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# Does Monetary Policy generate Asset Price Bubbles?\*

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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 effect of monetary shocks on these bubble components using local projections. The main result of this paper is that monetary policy does not affect asset price bubble components, except for the US stock market for which we find evidence in favor of the prediction of rational bubble models.

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

**JEL Classification:** E44, G12, E52.

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# 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 favour 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.<sup>1</sup> 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, Blot et al., 2015, and Collard et al., 2017). 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 debate echoes the critics raised by Taylor (2009) who suggests that the sustained period of low interest rates in the United States (US) between 2001 and 2004 has triggered the housing market boom and subprime crisis.

This policy debate reflects the lack of consensus in the theoretical literature on how to represent the formation and dynamics of bubbles.<sup>2</sup> Within existing bubble models, the role of monetary policy also remains disputed. The effect of monetary policy on asset price bubbles depends on the nature of the bubble. 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. Gali (2014) shows that bubbles are linked to monetary policy as 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.<sup>3</sup> 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’ behaviour 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 failure of rational arbitrageurs or by overconfidence of some investors.<sup>4</sup> 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.

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<sup>1</sup> 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.

<sup>2</sup> See Brunnermeier and Oehmke (2013) and Scherbina (2013) for surveys.

<sup>3</sup> Rational bubbles may also depend on fundamentals as illustrated by Froot and Obstfeld (1991).

<sup>4</sup> Those models emphasize the importance of informational frictions, heterogeneous agents, heterogeneous beliefs and incentive distortions. Kindleberger (2005) and Schiller (2015) have documented those episodes in financial history where exuberant increases in asset prices have been observed after technological booms.

We investigate whether monetary policy in the US and in the euro area (EA) affect asset price bubbles on stock, bond and housing markets.<sup>5</sup> Contrary to the vast literature dealing with the impact of monetary policy on asset prices, we focus on the effect of monetary policy on the bubble component of asset prices only.<sup>6</sup> 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.<sup>7</sup> 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 flow. 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 an overall bubble indicator for each geographical area and bubble indicators for each market.

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<sup>5</sup> 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” or “over and undervaluation”.

<sup>6</sup> Monetary policy is transmitted to the economy through its effects on asset prices, via the portfolio rebalancing and signaling channel for instance. Empirical evidence finds a positive link between expansionary monetary policy and asset prices. For standard monetary policy, see the literature developed by Angeloni and Ehrmann (2003), Rigobon and Sack (2004), Bernanke and Kuttner (2005) and Gürkaynak et al. (2005) and Bohl et al. (2008). A burgeoning literature has recently focuses on the impact of non-standard measures, see e.g. Krishnamurthy and Vissing-Jorgensen (2011), Joyce et al. (2011) or Rogers et al. (2014).

<sup>7</sup> 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.

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 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 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. When investigating the impact of monetary policy, we use local projections à la Jorda (2005) and are able to assess the response of the overall bubble indicator to shocks to different instruments and to compare the response of the bubble indicators across stock, bond and housing markets. In addition, we analyze the potential asymmetric effects of restrictive and expansionary monetary shocks.

The main result of this paper is that monetary policy does not affect asset price bubble components, except for the US stock market for which we find evidence in favor of the prediction of rational bubble models - a restrictive monetary shock produces an increase in the bubble component. This is consistent with Gali and Gambetti (2015) and confirmed with non-linear specifications. We then shed light on three policy issues. First, we find evidence of potential risks of expansionary unconventional policies are on the bond market in the EA, but not on other markets. Second, the case for a "leaning against the wind" approach seems fragile as we find no evidence that restrictive shocks to the policy rate in the US or in the EA would deflate bubbles, except for the stock market in the EA. Third, neither US nor EA expansionary interest rate policy in normal times would create asset price bubbles.

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 (equation 1) and using an error-correction model (ECM, equation 2).<sup>8</sup> Under rational expectations, without imperfect information 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). These 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:

$$y_t = \alpha_0 + \alpha_1 \cdot D_t + \alpha_2 \cdot r_t + \alpha_3 \phi_t + \epsilon_t^{OLS} \quad (1)$$

$$\begin{aligned} dy_t = & -\alpha \cdot (y_{t-1} - \alpha'_0 - \alpha'_1 \cdot D_t - \alpha'_2 \cdot r_t - \alpha'_3 \cdot \phi_t) \\ & + \alpha_4(L) \cdot dy_t + \alpha_5(L) \cdot dD_t + \alpha_6(L) \cdot dr_t + \alpha_6(L) \cdot d\phi_t + \epsilon_t^{ECM} \end{aligned} \quad (2)$$

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  $\phi_t$  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.

$$y_t = \beta_0 + \beta(L) \cdot y_t + \beta_1 \cdot M_t + \beta_2 \cdot F_t + v_t^{OLS} \quad (3)$$

$$\begin{aligned} dy_t = & -\theta \cdot (y_{t-1} - \beta'_0 - \beta'_1(L) \cdot M_t - \beta'_2(L) \cdot F_t) \\ & + \beta'_3(L) \cdot dy_t + \beta'_3(L) \cdot dM_t + \beta'_3(L) \cdot dF_t + v_t^{ECM} \end{aligned} \quad (4)$$

$M_t$  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

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<sup>8</sup> We discuss later alternative estimations of the expected discounted cash-flow model.



(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.<sup>9</sup> While equations 1 and 2 are 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 ( $\epsilon_t^{OLS}$ ,  $\epsilon_t^{ECM}$ ,  $\nu_t^{OLS}$  and  $\nu_t^{ECM}$  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), bubbles might not matter because they result from anomalies in financial markets, are likely to be small and have their own generating process. Therefore, small deviations from fundamentals are irrelevant so that the cumulated residuals would provide a better measure of significant and persistent deviations from fundamentals. Our proposed measure of bubble components,  $r_{i,t}$  for each model  $i$ , is the cumulative sum of the Christiano-Fitzgerald (CF) 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.

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

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.<sup>10</sup> A synthetic description of all models is presented in Table 1.

## 2.2. Data

We estimate these five models for three asset prices: stocks, 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&P 500 for the US and Eurostoxx index for the EA. 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.<sup>11</sup> In the US, we use the monthly Shiller's index.

<sup>9</sup> Specifications with leads have also been tested but do not change the result and the residual dynamics.

<sup>10</sup> 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.

<sup>11</sup> 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,<sup>12</sup> 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 would 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 first compute an overall indicator of asset bubbles by estimating the first component of all markets together so all 15 individual bubble components. We second 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

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<sup>12</sup> For the EA, we use confidence household and industry indicators are from the European Commission while in the US we use the Conference Board consumer confidence indicator and the ISM confidence indicator for firms.

characteristics of the estimation of our 4 bubble indicators for each geographical area. The overall indicator captures 23 and 25% of the variance of all individual components in the US and EA respectively, while 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 an econometric model.

The 15 individual bubble components and the 4 bubble indicators are plotted in Figures 1 and 2 for the US and the EA respectively. In the US, the bubble indicator for stock prices coincides with the dummy of the simple statistical approach where bubbles (respectively crashes) are identified by a significant deviation of prices above (respectively 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. 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.<sup>13</sup> 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 assumptions.

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<sup>13</sup> 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.

First, we may consider estimating the PCA directly on  $\epsilon_t^{OLS}$ ,  $\epsilon_t^{ECM}$ ,  $v_t^{OLS}$ ,  $v_t^{ECM}$  and  $r5$ , instead of estimating the PCA 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 PCA measures are then compared to the alternative ones. Table 4 shows their correlation and they are on average 0.84 and at minimum of 0.75, so the bubble indicators appear robust to a change in the ordering of the procedure.

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.<sup>14</sup>

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 gives more weight to close models with a high correlation and down-weighs models that stand alone. Table 2 shows that the correlation between  $\epsilon_t^{ECM}$  and  $v_t^{ECM}$  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 and at minimum of 0.48 in the case of 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)

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<sup>14</sup> Note that the samples when considering forward values are shorter of 12 or 36 observations than the baseline.

