigma_s^2}(e_t - e_{t-1}) \tag{5}$$

where a_t is the information set regarding dividend and σ_a^2 the variance of dividend shocks, σ_s^2 is the variance of interest rate shock and σ_e^2 the variance of noise shock and e_t the relative bubbles. Thus, prices are also derived as the sum of fundamental and non-fundamental components. What differs in equation 5 is that the fundamental component depends on both observable (a_t) and non-observable (e_t) information set about the future path of dividends. Therefore, after some manipulation, Equation 5 can be represent as:

$$p_t = q_t^F + q_t^B \tag{6}$$

$$\Delta q_t^F = \alpha(L)a_t + n(L)\nu_t \tag{7}$$

$$\Delta q_t^B = (1-L)\tilde{\beta}(L)e_t \tag{8}$$

where p_t is the sum of fundamental q_t^F and bubbly component q_t^B. The fundamental component Δq_t^F (Equation 7) is a function of dividend and interest rate shock (a_t and ν_t respectively). The non-fundamental component Δq_t^B (Equation 8) is a function of the noise shock e_t, which is stationary and orthogonal to economic fundamentals a_t and ν_t. In conclusion, the noise shock is obtained via a bivariate structural VAR:

$$\begin{pmatrix} \Delta d_t \\ \Delta p_t \end{pmatrix} = \begin{pmatrix} C(L)\sigma_a & 0 \\ \alpha(L)\sigma_a & \beta(L)\sigma_e \end{pmatrix} \begin{pmatrix} a_t/\sigma_a \\ e_t/\sigma_e \end{pmatrix} \tag{9}$$

In Figure 1, we summarise the three bubble series, and the red dashed vertical lines capture market booms and fallouts. The green line is the bubble series augmented with the risk premium. As expected, it is smoother than the one without the risk premium (blue line) because it captures fluctuations only in the bubbly component, not in the risk premium. Controlling for the risk premium enables us to derive the pure bubbly component. The red

[3] As a proxy for the risk premium, we consider the interest rate on BAA 10Y Bonds rated by Moody's (Caldara and Herbst, 2019).

line is the bubble obtained with the bivariate VAR (Forni et al., 2017). From its variability, we can appreciate that it depends on a noise shock. The S&P500 Index and its dividend series come from the "Online Data Robert Shiller"[4].

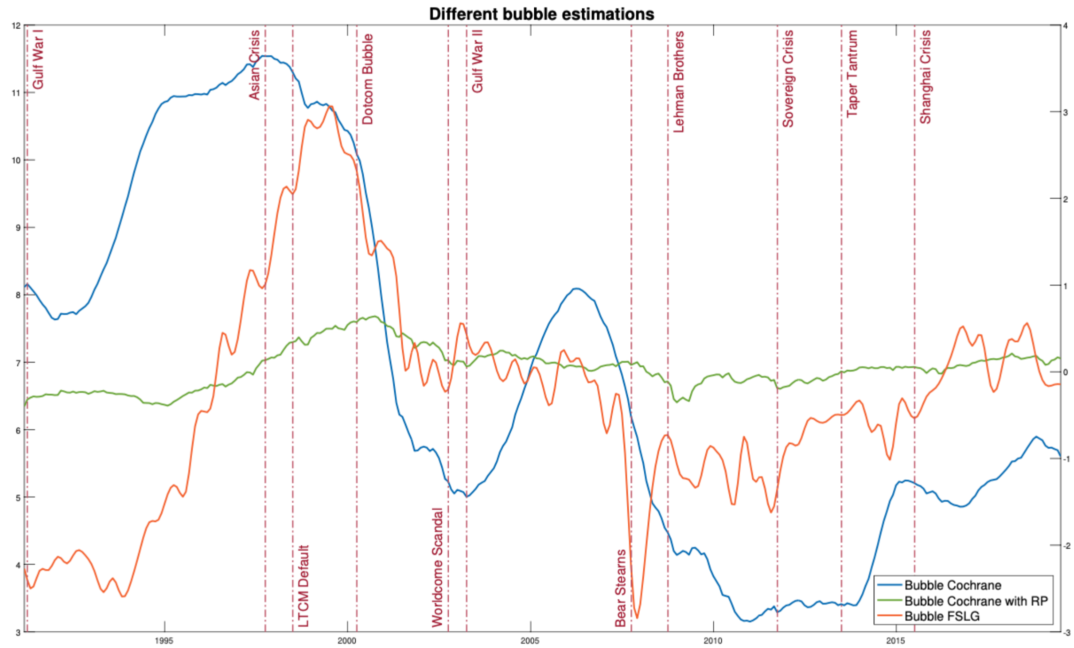

Figure 1: Bubble series for the S&P500 Index, i.e. blue line rational bubble with $\Lambda_1 = 0.94$ (Cochrane, 2001), green line rational bubble with $\Lambda_2 = 0.76$, red line rational bubble with bivariate VAR (Forni et al., 2017). Data are in logs.

2.2 US Monetary Policy and remaining variables

The paper's primary focus is assessing the LAW's efficacy by distinguishing the pure monetary policy shock from the central bank information shock. Thus, we exploit the data and the methodology by JK. Data refers to the surprise in the "policy indicator", i.e. the first principal component of the surprises in interest rate futures with maturities from 1 month to 1 year and in the surprise in the SP500 in the neighbour of the FOMC meetings.

By contrast, for representing the traditional monetary policy behaviour in the US, we choose the Federal Funds Rate (FFR), which is mainstream in literature. Although subject to some critiques regarding its capability of capturing pure monetary policy decisions, we follow Arias et al. (2019) who demonstrate that the FFR is the best instrument for

[4]For further details on data, see Appendix A.

identifying monetary policy actions since it reacts only to itself. Also, for Zero Lower Bound, which begins with the announcement of the first Quantitative Easing (November 2008) and ends with 2015 tapering, we substitute the FFR with the shadow rate. The shadow rate is the shortest maturity rate that would generate the observed yield curve had the ZLB not been binding. Thus, it can be negative. In addition, the Shadow Rate allows for unconventional monetary policy as in Debortoli et al. (2019) and Wu and Zhang (2017). In this way, we let the interest rate series be more sensible than it would have been if we had kept values close to zero. We use the shadow rate estimated by Wu and Xia (2016).

Other Variables The remaining variables are the real GDP and the inflation rate. All variables are monthly, seasonally adjusted, in logarithm, and come from the FRED Saint Louis. The inflation rate is the annualised rate of change in the GDP deflator. GDP comes from Chow-Lin interpolation with the Industrial Production Index. In conclusion, our set of variables is as follows:

$$\mathbf{y}_t = (FFRhf_t, S\&P500hf_t, S\&P500/q^B_{i,t}, S\&P500, GDP_t, \pi_t) \quad \text{where} \quad i = 1, ..., 4 \tag{10}$$

where FFRhf is the high-frequency surprise in the "policy rate", S&P500hf is the high-frequency surprise in the S&P500 Index, S&P500/q^B is the stock price-bubble ratio. At the same time, the subscript i in q^B indicates one of the two non-fundamental components: the rational (Equations 4) and the non-rational (Equation 8). S&P500 is the S&P500 Index in log real terms. GDP is the real US GDP, and π is the inflation rate.

