CENTRE DE RECHERCHE
SUR LES STRATÉGIES ÉCONOMIQUES

Does Monetary Policy generate Asset Price Bubbles?

Christophe Blot, Paul Hubert and Fabien Labondance

March 2017

Working paper No. 2017–6

CRESE
30, avenue de l'Observatoire
25009 Besançon
France
http://crese.univ-fcomte.fr/

UNIVERSITÉ DE FRANCHE-COMTÉ

Does Monetary Policy generate Asset Price Bubbles?*

Christophe Blot
Sciences Po - OFCE

Paul Hubert
Sciences Po - OFCE

Fabien Labondance
Univ. Bourgogne Franche-Comté, CRESE EA3190, F-25000 Besançon, France
Sciences Po - OFCE

February 2017

Abstract

This paper empirically assesses the effect of monetary policy on asset price bubbles and aims to disentangle the competing predictions of theoretical bubble models. First, we take advantage of the model averaging feature of Principal Component Analysis to estimate bubble indicators, for the stock, bond and housing markets in the United States and Euro area, based on the structural, econometric and statistical approaches proposed in the literature to measure bubbles. Second, we assess the linear and non-linear dynamic effects of monetary shocks on these bubble components using local projections. The main result of this paper is that expansionary monetary policy does not inflate asset price bubble components, except for the US stock market. Overall, evidence tends to favor the prediction of rational bubble models.

Keywords: Asset price bubbles, Monetary policy, Quantitative Easing, Federal Reserve, ECB.

JEL Classification: E44, G12, E52.

* We thank Refet Gürkaynak, Grégory Levieuge, Michael McMahon, Xavier Ragot, Ricardo Reis, Giovanni Ricco and Francisco Serranito and seminar participants at OFCE, the University of Warwick and the Bank of Estonia, and at the 2016 MMF, 2016 JEAM, 2016 Empirical Monetary Economics workshop and 4th Bordeaux Macro workshop for helpful discussion and comments. Any remaining errors are ours.

Corresponding author: paul.hubert@sciencespo.fr. Tel: +33144185427. Address: OFCE, 69 quai d'Orsay, 75007 Paris, France.

1. Introduction

Asset price bubbles are a threat to financial and macroeconomic stability. However, no consensus has been reached regarding how policymakers should deal with bubbles. The role of monetary policy remains disputed. Two closely related questions arise in the policy debate. First, does monetary policy contribute to fuel asset price bubbles? Second, is monetary policy able to deflate bubbles? This debate has recently resurfaced with the implementation of unconventional monetary policy since 2008 and their potential adverse effects on financial stability. There are two broad opposite views in the literature on this issue. Borio and Lowe (2002), Cecchetti et al. (2003) and Woodford (2012) are in favor of a "leaning against the wind" approach which considers that expansionary monetary policy contributes to the emergence of asset price bubbles and restrictive policies can reduce them.[1] More recently, Borio and Zabai (2016) and Juselius et al. (2016) fear that the benefits of unconventional monetary policies would decline while the risks to financial stability would increase. This view echoes the argument by Taylor (2009) that low interest rates in the United States (US) between 2001 and 2004 have triggered the housing market boom and subprime crisis. An alternative view, the "modified Jackson Hole consensus", would not recommend using monetary policy to deal with bubbles and financial stability issues and rely on macroprudential tools (see e.g. Gerlach, 2010, Svensson, 2012, and Collard et al., 2017).[2]

This policy debate reflects the lack of consensus in the theoretical literature on how to represent the formation and dynamics of bubbles.[3] Within existing bubble models, the role of monetary policy is not clearly established: its effect on asset price bubbles depends on the nature of bubbles. First, in a rational bubble model à la Blanchard and Watson (1982), asset price is decomposed into a fundamental value, equal to the sum of expected cash-flows, and a bubble component, which is a rational stochastic deviation from the fundamental value and grows with the discount factor.[4] Within this framework, Gali (2014) shows that bubbles are linked to monetary policy because the discount factor is related to the real interest rate. With nominal rigidities, central banks influence the real interest rate and restrictive monetary policy would increase the size of the bubble. Second, in models accounting for financial market imperfections, Allen and Gale (2000, 2004) suggest that expansionary monetary policy would feed bubbles through the credit dynamics. This transmission channel is also emphasized by Gruen et al. (2005) and Christiano et al. (2010) who suggest central banks to adopt a "leaning against the wind" approach by limiting sharp credit expansion. Third, Abreu and Brunnermeier (2003) and Ofek and Richardson (2003) develop models emphasizing informational frictions or heterogeneous beliefs. These models do not give much role to monetary policy as private agents' behavior is the key determinant of bubbles. They arise after some positive news, generally technology innovations, triggering a rise in the fundamental value, which is amplified either by coordination failures of rational arbitrageurs or by investors' overconfidence.[5] The objective of this paper is to shed light on the policy debate and to disentangle empirically the competing theoretical predictions about the effect of monetary policy on asset price bubbles.

---

[1] These authors also claim that price stability is not a sufficient condition to promote financial stability. Blot et al. (2015) find that there is no stable link between price and financial stability.

[2] Bernanke and Gertler (1999, 2001) suggest that a "cleaning afterward" approach would be more optimal. See Smets (2014) for a recent survey on the attitude of central banks towards financial stability.

[3] See Brunnermeier and Oehmke (2013) and Scherbina (2013) for surveys.

[4] Rational bubbles may also depend on fundamentals as illustrated by Froot and Obstfeld (1991).

[5] Those models emphasize the role of informational frictions, heterogeneous agents or beliefs and incentive distortions. Kindleberger (2005) and Schiller (2015) document those episodes in financial history when increases in asset prices have been observed after technological booms, which were believed to give rise to a "new era".

We investigate whether monetary policy in the US and in the euro area (EA) affect asset price bubbles on stock, sovereign bond and housing markets.[6] Contrary to the vast literature dealing with the impact of monetary policy on asset prices (see e.g. Rigobon and Sack, 2004), we focus on the effect of monetary policy on the bubble component of asset prices only. Bubbles are a concern for many reasons. First, they may generate a misallocation of capital. Second, increases in asset prices driven by the bubble component may entail risk for financial stability jeopardizing the functioning of the financial system. Third, bubble bursts are associated with financial crises and with deeper and longer recessions.[7] Fourth, the transmission of monetary policy may be impaired if the dynamic of bubbles goes against the response of fundamentals to monetary policy. Thus, it is crucial to disentangle asset price movements driven by fundamentals from movements resulting from the bubble component.

Because not all asset price variations are bubbles, we need to separate the wheat from the chaff. The main empirical challenge is to identify the fundamental value of an asset and its bubble component. Asset price bubbles arise in many theoretical frameworks, and empirical tests are generally ill-designed to identify bubbles as they fail to disentangle between bubbles and misspecifications of the underlying theoretical model (Gurkaynak, 2008). Three approaches may be considered to identify bubbles (structural, econometric and statistical), but none of them has reached consensus. First, according to a structural model, the bubble is a deviation of the asset price from expected discounted cash flows. Second, the fitted value of an econometric specification provides an approximation of the fundamental value accounting for a data-rich information set. Third, the literature has also relied on a statistical definition of excessive level of asset prices, measured with a statistical filter (see e.g. Bordo and Wheelock, 2007, Goodhart and Hofman, 2008, or Jordà et al., 2015). All these approaches present advantages and weaknesses to estimate the fundamental and non-fundamental components of asset prices.

The first contribution of this paper is to propose an agnostic and conservative method to single out the bubble component of a given asset. Using Principal Component Analysis (PCA), we extract the common denominator of structural, econometric and statistical approaches used in the literature and described above. Assuming that each of these approaches captures some properties of asset price bubbles, the main innovation of this method is to suppose that the first component, maximizing the common variance of these estimated models, will provide a robust measure of the bubble component. Said differently, the idiosyncratic dynamics of each approach will not be selected by the PCA. This method boils down to a model averaging of the structural, econometric and statistical approaches. To that end, we first estimate fundamental values from each approach and extract bubble components. We do so for stock, bond and housing prices in the US and the EA. Second, using the PCA, we compute bubble indicators for each market and each geographical area.

The question of whether monetary policy may trigger asset price booms and busts has been extensively dealt with in the literature. Detken and Smets (2004), Ahrend et al. (2008) and Khan (2010) observe that stock and housing prices tend to increase excessively when short-term interest rates are below the level suggested by a Taylor rule. Taylor (2009) asserts that monetary policy in the early 2000s has fuelled the housing boom in the US. This view has been challenged by Dokko et al. (2009) and Kuttner (2012) who suggest that the housing market dynamic would not have been strongly modified if interest rates had followed the

[6] We use the term “bubble” to describe significant deviations of a given asset price from its fundamental value (or best in-sample prediction or trend). The term “bubble” may be used interchangeably with the terms “deviations”, “booms and busts”, “misprincing” or “over and undervaluation”.

[7] It must be noted that financial crises are not only triggered by asset price bubble bursts. Financial leverage and credit booms also matter for financial stability (see Adrian and Shin, 2008). This issue is left for further research.

Taylor rule, and by Del Negro and Otrok (2007) who also concluded that monetary policy weakly contributed to the housing price dynamic in the US. Besides, Bordo and Wheelock (2007) provide evidence of a weak correlation between interest rates and excessive stock price increases. However, these papers do not rely on a structural identification of the bubble component of asset prices but focus on episodes of asset price dynamics that they consider as excessive. The closest papers to ours are Basile and Joyce (2001) and Gali and Gambetti (2015), but they only rely on the rational bubble model. The former assess the contribution of monetary policy to the variance of bubbles. The latter suggest that monetary policy tightening in the US may increase asset prices depending on the size of the bubble component. A policy rate hike reduces the fundamental value, but increases the bubble component - since the bubble grows with the interest rate. For a small bubble component, the standard negative effect on the fundamental value dominates, whereas monetary policy tightening feeds the bubble and increases asset price when the bubble component is large.

The second contribution of this paper is to assess the dynamic impact of monetary policy shocks on our bubble indicators. It departs from Gali and Gambetti (2015) in three ways. First, our definition of the bubble component does not rely exclusively on a rational bubble model but hinges on different representations of bubbles. Second, monetary shocks are identified by orthogonalizing the policy instrument to the central bank information set as well as to macroeconomic and financial variables following the Romer and Romer (2004) approach. Third, we account for both standard and unconventional monetary policy by using shadow rates estimated by Wu and Xia (2016) and Krippner (2013, 2014) as a single indicator of the overall monetary policy stance. We also disentangle the effects specific to the policy rate and central bank's balance sheet policies in a second step. We investigate the dynamic impact of monetary policy by estimating local projections à la Jorda (2005) over a 2-year horizon, and are able to compare the response to shocks to different instruments of the bubble indicators across stock, sovereign bond and housing markets. We take advantage of the flexibility of local projections to analyze the potential asymmetric effects of restrictive and expansionary monetary shocks.

The main result of this paper is that the impact of monetary policy on asset price bubbles is limited overall. A key message is that these effects are not symmetric and this calls for differentiating the responses to restrictive and expansionary shocks. The hypothesis that expansionary monetary policy does inflate bubbles is rejected in all cases except for stock market bubbles in the US. At the opposite, we find that expansionary monetary policy would slightly deflate bubbles on the US housing market and on the EA bond and housing markets, consistent with the prediction of rational bubble models. We then shed light on three policy issues. The risk that unconventional policies would inflate asset price bubbles does not materialize in the data and evidence even tends to support the opposite mechanism, i.e. the prediction of rational bubble models. We also find that the "leaning against the wind" strategy would not be able to deflate asset price bubbles except on the EA stock market. At the opposite, an expansionary interest rate policy would inflate stock market bubbles on the US and EA, but deflate them on EA bond and housing markets, once again consistent with the prediction of rational bubble models.

The remainder of this paper is organized as follows. Section 2 addresses the identification of asset price bubbles and section 3 the empirical strategy. Section 4 presents the main results while section 5 focuses on the policy issues. Section 6 concludes.

2. Identifying asset price bubbles

Bubbles are not observed, so the main challenge of this paper is to measure them. However, there is no consensus on the most appropriate way to identify empirically asset price bubbles, which reflects theoretical controversies. These are illustrated by Brunnermeier (2008): "*Bubbles are typically associated with dramatic asset price increases followed by a collapse. Bubbles arise if the price exceeds the asset's fundamental value*". Two interpretations of bubbles emerge from this definition. Bubbles would either rely on the notion of a fundamental value or on excessive variations in asset prices. Thus, we consider alternative specifications based on structural, econometric and statistical approaches. None of these models has reached consensus, however all together they may capture the main properties of asset price bubbles.

2.1. A range of bubble models

First, we estimate a simplified representation of the expected discounted cash-flow model by OLS and using an error-correction model (ECM).[8] Under full information rational expectations and when agents are risk-neutral, the asset fundamental value is the expected discounted cash-flows. For stock and housing markets, prices are determined either by dividends or rents, and the long term interest rate considered as a discount factor. We depart from the standard model by adding a proxy for the risk-premium, which would account for a risk-taking channel of monetary policy. Consequently, the bubble component is supposed to be purged from risk premia, which may also influence asset prices. For the bond market, prices are determined by the long-term interest rate and the proxy for the risk premium (coupons being constant over the lifetime of the asset). The three models are estimated with a standard estimation method: OLS (equation 1) and with an ECM (equation 2) to capture the possibility that prices are a combination of a long-run trend and short-run dynamics:

$$y_t = \alpha_0 + \alpha_1.D_t + \alpha_2.r_t + \alpha_3\phi_t + \epsilon_t^{OLS} \tag{1}$$

$$\begin{aligned} dy_t = -\alpha.(y_{t-1} - \alpha_0' - \alpha_1'.D_t - \alpha_2'.r_t - \alpha_3'.\phi_t) \\ + \alpha_4(L).dy_t + \alpha_5(L).dD_t + \alpha_6(L).dr_t + \alpha_6(L).d\phi_t + \epsilon_t^{ECM} \end{aligned} \tag{2}$$

where y_t is the asset price, D_t is the associated cash flow, r_t is the discount factor measured by the risk-free interest rate, and ϕ_t a proxy for the risk premium. Equations (1) and (2) enable to decompose a given asset price between two components: a fundamental component, that includes a component related to risk-taking, and the residuals.