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 and may lead to some discrepancies in the responses to monetary policy shocks.<sup>15</sup> 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 Jordà (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 Jordà's Local Projection method. Whereas the first method enables to take into account the intertwined dynamics of a set of variables, it may put too much structure on data. The second method offers more flexibility in the estimation. Considering that exogenous structural shocks are known, Jordà (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  $t$ :

$$y_{t+h} = \alpha_h + \beta_h \epsilon_t + \sum_{i=1}^K \phi_{h,i} \cdot y_{t-i} + \eta_{t+h} \quad (6)$$

where  $y_{t+h}$  is the dependent variable - the bubble indicator - at the horizon  $h$ ,  $\epsilon_t$  represents the monetary shock, either to the overall policy stance or to conventional and unconventional measures specifically, and  $y_{t-i}$  are lags of the dependent variable. We set  $K$  to 3 based on the non-significance of additional lags. This equation may be easily modified to account for non-linearities:

$$y_{t+h} = \alpha_h + \beta_h \epsilon_t \cdot D_t + \beta_h \epsilon_t \cdot (1 - D_t) + \sum_{i=1}^K \phi_{h,i} \cdot y_{t-i} + \eta_{t+h} \quad (7)$$

where  $D_t$  is a dummy variable for restrictive monetary policy shocks. This specification aims to single out the potential asymmetric effects of restrictive and expansionary monetary shock 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.<sup>16</sup> This correction also enables to control for potential heteroskedasticity and auto-correlation of the residuals.

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<sup>15</sup> See Coibion (2012) for a discussion.

<sup>16</sup> 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

### 3.2. Identification of monetary shocks

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) resort to a *narrative* approach where they first derive a policy variable – the intended federal funds rate change – and then regress the resulting series on the information set of the monetary authority to purge from endogenous reactions about current and future economic developments.

Because of different information set (Romer and Romer 2000, Blinder et al. 2008, Hubert 2015), 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:

$$\Delta i_t = \beta_0 + \beta_1 i_{t-1} + \beta_2 \Omega_t + \beta_3 \Psi_t + \beta_4 X_{t-1} + \beta_5 Z_t + \epsilon'_t \quad (8)$$

$$\epsilon'_t = \beta_6 + \beta_7 \epsilon'_{t-j} + \epsilon_{rr,t} \quad (9)$$

where  $i_t$  is the monetary policy instrument. We assume that the monetary shock must be orthogonal to the contemporaneous policymakers' information set  $\Omega_t$ , to the private agents' one  $\Psi_t$ , to lagged financial market variables embedded in  $X_{t-1}$ , and to a vector  $Z_t$  of

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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.

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.<sup>17</sup> The policymakers' information set  $\Omega_t$  comprises the level and change in ECB (resp. FOMC) inflation and output projections for current and next calendar years,  $\Psi_t$  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.<sup>18</sup>

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 during the first week of 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 key macroeconomic variables – inflation, real and nominal GDP growth, and unemployment – 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 late January/early February and late June/early 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 each individual FOMC member's forecasts: the "full range" includes the highest and the lowest forecasts while the "central tendency" removes

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<sup>17</sup> 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.

<sup>18</sup> 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.

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 experts 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. 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:

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

$\epsilon_{kutt,t}$  is the unexpected interest rate variation which constitutes a monetary shock,  $f_{m,d}^0$  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 appears auto-correlated. 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. Therefore, bubbles may also be disconnected from monetary policy. The empirical strategy presented here may then help 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 effects of the overall monetary stance**

The responses of the US asset price bubbles – overall, stock, bond and housing – over 24 months to the baseline and alternative restrictive monetary shocks (MP-Shocks-RR, MP-Shocks-TR and MP-Shocks-HF) is illustrated by figure 4 while the responses of asset price bubble indicators in the EA to restrictive monetary shocks are shown in figure 5. The 90% confidence interval is plotted for the baseline shock only (MP-Shocks-RR).

Starting with the US, the response of the overall bubble indicator to monetary shocks is not significant. When looking at markets separately, the response of the bubble indicator on the stock market is positive and significant around the 18<sup>th</sup> and 19<sup>th</sup> months after the shock. This result is consistent with the main results of Gali and Gambetti (2015). The increase in 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 bubble indicators for the bond and housing market show dynamics similar to the overall bubble indicator. The response of the bubble indicator is not significant on the bond market and evidence is inconclusive for the housing market. The response of the bubble indicator is significantly negative with the baseline monetary shock (MP-Shocks-RR) and Taylor rule-type shock (MP-Shocks-TR), but is positive with High-Frequency shocks (MP-Shocks-HF), so the outcome is mixed. 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 seven out of eight 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

First, we resort to a VAR model which has the advantage to simultaneously identify the monetary policy shock and the responses of the bubble indicators. We augment the canonical VAR used for monetary policy analysis with the bubble indicators of each market. The vector of endogenous variables includes real GDP growth (GDP), inflation (CPI), the policy instrument (the shadow rate), the three bubble indicators, oil prices and a financial stress index (the VIX for the US and the CISS for the EA). Let  $Z_t = [\text{GDP}, \text{CPI}, \text{Oil}, \text{Financial stress}, \text{PCA\_Bubble\_Housing}, \text{PCA\_Bubble\_Stock}, \text{PCA\_Bubble\_Bonds}, \text{shadow rate}]'$  represents the  $(8 \times 1)$  vector that contains the endogenous variables at date  $t$ :

$$AZ_t = a + \sum_{k=1}^4 B_k Z_{t-k} + CE_t \quad (13)$$

where the  $B$  matrix is  $(8 \times 8)$  and  $A = I_8$ . The reduced-form errors  $E_t$  combine the structural innovation to a given variable with the contemporaneous responses to the other variables. Here, we adopt the recursive identification assumption postulating that the structural errors are independent, and that reduced-form errors are related to structural errors through a lower triangular  $C$  matrix. This means that the covariance between the reduced-form errors is attributed to the structural error of the variable previously ordered in  $Z_t$ , and that the structural error is uncorrelated to the reduced-form errors of the preceding variables. This recursive identification therefore depends on the ordering of the variables in the  $Z_t$  vector. We assume that shifts in real GDP and inflation may produce a contemporaneous change in all financial markets (oil, financial stress index and bubble indicators) and policy variables. The market variables react to monetary shocks only with a lag. While this assumption seems fragile as financial market variables may react instantaneously to a policy decision, the rationale here is to put the policy variable last in the vector of endogenous variables so monetary policy may react instantaneously to all other variables in order to get the most conservative estimates of the monetary shock. Concerning the relative position of the three bubble indicators, we assume that the housing market is the slowest to react following Drehman et al. (2012). We assume that bond markets react more quickly than stock markets because of higher volumes traded and liquidity. All eigenvalues lie inside the unit circle, so the VAR model satisfies the stability condition to interpret impulse-response functions.

The upper panel of Figure 6 plots the responses of the three bubble indicators. The stock market bubble indicator increases significantly in the US and in the EA after a restrictive monetary shock. The transmission lag is longer in the US than in the EA and is close to the lags estimated with the local projection approach. These results for the stock market bubble indicator are consistent with Gali and Gambetti (2015). This pattern only holds for the stock market. The responses of the bond market and housing bubble indicators in the US are not significant and confirm the baseline results. In the EA, the response of the housing bubble indicator is not significant too, but the response of the bond market bubble indicator is negative and significant. This result is at odd with the local projection outcomes.

Second, in order to check that the absence of significant results in most of our 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. The lower panel of Figure 6 plots these individual responses (with confidence intervals for the  $r1$  model only for clarity as they all 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 7 and 8 for the US and the EA respectively. For comparison, the linear response of bubble indicators is also represented.

For the US, the response of the overall bubble indicator shows that a restrictive shock has no significant effect whereas an expansionary shock would reduce the size of the bubble. The pattern is similar for the stock market bubble. The effect of expansionary shocks is consistent with the main result of Gali and Gambetti (2015). The bubble component of the bond market decreases after both restrictive and expansionary shocks. Finally, the response of the bubble indicator of the housing market to an expansionary shock is not significant, but is negative after 21 months after a restrictive shock. This pattern is similar to the outcome evidenced in the linear specification, but suffers the same weakness. For the EA, we find that restrictive monetary shocks have no effect on stock market bubbles. For the bond market, the bubble indicator responds negatively after 3 to 6 months, but positively after 18 to 20 months, so the overall picture is mixed. The housing bubble increases slightly after 13 months. Expansionary shocks do not affect much more bubble indicators. The response of the bubble component on the stock market is slightly positive at the very end while the response of the bubble indicator on the bond market is negative between the 2<sup>nd</sup> and 7<sup>th</sup> months.