2.3 Model set-up

This paper aims to shed light on the efficacy of the LAW policy and test whether the traditional identification of monetary policy shock is responsible for the ambiguous effects of the LAW policy documented in the literature. This test requires an empirical framework with two key characteristics. One is the possibility of disentangling a pure monetary shock from a central bank information shock. The other one is to remain agnostic concerning the relationship between monetary shocks and asset price composition. Thus, we exploit the Bayesian VAR framework by JK. To trace out the dynamics of the response of S&P500 Index components to monetary shocks, we estimate a Bayesian VAR that, in its reduced form, is:

$$\mathbf{y}_t = \sum_{i=1}^{p} \mathbf{A}_i \mathbf{y}_{t-i} + \mathbf{u}_t \tag{11}$$

where $\mathbf{y}_t$ is the vector of variables in Equation 10, $\mathbf{A}$ is the matrix of reduce-form parameters and $\mathbf{u}_t \sim N(0, \Sigma_u)$ is the vector of reduced form shocks. Following JK, we use the original Minnesota prior (Litterman et al., 1986) and we estimate the VAR with 12. We assume that the variables are close but not fully stationary; hence the diagonal elements of $\mathbf{A}_1$ are fixed equal to 0.8 and the off-diagonal equal to zero. Indeed, the prior variability is specified for the ij^{th} element of the matrix $\mathbf{A}_i$, and it follows a hierarchical structure related to four fundamental hyperparameters

$$\sigma^2_{a_{ij}} = \left(\frac{\lambda_1}{\text{lag}^{\lambda_3}}\right)^2 \tag{12}$$

$$\sigma^2_{a_{ij}} = \left(\frac{\sigma^2_i}{\sigma^2_j}\right)\left(\frac{\lambda_1\lambda_2}{\text{lag}^{\lambda_3}}\right)^2 \tag{13}$$

$$\sigma^2_{c_i} = \sigma^2_i(\lambda_1\lambda_4) \tag{14}$$

where the hyperparameter λ_1 is the overall tightness hyperparameter, λ_2 is the cross-variance hyperparameter, λ_3 is the scaling hyperpamater controlling the shrinkages of lag decay λ_4 is another tightness parameter. All the hyperparameters are optimised according to Giannone et al. (2015). Finally, σ^2_i and σ^2_j are the residual variances of the autoregressive model estimated with OLS for variable i and j (Alistair et al., 2018).

2.4 Identification Strategy

We need to define an identification strategy for the matrix of structural coefficients to derive the impulse response functions (IRFs) from the VAR reduced form. Common in the empirical literature is to map reduced-form shocks to innovation in the structural form using the lower triangular Cholesky decomposition (Galì and Gambetti 2015, Aastveit et al. 2017), which implies the imposition of a recursive scheme on the matrix of the structural coefficients. In this paper, we base our model identification strategy on mixed zero-sign restrictions (Arias et al., 2018). Even if computationally challenging, the use of sign restrictions is particularly appropriate in a model with six identified shocks (Furlanetto et al., 2017). Mixed zero-sign restrictions imply that the impact effects matrix is set-identified instead of point-identified. Namely, we only bound the sign of the parameters of interest without estimating the true value, and we can impose orthogonality via the zero.

Arias et al. (2018) algorithm exploits the QR decomposition in the Haar space and the Haar concept of orthogonality. The QR decomposition exploits the definition of a VAR in its reduced form, as in Equation 11, and defines the reduced form errors as

$$\mathbf{u}_t = \mathbf{PQQ'e}_t = \mathbf{PQ}\varepsilon^*_t \tag{15}$$

where $\mathbf{e}_t = \mathbf{P}^{-1}\mathbf{u}_t$ is the transformed error from the Cholesky factorisation of the reduced covariance matrix $\mathbf{\Omega}$ such that $E(\mathbf{e}_t\mathbf{e}'_t) = \mathbf{P}^{-1}\mathbf{\Omega}\mathbf{P}^{-1'} = \mathbf{P}^{-1}\mathbf{PP}'\mathbf{P}^{-1'} = \mathbf{I}_m$. Then, the algorithm searches for a large number of combinations between ε^*_t and $\mathbf{e}_t$ and between $\mathbf{u}_t$ and $\mathbf{e}_t$ knowing that $\varepsilon^*_t = \mathbf{Q}'\mathbf{e}_t$ where $\mathbf{Q}'$ is an orthogonal matrix such that that sign restrictions are satisfied. Hence, the ε^*_t is admissible for $\mathbf{e}_t$ if, given the estimates of $\mathbf{u}_t$ and $\mathbf{\Omega}$ from the reduced form VAR, the implied structural impact matrix $\mathbf{PQ}$ satisfies sign restrictions. The procedure consists in generating a large number of candidates $\mathbf{Q}$ from the set of all orthogonal matrices $\upsilon_m = \mathbf{Q}|\mathbf{Q}\mathbf{Q}' = \mathbf{I}_m$ and retaining only those consistent with the set of restrictions. Hence, sign restrictions are imposed only on the draws from the posterior distribution. There is no need to set any further artificial restrictions when estimating the IRFs, as it was with the previous algorithms (Jordà 2005, Rubio-Ramirez et al. 2010, Fry and Pagan 2011).

Table 2.4 presents our assumptions regarding the baseline model identification strategy. The crucial point in this paper is to disentangle between the pure monetary policy shock and central bank information shock in addition to a pure financial shock and a shock in the non-fundamental component. First, we separate the pure monetary policy shock from the central bank information shock using the JK identification. Hence, a pure tighten monetary policy shock reduces the S&P500 high-frequency Index due to the inverse relationship between interest rates and asset price. On the other side, an increase in the policy rate, apparently not justified by the economic cycle, discloses information about the future path of economic growth. Thus, an increase in the asset price, which includes the expectation of future economic growth, follows a policy rate tightening. Since these shocks are identified via high-frequency movements, orthogonality with a real slow-moving variable like GDP is straightforward and orthogonality with real side shocks (JK). Second, we disentangle a pure financial shock from a shock in the non-fundamental component. To do so, we take S&P500 Price Index and the ratio between the S&P500 Index and its non-fundamental component. Following Furlanetto et al. (2017), we define a positive, pure financial shock as a shock to the demand for capital. Thus, we impose positive signs to GDP and Inflation driven by an increase in the demand for capital. To distinguish the fundamental shock from the non-fundamental, we set a positive sign on the ratio between the S&P500-bubble ratio. According to Forni et al. (2017), a positive, pure financial shock increases asset price through the fundamental component. Thus, the S&P500 Index fundamental component grows faster than the bubbly component exhibiting a positive sign, both in itself and in the ratio. On the other hand, in our view, a positive non-fundamental shock makes the asset price grow through the bubbly component, which increases faster than the fundamental component, dampening the S&P500-bubble ratio[5]. Here is the negative sign between the S&P500 Index and its non-fundamental component. Moreover, we assimilate the non-fundamental shock to a positive demand shock (Castelnuovo and Nistico 2010, Caballero and Simsek 2020) driven by sentiment (Patella and Tancioni, 2021). Hence, we impose positive reactions to GDP and prices given that a bubble can prevent economic recession

[5]Recall that we are using variables in levels and logs, thus

$$S\&P500 = q^F + q^B$$
$$\ln\left(\frac{S\&P500}{q^B}\right) = q^F + q^B - q^B = q^F$$

(Caballero and Simsek, 2020).

The other assumptions are mainstream in literature. The identification scheme for supply and demand shocks follows (Furlanetto et al., 2017) and behaves according to a standard New-Keynesian model. Thus, a positive supply shock increases GDP while it reduces inflation. On the other hand, demand shock positively relates to GDP and price level. We left S&P500 unrestricted and imposed orthogonality to the S&P500-bubble ratio to avoid assumptions about which of the two components reacts first. All the restrictions are imposed only at the impact (Canova and Paustian, 2011).