An alternative approach –econometric– is to estimate empirical models where asset prices are represented by projections against a wide range of variables. By selecting a large set of macroeconomic and financial variables, equations (3) and (4) provide estimates, using OLS and ECM models respectively, of the best in-sample prediction of a given asset price conditional to a given information set.

$$y_t = \beta_0 + \beta(L).y_t + \beta_1.M_t + \beta_2.F_t + \nu_t^{OLS} \tag{3}$$

$$\begin{aligned} dy_t = -\theta.(y_{t-1} - \beta_0' - \beta_1'(L).M_t - \beta_2'(L).F) \\ +\beta_3'(L).dy_t + \beta_3'(L).dM_t + \beta_3'(L).dF_t + \nu_t^{ECM} \end{aligned} \tag{4}$$

M_t and F_t are vectors of macroeconomic (rents and dividends, industrial production, GDP, real disposable income, inflation, confidence indicators and oil prices) and financial variables (real long term interest rate, monetary and credit aggregates, other asset prices and the VIX indicator). Lags of the endogenous variable are also included in the estimation. For all explanatory variables, 3 lags are included in the specification.[9] While equations 1 and 2 are

[8] We discuss later alternative estimations of the expected discounted cash-flow model.
[9] Specifications with leads have also been tested but do not change the result and the residual dynamics.

considered as representing the standard structural model for asset prices adjusted for a time-varying risk premium, the econometric approach of equations 3 and 4 is agnostic and should be considered as the best in-sample prediction of asset prices taking into account a large set of relevant information.

Our estimated bubble components are based on the definition that asset prices are a linear combination of the fundamental component and a remaining part that we label the bubble component. Because standard residuals (ϵ_t^{OLS}, ϵ_t^{ECM}, ν_t^{OLS} and ν_t^{ECM} in the present case) would only capture a static and instantaneous deviation of a given asset price from its fundamental value, we consider a measure that takes into account the cumulative and dynamic process associated with a bubble formation. According to Filardo (2004), small deviations from fundamentals are irrelevant. These bubbles would result from anomalies in financial markets, are likely to be small and have their own generating process. Therefore, the cumulated residuals would provide a better measure of significant and persistent deviations from fundamentals.

The construction of our model-specific bubble components consists in two steps. First, residuals of equations (1) to (4) are filtered using the Christiano-Fitzgerald (CF) method, so that we focus on the low-frequency deviations from fundamentals not the high-frequency ones. Second, the filtered residuals are cumulated. For each model i, we call $r_{i,t}$ the cumulative sum of the filtered residuals $fr_{i,t}$ as long as these residuals have the same sign. This measure is reset to zero whenever the CF-filtered residuals change sign.

$$\begin{cases} r_{i,t} = fr_{i,t} + r_{i,t-1} & \text{if } fr_{i,t} \text{ and } fr_{i,t-1} \text{ have the same sign} \\ r_{i,t} = fr_{i,t} & \text{if } fr_{i,t} \text{ and } fr_{i,t-1} \text{ have different signs} \end{cases} \tag{5}$$

We also consider a model corresponding to the statistical approach where bubbles are defined as significant deviations from a trend. Most of the papers in the literature have relied on a statistical filter to decompose asset prices between trend and cycle. Goodhart and Hofman (2008) define boom periods as a persistent deviation from the trend of more than 5% and lasting at least 12 months while Detken and Smets (2004) use a 10% threshold. Alessi and Detken (2011) and Bordo and Jeanne (2002) define the boom as a 1.75 and 1.3 standard deviation at least from the trend respectively. For Bordo and Landon-Lane (2013), the boom occurs if a 5 % increase in house prices (10% for stock prices) is followed by a 25% correction within two years. In Jorda et al. (2013, 2015), the bubble is identified after a 1 standard deviation from the trend followed by a correction of 15% at least, over a 3-year period. Here, we identify bubbles as a 1.5 standard deviation at least from the CF-trend, so 87% of the data lies within the bounds.[10] A synthetic description of all models is presented in Table 1.

2.2. Data

We estimate these five models for three asset prices: stocks, sovereign bonds and housing. Data are available from January 1986 to August 2016 in the US and from January 1999 to June 2016 for the EA (see Table A in appendix for data description and sources and Table B for descriptive statistics). The stock price indexes are the S&P500 for the US and the Eurostoxx for the EA (listing the largest 295 firms). Each asset price is deflated by the CPI. Bond prices are government 10-year benchmark bonds. House prices in the EA stem from a quarterly index for residential property prices calculated by the ECB.[11] In the US, we use Shiller's benchmark monthly index.

---

[10] The main advantage of the CF filter compared to the Hodrick-Prescott filter is that the former is one-sided so that the estimation does not affect the last point of the sample.

[11] Quarterly data have been linearly interpolated to monthly frequency.

Considering the cash-flow model for asset prices, fundamental value is a function of cash-flows (dividends for stocks and rents for housing prices) and the discount factor. In the US, the Bureau of Economic Analysis provides dividends series paid by corporations and rents received by households. Data are available at a quarterly frequency. For the EA, quarterly dividends paid by financial and non-financial corporations and quarterly rents received by households are available from Eurostat for the five biggest EA countries. The long-term interest rates – from benchmark government bonds – are used as the discount factor. The standard model may be extended to account for a time-varying risk-premium. To this end, we use the VIX indicator – the Chicago board of trade volatility index –, which is often used as a proxy for uncertainty and market appetite for risk. Yet, this model may not fully account from all available information. We also identify the fundamental component with a model estimated on a large set of information, including macroeconomic and financial indicators such as: real disposable income, inflation, real GDP, industrial production, oil prices, confidence indicators,[12] financial stress indicators (VIX and CISS), 3-month interbank interest rate, monetary (M2 in the US and M3 for the EA) and credit aggregates (credits granted by commercial banks in the US and credit counterparties of monetary aggregate in the EA).

We estimate the five models for the three asset prices for the US and EA and extract 15 bubble components for each area. Table C in appendix provides descriptive statistics for the 30 series. Table 2 provides the correlation structure for each market and geographical area as well as *p*-values for the Cumby-Huizinga test for autocorrelation and for the Portmanteau test for white noise. These tests suggest that these residuals are not perfectly independent and identically distributed (i.i.d.) as expected in the light of our research question and may be capturing the persistent deviations from a fundamental price that we label as bubbles.

2.3. A Principal Component Analysis of bubbles

In order to summarize the information provided by the cumulative and dynamic residuals of the four estimated models and by the statistical model, we perform a Principal Component Analysis (PCA) to estimate a unique indicator maximizing the common variance of the individual bubble series. In addition to reduce information in one single series, another advantage of the PCA is to remove the evolution of each series that would be specific to that model and provides a robust measure of the bubble component of asset prices.

More specifically, PCA seeks a linear combination such that the maximum variance is extracted from the variables. Components reflect both common and unique variance of the variables and may be seen as a variance-focused approach seeking to reproduce both the total variable variance with all components and to reproduce the correlations. In practice, computing PCA of a dataset X, an ($m \times n$) matrix, where m is the number of variables and n is the number of observations, entails computing the eigenvectors and eigenvalues of the covariance matrix of X. The eigenvector with the highest eigenvalue, measuring the variance in all variables which is accounted for by that eigenvector, is the first component.
We compute bubble indicators for each market (stock, bond and housing) by estimating the first component of the 5 individual bubble components of each market. Table 3 provides the main characteristics of the estimation of our three bubble indicators for each geographical area. The stock, bond and housing bubble indicators capture 45, 40 and 44% of the variance of the respective 5 bubble components in the US and 39, 41 and 39% in the EA. Besides, the highest loading factors are generally on the error correction model estimation of the cash-flow model and the econometric model. The 15 individual bubble components and the 3 bubble indicators are plotted in Figures 1 and 2 for the US and the EA respectively.

[12] For the EA, we use the European Commission confidence household and industry indicators while in the US we use the Conference Board consumer confidence indicator and the ISM confidence indicator for firms.

In the US, the bubble indicator for stock prices coincides with the dummy of the statistical approach where bubbles (crashes) are identified as at least a 1.5 standard-deviation of prices above (below) their trend. The dotcom bubble is also clearly identified by the PCA and the pure statistical approach. The bubble period would have started in 1999 and would have stopped in 2000. A bubble is also identified in 2007 followed by a crash in stock markets in late 2008. For the bond markets, there are peaks in 1993, 1998 and troughs in 1995 and 2000, but much less over or undervaluation afterwards. Turning to the housing market, there is a clear disconnection between the outcome of the statistical approach and the PCA bubble indicator. A peak for the PCA is reached by the end of 2006 and has then been followed by a bust in 2008. Over the end of period, the PCA is growing positively, indicating a bubble on the US housing market, but which is yet of lesser magnitude than in 2006.

In the EA, a stock price bubble, signaled by a positive dummy, would have occurred from 2000 until 2001 and from 2007 until 2008. Bust periods in the EA stock markets are identified from the end of 2002 to mid-2003 and from 2008 – after the Lehman Brother collapse – until 2009. On the EA bond markets, peaks for PCA are observed in 2005, 2010, 2012 and 2015. It should be pointed out that the PCA indicator is positive from 2008 until 2010, which is counterintuitive as this period has been marked by the start of the European sovereign debt crisis. The positive bubble is also identified in the period preceding the "Whatever it takes" announcement made by Mario Draghi in July 2012 at a time where sovereign risk premia rose significantly in the peripheral EA countries. On the housing market, the peak of PCA is reached later in 2010, a date considered as a bust period with the statistical approach. This suggests that our identification matches periods where this issue has been raised in the media and in the public debate. Finally, the bubble indicators at the end of the sample look on the upside in the US and this pattern is common to the 3 markets, whereas evidence of a growing bubble appears only on the housing market in the EA.

Table 4 shows the correlation structure between the different bubble indicators. They appear more correlated between themselves in the US than in the EA. The correlation is between 0.18 and 0.34 in the US whereas around -0.24 and 0.37 in the EA. Moreover, Table 4 also provides the correlation for each market between the bubble indicator and its related estimated fundamental.[13] It appears that the correlation is negative on all markets in the US, while it is positive for the EA stock market and negative otherwise.

2.4. Sensitivity analysis

The baseline bubble indicators are based on a set of hypotheses. We provide an analysis of the sensitivity of the properties of our bubble indicators to some of these assumptions. First, we may consider reversing the order of the steps of the construction of the indicator. The PCA is estimated on ϵ_t^{OLS}, ϵ_t^{ECM}, ν_t^{OLS}, ν_t^{ECM} and r5, instead of being estimated on cumulated-filtered residuals. We then filter the estimated first principal component and apply the cumulative sum to the filtered series. The model averaging step is therefore performed on the deviations from fundamental values and trend, and then we compute the filtered and cumulated components to capture the bubble processes. The baseline measures are then compared to the alternative ones. Table 4 shows that their correlations are on average 0.84, so the bubble indicators appear robust to a change in the ordering of the procedure.

[13] The fundamental is computed as the first component of a PCA estimation comprising the predicted values of the four estimated models listed above and a dummy that equals one when a given asset price is within the 1.5 standard-deviation bands around its trend.

Second, the estimation of the cash flow model could be biased by endogeneity. To account for potential endogeneity issues, we estimate equation (1) with GMM, using industrial production and GDP as instruments for cash flows. Moreover, one limitation of our analysis due to data availability is that we include contemporaneous cash-flows whereas the expected cash-flow model relies on the forward-looking nature of asset prices. This may introduce a bias in the measurement of bubbles. Consider the case where the central bank implements an expansionary monetary policy. Due to the transmission lags, the fundamentals do not immediately improve. However, rational investors anticipate an improvement of economic perspectives and henceforth a rise in future cash-flows, so the asset price increases. If our model fails to account for this rise in expected cash-flows, the increase in the asset price is mistakenly considered as a bubble. In order to account for expected cash-flows, we estimate equation (1) including the forward values, 12 months and 36 months ahead, of the respective cash-flows. We estimate this second model with GMM and use private and central bank output forecasts as instruments for future cash-flows. We acknowledge that the realized forward values are not expectations of these cash-flows, but such data series are not available at the aggregate level or over our whole sample. Yet, estimating equation (1) with forward values and GMM enables to assess, under some assumptions, the sensitivity of our baseline estimates to the forward-looking behavior of investors. The correlations with the baseline bubble indicators, shown in Table 4, are on average 0.97 and at minimum of 0.91.[14]

We assess whether the estimation of the different bubble indicators depends on the sample considered. Therefore we estimate the PCA model over 3 subsamples in each area (1986-1996, 1996-2006 and 2006-2016 in the US and 1999-2005, 2005-2010 and 2010-2016 in the EA) and predict the first principal component over the entire sample using the subsample estimates. Table 4 also provides the correlation coefficients of baseline bubble indicators with subsample-estimated ones. The correlations are on average 0.92 and at minimum of 0.67.

We also examine how much the identification of our bubble components is driven by specific bubble models. By construction, the PCA overweighs models with a high correlation and down-weighs models that stand alone. Table 2 shows that the correlation between ϵ_t^{ECM} and $\nu_t^{ECM}$is high across markets and geographical areas, and Table 3 confirms that the PCA therefore attributes higher eigenvalues to the corresponding two series: *r2* and *r4*. We thus estimate alternative bubble components without the *r4* series. The correlations with baseline bubble indicators are on average 0.79 (with a minimum of 0.48 for the US bond market).

Finally, we investigate how much the parameters of the CF band-pass filter affect our estimation of the duration of bubble cycles. In the baseline, the procedure filters out stochastic cycles for periods smaller than 18 months and higher than 96 months (8 years) and this assumption constrains the duration of the estimated bubble cycles. Drehman et al. (2012) characterize the length of cycles disentangling short-term and medium-term cycles for several indicators, including house and equity prices. They suggest that house and equity price medium-term cycles have a duration of 10 ½ years and 9 ½ years respectively. To account for a longer duration of cycles, we augment this range to 15 from 144 months. The correlations with baseline bubble indicators are on average 0.75 and at minimum of 0.58 in the case of the US housing market.

3. The empirical strategy

Analyzing the effects of monetary policy requires addressing issues about the identification of exogenous monetary shocks. Several methods have been used in the empirical literature

[14] Note that the samples when considering forward values are shorter of 12 or 36 observations than the baseline.

and may lead to some discrepancies in the responses to monetary policy shocks.[15] Our baseline choice is to resort to the Romer and Romer (2004)'s approach augmented following insights from the information friction literature. Concretely, the identification of shocks accounts for the information set of both policymakers and private agents. We also use alternative approaches based on high frequency event-study assumptions following Kuttner (2001) or based on the estimation of forward-looking Taylor rules where residuals are considered as the monetary innovation. We then assess the impact of monetary shocks on asset price bubbles with the local projection method proposed by Jorda (2005). This method is flexible and may easily account for potential asymmetries in the transmission of monetary policy, and allow us to disentangle the impact of restrictive and accommodative shocks.