Considering non-linear responses of asset price bubbles does not alter the main picture highlighted in the linear specification. Generally, asset price bubbles do not react significantly to monetary shocks in the EA. In the US, the outcome for the stock and bond market indicates that restrictive shocks do not deflate bubble indicators whereas expansionary shocks would, 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?

We first analyze the effect of unconventional monetary shocks identified after July 2008. We only consider expansionary monetary shocks in the US and in the EA (figure 9), 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 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 positive but not significant though they have simultaneous peaks. The bubble indicator on the bond market does not respond positively to expansionary policy. Results are different for the EA. The bubble indicator on the bond market reacts positively to unconventional policies in the first year following the shock, whereas the stock market bubble indicator responds negatively after 11 months. It may be noted that the positive response of the bubble of the bond market 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 is captured by our indicator. Finally, there is no positive and significant response of the bubble indicator of the stock and housing market. The main risks of unconventional policies to monitor are in the bond market in the EA.

### **5.2. Would a “leaning against the wind” approach be effective?**

Figure 10 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 no effect on asset price bubbles. The case for a “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, while evidence based on the overall monetary stance showed no effect. The response is null for the housing market and mixed for the bond market.

### **5.3. Have interest rates been “too low for too long”?**

Figure 11 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 the stock market bubble responds negatively to an expansionary interest rate shock in the US. The same holds in the EA. The decrease of the bubbles occurs after 8 months in the US and 13 months in the EA. These results are consistent with the rational bubble model as emphasized by Gali (2014). It is also shown that the response of the bubble of the housing market is neither positive nor negative in the US and the EA respectively. 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. The bubble indicator of the bond market in the US does not react significantly to the expansionary shock, while in the EA, the response is first then positive, so evidence is mixed overall.

## **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. 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 our indicator based on a model averaging approach will provide a better representation of bubbles. On the recent period – 1986 for the US and 1999 for the EA – several booms and busts have been identified.

Our main result is that monetary policy does not affect asset price bubble components, except in the US where a restrictive monetary policy shock has a positive effect on the bubble component of the stock market confirming Gali (2014). Considering some specific policy issues, we find that unconventional measures cause a bubble in the EA bond market but not in other markets. Estimates on a pre-June 2008 sample also suggest that expansionary interest rate policies do not inflate bubbles. Finally, our results on the effects of restrictive interest rate shocks suggest that central bankers would not be able to dampen the size of asset price bubbles with this instrument.

These results suggest that monetary policy, overall, is neither fueling nor 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.

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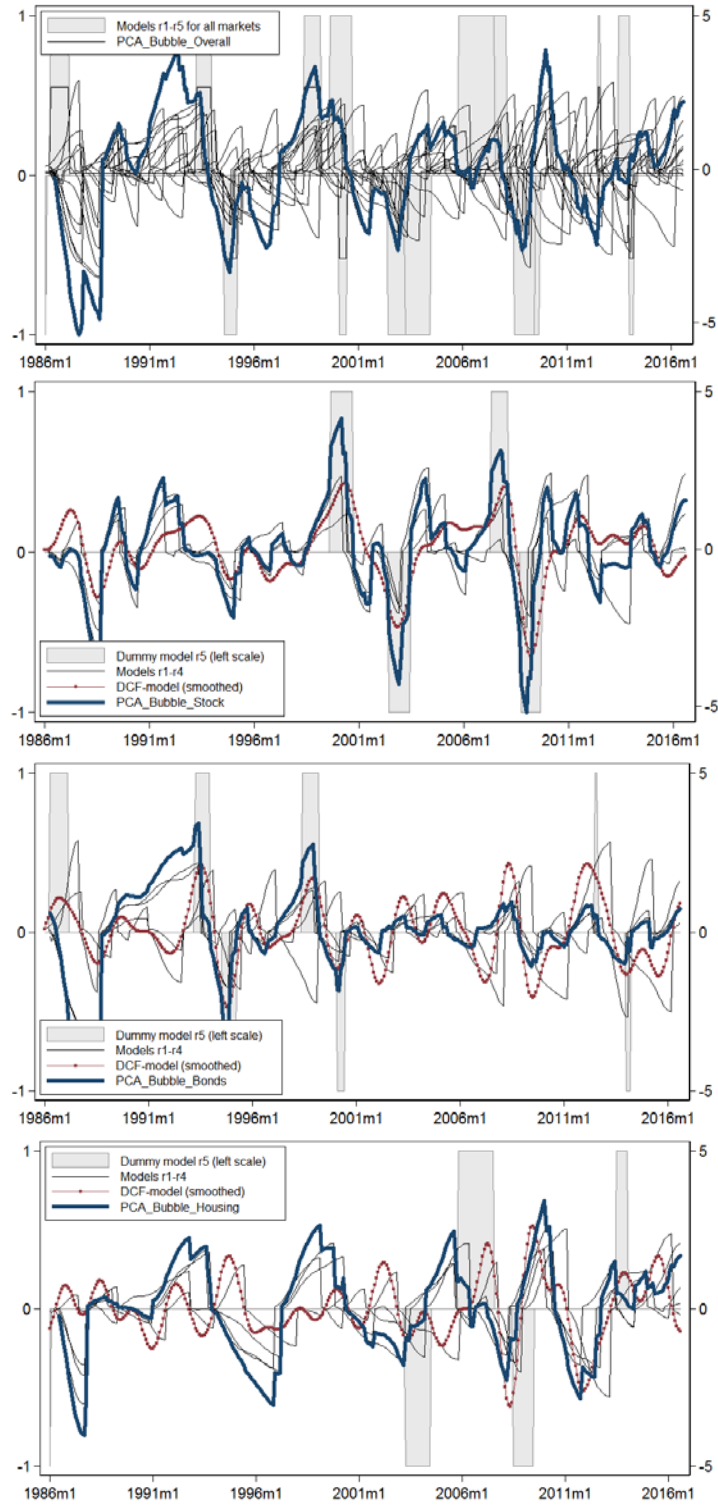
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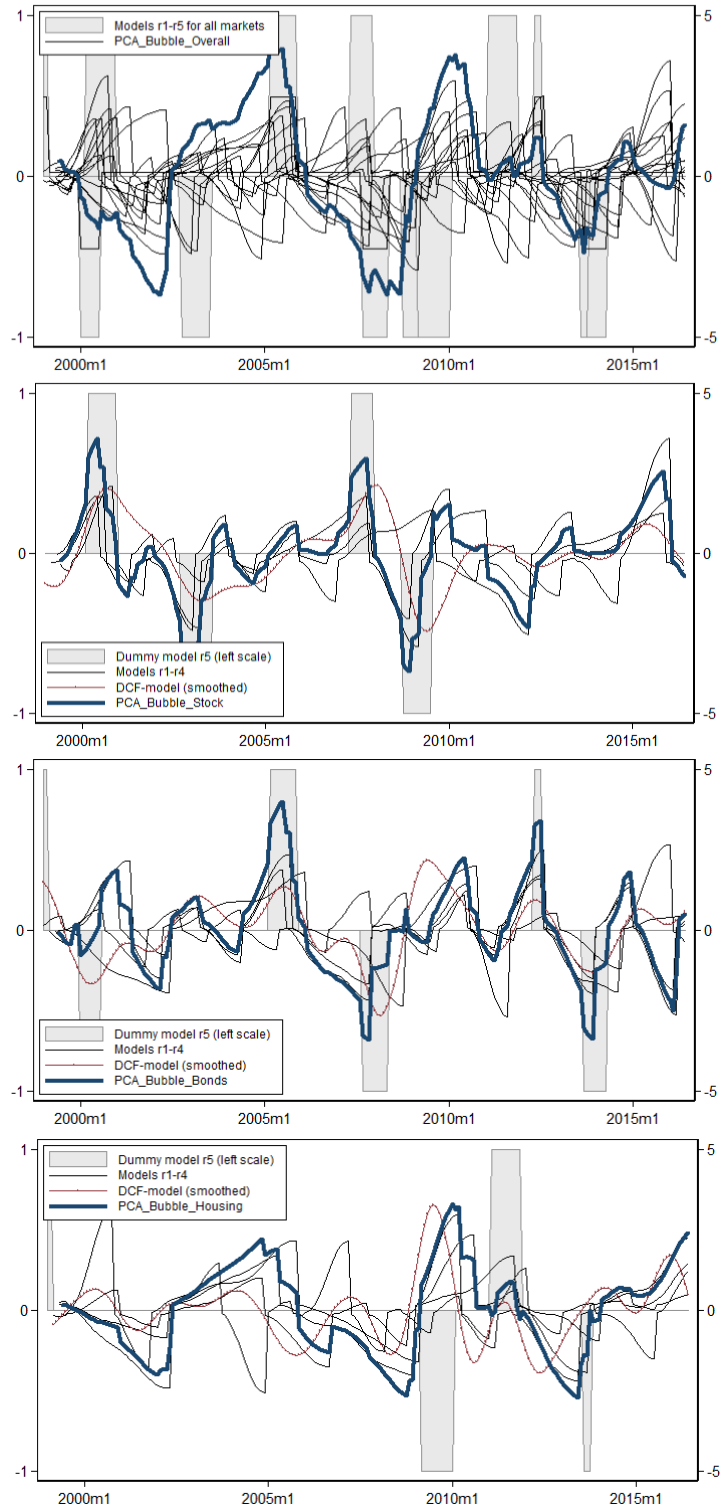