	Pure Monetary	CBI	Supply	Demand	Fundamental	Non-Fundamental
FFRhf	+	+	0	0	0	0
S&P500hf	-	+	0	0	0	0
GDP	-		+	+	+	+
Inflation	-		-	+	+	+
S&P500						+
S&P500/Q^B				0	+	-

Table 1: The Table shows the restrictions for each variable (rows) for each shock (columns). Blank boxes mean that the variable is unrestricted.

3 The impact of monetary shocks

In this Section, we reassess the impact of the monetary shock on both the S&P500 Index and its components, focusing specifically on the influence of a pure monetary shock and a central bank information shock. Shocks are normalised to a 1% increase in the standard deviation. First, we revisit the well-known results in the literature. Galì and Gambetti (2015) provide the main results in the empirical LAW literature. We replicate this model with our monthly data and the two rational bubble estimations. We preserve the same variable ordering but use the bubble estimate directly. For the sake of simplicity, we omit the World Consumer Price Index. Thus, the results exhibit a price and output puzzle.

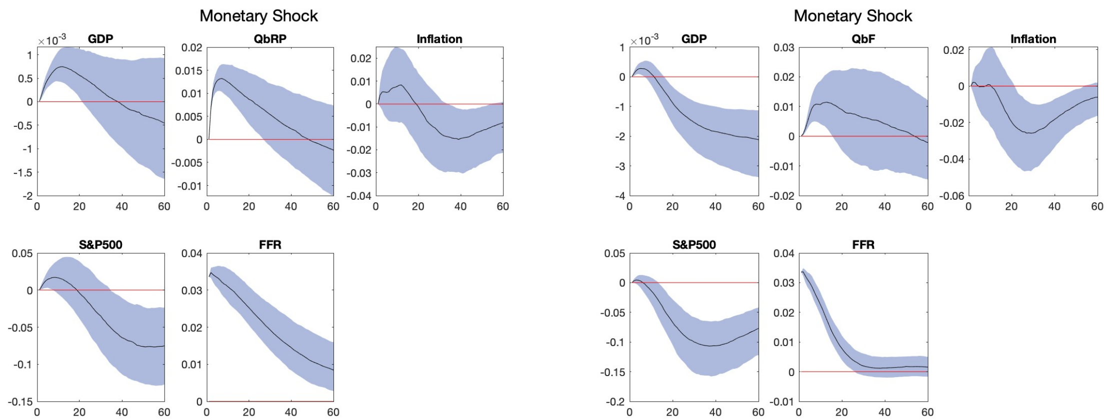

Figure 2: IRFs of the Galì and Gambetti (2015) at 68% to a monetary shock with rational non-fundamental component as in Equation 4 (LHS) and non-rational 8 (RHS).

We can appreciate that, in both cases, the bubbly component increases following a tightening monetary policy, consistently with the baseline specification. Allen et al. (2018) proves that the results obtained by Galì and Gambetti (2015) are susceptible to the model specification and light changes in the parameters lead to very different results. In this spirit, we contribute to the debate in two ways. First, we show that a pure monetary policy shock reduces the fundamental component and grows the bubble. Second, we prove that asset price components respond differently to a central bank information shock.

The baseline specification of our BVAR model follows Jk and it is described by Equation 11 where the vector $\mathbf{y}$ contains the variable in the list 10. We start by analysing the responses to the pure monetary shock (see Figure 3). The shock causes S&P500 to drop by about 2% in the first three months, and the S&P500-bubble ratio declines by about 1% in 18 months for the rational bubble as in Equation 4. A milder but sharper decline occurs for the non-rational bubble obtained by Equation 8. The shock also generates a decline in GDP and inflation. The negative response of the S&P500-bubble ratio means that the bubble is growing faster than the stock prices. This is in line with the theory of rational bubbles. Given that the bubble increases at the same pace as the real interest rate, a rise in the policy rate makes the bubble grow. Also, consider that the asset price is the sum of the fundamental and the bubble component, where the fundamental value is the actualised sum of dividend flows. A rate hike causes the discount rate to jump higher, reducing the discounted value of the dividend. Thus, the fundamental component declines instead of the bubble, which comes at the cost of a mild recession. These results are broadly in line with the literature. First of all, the milestone work by Galì and Gambetti (2015) proves monetary policy to be unsuccessful in deflating the bubble, followed by the more recent empirical investigation by Forni et al. (2017). Also, Aastveit et al. (2017) outlines the role of an increase in the interest rate in feeding the non-fundamental component. Finally, Svensson (2017) sustains the inefficacy of preventing a bubble from rising using interest rate rise as well as Schularick et al. (2021).

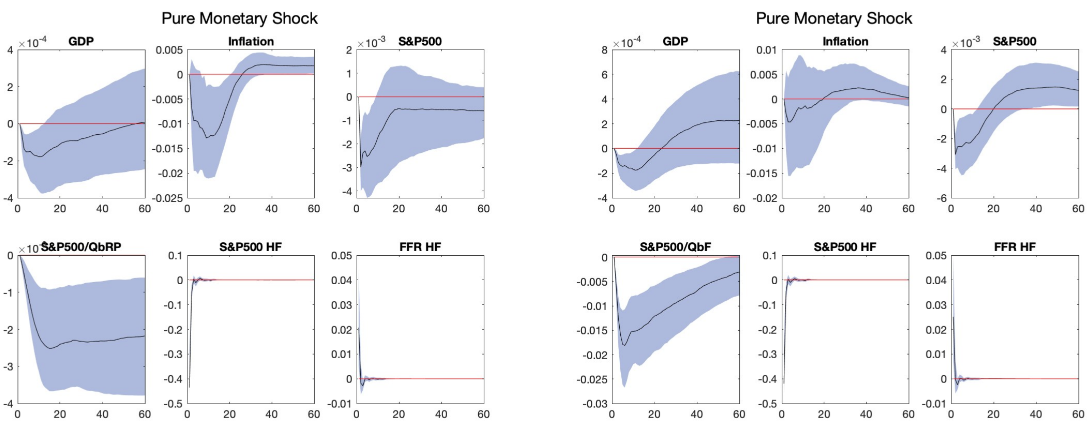

Figure 3: IRFs at 68% to a pure monetary shock with rational non-fundamental component as in Equation 4 (LHS) and non-rational 8 (RHS).

The following two panels present the responses to the central bank information shock (see Figure 4). The central bank information shock is entirely different from the pure monetary policy shock by construction. It discloses positive information about central bank expectations about the economy's future path. Thus, it leads to different results. It causes the S&P500 Index to increase by 1% in almost six months before returning to the steady state. The S&P500-bubble ratio with rational bubble as in Equation 4 (LHS panel) exhibits a substantial positive jump at 3%, which remains stable over time. We find a hump-shaped response of the opposite sign for the S&P500-bubble ratio with non-rational as in Equation 8 that tends to be positive after almost two years but with a lack of significance. In this framework, the foreseen economic growth makes expectations about positive future dividend flows stronger than the increase in the discount rate, causing the fundamental component to widen. In line with the idea that the monetary authority carries positive information about the economy, GDP and inflation react positively coherently with the JK baseline and poor man model. These results support the portion of literature in favour of monetary policy intervention. We appreciate that monetary policy maximises all its targets: it contains inflation and reduces the bubble without causing a recession (Martin and Ventura 2016, and Martin and Ventura 2018). Also, we can think of this policy intervention as a mild *laissez-faire*. The central bank let the bubble grow up to the point where it fosters economic growth (Caballero and Simsek, 2020). If the monetary authority intervenes at this point, the bubbly component drops in favour of the fundamental, fed by economic growth.