3.1. Local Projections

Assessing the impact of shocks on a given economic variable may be realized either through VAR models or with Jorda's Local Projection method. Whereas the first method enables to take into account the intertwined dynamics of a set of variables, it may be imposing excessive restrictions on the endogenous dynamics and may be prone to bias if the model is misspecified. The second method offers more flexibility in the estimation. In linear stationary settings, the out-of-sample forecasting performance of VARs and local projections is quite similar (see Marcellino et al., 2006, and Kilian and Kim, 2011). However, because a linear low-order autoregressive representation of the data generating process of macroeconomic time series may be deceptive, the robustness of local projections to model misspecification and non-linearity makes them an appealing procedure to recover dynamic responses to exogenous shocks. Considering that these exogenous structural shocks are identified *ex ante*, Jorda (2005) suggests estimating a set of h regressions representing the impulse response of the dependent variable at the horizon h to a given shock at time t:

$$y_{t+h} = \alpha_h + \beta_h \epsilon_t + \sum_{i=1}^{3} \phi_{h,i} . y_{t-i} + x_t + \eta_{t+h} \tag{6}$$

where y_{t+h} is the dependent variable – the bubble indicator - at the horizon h, ϵ_t represents the monetary shock, either to the overall policy stance or to conventional and unconventional measures specifically, y_{t-i} are lags of the dependent variable (that we set to 3 based on the non-significance of additional lags), and x_t is a vector of controls including the bubble indicators of the two other asset price markets. We set h to 24 periods to measure the effect of monetary shocks on bubble indicators over 2 years. This equation may be easily modified to account for non-linearities:

$$y_{t+h} = \alpha_h + \beta_{Ih} \epsilon_t . D_t + \beta_{\epsilon h} \epsilon_t + \beta_{Dh} D_t + \sum_{i=1}^{3} \phi_{h,i} . y_{t-i} + x_t + \eta_{t+h} \tag{7}$$

where D_t is a dummy variable for expansionary monetary policy shocks. This specification aims to single out the potential asymmetric effects of restrictive ($\beta_{\epsilon h}$) and expansionary ($\beta_{\epsilon h} + \beta_{Ih}$) monetary shocks on bubble indicators. Finally, because the estimated monetary shocks used in equations (6) or (7) are generated regressors that might cause biased standard errors, we compute heteroskedasticity and autocorrelation robust Newey-West standard errors assuming that the autocorrelation dies out after three lags.[16] This correction also enables to control for potential heteroskedasticity and auto-correlation of the residuals.

3.2. Identification of monetary shocks

[15] See Coibion (2012) for a discussion.

[16] We have also computed standard errors robust to misspecification using the Huber-White-sandwich estimator and they provide smaller confidence intervals around the point estimate. This generated regressor issue is common to all empirical studies estimating exogenous shocks in a first step as in Romer and Romer (2004), but is more acute when the generated regressors are not normally distributed.

The local projection method requires identifying monetary shocks *ex ante*. The question of the most relevant identification strategy remains an open question. Empirical literature on monetary policy has often resorted to VAR models. However, timing assumptions in recursive identifications – reasonable for real variables and their sluggish reaction to shocks and low sampling frequency – are not relevant when applied to financial variables or fast-moving variables. There is indeed no rationale to suppose that some asset prices move faster than others. Romer and Romer (2004) regress the intended federal funds rate change on the information set of the monetary authority to purge endogenous responses to current and expected future economic developments.

Because of different information sets (Romer and Romer, 2000, or Blinder et al., 2008), the Romer and Romer (2004)'s identification approach may underestimate the extent to which market participants are able to predict future interest rate decisions. As discussed in Blanchard et al. (2013) and Ricco (2015), the presence of information frictions significantly modifies the identification problem. We propose an identification that combines insights from Romer and Romer (2004) and from the information frictions literature. We thus require the estimated monetary shocks to be orthogonal to both central bank's and private agents' information sets and to macro and financial market information. Finally, in a context of imperfect information, the new information is only partially absorbed over time and, estimated surprises are likely to be a combination of both current and past structural shocks.

Our baseline measures of exogenous monetary shocks are based on the shadow rate measure of Wu and Xia (2016). Because monetary policy has taken many different dimensions over the last years and we ought to consider shocks to unconventional instruments and communication policies (forward guidance, for instance) in addition to shocks to the conventional instrument, we use this shadow rate measure that translates these various dimensions in a single variable expressed in interest rate space to measure the overall stance of monetary policy (labelled *MP*). In a second step, we also estimate shocks specific to the policy rate (labelled *PR*) and to an indicator of the central bank balance sheet size (labelled *Unconv*) to further analyse the response of bubble indicators to conventional and unconventional policies in normal and exceptional times respectively. For the former, we consider the federal funds target rate for the US and the EONIA rate for the EA. For the latter, we consider the monthly change in the size of the balance sheet for the Federal Reserve and the monthly change in the sum of two items of the ECB weekly financial statements: the long-term refinancing operations (item 5.2) and securities held for monetary policy purposes (item 7.1 including the securities market program, the three covered bond purchase programs, the asset-backed securities purchase program and the public sector purchase programme).
The baseline shock to the overall monetary stance and its two alternatives are estimated with the following equations from which we extract the residuals:

$$\Delta i_t = \beta_0 + \beta_1 \, i_{t-1} + \beta_2 \, \Omega_t + \beta_3 \, \Psi_t + \beta_4 \, \mathrm{X}_{t-1} + \beta_5 \, \mathrm{Z}_t + \epsilon_t' \tag{8}$$

$$\epsilon_t' = \beta_6 + \beta_7 \epsilon_{t-j}' + \epsilon_{rr,t} \tag{9}$$

where i_t is the monetary policy instrument. We assume that the monetary shock must be orthogonal to the contemporaneous policymakers' information set □$_t$, to the private agents' one □$_t$, to lagged financial market variables embedded in X_{t-1}, and to a vector Z_t of contemporaneous macroeconomic variables. This shock to the overall monetary policy stance is labelled MP-Shocks-RR. A consequence of the timing of the right-hand-side vectors in equation (8) is that monetary shocks affect contemporaneously financial market variables, but do not affect contemporaneously central bank's and private agents' information sets or macroeconomic variables. We believe that the opposite assumptions that monetary shocks are only based on past data or that they do not influence financial markets in real-time are fragile.[17] The policymakers' information set $\square_t$ comprises the level and change in ECB (resp. FOMC) inflation and output projections for current and next calendar years, $\square_t$ includes the level and change in ECB (resp. US) SPF inflation forecasts for 1, 2 and 5 years ahead (resp. next quarter and next year), X_t contains the CISS (resp. the VIX) and the oil price growth rate, and Z_t comprises current and lagged values of the inflation rate, industrial production and the monthly-interpolated real GDP growth rate.[18]

When extracting exogenous monetary shocks, the inclusion of both private and central bank forecasts in the regression model enables us to deal with three concerns. First, private agents and policymakers' information sets include a large number of variables. Forecasts have the advantage of encompassing rich information sets. Bernanke et al. (2005) show that a data-rich environment approach modifies the identification of monetary shocks. Forecasts work as a FAVAR model as they summarise a large variety of macroeconomic variables as well as their expected evolutions. Second, forecasts are real-time data. Private agents and policymakers base their decisions on their information set in real-time, not on ex-post revised data. Orphanides (2001, 2003) show that Taylor rule-type reaction functions estimated on revised data produce different outcomes when using real-time data. Third, private agents and policymakers are mechanically incorporating information about the current state of the economy and anticipate future macroeconomic conditions in their forecasts and we need to correct for their forward-looking information set.

We use macroeconomic forecasts from central banks (ECB and FOMC projections) and private agents: ECB and US Surveys of Professional Forecasters (SPF). The ECB/Eurosystem staff macroeconomic projections for the EA are produced quarterly since June 2004. They are published in March, June, September and December and are presented as ranges for annual percentage changes in both HICP (the Harmonized Index for Consumer Prices) and real GDP. The FOMC publishes forecasts for inflation and real GDP growth twice a year in the Monetary Policy Report to the Congress since 1979. Since October 2007, the publication of these FOMC forecasts has become quarterly and its horizon extended by one additional year. FOMC forecasts for current and next year was realized each year in January/February and June/July until 2007Q3, then in January, April, June and October until 2012Q4, and since then in March, June, September and December. We consider forecasts of the Personal Consumption Expenditures (PCE) measure of inflation and real GDP. These forecasts are published as two ranges encompassing all individual FOMC member's forecasts: the "full range" includes all forecasts while the "central tendency" removes the three highest and three lowest forecasts. As standard in the literature, we use the midpoint of the full range. The ECB's SPF is a quarterly survey of expectations for the rates of inflation, real GDP growth and unemployment in the EA. Participants are affiliated with financial or non-financial institutions in the European Union. SPF forecasts are produced in February, May, August and November. HICP is measured as average annual percentage change for current and next years. The US SPF is collected from approximately 40 panelists and published by the Federal Reserve Bank of Philadelphia. SPF forecasts are also published in February, May, August, and November, and CPI forecasts are provided as year-over-year percent changes. We consider the median of individual responses as the SPF inflation forecast in our analysis.

[17] One could argue that there may also be information frictions in financial markets and that financial variables in *t-1* do not incorporate information news from *t-2*, *t-3*, etc. We control for this by estimating equation (8) with two additional lags. The correlation between this alternative series and the baseline is 0.99 and 0.96 in the US and in the EA respectively. These estimates are available from the authors upon request.

[18] As ECB projections are available since 2004, equations (8)-(9) are estimated with SPF forecasts only before 2004 and including both after 2004. FOMC projections are available since the beginning of the sample, but with a lower frequency. The series have been constant-interpolated to monthly frequency. We assess the robustness of our identification with Greenbook projections which have a higher frequency. The alternative series of monetary shocks using Greenbook projections instead of FOMC projections has a 0.91 correlation with the baseline series.

These benchmark monetary shocks are estimated over the full sample for the US but only since 2004 for the EA because of the data availability constraint mentioned beforehand.

3.3. Alternative measures of monetary shocks

A first alternative is to follow Kuttner (2001)'s high frequency methodology to identify monetary policy shocks in both the EA and the US using changes in the price of futures contracts. Kuttner (2001) identifies monetary surprises by accounting for the forward-looking nature of financial data. For a monetary policy event on day d of the month m, the monetary shock can be derived from the variation in the rate implied by current-month futures contracts on that day. The price of the future being computed as the average monthly rate, the change in the futures rate must be augmented by a factor related to the number of days in the month affected by the change:

$$\epsilon_{kutt,t} = \frac{D}{D-d}(f^0_{m,d} - f^0_{m,d-1}) \quad (10)$$

$\epsilon_{kutt,t}$ is the unexpected interest rate variation which constitutes a monetary shock, $f^0_{m,d}$ is the current-month futures rate and D is the number of days in the month and d the day of the decision. One issue with the Kuttner measure is that it focuses on futures contracts about interest rate only. However, monetary policy has taken many different dimensions over the last years and Wu and Xia (2016) have proposed shadow rate measures that capture the different dimensions of monetary policy in a single variable expressed in interest rate space. However, their measure has a monthly frequency. Krippner (2013, 2014) has estimated shadow short rate (SSR) series at the daily frequency and it therefore enables to apply the Kuttner's high frequency event-study identification of monetary surprises to the daily variation in SSR_t on the policy announcement day:

$$\epsilon_{kripp,t} = SSR_t - SSR_{t-1} \quad (11)$$

Because shadow rate measures are not calendar-based instruments like fed funds futures, there is no need for an adjustment for the remaining number of days. These shocks (labelled MP-Shocks-HF) rely on the financial market participants' interpretation of the overall monetary news disclosed that day, and include private reactions to central bank conventional or unconventional decisions, and central bank communication released at the same time.

A second alternative for identifying monetary surprises is to estimate a forward looking Taylor rule equation augmented with oil prices and a financial stress index (included in the vector Y_t). This equation is estimated over the full sample. The monetary policy shock (labelled MP-Shocks-TR) is then the residuals of the following equation:

$$i_t = \beta_8 + \beta_9\, i_{t-1} + \beta_{10}\pi_{t+6} + \beta_{11}y_{t+6} + \beta_{12}Y_{t+6} + \epsilon_{tr,t} \quad (12)$$

Figure 3 plots the shocks to the overall monetary policy stance using the baseline approach following Romer and Romer (2004) and the two alternative shock series described in this subsection, for the US and the EA. Table 5 provides descriptive statistics for these different monetary shocks and their correlation.

3.4. Relevance of monetary shock measures

We assess the relevance of the identification strategy in two ways. First, we assess the normality and autocorrelation of the estimated shock series. Table 5 also provides the outcomes of these standard tests. These results call for putting less emphasis on Taylor rule type shocks in the US as these shocks exhibit auto-correlation. Figure A in the Appendix plots the distribution of the estimated shocks. Second, for our estimated series of monetary shocks to be relevant, they need to be unpredictable from movements in data. We assess the predictability of the estimated shock series with Granger-causality type tests using 9 macroeconomic and financial variables. Table 5 shows the adjusted R^2 and F-stats of an OLS estimation that aims to test the null hypothesis that our estimated series of exogenous shocks are not predictable. It shows that the Romer-Romer-type shock series are relevant to be used in our second-stage estimations.

4. The effect of monetary policy on asset price bubbles

As emphasized previously, there is no consensus in the theoretical literature about the effect of monetary policy on asset price bubbles. In the "leaning against the wind" approach, a restrictive monetary policy shock would reduce the size of bubbles. However, Gali (2014) show that a restrictive monetary policy would increase the size of bubbles. Finally, other models of asset price bubbles mainly focus on the behaviour of investors to explain the rise and growth of bubbles, so that bubbles are disconnected from monetary policy. The empirical strategy aims to disentangle between these three possible responses of asset price bubbles to monetary shocks. To that end, we first deal with the linear effect of monetary policy and then analyse potential asymmetries in the response of asset price bubbles to expansionary and restrictive shocks.

4.1. The linear effects of the overall monetary stance

The responses over 24 months of the US and EA asset price bubbles – stock, bond and housing – to the baseline and alternative restrictive monetary shocks (MP-Shocks-RR, MP-Shocks-TR and MP-Shocks-HF) is illustrated by figure 4. For clarity, the 95% confidence interval is plotted for the baseline shock only (MP-Shocks-RR).

Starting with the US, the response of the bubble indicator for the stock market is positive and significant around the 14^{th} and 18^{th} months after the shock. This result appears consistent with the main results of Gali and Gambetti (2015). The increase in the shadow rate would inflate the bubble on the stock market instead of reducing it. The responses to the alternative monetary shocks have similar dynamics. The response of bubble indicators for the bond and housing market are not significant. For the EA, none of the responses to monetary shocks are significant up to the 24-month horizon. Overall, the absence of significant responses of asset price bubbles in five out of six cases suggests that monetary policy, both in the US and in the EA, does not fuel bubbles and would not be able to deflate them.