**Figure 1. Bubbles in the US**



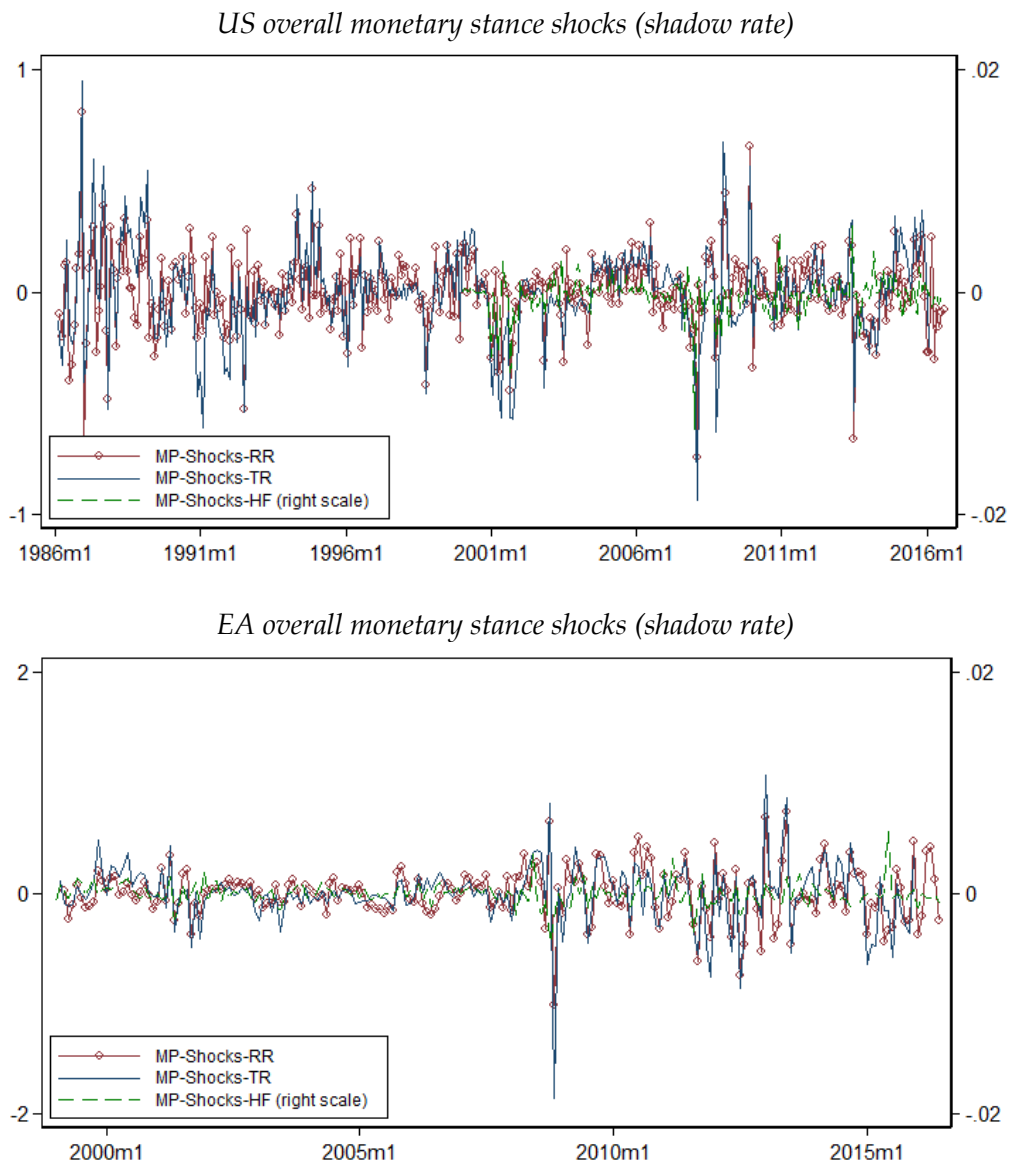
Note: authors' estimations described in section 2.

**Figure 2. Bubbles in the EA**



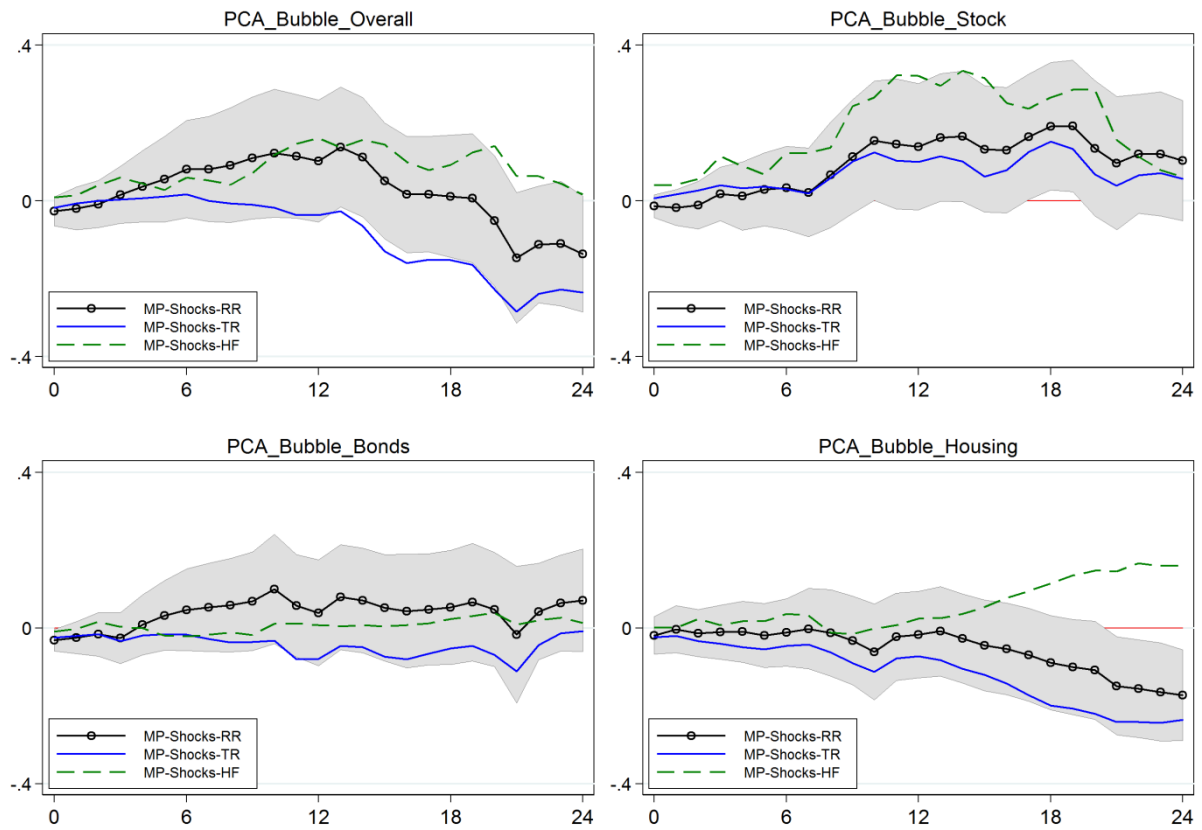
Note: authors' estimations described in section 2.