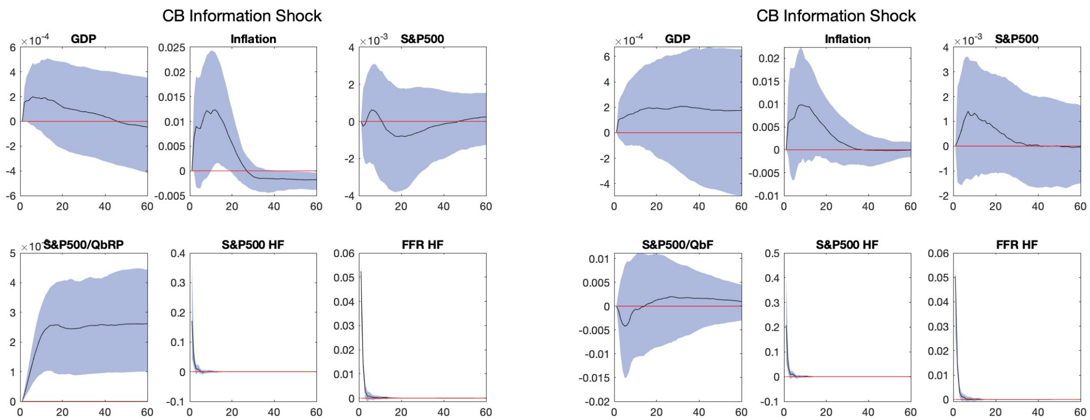

Figure 4: IRFs at 68% to a central bank information shock with rational non-fundamental component as in Equation 4 (LHS) and non-rational 8 (RHS).

4 Robustness checks

To assess the validity of our baseline models, we perform two different exercises. First, we test if the BVAR copes with a local projections (LPs) model, where shocks are externally identified. Since the seminal work by Jordà (2005), LPs have emerged as a cheap, viable option for investigating the dynamics in the transmission of the shocks. Also, Stock and Watson (2018) enlarges the application and efficacy of LPs by proposing externally identified shock. Then, as external shocks, we deal with the monetary factors extracted in JK, one for pure monetary shock and one for central bank information shock. Later, we repeat the same exercise using as external shocks the factors obtained by Miranda-Agrippino and Ricco (2021) (MAG from now on)[6]. Moreover, thanks to the flexibility of the LPs model, we can directly investigate the impact of the two shocks on the asset price composition, namely on the asset price itself and the bubbly component.

4.1 The baseline model

The baseline specification of our LPs model is described by Equation 16. The left-hand-side variable is represented alternatively by the S&P500 Index, the S&P500-bubble ratio and the bubble itself in terms of Equation 4 or 8. The main regressors are the monetary surprise series constructed by JK. We include among the controls GDP, inflation, S&P500 and the complementary monetary shock, with 12 lags. The estimation sample runs from

[6]MAG available shock series run from 1991M1 to 2015M12. Thus, we select 24 horizons for the LPs estimates to avoid excessive sample cutting and keep estimation consistent.

February 1991 to June 2019.[7].

$$y_{t \to h} = \alpha_h MP_t^i + \beta_h y_{t-1} + \Gamma_h(L) X_{t-s} + \varepsilon_{t,h} \qquad h = 0, ..., 24 \tag{16}$$

Where y is the endogenous variable of interest. MP is the JK surprise series, where i refers to the pure monetary policy shock and central bank information shock. X is the set of control variables. In computing the IRFs, we focus on the representative pure monetary policy shock associated with a median increase of 5 basis points in the three-month fed funds futures and a median 42 basis points drop in the S&P500 Index in the 30 minutes around the FOMC statements. Figure 5 shows the impulse response The pure monetary tightening has a recessionary impact on the S&P500-bubble ratio (-0.5% for the rational bubble in Equation 4 and -1.5% for the non-rational bubble in Equation 8). A decline in the ratio implies that the non-fundamental component increases faster than the fundamental. The sign of the response is in line with the theory of rational bubbles. According to theory, a bubble increases at the same pace as the real interest rate. Hence, a policy rate raise makes the bubble grow for almost two years. Also, recall that the bubble is obtained as the difference between the price and the fundamental component. Given that the fundamental component is the actualised sum of dividend flows, a higher interest rate augments the discount factor at which divided are discounted and reduces the fundamental value. Thus, the bubble becomes bigger.

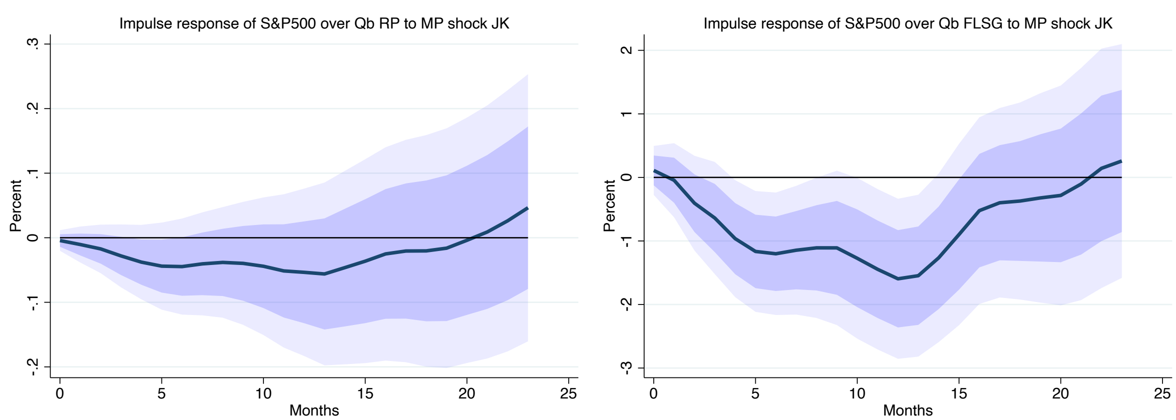

Figure 5: IRFs at 68% and 90 % of the LPs with pure JK monetary shock on S&P500 over its non-fundamental component defined as in Equation 4 (LHS) and 8 (RHS)

To further corroborate this hypothesis, we directly test the effect of the pure tightening on the bubbly component. Figure 6 plots the IRFs for the two bubbles. The response of the rational non-fundamental component (Equation 4) suggests a rise in the bubble (+1%)

[7]All the IRFs are calculated considering the Newey-West correction for error terms.

despite being extremely noisy. Indeed, the non-rational bubble (Equation 8) exhibits a better dynamic, showing a positive hill-shaped response (at peak +1.5%) that tends to vanish after two years.