4.2. Alternative estimates

We assess the hypothesis that the absence of significant results in most of the previous cases is not a statistical artefact resulting from the model-averaging feature of the PCA. We estimate the effect of monetary shocks on the individual *r1*, *r3* and *r5* series using the same framework as in the baseline case (see equation 6). The null hypothesis we test here is that these individual responses are different one from each other and have opposite signs. Figure 5 plots these individual responses (with confidence intervals for the *r1* model only for clarity as all confidence intervals are overlaid on each other) for each market in the US and EA. It shows that the responses do not differ significantly, so we can reject this null hypothesis. The baseline results do not mask heterogeneity in the individual responses among the several models used to compute the bubbles indicators or significant responses of a specific model.

4.3. Non-linear evidence

We then investigate the potential asymmetries in the response of bubbles to monetary shocks. We disentangle between restrictive and expansionary shocks. Responses of bubble indicators to the baseline monetary shock are plotted in figures 6 and 7 for the US and the EA respectively. For comparison, the linear response of bubble indicators is also represented.

For the US, the responses of the stock bubble indicator shows that a restrictive shock has no significant effect whereas an expansionary shock would increase the size of the bubble. This effect is significantly different from zero and from the linear response. Monetary shocks account for around 3% of the variance of the bubble component.[19] The effect shown in Figure 4 therefore seems to stem from the assumption that the impacts of restrictive and expansionary shocks are symmetric. The asymmetric result suggests that restrictive monetary policy would neither be able to deflate stock price bubbles as proposed by the "leaning against the wind" literature nor inflate them as predicted by rational bubble models, but expansionary monetary policy would inflate them. The bubble component of the bond market is not significant after both restrictive and expansionary shocks. Finally, the response of the bubble indicator of the housing market to a restrictive shock is not significant, but is very slightly negative after 12 months after an expansionary shock.

For the EA, we find that neither restrictive nor expansionary monetary shocks have an effect on stock market bubbles. For the bond market, the bubble indicator responds positively after 15 to 20 months to a restrictive shock and slightly negatively to an expansionary shock after 10 months, consistent with the result of Gali and Gambetti (2015). The pattern is similar for the housing bubble which responds slightly positively to a restrictive shock after 10 months and negatively to an expansionary shock after 4 to 6 months. Monetary shocks account for between 3 and 5% of the variance of the two bubble components.

Considering non-linear responses overall suggests that the impact of monetary policy on asset price bubbles is limited. In the US, only the stock market bubble would be inflated by expansionary monetary policy. At the opposite, expansionary monetary policy would slightly deflate bubbles on the US housing market and the EA bond and housing markets, consistent with the prediction of rational bubble models.

5. Insights about three policy debates

The methodology described in sections 3 and 4 is used to address some specific policy issues. Two questions have been raised in the policy debate. Concerns have emerged about potential adverse effects of unconventional measures and notably quantitative easing policies, which might have fueled asset price bubbles. This debate is actually a variation of the debate on the risks associated to periods of prolonged expansionary policy when policy rates remain "too low for too long". In reaction to this, it has been advocated that a "leaning against the wind" policy would help to mitigate asset price bubbles that may end in financial crises. These issues are dealt with by disentangling the non-linear effects of shocks to the policy rate before July 2008 and shocks to unconventional policies since July 2008.

5.1. Does expansionary unconventional monetary policy create asset price bubbles?

[19] We compute the variance decomposition using partial R^2 that indicates the fraction of the improvement in R^2 that is contributed by the excluded covariate.

We first analyze the effect of unconventional monetary shocks identified after July 2008.[20] We only consider expansionary monetary shocks in the US and in the EA (figure 8), which may be easily justified by the stance of monetary policy after 2008. The identification of shocks is realized with the method described in section 3 but for a shorter sample period and considering unconventional policies only. In the US, the responses of all three asset price bubbles to expansionary shocks suggest that unconventional measures would not feed bubbles. The response of the stock and the housing market bubbles is even negative, after 5 months and between 2 and 10 months respectively. The bubble indicator on the bond market does not respond significantly to expansionary policy. Results for the EA lead to the same conclusion that unconventional policy has not inflated asset price bubbles. The bubble indicators of the three markets do not respond significantly to monetary shocks. The asset price bubble risk of unconventional policies does not materialize in the data.

5.2. Would a "leaning against the wind" approach be effective?

Figure 9 plots the responses of asset price bubbles to restrictive interest rate shocks based on estimations realized on a sub-sample ending in June 2008. In the US, results suggest that increasing interest rates would have a positive effect on stock price bubbles after 18 months, consistent with Gali and Gambetti (2015), but no effect on other asset price bubbles. The case for the "leaning against the wind" approach seems fragile as we find no evidence that restrictive monetary policy in the US would deflate bubbles. Contrary to the US, a restrictive shock to the policy rate produces a strong negative response of bubbles on the stock market in the EA between 15 and 24 months forward which accounts for up to 18% of the variance of the stock bubble indicator, while evidence based on the overall monetary stance showed no effect. The response is not significant for the bond and housing markets.

5.3. Have interest rates been "too low for too long"?

Figure 10 provides an assessment of the risks associated with expansionary monetary policy in normal times, when central banks use the policy rate as instrument of monetary policy. The results suggest that the stock market bubble responds positively to an expansionary interest rate shock in the US and in the EA. The effects are significant during almost the first 12 months in the US and around 12 to 15 months in the EA. An interest rate policy that would be too loose would then fuel a stock bubble. It would however have no effect on the bond and housing markets in the US. At the opposite, the same expansionary interest rate policy has a negative effect on the bubble components of bond and housing markets in the EA, consistent with the prediction of rational bubble models. The evidence provided here goes against the argument of Taylor (2009) that monetary policy would have been responsible for the housing bubble in the US after 2001.

6. Conclusion

Financial stability is now an objective for policymakers. The issue remains about whether central banks should change the conduct of monetary policy to achieve this goal. The answer to this question critically hinges on the influence of monetary policy on asset prices. Yet, it must be reminded that the reaction of asset prices is also part of the transmission channel of monetary policy. Central bankers must then avoid schizophrenic behavior, seeking to increase or decrease asset price as a way to stimulate the transmission channels of monetary policy and thwarting simultaneously asset price movements fearing financial instability.

[20] It may be noted that the response of the bond market bubble might actually capture the transmission channel of QE policies, which consist in bond purchases. The aim of these asset purchases is precisely to trigger price distortions, which would be captured by our indicator.

Consequently, central banks need to know if asset price movements are desirable or when monetary policy has negative side-effects. This paper deals with this issue and assesses the impact of monetary policy shocks on asset price bubbles.

To this end, we propose to identify bubbles on stocks, bonds and housing markets based on a PCA analysis applied to a range of bubble models usually used in the literature. As none of existing models have reached consensus, we expect that these indicators based on a model-averaging approach will provide a more comprehensive and relevant representation of asset price bubbles.

The main result of this paper is that the impact of monetary policy on asset price bubbles is limited overall. Second, an important lesson is that the response of bubbles is not symmetric and calls for differentiating the responses to restrictive and expansionary shocks in empirical analyses. The hypothesis that expansionary monetary policy does inflate bubbles is rejected in all cases except for stock market bubbles in the US. At the opposite, expansionary monetary policy would slightly deflate bubbles on the US housing market and on the EA bond and housing markets, consistent with the prediction of rational bubble models. The risk that unconventional policies would inflate asset price bubbles does not materialize in the data and evidence even tends to support the opposite mechanism, consistent with the prediction of rational bubble models. We also find that the "leaning against the wind" strategy would not be able to deflate asset price bubbles except on the EA stock market. At the opposite, an expansionary interest rate policy would inflate stock market bubbles on the US and EA, but deflate them on EA bond and housing markets, consistent with the prediction of rational bubble models.

These results suggest that monetary policy, overall, is not a relevant instrument for central banks to control asset price bubbles. However further research is still needed as financial instability may not only be seen through asset *price* bubbles leaving a role for monetary policy to dampen financial risks.

References

Abreu, D. and M. Brunnermeier (2003). "Bubbles and crashes", *Econometrica*, 71(1), 173-204.

Adrian, T. and H. Shin (2008). "Financial intermediaries, financial stability and monetary policy", *FRB of New York staff report, n*°346.

Alessi, L. and C. Detken (2011). "Quasi-real time early warning indicators for asset price boom/bust cycles: a role for global liquidity", *European Journal of Political Economy,* 27, 520-533.

Allen, F. and D. Gale (2000). "Bubbles and crises", *Economic Journal*, 110(460), 236-255.

Allen, F. and D. Gale (2004). "Asset price bubbles and monetary policy", in Global Governance and Financial Crises, edited by M. Desai and Y. Said, 19-42.

Ahrend, R., B. Cournède and R. Price (2008). "Monetary policy, market excesses and financial turmoil", *OECD Working Paper,* n°597.

Basile, A. and J.P. Joyce (2001). "Asset bubbles, monetary policy and bank lending in Japan: an empirical investigation, *Applied Economics*, 33, 1737-1744.

Bernanke, B. and M. Gertler (1999). "Monetary Policy and Asset Price Volatility", *Jackson Hole Conference*, Federal Reserve Bank of Kansas City.

Bernanke, B. and M. Gertler (2001). "Should central banks respond to movements in asset prices?", *American Economic Review*, 91(2), 253-257.

Bernanke, B., J. Boivin and P. Eliasz (2005). "Measuring the Effects of Monetary Policy: A Factor-augmented Vector Autoregressive (FAVAR) Approach", *Quarterly Journal of Economics*, 120(1), 387–422.

Blanchard, O. and M. Watson (1982). "Bubbles, rational expectations and financial markets", in *Crisis in the Economic and Financial Structure*, ed. P. Wachtel. Lexington, MA:Lexington.

Blanchard, O., J.-P. L'Huillier and G. Lorenzoni (2013). "News, Noise, and Fluctuations: An Empirical Exploration," *American Economic Review*, 103(7), 3045–70.

Blinder, A., M. Ehrmann, M. Fratzscher, J. De Haan, and D-J. Jansen (2008). "Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence," *Journal of Economic Literature*, 46(4), 910–45.

Blot, C., J. Creel, P. Hubert, F. Labondance and F. Saraceno (2015). "Assessing the link between price and financial stability". *Journal of Financial Stability*, 16, 71-88.

Bordo, M. and O. Jeanne (2002). "Monetary policy and asset prices: does 'Benign Neglect' make sense?", *International Finance*, 5(2),139–164.

Bordo, M. and D. Wheelock (2007). "Stock market booms and the monetary policy in the twentieth century", *Federal Reserve Bank of St. Louis Review*, March-April, 91-122.

Bordo, M. and J. Landon-Lane (2013). "Does expansionary monetary policy cause asset price booms; some historical and empirical evidence", *NBER Working Paper,* n°19585.

Borio, C. and P. Lowe (2002). "Asset prices, financial and monetary stability: exploring the nexus", *BIS Working Paper,* n°114.

Borio, C. and A. Zabai (2016). "Unconventional monetary policies: a re-appraisal", *BIS Working Paper*, n°570.

Brunnermeier, M. (2008). "Bubbles", *The New Palgrave Dictionary of Economics,* second edition edited by S.N. Durlauf and L.E. Blume.

Brunnermeier M. and M. Oehmke (2013). "Bubbles, financial crises, and systemic risk", in *Handbook of the Economics and Finance*, 2(B), 1221-1288.

Cecchetti, S.G., H. Genberg and S. Wadhwani (2003). "Asset prices in a flexible inflation targeting framework", in Asset Price Bubbles: The Implication for Monetary, Regulatory, and International Policies, ed. W.C Hunter, G.G. Kaufman and M. Pomerleano, MIT Press, 427-444.

Christiano, L., C. Ilut, R. Motto and M. Rostagno (2010). "Monetary Policy and Stock Market Booms", *Jackson Hole Conference*, Federal Reserve Bank of Kansas City.

Coibion, O. (2012). “Are the effects of monetary policy shocks big or small”, *American Economic Journal: Macroeconomics*, 4(2), 1-32.
Collard, F., H. Dellas, B. Diba and O. Loisel (2017). "Optimal Monetary and Prudential Policies." *American Economic Journal: Macroeconomics*, 9(1): 40-87.
Del Negro, M. and C. Otrok (2007). “99 Luftballons: monetary policy and the house price boom across the US states”, *Journal of Monetary Economics,* 54, 1962-1985.
Detken, C. and F. Smets (2004). “Asset price booms and monetary policy”, *ECB Working Paper,* n°364.
Dokko, J., B. Doyle, M. Kiley, J. Kim, S. Sherlund, J. Sim and S. Van den Heuvel (2009). “Monetary policy and the housing bubble”, *Federal Reserve Board Discussion Series,* 49.
Drehman, M., C. Borio and K. Tsatsaronis (2012). “Characterising the financial cycle: don’t lose sight of the medium term!”, *BIS Working Paper,* n°380.
Filardo, A. (2004). “Monetary policy and asset price bubbles: calibrating the monetary policy trade-offs”, *BIS Working Paper,* n°155.
Froot, K. and M. Obstfeld (1991). “Intrinsic Bubbles: The Case of Stock Prices”, *American Economic Review*, 81(5), 1189-1214.
Gali, J. (2014). “Monetary Policy and Rational Asset Price Bubbles”, *American Economic Review*, 104(3), 721-752.
Gali, J. and L. Gambetti (2015). “The Effects of Monetary Policy on Stock Market Bubbles: Some Evidence”, *American Economic Journal: Macroeconomics*, 7(1), 233-57.
Gerlach, S. (2010). “Asset Prices and Monetary Policy: Some Sceptical Observations.” In *The Quest for Stability: The Macro View*, ed. M. Balling, J. M. Berk, and M. O. Strauss-Kahn, 45–60. Vienna: SUERF.
Goodhart, C. and B. Hofmann (2008). “House prices, money, credit, and the macroeconomy”, *Oxford Review of Economic Policy*, 24(1), 180–205.
Gruen, D., M. Plumb and A. Stone (2005). “How should monetary policy respond to asset-price bubbles?”, *International Journal of Central Banking*, 1(3), 1-31.
Gürkaynak, R. (2008). “Econometric test of asset price bubbles: taking stock”, *Journal of Economic Surveys*, 22(1), 166-186.
Jordà, O. (2005). “Estimation and inference of impulse responses by local projections”, *American Economic Review,* 95(1), 161-182.
Jordà, Ò., M. Schularick and A.M. Taylor (2015). “Leveraged Bubbles”, *Journal of Monetary Economics,* 76, 1-20.
Jordà, Ò., M. Schularick and A. Taylor (2013). “When credit bites back”, *Journal of Money Credit and Banking*, 45(s2), 3-28.
Juselius, M., C. Borio, P. Disyatat and M. Drehmann (2016). “Monetary policy, the financial cycle and ultra-low interest rates”, *BIS Working Paper*, n°569.
Kahn, G. (2010). “Taylor rule deviations and financial imbalances”, Federal Reserve Bank of Kansas City Economic Review, Second Quarter, 63-99.
Kilian, L. and Y. Kim (2011). “How Reliable Are Local Projection Estimators of Impulse Responses?,” *The Review of Economics and Statistics*, 93(4), 1460–1466.
Kindleberger, C. (2005). *Manias, Panics and Crashes: A History of Financial Crises*, 5th Edition, New York Wiley.
Kuttner, K. (2001). “Monetary policy surprises and interest rates: evidence from the fed funds futures market”, *Journal of Monetary Economics*, 47, 523-544.
Kuttner, K. (2012). “Low interest rates and housing bubbles: still no smoking gun”, *mimeo*.
Krippner, L. (2013). “Measuring the stance of monetary policy in zero lower bound environments”, *Economics Letters*, 118(1), 135-138.
Krippner, L. (2014). “Measuring the Stance of Monetary Policy in Conventional and Unconventional Environments”, Centre for Applied Macroeconomic Analysis Working Paper, No. 6/2014.