**Figure 3. Monetary shocks**



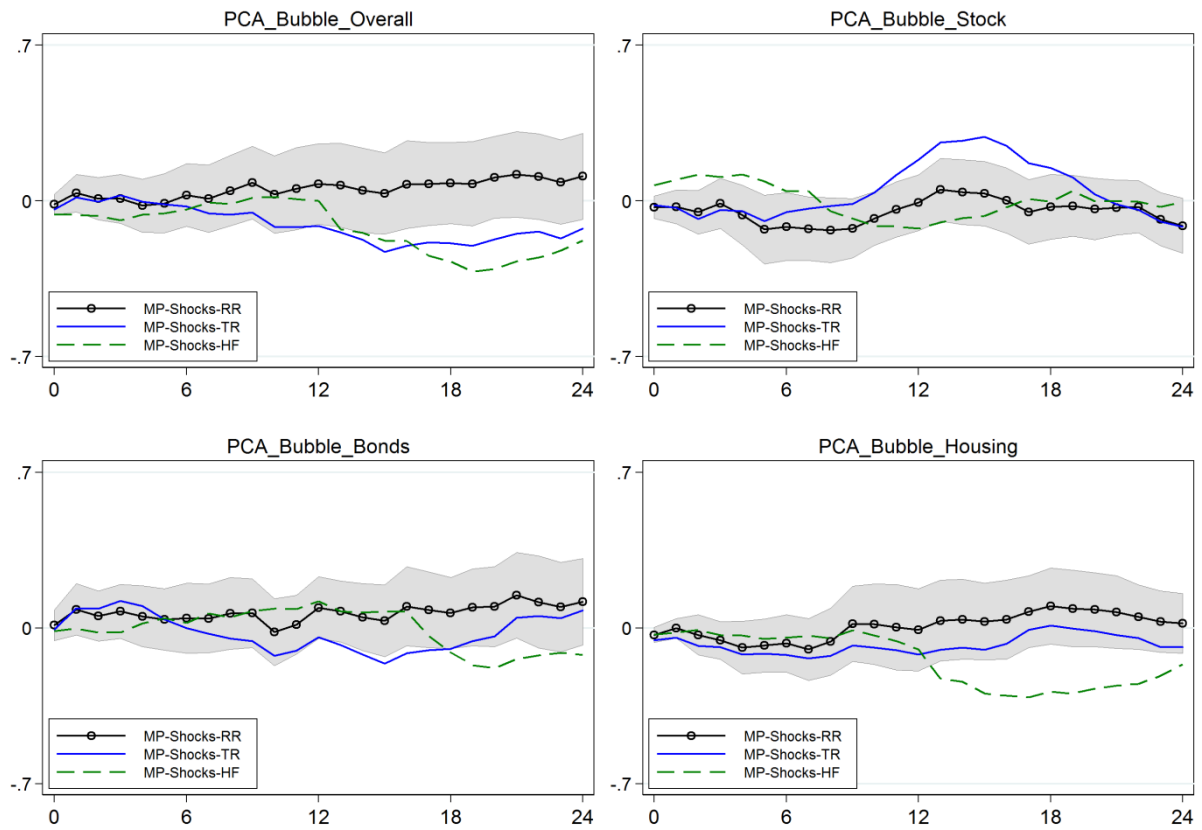
Note: Monetary shocks are computed by estimated equations (8)-(9), (11) and (12) described in section 3.

**Figure 4. Bubble responses to a positive (contractionary) shock to the overall monetary stance in the US**



Note: Shaded area represents the 90 per cent confidence interval of the response of the baseline shock (MP-Shocks-RR).

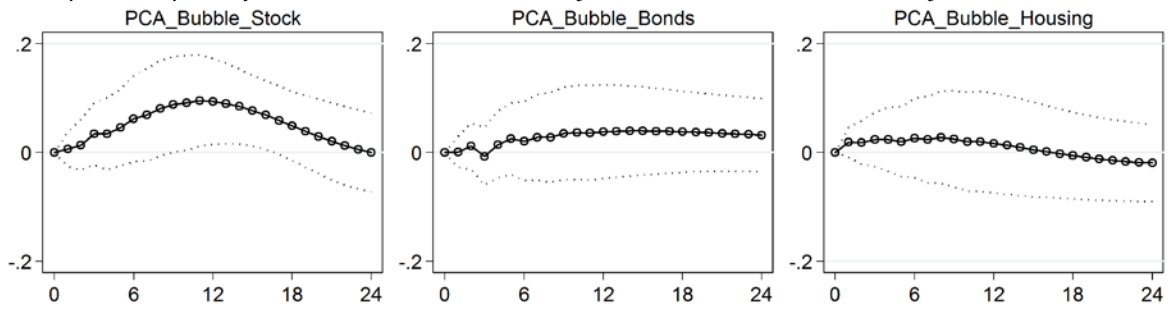
**Figure 5. Bubble responses to a positive (contractionary) shock to the overall monetary stance in the Euro area**



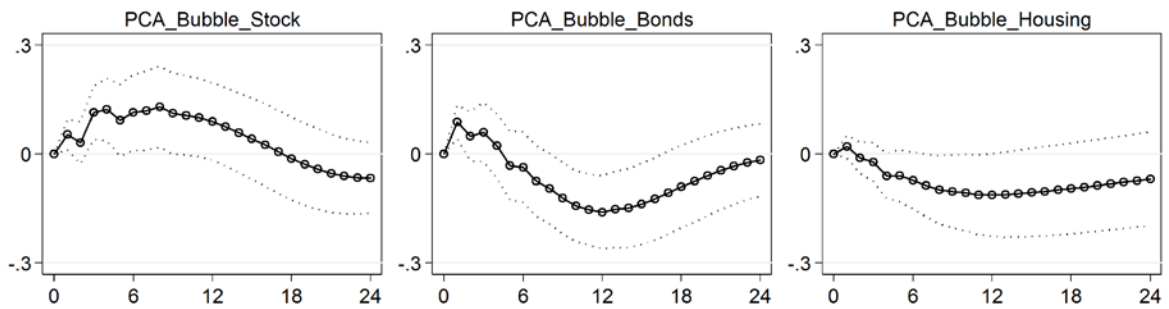
Note: Shaded area represents the 90 per cent confidence interval of the response of the baseline shock (MP-Shocks-RR).

**Figure 6. Robustness analysis**

*Impulse response functions to a contractionary shock to the overall monetary stance in the US*

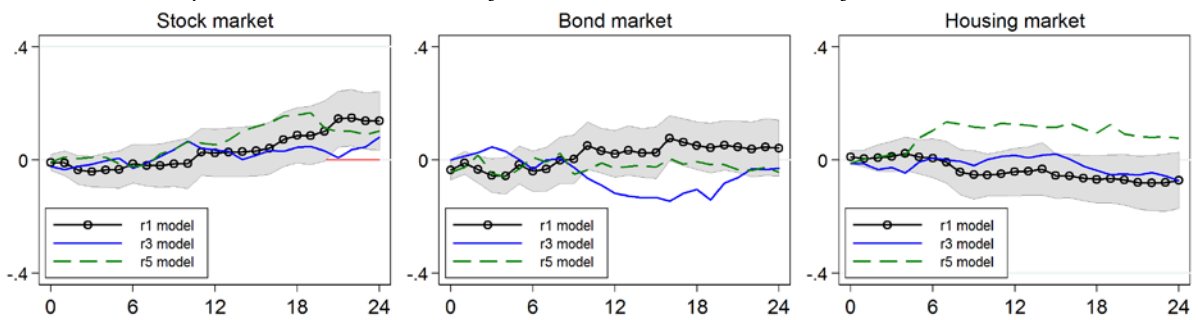


*Impulse response functions to a contractionary shock to the overall monetary stance in the EA*

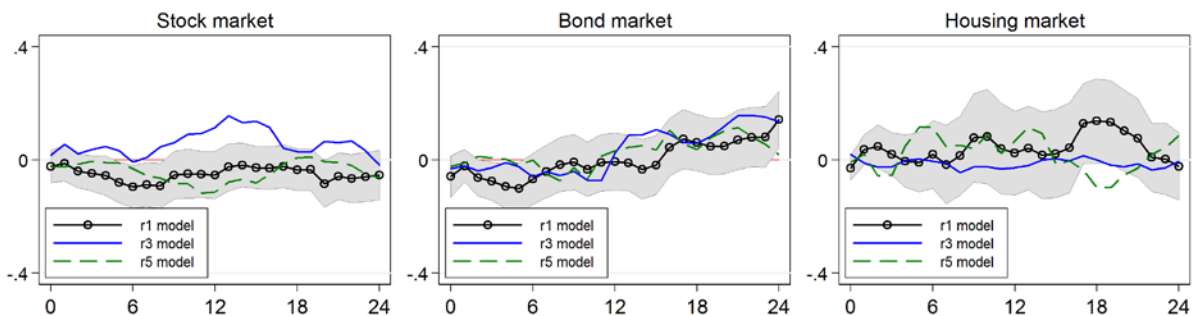


Note: Dotted lines represent the 90 per cent confidence interval.