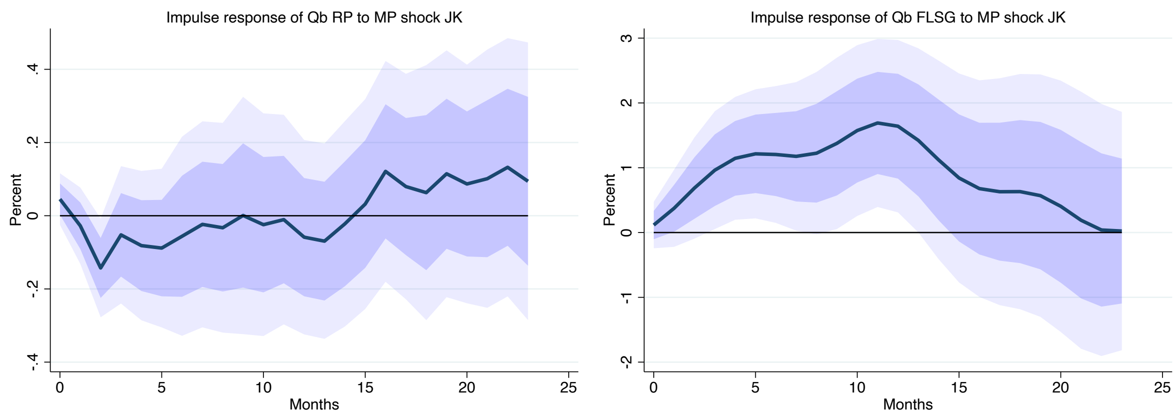

Figure 6: IRFs at 68% and 90 % of the LPs with pure JK monetary shock with non-fundamental component as in Equation 4 (LHS) and 8 (RHS)

The responses of asset price composition to the pure monetary policy shock favour Galì and Gambetti (2015) and Jordà et al. (2015). An increase in interest rate enhances bubble growth, as Galì and Gambetti (2015) shows in their Time Varying VAR, even more sustained when bubbles are leveraged (Jordà et al., 2015). Also, Aastveit et al. (2017) points out that an increase in interest rate feeds the non-fundamental component of stock prices. From the theoretical perspective, these results are also coherent with Schularick et al. (2021) who affirm that a monetary intervention against asset booms may trigger a crisis from the bubble burst.

The next step is investigating whether the propagation mechanism changes considering the information channel (Jarociński et al. 2018, Jarociński and Karadi 2020, Miranda-Agrippino and Ricco 2021). The central bank information shock is associated with a median increase of 3 bps in fed funds futures and a median increase of 28 bps in the S&P500 Index in the 30 minutes around the FOMC statements. Figure 7 presents the impulse response functions where we can appreciate that the central bank information shock triggers an entirely different dynamic. Consistently with the idea that the central bank discloses information about the economy's future path (Jarociński et al. 2018, Jarociński and Karadi 2020, Miranda-Agrippino and Ricco 2021), we find a positive response of the S&P500 Index-bubble ratio. As already explained, an increase in the ratio means that the fundamental component is growing faster than the bubble (+1% for the rational bubble and +4% at its peak for the non-rational bubble). Recall that we define the fundamental component as the discounted flows of expected dividends. Hence, expected economic growth also induces positive expectations about future dividend flows, which have to be higher than the rise in the dividend discount factor. Thus, the fundamental value of asset prices widens.

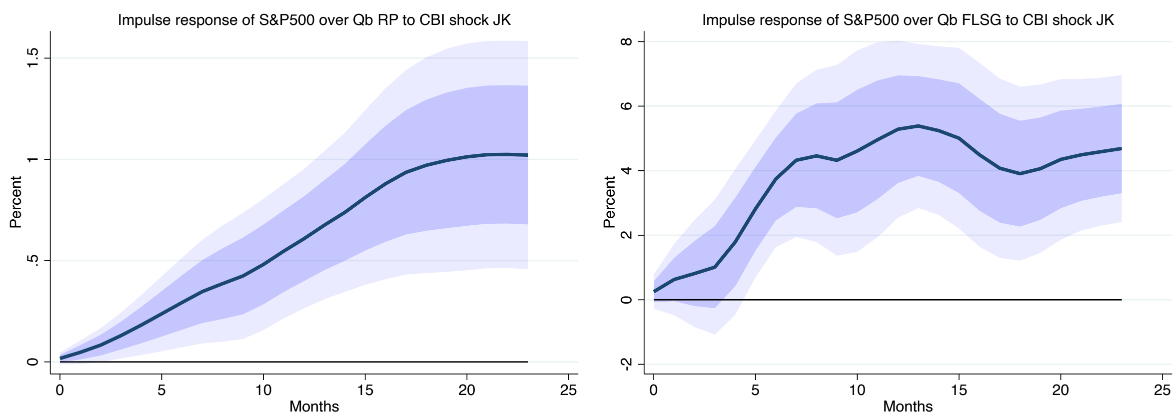

Figure 7: IRFs at 68% and 90 % of the LPs with JK information shock on S&P500 over its rational non-fundamental component defined as in Equation 4 (LHS) and non-rational 8 (RHS)

We furthermore confirm these results by inspecting the dynamics of the bubbles themselves. For both the two non-fundamental components, we observe a persistent decline (-1% for the rational bubble and -4% for the non-rational bubble) that either does not revert to zero values after two years

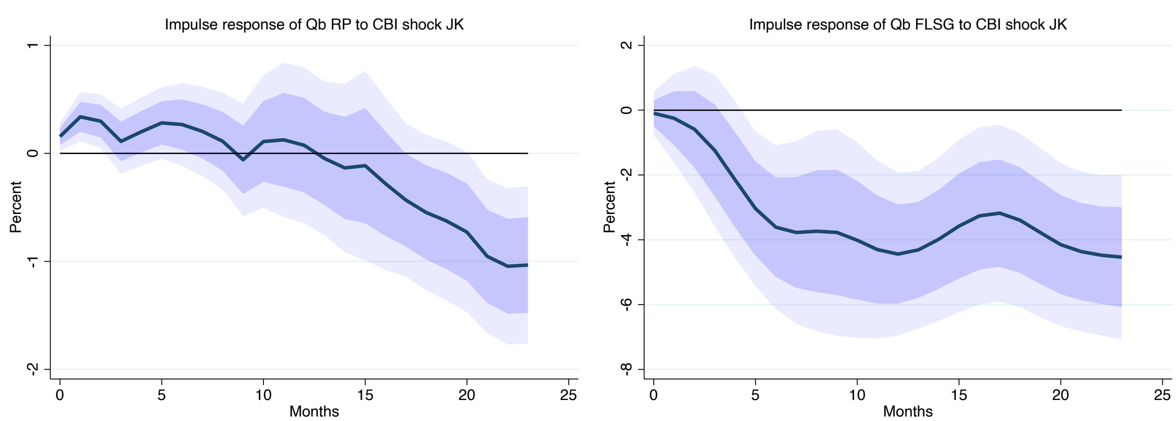

Figure 8: IRFs at 68% and 90 % of the LPs with JK information shock with rational non-fundamental component as in Equation 4 (LHS) and non-rational 8 (RHS)

The responses to the central bank information shock are at the edge of those to the purely monetary. The monetary tightening succeeds in reducing the bubble by disclosing information about the economy. This is not surprising. The fundamental component depends on the expected dividend growth. Thus, the information channel becomes crucial. Consistently with Allen et al. (2017) and Allen et al. (2018), a central bank commitment to target bubble for pursuing macroeconomic stability can increase social welfare. In other words, according to Caballero and Simsek (2020), if the central bank feeds the bubble up to a certain point, it can foster economic growth. Thus, an increase in the interest rate when the economy is expected to grow prevents the bubble from increasing. The fundamental component displaces the bubble in the price composition, thus avoiding the risk of the bubble arising and sustaining economic well-being (Allen et al., 2018). Also, expected dividend growth makes riskier investments less attractive, hence favouring the fundamental component rather than the bubble (Allen et al., 2022).