Marcellino, M., J. Stock and M. Watson (2006). "A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series", *Journal of Econometrics*, 135(1-2), 499–526.

Ofek, E. and M. Richardson (2003). "DotCom mania: the rise and fall of internet stock prices", *Journal of Finance*, LVIII(3), 1113-1137.

Orphanides, A. (2001). "Monetary Policy Rules Based on Real-Time Data", *American Economic Review*, 91, 964–985.

Orphanides, A. (2003). 'Historical monetary policy analysis and the Taylor rule', *Journal of Monetary Economics*, 50, 983–1022.

Ricco, G. (2015). "A new identification of fiscal shocks based on the information flow," *European Central Bank Working Paper*, No. 1813.

Rigobon, R. and B. Sack (2004). "The impact of monetary policy on asset prices", *Journal of Monetary Economics*, 51(8), 1553–1575.

Romer, C. and D. Romer (2000). "Federal Reserve Information and the Behavior of Interest Rates," *American Economic Review*, 90 (3), 429–457.

Romer, C. and D. Romer (2004). "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, 94(4), 1055–1084.

Scherbina, A. (2013). "Asset price bubble: a selective survey", *IMF Working paper* n°13/45.

Schiller, R. (2015). *Irrational Exuberance,* 3rd edition Princeton University Press.

Smets, F. (2014). "Financial stability and monetary policy: How closely interlinked?", *International Journal of Central Banking* vol.10 n°2, 263-300.

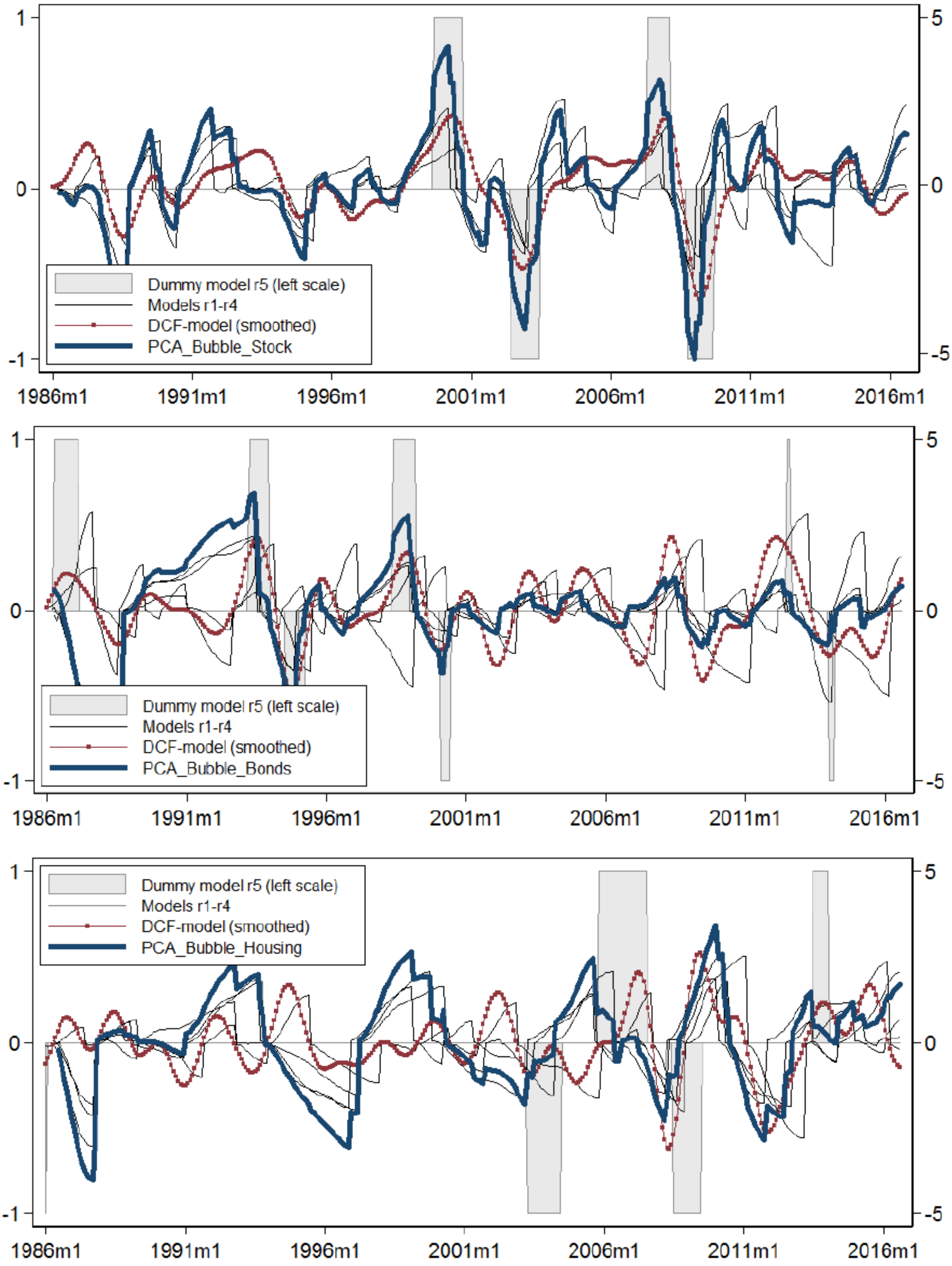
Svensson, L. E. (2012). "The relation between monetary policy and financial policy" . *International Journal of Central Banking*, Vol. 8 (supplement 1), 293-295.

Taylor, J. (2009). "The financial crisis and the policy responses: an empirical analysis of what went wrong", *NBER Working Paper*, No. 14631.

Woodford M. (2012). "Inflation targeting and financial stability", *Sveriges Riksbank Economic Review* 1, 7-32.

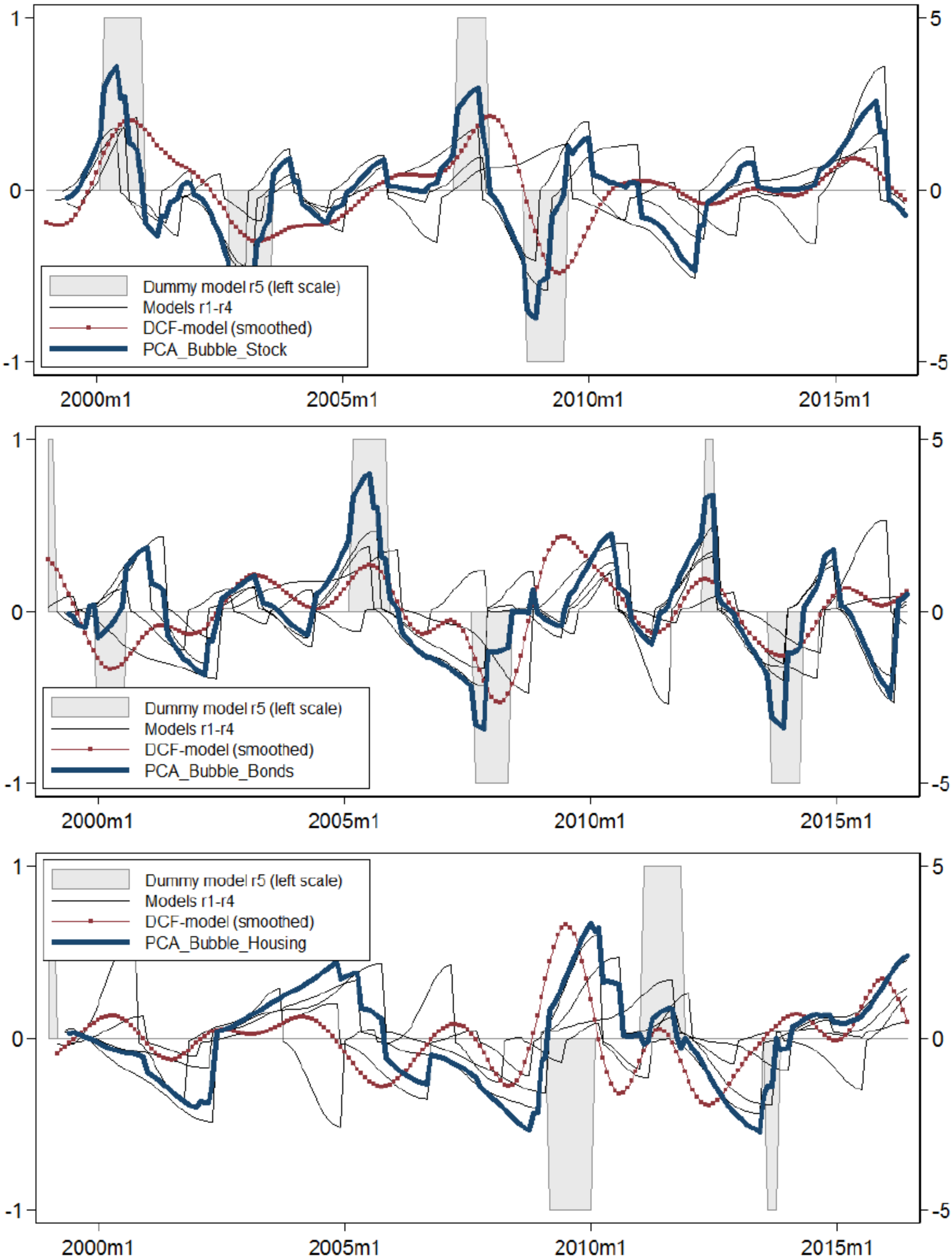
Wu, J. and F. Xia (2016). "Measuring the macroeconomic impact of monetary policy at the Zero lower bound", *Journal of Money Credit and Banking*, 48(2-3), 253-291.

Figure 1. Bubbles in the US



Note: authors' estimations described in section 2.

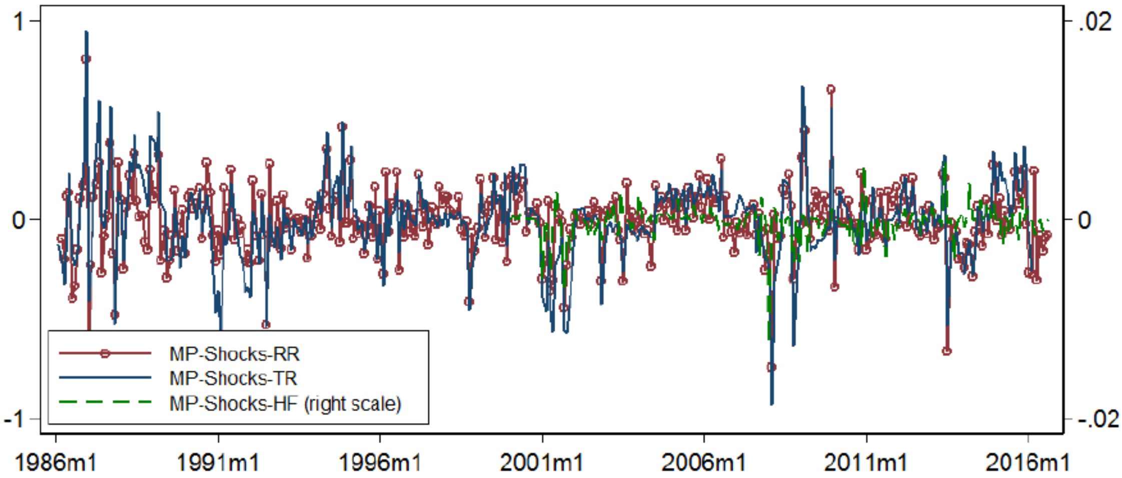
Figure 2. Bubbles in the EA



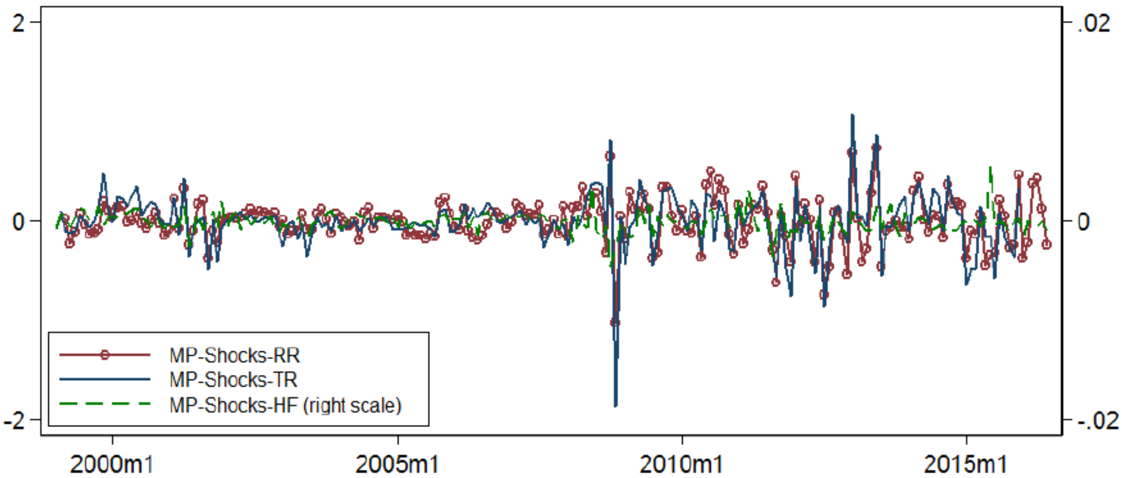
Note: authors' estimations described in section 2.