*Responses to a contractionary shock to the overall monetary stance in the US*

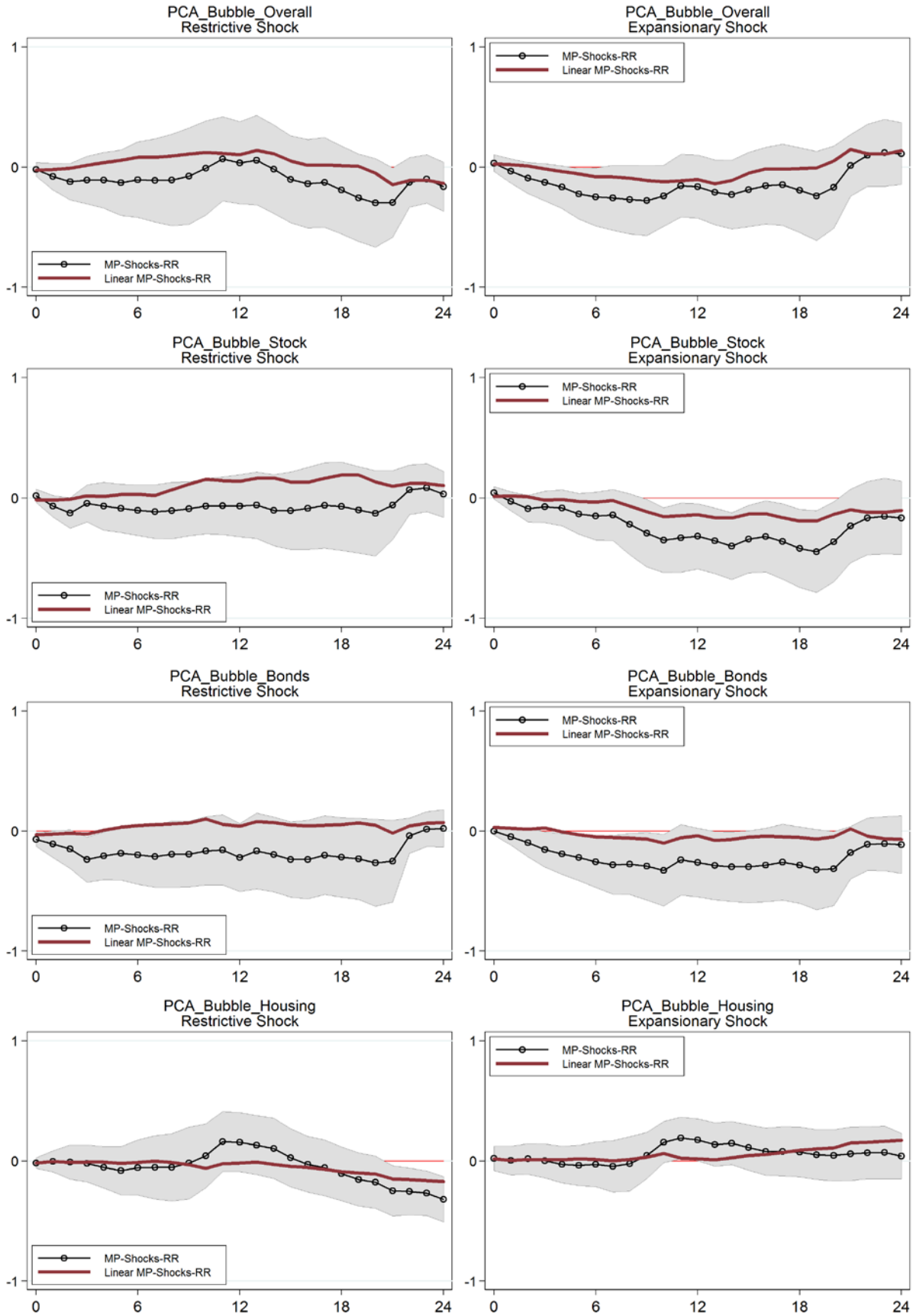


*Responses to a contractionary shock to the overall monetary stance in the EA*



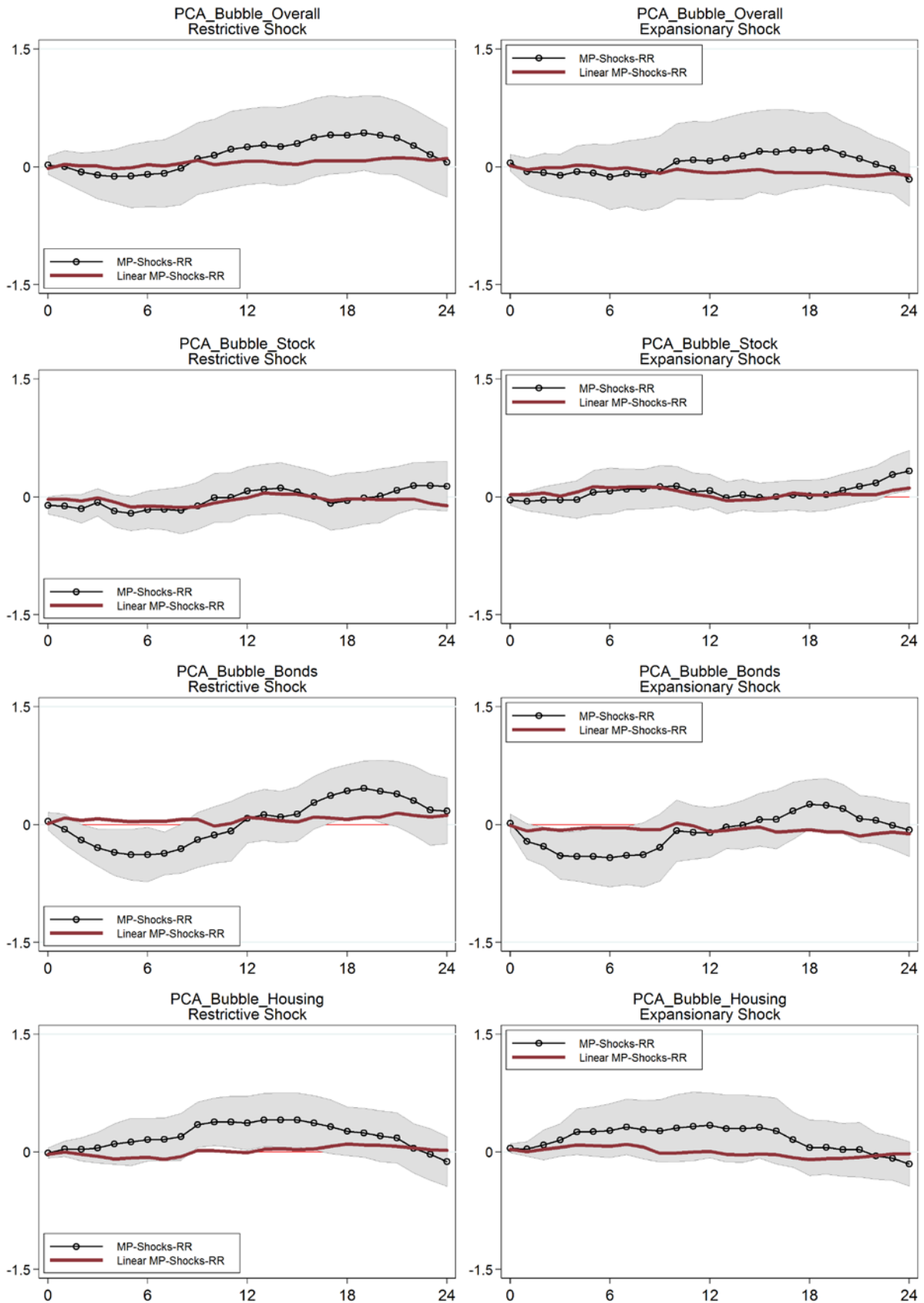
Note: Shaded area represents the 90 per cent confidence interval around the r1 model response.