4.2 Alternative specification

The alternative specification of the model in Equation 16 uses the monetary surprises constructed by MAG as main regressors. Differently from JK, MAG uses no sign restriction for shock identification. Instead, they exploit a novel instrument that considers both high-frequency and narrative approaches to obtain the instrument as the residuals of the regression of high-frequency movements in fourth federal funds futures on the deviation of the expected economic forecast. They extract two factors exploiting the instruments: one is the monetary policy shock, and the other one is the information shock. They are normalised to represent a 1% increase in the policy rate. Figure 9 retrieves the dynamic responses of the S&P500 Index-bubble ratio to the pure monetary policy shock in the spirit of MAG. Also, in this case, we can appreciate a declining path (-2% on average) over the two years considered, confirming that a tightening monetary policy increases the bubble.

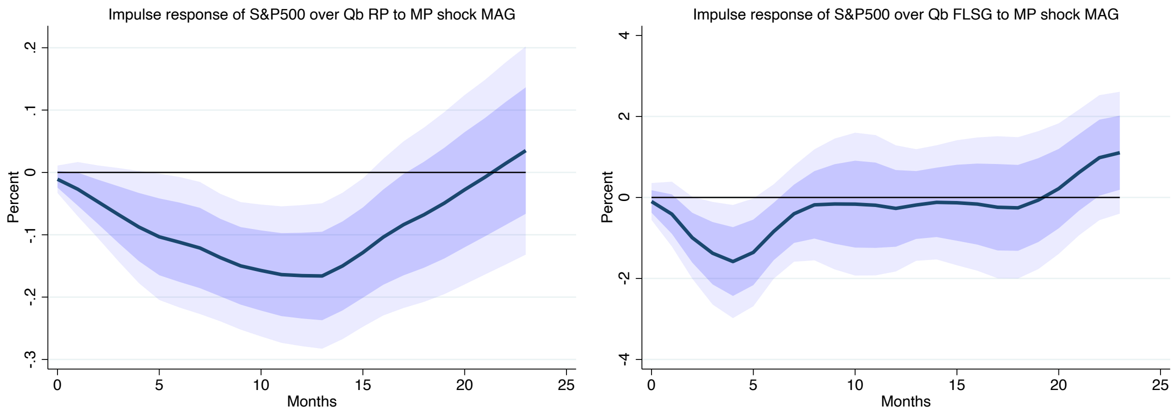

Figure 9: IRF at 68% and 90 % of the LPs with pure MAG monetary shock on S&P500 over its rational non-fundamental component defined as in Equation 4 (LHS) and non-rational 8 (RHS)

We further discuss the dynamics of the responses of the bubbles by directly observing them in Figure 10. We do not observe an apparent persistent increase in this case: the rational bubble from Equation 4 is noisy. In contrast, the non-rational bubble from Equation 8 rises in the first five months up to +1.5% but immediately returns to zero with a lack of significance.

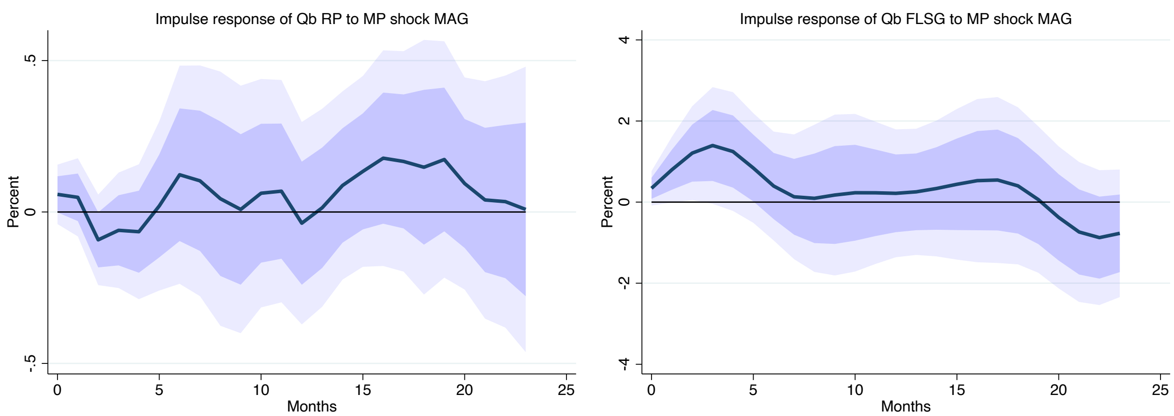

Figure 10: IRF at 68% and 90 % of the LPs with MAG pure monetary shock on S&P500 over its rational non-fundamental component defined as in Equation 4 (LHS) and non-rational 8 (RHS)

Finally, we document the results for the central bank information shock in the spirit of MAG, which is more robust than the pure monetary responses. Figure 11 presents the IRFs for the central bank information shock to the S&P500 over its bubbly component. The dynamic is highly persistent over time, showing an increase in the S&P500 Index of the 3%

in the rational bubble case and more than 10% in the non-rational bubble. After two years, they still exhibit positive behaviour without returning to their steady state. This behaviour might be due to the identification behind the instrument. The one identified by JK exploits sign restrictions and high-frequency movements in financial markets, making the factor transitory. On the contrary, MAG combines high-frequency movements in the fed future funds with narrative approach, which may lead to more persistent factors. The persistent expected economic growth translates into higher expected non-transitory dividends.

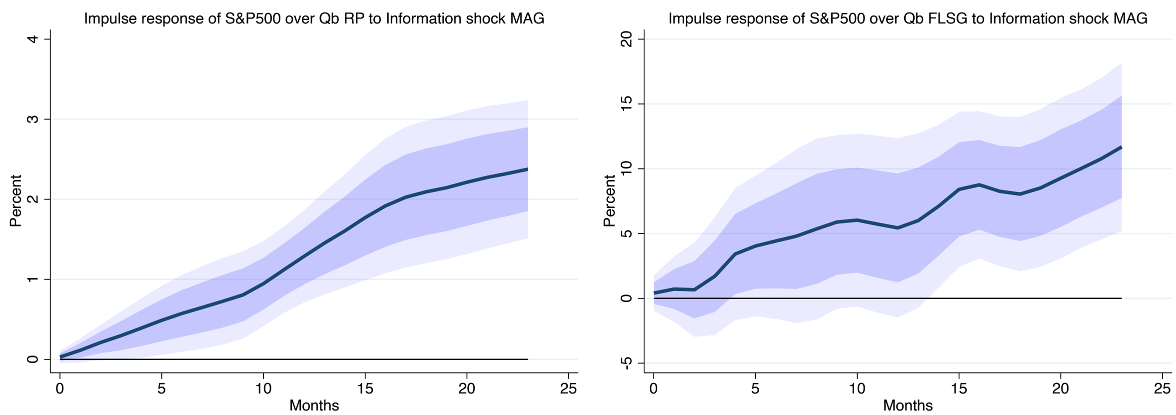

Figure 11: IRFs at 68% and 90 % of the LPs with pure MAG monetary shock on S&P500 over its rational non-fundamental component defined as in Equation 4 (LHS) and non-rational 8 (RHS)

In conclusion, we observe the changing in the non-fundamental component in Figure 12. Consistently with the previously discussed results, we find an enduring decline in the value of the non-fundamental component.