Figure 3. Monetary shocks

US overall monetary stance shocks (shadow rate)



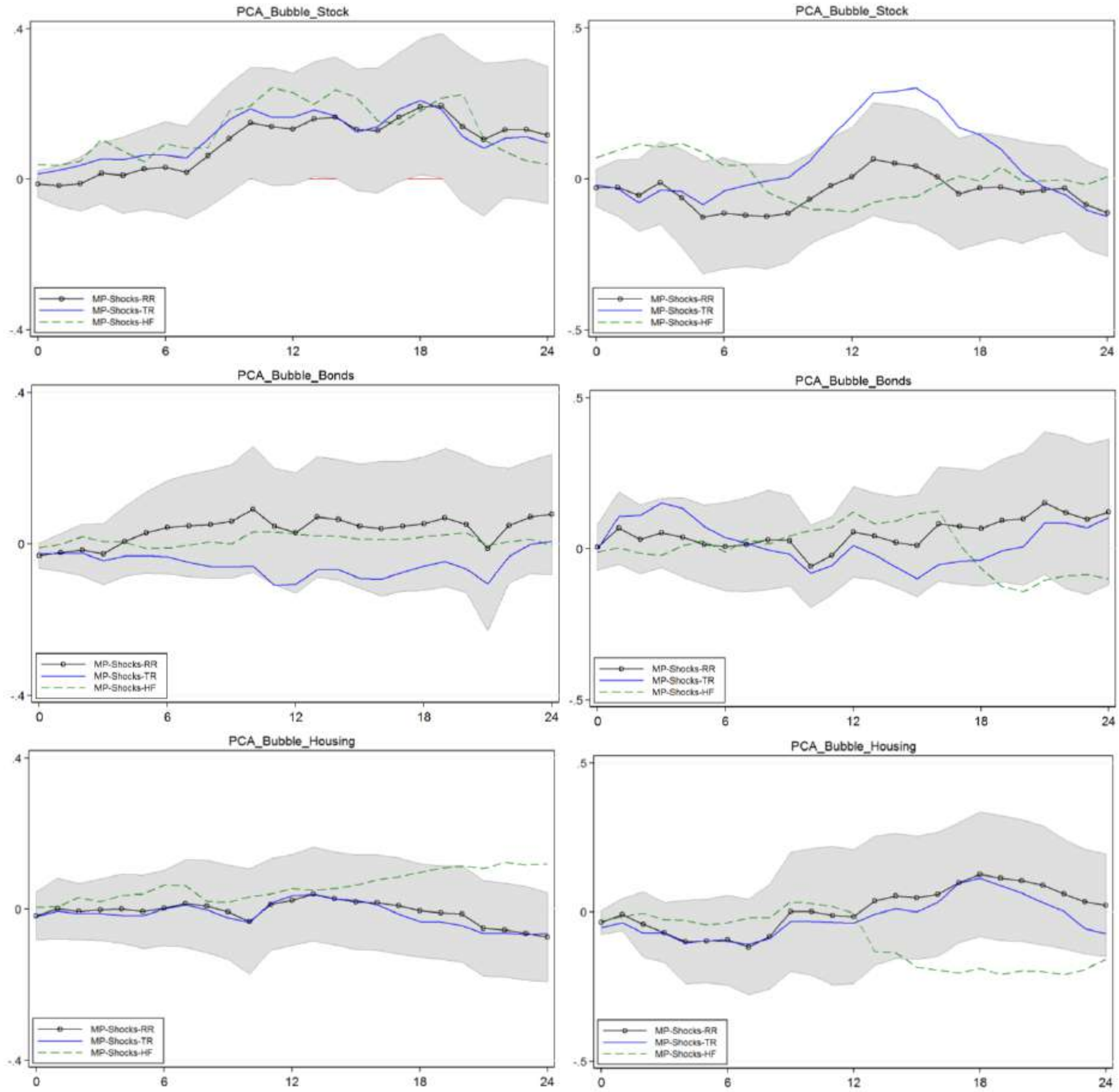
EA overall monetary stance shocks (shadow rate)



Note: Monetary shocks are computed by estimated equations (8)-(9), (11) and (12) described in section 3.

Figure 4. Linear bubble responses to a restrictive (positive) shock to the overall monetary stance

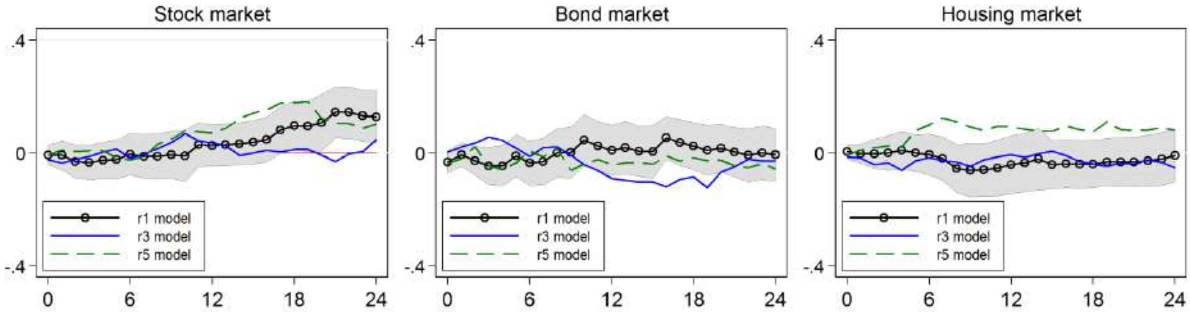
United States *Euro Area*



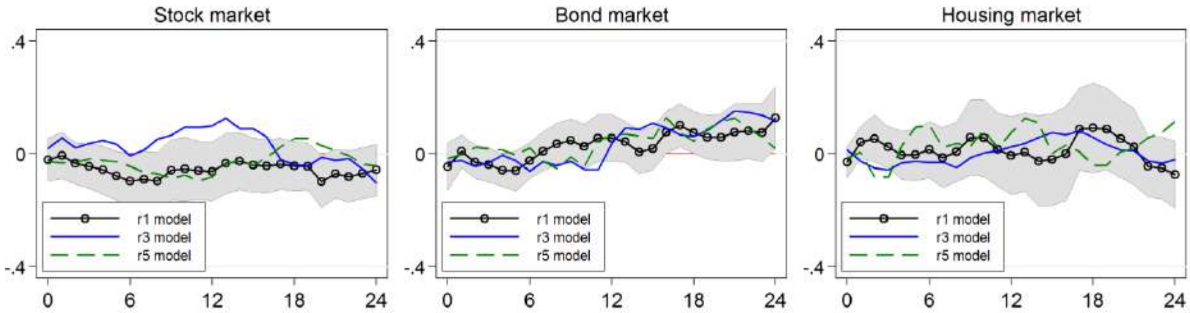
Note: Shaded area represents the 95 per cent confidence interval of the response of the baseline shock (MP-Shocks-RR).

Figure 5. Robustness analysis

Responses to a restrictive shock to the overall monetary stance in the US

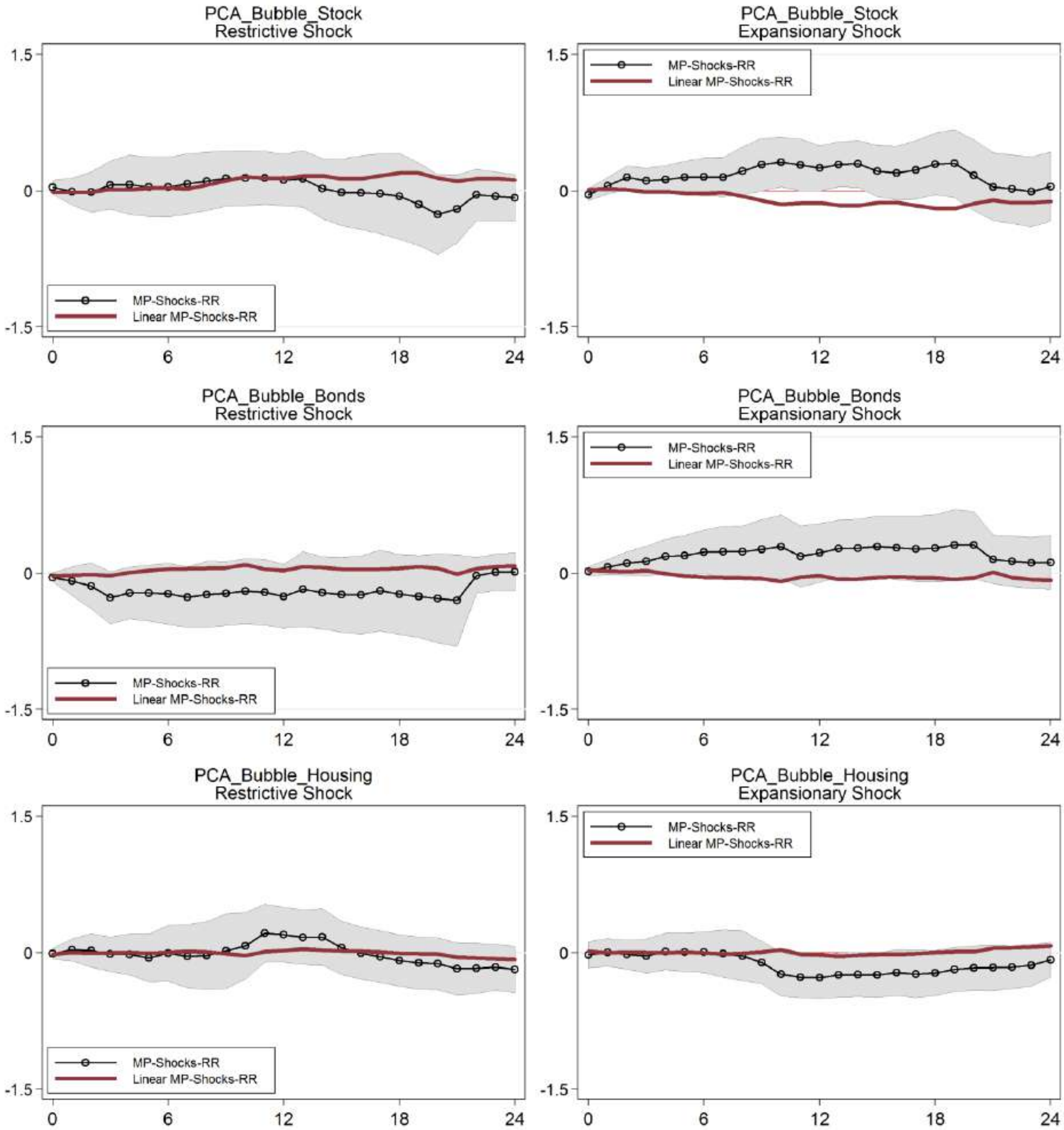


Responses to a restrictive shock to the overall monetary stance in the EA



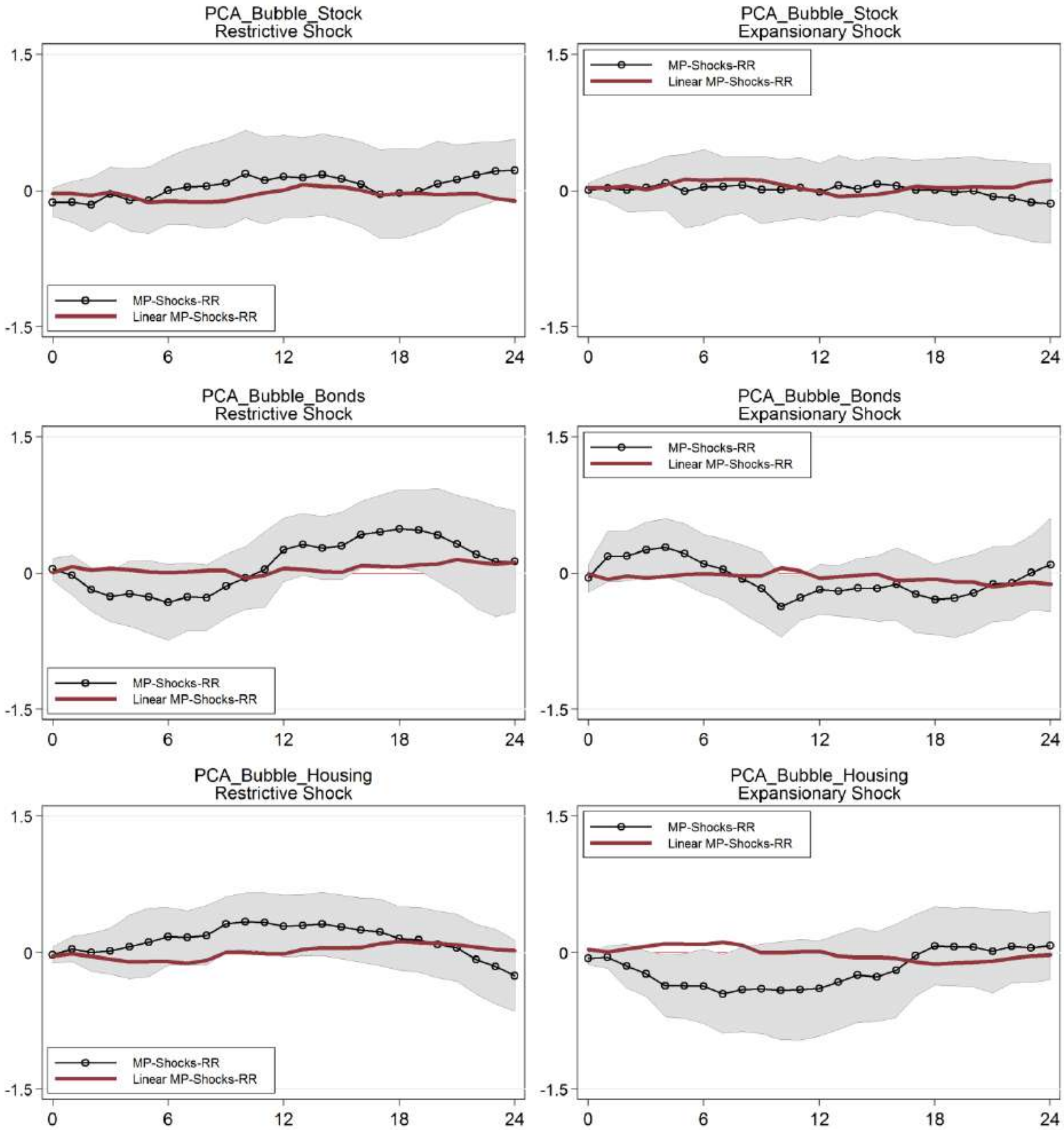
Note: Shaded area represents the 95 per cent confidence interval around the r1 model response.