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



Note: Shaded area represents the 90 per cent confidence interval around the non-linear response.

**Figure 8. Non-linear effects of shocks to the overall monetary stance in the EA**



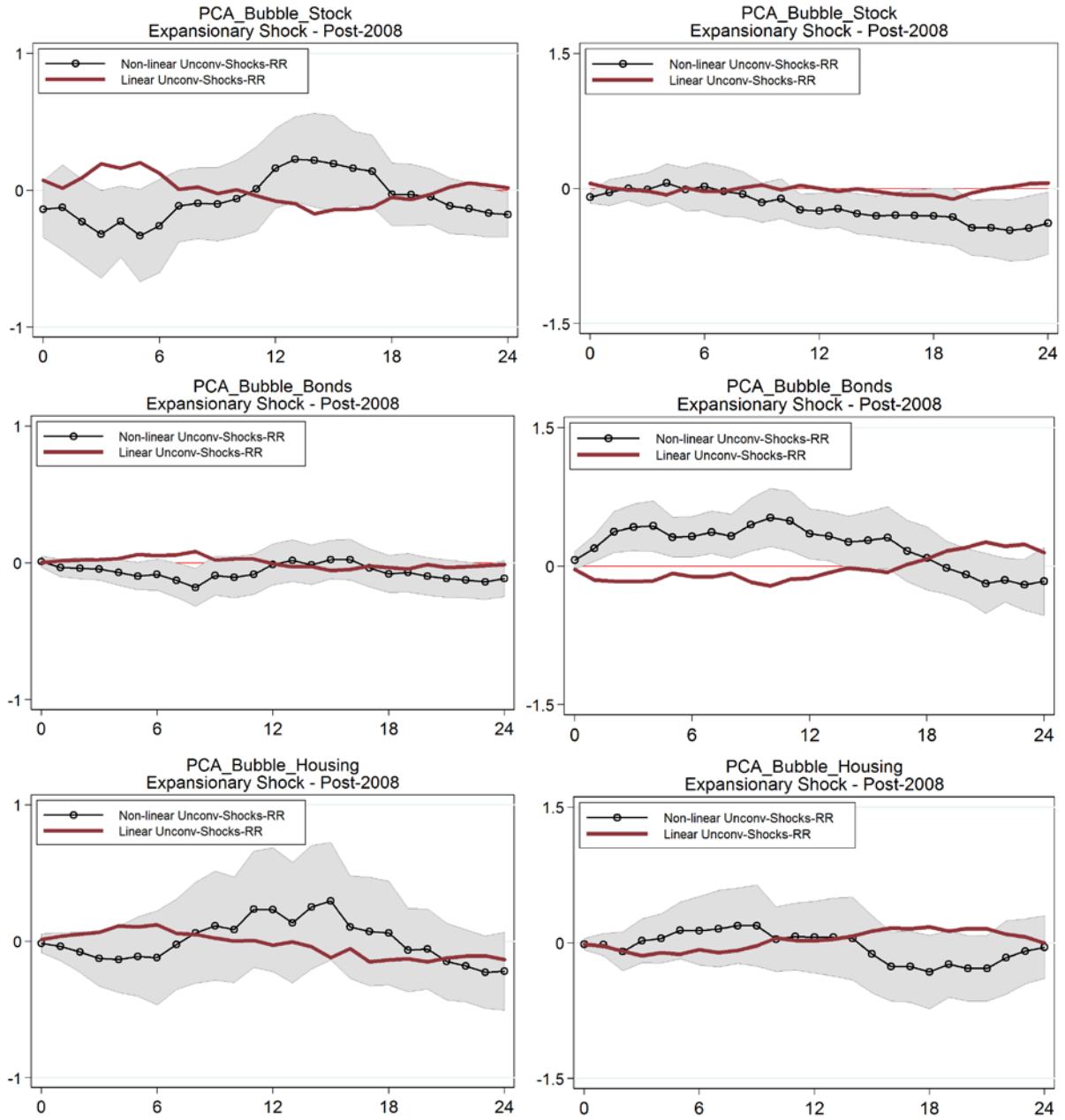
Note: Shaded area represents the 90 per cent confidence interval around the non-linear response.



**Figure 9. Effects of expansionary shocks to unconventional policies**

*United States*

*Euro Area*

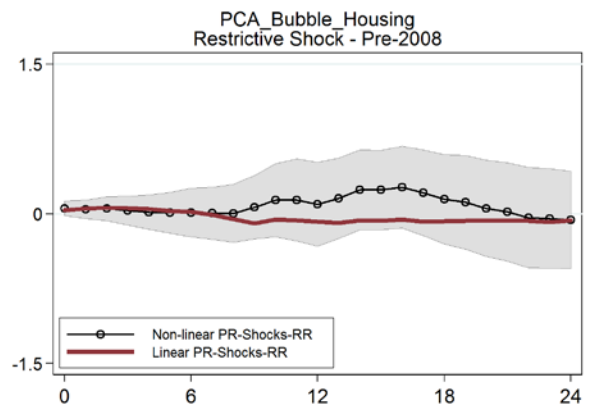
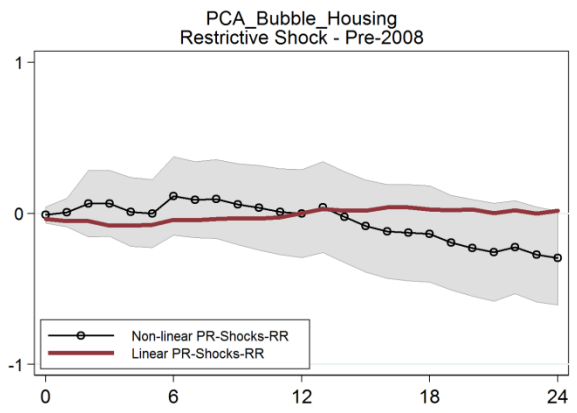
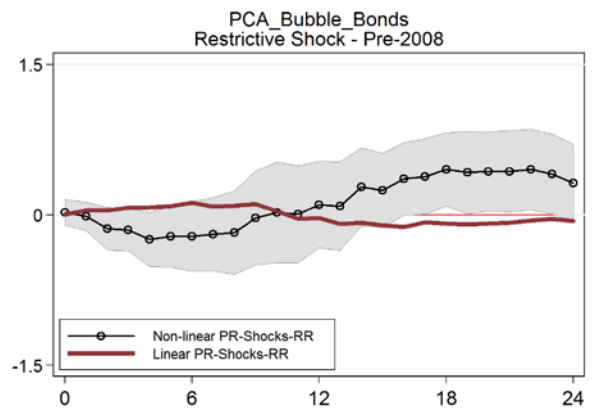
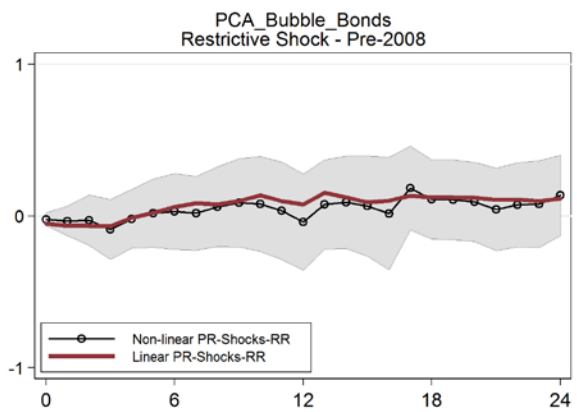
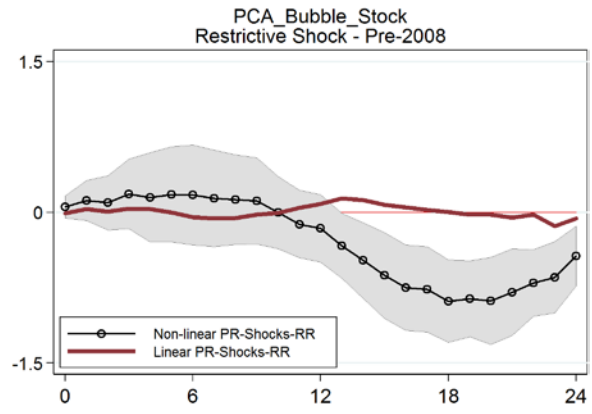
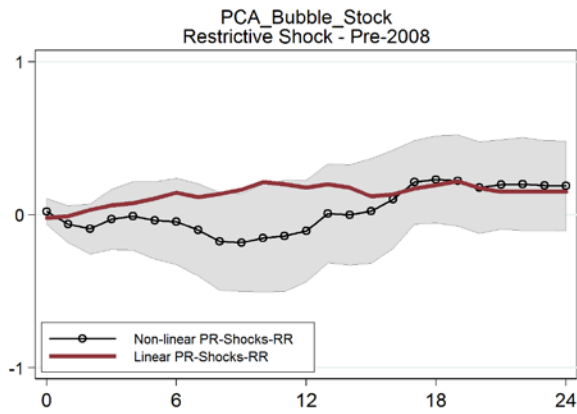