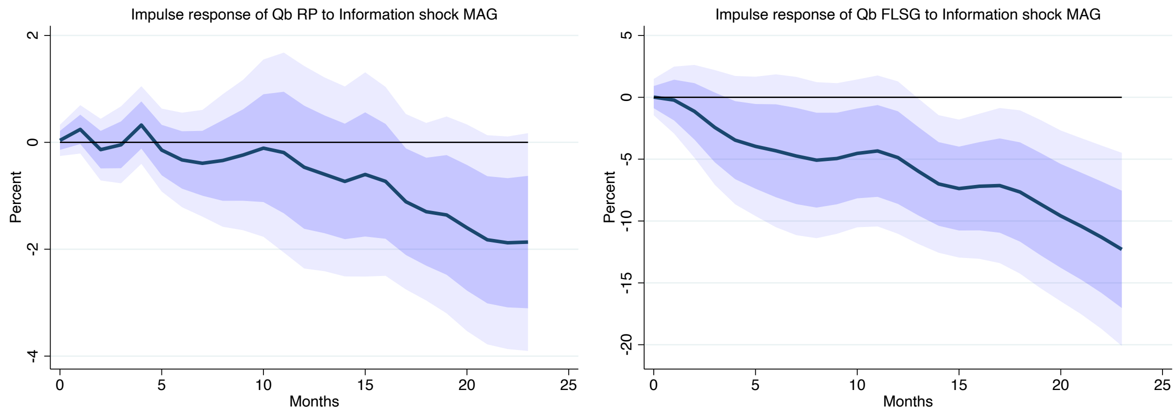

Figure 12: IRFs at 68% and 90 % of the LPs with pure MAG monetary shock on S&P500 over its rational non-fundamental component defined as in Equation 4 (LHS) and non-rational 8 (RHS)

5 Conclusion

This paper studies the effect of the leaning against the wind policy on asset price composition and sheds light on the ambiguity of the LAW efficacy. We show that the ambiguity of the well-known results in the literature depends on the monetary policy identification shock. To investigate the mechanism, we follow the approach by Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021) to disentangle a pure monetary policy shock from a central bank information shock. The analysis suggests that the asset price and bubble responses differ with the monetary shock. On average, a pure monetary tighten is associated with a general reduction in the S&P500 Index due to the inverse relationship between asset price and interest rate. Also, the bubbly component widens consistently with the definition of a rational bubble and with the dampening of the fundamental component. Conversely, a central bank information shock reduces the bubbly component favouring the fundamental, fed by expected economic growth. Therefore, the efficacy of the leaning against the wind policy depends on the reason for monetary tightening. Our results highlight that, in the case a bubble exists, the central bank is desirable to intervene once the bubble has fostered economic growth and the fundamental value can displace in the asset price composition.

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A Data

We use monthly data in logarithms for the US economy spanning from 1991M2-2019M6. All the variables are seasonally adjusted with the TRAMO-SEATS filter. Table A provides all the details. Monthly series as GDP is obtained with Chow-Lin interpolation with Industrial Production. Column *Bubble Contribution* indicates to which non-fundamental component estimation the variable contributes. Bubble 1 is obtained by Equation 4 with risk-premium and 2 by Equation 8.

Variable	Source	Derivation	Bubble Contribution
Real Gross Domestic Product	FRED St. Louis		
Gross Domestic Product	FRED St. Louis		
Inflation		Annualized rate of change of GDP deflator	1, 2
Personal Consumption Expenditure - Durable Goods	FRED St. Louis		2
Personal Consumption Expenditure - Non Durable Goods	FRED St. Louis		2
Fixed Private Investment	FRED St. Louis		2
Federal Funds Rate	FRED St. Louis		1, 2
Industrial Production Index	FRED St. Louis		
BAA 10Y Moody's	FRED St. Louis		1
Real Disposable Income	FRED St. Louis		2
Shadow Rate	Wu and Xia (2016)		1, 2
S&P500 Price Index	Robert Shiller On-line		1, 2
S&P500 Divided	Robert Shiller On-line		1, 2
S&P500 HF	Marek Jarocinski web-site		
FFR HF	Marek Jarocinski web-site		
Monetary Factor JK	Marek Jarocinski web-site		
CBI Factor JK	Marek Jarocinski web-site		
Monetary Factor MAG	Giovvanni Ricco web-site		
CBI Factor MAG	Giovanni Ricco web-site		

Table 2: The Table provides insight into the data source and bubble estimation contribution.

B Structural Shocks

Since we present the IRFs of the reduced form VAR, we provide an insight into the Structural Shocks in this Section. All the shocks behave as mean-reverting series.

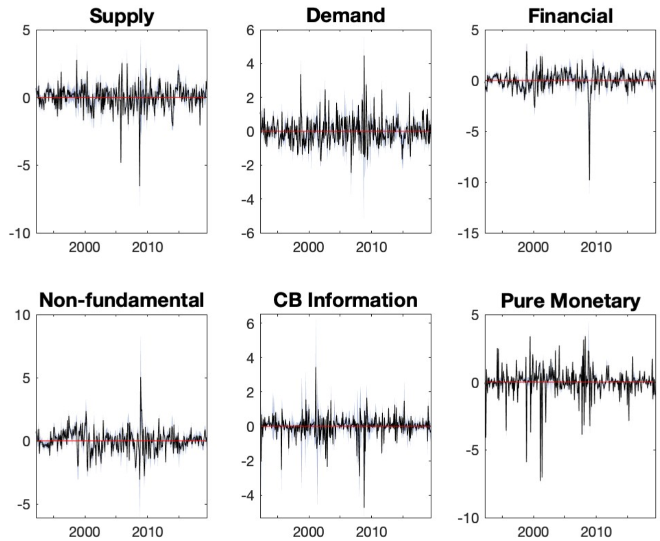

Figure 13: Structural Shocks of the baseline model estimated with the non-fundamental component in Equation 4

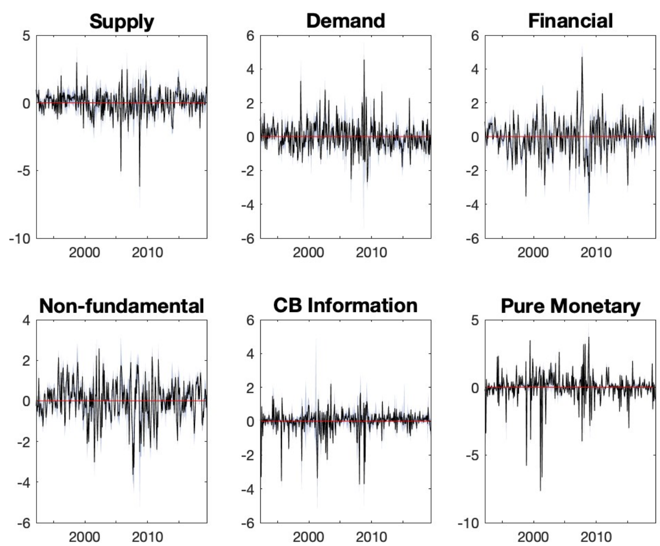

Figure 14: Structural Shocks of the baseline model estimated with the non-fundamental component in Equation 8

Section Complete set of IRFs For completeness of exposition, we report in this Section the full set of IRFs, i.e. the response of each variable to each shock, for the Galì and Gambetti (2015) identification and the baseline models.