Figure 6. Non-linear effects of shocks to the overall monetary stance in the US



Note: Shaded area represents the 95 per cent confidence interval around the non-linear response.

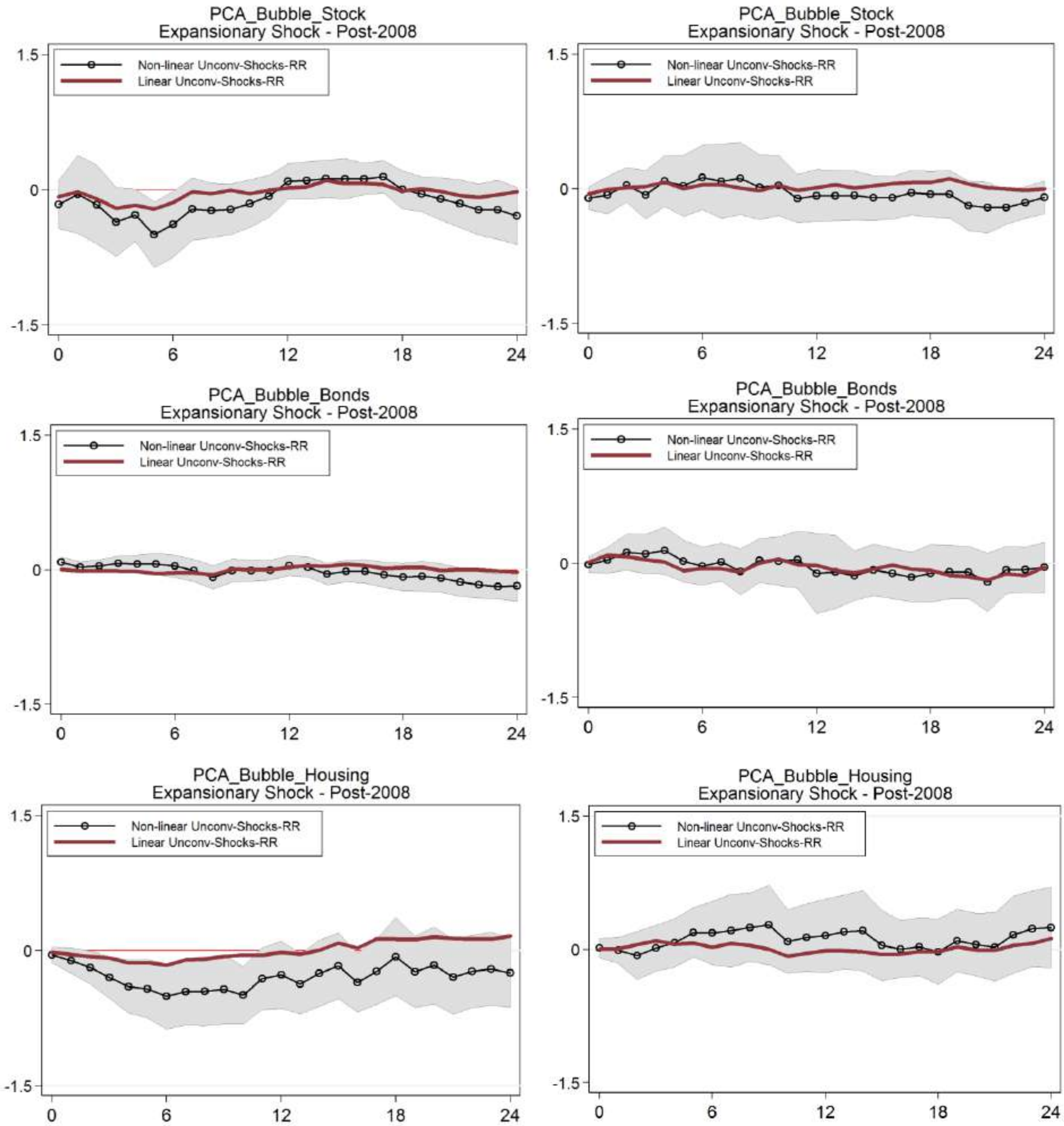
Figure 7. Non-linear effects of shocks to the overall monetary stance in the EA



Note: Shaded area represents the 95 per cent confidence interval around the non-linear response.

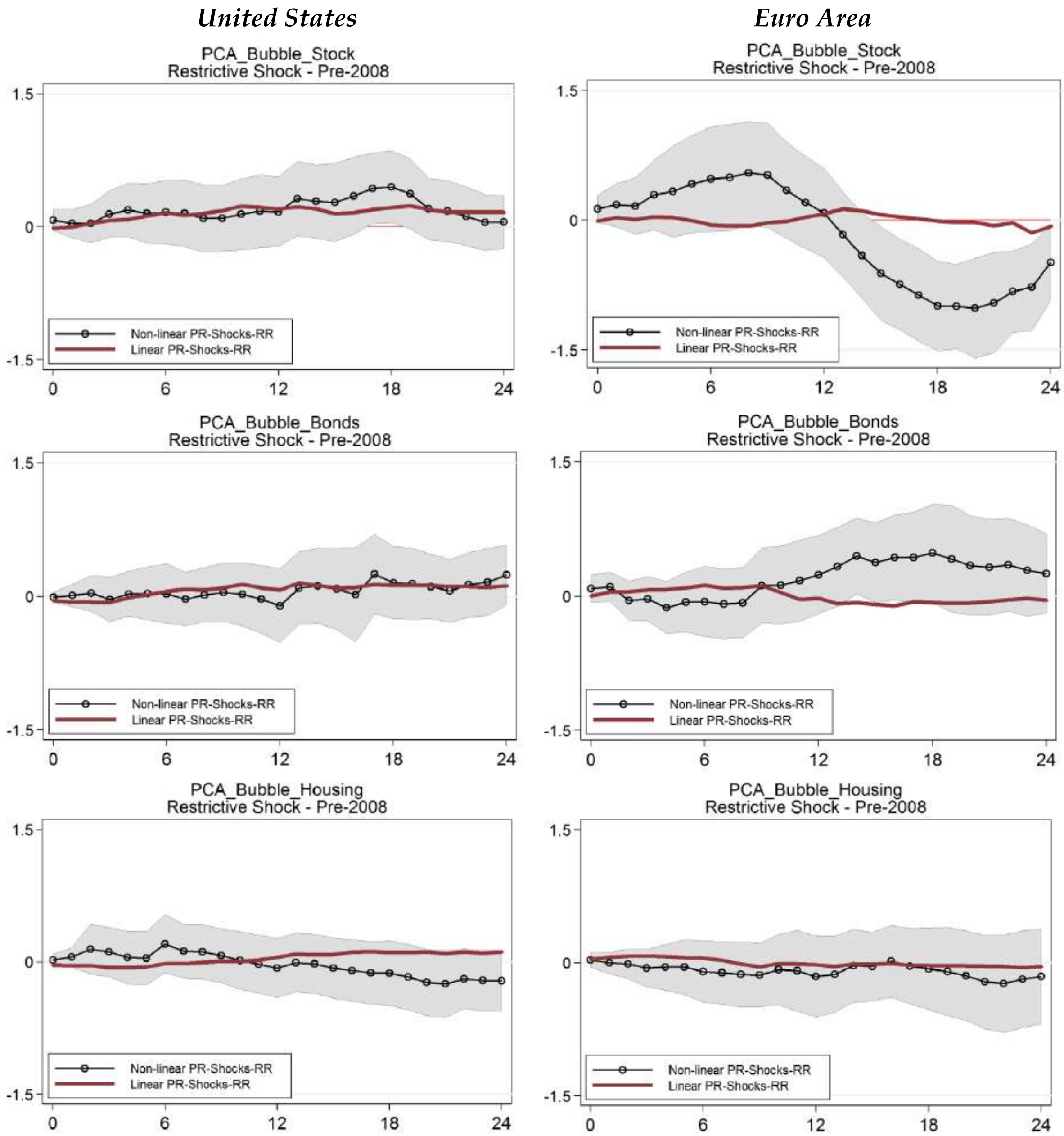
Figure 8. Effects of expansionary shocks to unconventional policies

United States *Euro Area*



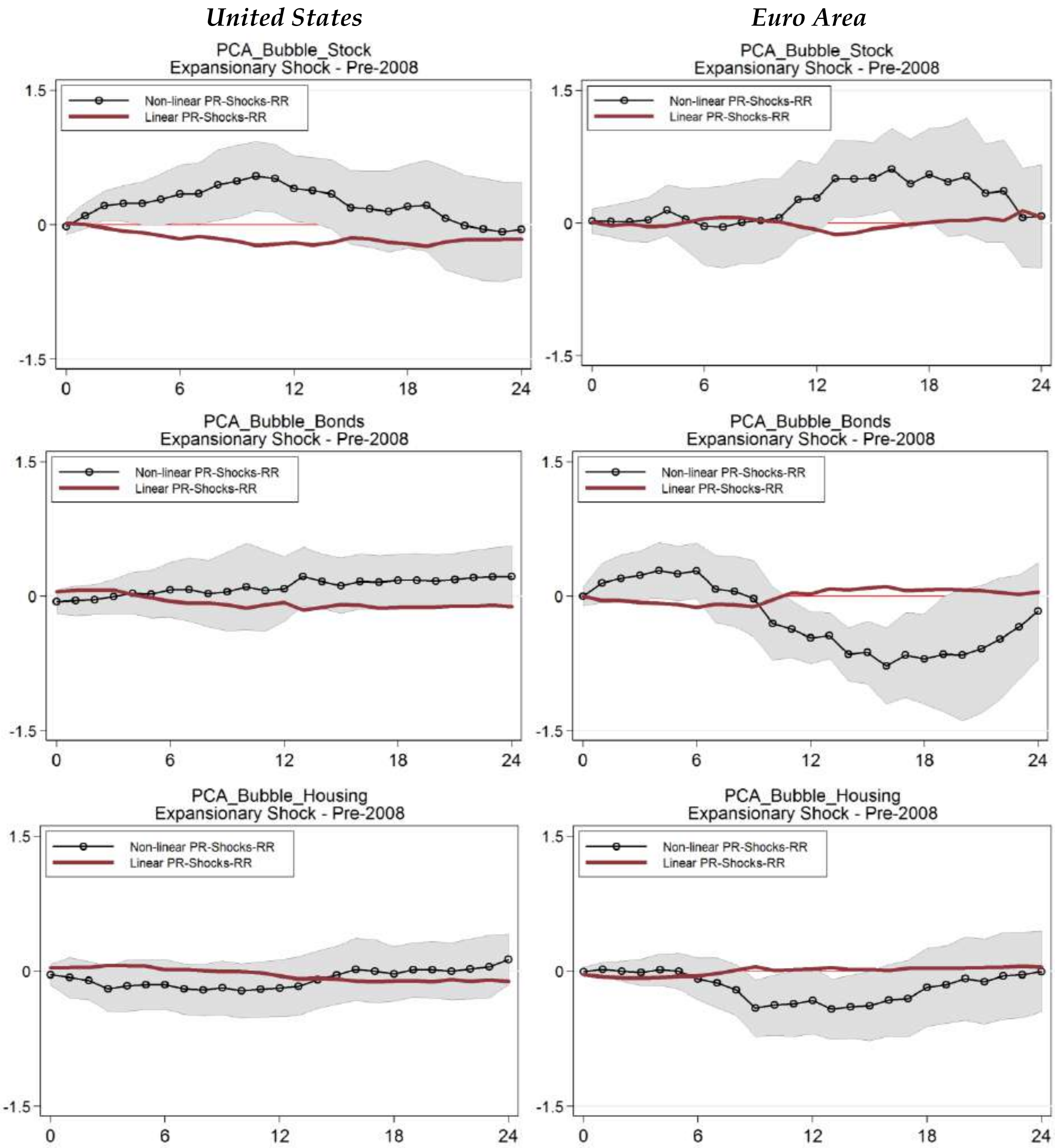
Note: Shaded area represents the 95 per cent confidence interval around the non-linear response.

Figure 9. Effects of restrictive shocks to the policy rate



Note: Shaded area represents the 95 per cent confidence interval around the non-linear response.

Figure 10. Effects of expansionary shocks to the policy rate



Note: Shaded area represents the 95 per cent confidence interval around the non-linear response.

Table 1. Range of bubble models

ID	Model	Estimation Method	Bubble identification
r1	Expected cash-flow	OLS	Filtered and cumulated residual
r2	Expected cash-flow	ECM	Filtered and cumulated residual
r3	Data rich information	OLS	Filtered and cumulated residual
r4	Data rich information	ECM	Filtered and cumulated residual
r5	Statistical approach	Christiano-Fitzgerald Filter	Deviation from the trend beyond 1.5 standard deviation

Table 2. Autocorrelation and white noise tests for residuals and correlation structure between individual bubble series

United States					Euro Area				
Autocorrelation and white noise tests									
Stock									
	OLS	ECM	OLS	ECM		OLS	ECM	OLS	ECM
CumbyHuizinga	0.00	0.65	0.85	0.57	CumbyHuizinga	0.00	0.13	0.69	0.21
Portmanteau	0.00	0.98	0.85	0.99	Portmanteau	0.00	0.36	0.14	0.74
Bonds									
	OLS	ECM	OLS	ECM		OLS	ECM	OLS	ECM
CumbyHuizinga	0.00	0.00	0.50	0.00	CumbyHuizinga	0.00	0.33	0.28	0.24
Portmanteau	0.00	0.03	0.00	0.02	Portmanteau	0.00	0.14	0.02	0.03
Housing									
	OLS	ECM	OLS	ECM		OLS	ECM	OLS	ECM
CumbyHuizinga	0.00	0.00	0.00	0.00	CumbyHuizinga	0.00	0.29	0.00	0.00
Portmanteau	0.00	0.00	0.00	0.00	Portmanteau	0.00	0.00	0.00	0.00

Correlation structure between individual bubble series										
Stock										
	r1	r2	r3	r4	r5		r1	r2	r3	r4	r5
r1	1					r1	1				
r2	0.00	1				r2	-0.10	1			
r3	0.14	0.37	1			r3	0.22	0.06	1		
r4	-0.24	0.72	0.36	1		r4	-0.18	0.57	0.25	1	
r5	0.49	0.41	0.38	0.20	1	r5	0.27	0.53	0.13	0.22	1
Bonds											
	r1	r2	r3	r4	r5		r1	r2	r3	r4	r5
r1	1					r1	1				
r2	-0.01	1				r2	0.00	1			
r3	0.01	-0.09	1			r3	0.19	-0.02	1		
r4	-0.02	0.96	-0.11	1		r4	0.22	0.83	-0.03	1	
r5	0.33	0.13	-0.10	0.13	1	r5	0.41	0.25	0.14	0.28	1
Housing											
	r1	r2	r3	r4	r5		r1	r2	r3	r4	r5
r1	1					r1	1				
r2	0.22	1				r2	0.59	1			
r3	0.05	0.54	1			r3	0.05	-0.01	1		
r4	-0.12	0.70	0.57	1		r4	0.16	0.64	-0.02	1	
r5	0.16	-0.05	0.21	-0.14	1	r5	-0.32	-0.03	0.09	0.16	1

Note: For each market, the lower panel reports *p*-values of autocorrelation and white noise tests.