Note: Shaded area represents the 90 per cent confidence interval around the non-linear response.

**Figure 10. Effects of restrictive shocks to the policy rate**

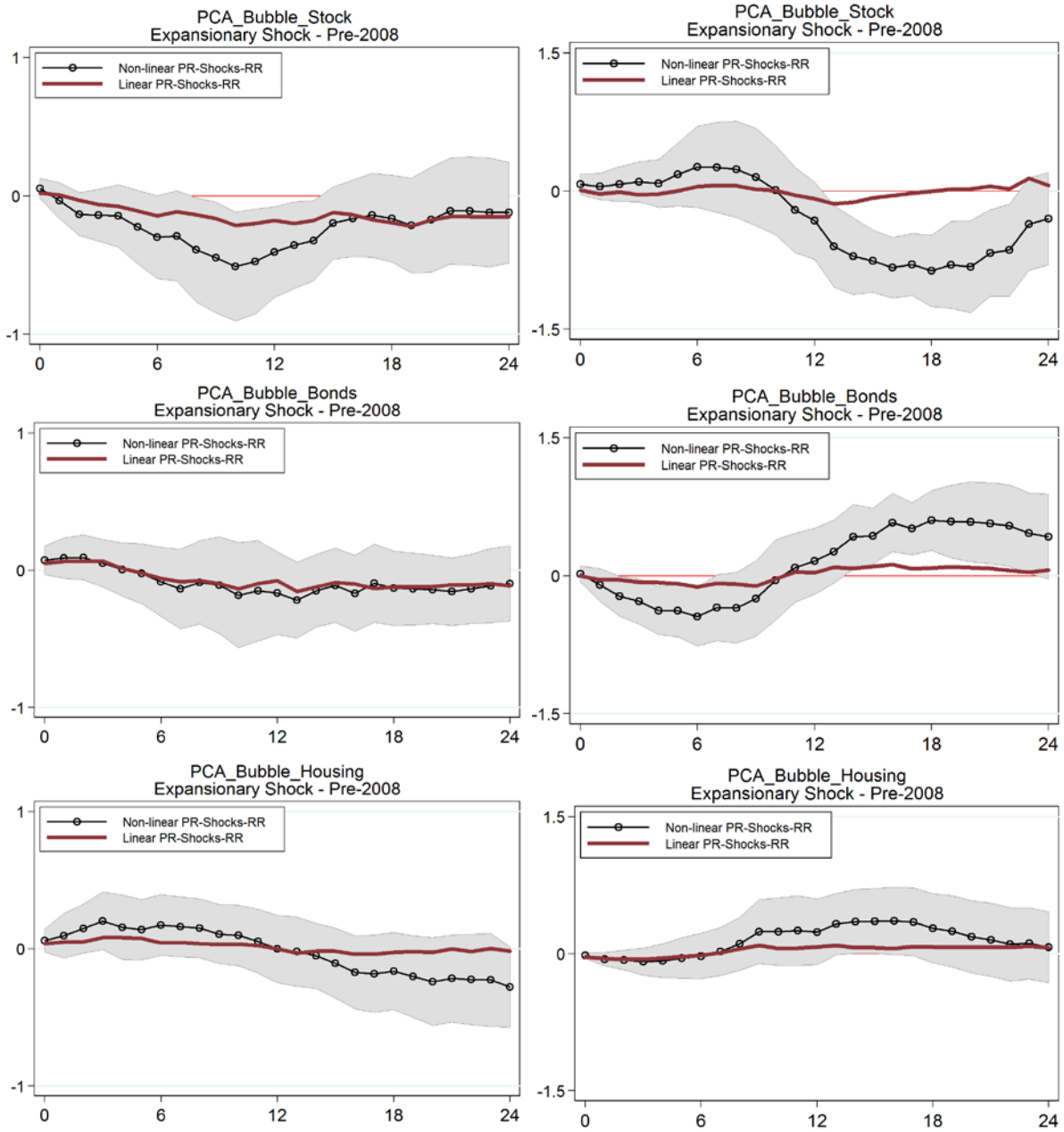
*United States*

*Euro Area*



Note: Shaded area represents the 90 per cent confidence interval around the non-linear response.

**Figure 11. Effects of expansionary shocks to the policy rate**  
*United States* *Euro Area*



Note: Shaded area represents the 90 per cent confidence interval around the non-linear response.

**Table 1. Range of bubble models**

<b>ID</b>	<b>Model</b>	<b>Estimation Method</b>	<b>Bubble identification</b>
<b>r1</b>	Expected cash-flow	OLS	Filtered and cumulated residual
<b>r2</b>	Expected cash-flow	ECM	Filtered and cumulated residual
<b>r3</b>	Data rich information	OLS	Filtered and cumulated residual
<b>r4</b>	Data rich information	ECM	Filtered and cumulated residual
<b>r5</b>	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											
	$\varepsilon^{OLS}$	$\varepsilon^{ECM}$	$v^{OLS}$	$v^{ECM}$		$\varepsilon^{OLS}$	$\varepsilon^{ECM}$	$v^{OLS}$	$v^{ECM}$		
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											
	$\varepsilon^{OLS}$	$\varepsilon^{ECM}$	$v^{OLS}$	$v^{ECM}$		$\varepsilon^{OLS}$	$\varepsilon^{ECM}$	$v^{OLS}$	$v^{ECM}$		
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											
	$\varepsilon^{OLS}$	$\varepsilon^{ECM}$	$v^{OLS}$	$v^{ECM}$		$\varepsilon^{OLS}$	$\varepsilon^{ECM}$	$v^{OLS}$	$v^{ECM}$		
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_Overall	3.50	0.23	0.61	PCA_Overall	3.79	0.25	0.63
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				
	Overall	Stock	Bonds	Housing		Overall	Stock	Bonds	Housing
Overall	1				Overall	1			
Stock	0.64	1			Stock	-0.07	1		
Bonds	0.73	0.29	1		Bonds	0.68	-0.24	1	
Housing	0.74	0.18	0.34	1	Housing	0.84	0.08	0.37	1
Bubble-Fundamental correlation					Bubble-Fundamental correlation				
Bubble:	Stock	Bonds	Housing		Bubble:	Stock	Bonds	Housing	
Fundam.					Fundam.				
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**

<b>United States</b>					
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 <sup>2</sup>
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
<b>Euro area</b>					
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 <sup>2</sup>
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
<b>Asset Prices</b>								
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
<b>Cash-flow model</b>								
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
<b>Data rich information</b>								
Income	rdp	real disposable income	Eurostat	Quarterly	rdp	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	Quarterly
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
<b>Monetary policy</b>								
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
Unconventional 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
<b>Stock</b>											
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
<b>Bonds</b>											
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
<b>Housing</b>											
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