B.1 Cholesky Identification

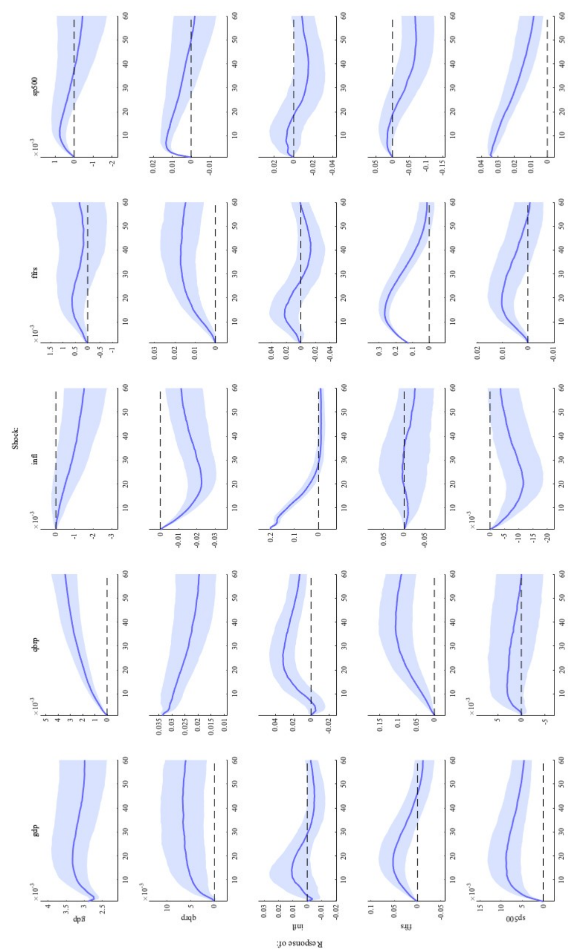

Figure 15: IRFs of the model à la Galì and Gambetti (2015) estimated with non-fundamental component in Equation 4

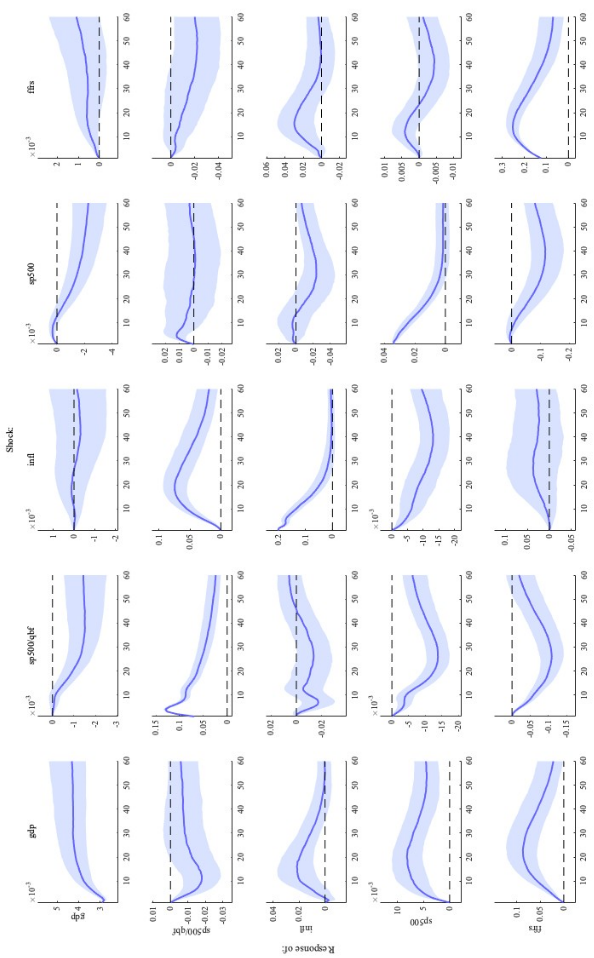

Figure 16: IRFs of the model à la Galì and Gambetti (2015) estimated with non-fundamental component in Equation 8

B.2 Baseline Models

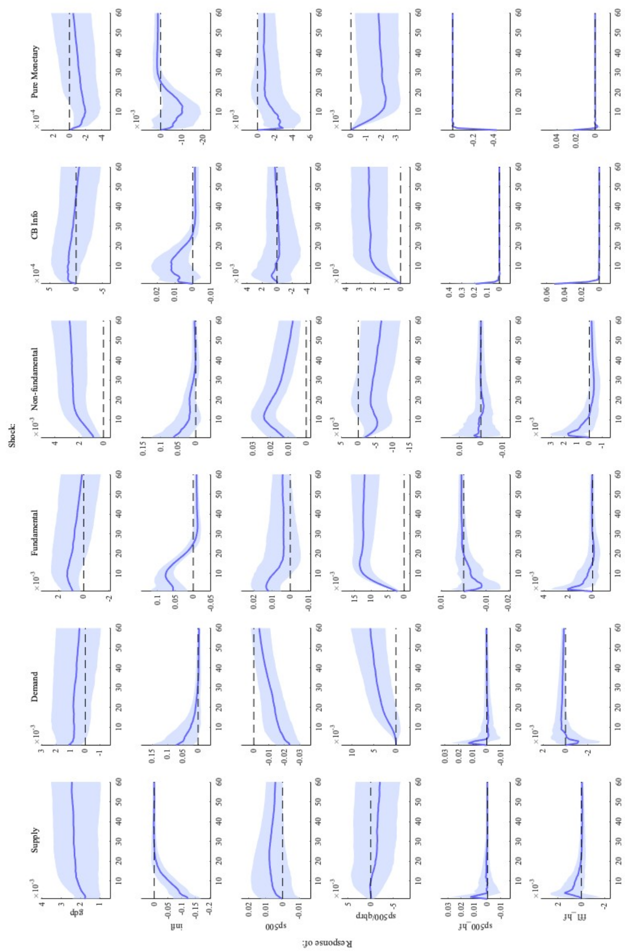

Figure 17: IRFs of the baseline model estimated with the non-fundamental component in Equation 4

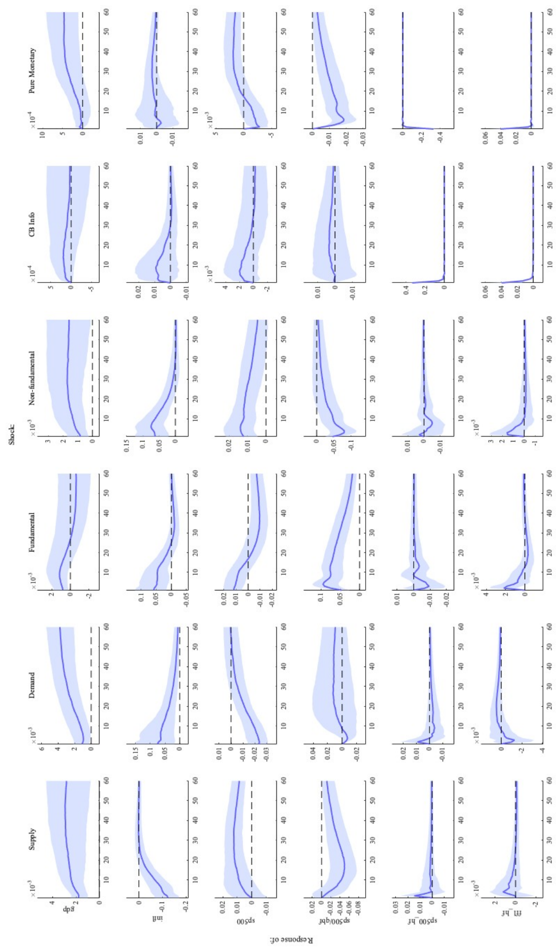

Figure 18: IRFs of the baseline model estimated with the non-fundamental component in Equation 8