Table 3. PCA estimation

United States				Euro Area			
Principal components/correlation			Obs = 365	Principal components/correlation			Obs = 205
Rotation: (unrotated=principal)				Rotation: (unrotated=principal)			
	Eigenvalue	Proportion	KMO stat		Eigenvalue	Proportion	KMO stat
PCA_Stock	2.27	0.45	0.60	PCA_Stock	1.96	0.39	0.49
PCA_Bonds	2.02	0.40	0.51	PCA_Bonds	2.07	0.41	0.47
PCA_Hous.	2.22	0.44	0.55	PCA_Hous.	1.96	0.39	0.46
PC scoring coefficients (eigenvectors)				PC scoring coefficients (eigenvectors)			
Variable	PCA_Stock	PCA_Bonds	PCA_Hous.	Variable	PCA_Stock	PCA_Bonds	PCA_Hous.
r1	0.13	0.04	0.08	r1	0.04	0.30	0.53
r2	0.57	0.68	0.59	r2	0.61	0.58	0.67
r3	0.46	-0.15	0.54	r3	0.26	0.08	0.00
r4	0.50	0.68	0.59	r4	0.54	0.62	0.51
r5	0.45	0.20	0.01	r5	0.51	0.43	-0.12

Note: Kaiser-Meyer-Olkin measure of sampling adequacy

Table 4. Correlation structure between bubble indicators and with fundamentals

United States				Euro Area			
Bubbles correlation				**Bubbles correlation**			
	Stock	Bonds	Housing		Stock	Bonds	Housing
Stock	1			Stock	1		
Bonds	0.29	1		Bonds	-0.24	1	
Housing	0.18	0.34	1	Housing	0.08	0.37	1
Bubble-Fundamental correlation				**Bubble-Fundamental correlation**			
Bubble: Fundam.	Stock	Bonds	Housing	Bubble: Fundam.	Stock	Bonds	Housing
Stock	-0.11			Stock	0.23		
Bonds		-0.14		Bonds		-0.07	
Housing			-0.14	Housing			-0.01
Sensitivity tests							
Inverting steps							
Baseline:	Stock	Bonds	Housing	Baseline:	Stock	Bonds	Housing
PCA_cumfil	0.831	0.754	0.862	PCA_cumfil	0.879	0.845	0.904
DCF model with GMM							
	Contemp.	12m	36m		Contemp.	12m	36m
PCA_Stock	0.999	0.999	0.998	PCA_Stock	0.999	0.999	0.984
PCA_Bonds	0.999	0.996	0.970	PCA_Bonds	0.961	0.956	0.934
PCA_Hous	0.969	0.972	0.999	PCA_Hous	0.999	0.879	0.914
Subsample PCA estimation							
	1986-96	1996-06	2006-16		1999-05	2005-10	2010-16
PCA_Stock	0.957	0.995	0.996	PCA_Stock	0.974	0.765	0.881
PCA_Bonds	0.890	0.984	0.972	PCA_Bonds	0.674	0.760	0.974
PCA_Hous	0.918	0.964	0.991	PCA_Hous	0.978	0.942	0.848
Removing r4							
	Stock	Bonds	Housing		Stock	Bonds	Housing
PCA_without r4	0.889	0.476	0.883	PCA_without r4	0.877	0.752	0.890
CF parameter: min: 15 & max: 144 periods							
	Stock	Bonds	Housing		Stock	Bonds	Housing
PCA_alt-CF	0.806	0.774	0.575	PCA_alt-CF	0.889	0.622	0.834

Table 5. Properties of estimated monetary shocks

United States

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
mpshock_rr	366	0.00	0.18	-0.74	0.80
mpshock_tr	361	0.00	0.21	-0.93	0.95
mpshock_hf	200	0.00	0.00	-0.01	0.01
prshock_rr	267	0.00	0.14	-0.65	0.47
uncshock_rr	97	0.00	0.04	-0.14	0.16

Correlation

	mpshock_rr	mpshock_tr	mpshock_hf	prshock_rr	uncshock_rr
mpshock_rr	1				
mpshock_tr	0.84	1			
mpshock_hf	0.25	0.33	1		
prshock_rr	0.81	0.68	0.21	1	
uncshock_rr	-0.15	-0.12	-0.03	x	1

Shapiro-Francia normality test

Variable	Obs	W'	V'	z	Prob>z
mpshock_rr	366	0.94	15.78	5.93	0.00
mpshock_tr	361	0.95	13.47	5.59	0.00
mpshock_hf	200	0.79	34.51	7.32	0.00
prshock_rr	267	0.97	5.73	3.68	0.00
uncshock_rr	97	0.87	11.56	4.83	0.00

Autocorrelation test		Predictability of exogenous shock series			
	AR(1) coef.		F-stat	p-value	Adjusted R^2
mpshock_rr	0.00	mpshock_rr	0.69	0.73	-0.01
mpshock_tr	0.45***	mpshock_tr	3.81	0.00	0.07
mpshock_hf	0.04	mpshock_hf	2.24	0.02	0.06
prshock_rr	0.01	prshock_rr	2.74	0.00	0.06
uncshock_rr	-0.03	uncshock_rr	0.49	0.89	-0.06

Euro area

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
mpshock_rr	208	0.00	0.24	-1.12	0.90
mpshock_tr	203	0.00	0.28	-1.86	1.07
mpshock_hf	210	0.00	0.00	0.00	0.01
prshock_rr	111	0.00	0.10	-0.37	0.39
uncshock_rr	95	0.00	0.11	-0.31	0.50

Correlation

	mpshock_rr	mpshock_tr	mpshock_hf	prshock_rr	uncshock_rr
mpshock_rr	1				
mpshock_tr	0.84	1			
mpshock_hf	0.23	0.26	1		
prshock_rr	0.72	0.60	0.18	1	
uncshock_rr	0.01	0.06	0.02	x	1

Shapiro-Francia normality test

Variable	Obs	W'	V'	z	Prob>z
mpshock_rr	208	0.94	10.07	4.79	0.00
mpshock_tr	203	0.87	22.13	6.41	0.00
mpshock_hf	210	0.91	15.57	5.70	0.00
prshock_rr	111	0.95	4.68	3.07	0.00
uncshock_rr	95	0.89	9.98	4.53	0.00

Autocorrelation test		Predictability of exogenous shock series			
	AR(1) coef.		F-stat	p-value	Adjusted R^2
mpshock_rr	-0.02	mpshock_rr	1.06	0.39	0.00
mpshock_tr	0.00	mpshock_tr	4.87	0.00	0.16
mpshock_hf	0.02	mpshock_hf	2.09	0.03	0.05
prshock_rr	-0.01	prshock_rr	1.56	0.13	0.05
uncshock_rr	-0.01	uncshock_rr	0.30	0.98	-0.08

Note: The vector of variables for predictability tests includes lagged values of inflation, ipi, gdp, shadow, eonia (or ffr), oil, m3 (or m2), ciss (or vix), and bonds.

APPENDIX
NOT FOR PUBLICATION

Table A. Data sources and Description

Concept	Euro Area				United States			
	Abbreviation	Description	Source	Frequency	Abbreviation	Description	Source	Frequency
Asset Prices								
Stock	eurostoxx	Eurostoxx	Datastream	Monthly	sp500	S&P 500	Datastream	Monthly
Bonds	bonds	Government 10-year benchmark bonds	Datastream	Monthly	bonds	Government 10-year benchmark bonds	Datastream	Monthly
Housing	housep	residential property prices	ECB	Quarterly	housep	Shiller Index	Shiller	Monthly
Cash-flow model								
Dividends	divid_rsa	Dividends paid by financial and non-financial corporations (5 EA countries)	Datastream	Monthly	divid_rsa	Paid dividends by corporations	BEA	Quarterly
Rents	rent	Rents received by households (5 EA countries)	Datastream	Quarterly	rent	Rents received by households	BEA	Quarterly
Discount factor	txlg	long-term interest rates	Datastream	Monthly	txlg	long-term interest rates	Datastream	Monthly
Risk Premium	vix	Volatility Index	Chicago Board Options Exchange	Monthly	vix	Volatility Index	Chicago Board Options Exchange	Monthly
Data rich information								
Income	rdb	real disposable income	Eurostat	Quarterly	rdb	real disposable income	BEA	Quarterly
Real GDP	gdp	real GDP	Eurostat	Quarterly	gdp	real GDP	BEA	Quarterly
IndPro	ipi	industrial production	Eurostat	Monthly	ipi	industrial production	BEA	Monthly
Oil prices	oil	oil prices	Datastream	Monthly	oil	oil prices	Datastream	Monthly
Inflation	inf	Inflation	Eurostat	Monthly	inf	inflation	BEA	Monthly
Confidence indicators	csind & cscons	Confidence indicators for households and industry	European Commission	Monthly	csind & cscons	Confidence indicators for consumers and firms	Conference Board & ISM	Monthly
Financial stress	ciss	CISS	ECB	Monthly	kcfsi	Kansas City Financial indicator	FRED	Monthly
Monetary Aggregate	m3	M3	Datastream	Monthly	m2	M2	Datastream	Monthly
Credit Aggregate	m3_credit	Credit counterparties of monetary aggregate	Datastream	Monthly	credit	Credits granted by commercial banks	Datastream	Monthly
Monetary policy								
Policy rate	eonia	EONIA rate	Datastream	Monthly	fedfunds	Effective FFR	Federal Reserve	Monthly
Policy target	MRO	MRO rate	ECB	Monthly	fedtarget	FFR target	Federal Reserve	Monthly
shadow rate	wu&xia	shadow rate	Wu & Xia (2015)	Monthly	wu&xia	shadow rate	Wu & Xia (2015)	Monthly
shadow rate	krippner	shadow rate	Krippner(2016)	Daily	krippner	shadow rate	Krippner(2016)	Daily
Unconven-tional measures	unconv	Securities Held for Monetary Policy Purposes (SHMPP) + LTRO	ECB	Monthly	unconv	Table H.4.1 Fed's total assets	Federal Reserve	Monthly

Note: All nominal variables are deflated by the CPI. BEA = Bureau of Economic Analysis

Table B. Dataset - Descriptive statistics

United States						Euro Area					
Variable	Obs	Mean	Std. Dev.	Min	Max	Variable	Obs	Mean	Std. Dev.	Min	Max
sp500_r	368	6.36	0.47	5.36	7.11	eurostoxx_r	210	5.82	0.25	5.31	6.40
bonds_r	368	4.25	0.14	4.01	4.66	bonds_r	210	4.80	0.08	4.64	5.01
housep_r	368	4.16	0.16	3.96	4.52	housep_r	208	4.60	0.08	4.41	4.73
divid_rsa	368	4.30	0.44	3.43	4.96	divid_rsa	210	11.29	0.11	10.98	11.43
txlg_r	368	2.59	1.70	-1.85	6.03	txlg_r	210	1.88	0.94	0.34	4.39
rent_r	368	3.40	0.82	1.62	4.59	rent_r	210	6.37	0.04	6.28	6.46
rdb_r	368	7.25	0.20	6.88	7.58	rdb_r	208	6.27	0.04	6.18	6.33
ipi	368	-0.17	0.20	-0.56	0.06	ipi	210	4.62	0.05	4.50	4.74
gdp	368	8.29	0.23	7.86	8.63	gdp_r	210	6.65	0.06	6.51	6.73
inf	368	2.64	1.37	-1.96	6.38	inf	210	1.78	0.98	-0.62	4.13
m2_r	368	8.21	0.12	8.01	8.49	m3_r	210	9.06	0.18	8.70	9.31
credit_r	368	7.98	0.33	7.46	8.54	m3_credit_r	210	9.19	0.15	8.85	9.39
csind	368	52.04	4.85	33.10	61.40	csind	210	-0.10	1.03	-3.89	1.47
cscons	368	92.51	25.61	25.30	144.70	cscons	210	-0.14	1.10	-3.45	2.00
oil_r	368	2.96	0.54	1.82	4.11	oil_r	210	4.10	0.53	2.65	4.98
vix	368	2.96	0.36	2.33	4.18	vix	210	2.98	0.39	2.33	4.18
wu&xia	359	3.43	3.23	-2.99	9.85	wu&xia	210	1.56	2.20	-4.79	5.13
krippner	368	3.05	3.63	-5.37	9.85	krippner	210	1.21	2.55	-6.15	4.92

Table C. Individual bubble series - Descriptive statistics

United States						Euro Area					
Model	Obs	Mean	Std. Dev.	Min	Max	Model	Obs	Mean	Std. Dev.	Min	Max
						Stock					
r1	368	0.150	1.865	-4.403	4.664	r1	210	0.172	2.519	-5.010	5.559
r2	366	0.010	0.148	-0.468	0.326	r2	208	0.039	0.142	-0.372	0.293
r3	365	0.006	0.083	-0.191	0.205	r3	205	0.016	0.067	-0.089	0.259
r4	366	0.007	0.117	-0.296	0.309	r4	206	0.005	0.105	-0.261	0.215
r5	368	-0.005	0.362	-1	1	r5	210	-0.010	0.426	-1	1
						Bonds					
r1	368	-0.066	0.797	-2.068	2.182	r1	210	-0.022	0.468	-1.123	0.915
r2	366	0.000	0.101	-0.359	0.215	r2	208	-0.003	0.033	-0.074	0.068
r3	365	0.000	0.007	-0.019	0.020	r3	205	0.000	0.010	-0.026	0.026
r4	365	0.003	0.107	-0.372	0.235	r4	206	-0.003	0.035	-0.096	0.080
r5	368	0.043	0.359	-1	1	r5	210	-0.048	0.424	-1	1
						Housing					
r1	368	0.028	0.615	-1.691	1.579	r1	208	0.044	0.339	-0.700	1.052
r2	366	0.000	0.010	-0.030	0.025	r2	206	-0.003	0.018	-0.039	0.038
r3	363	0.000	0.009	-0.019	0.018	r3	205	0.000	0.002	-0.006	0.008
r4	365	-0.001	0.010	-0.021	0.021	r4	206	-0.002	0.010	-0.026	0.020
r5	368	0.000	0.391	-1	1	r5	210	-0.010	0.353	-1	1

Figure A. Distribution of overall monetary stance shocks