

Monetary Policy Shocks vs. Bubbles in the Stock and Housing Markets

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Abstract

We study the interactions between monetary policy shocks and stock and housing market bubbles using a Mixed-Frequency VAR that combines monthly data for bubbles with quarterly macroeconomic data. We find that the two bubbles respond immediately to 25 bps monetary policy shocks, with a negative peak response of -2% for the stock market bubble and a positive peak response of 1% for the housing market bubble. However, we also find time-varying responses that show the ability of the Fed to lean against the wind has either dissipated (stock market) or become unclear (housing market).

Keywords: Bubbles, Stock market, Housing market, Mixed-Frequency VAR, Monetary policy

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1. Introduction

Following the last financial crisis, a lot of work has focused on the issue of whether central banks should lean against the wind or not. The debate is not settled yet, although a few contributions should be underscored. Even before the crisis, Bernanke and Gertler (2001) argued that there are no real benefits of central banks reacting to asset prices increases when they have already adopted an inflation targeting regime, while Borio and Lowe (2002) defended the leaning against the wind policies on the basis of historical evidence that periods of rapid asset growth were followed by recessions or financial crises.

In this paper, we investigate several research questions that are not well answered in the literature in relation to the responses of stock and housing market bubbles to monetary policy decisions, such as: Do bubbles in the stock and housing markets respond negatively to monetary policy shocks? How do bubbles affect the GDP? Do bubbles in different markets interact significantly with each other? Have bubble responses changed over time? We also thoroughly test the robustness of the responses to changes in the bubble proxy, selected variables, or model specification. We thus contribute to several strands of literature: the reaction of bubbles to monetary policy, the econometric approach based on a Mixed-Frequency VAR (MF-VAR hereafter) framework and the measurement of bubbles. Below we detail our contributions.

First, we provide new evidence regarding the reaction of stock and housing market bubbles to monetary policy shocks. While some evidence exists with

respect to the reaction of stock market bubbles, the literature on the reaction of housing market bubbles is rather limited.¹ Also, in contrast to previous approaches, we take into account the interactions between the two.

The focus on housing market bubbles is well justified by the literature indicating that recessions following bubbles in this market tend to be deeper and more persistent, see Reinhart and Rogoff (2008) or Jordà, Schularick and Taylor (2015). Another argument is that the housing market plays a key role in the transmission mechanism of monetary policy, see Catte, Girouard, Price and André (2005) or Mishkin (2007). Furthermore, several significant studies point to the buildup of a bubble in the housing market before the last financial crisis, see Fabozzi and Xiao (2019), who identified that a bubble existed before the crisis, or Lai and Van Order (2017), who showed that there was a positive gap between housings prices and fundamentals especially after 2003. Although it is possible to use the theoretical framework in Gali (2014), with imputed rents taken as a proxy for dividends, we don't have similar quality series for housing prices and rents as we do for stock prices and dividends, making the measuring of bubbles in the housing market more difficult.

Second, we contribute to the rapidly growing literature that discusses the role of frequency in determining the reaction function of macroeconomic and

¹Some empirical evidence on the relationship between housing markets bubbles and monetary policy has recently emerged (e.g., André, Caraiani, Čalin and Gupta (2018) or Caraiani and Calin (2020b)).

financial variables to various shocks. The new econometric contribution by Ghysels (2016) showed that the combination of variables at different frequencies in a MF-VAR model enriches our understanding of the impact of shocks. Our paper is related to recent evidence on the dependency of empirical results involving macroeconomic and financial variables to the frequency used. We follow Ghysels (2016) and employ various specifications within the MF-VAR to also test whether the reactions of bubbles in the stock or housing markets are sensitive to the frequency used for the bubble proxies. In contrast to previous approaches, we thus exploit the higher frequency at which bubbles can be measured while retaining the traditional quarterly frequency for the other macroeconomic and financial variables in the model(s).

Third, we take a new look at the relationship between interest rates and bubbles by measuring the latter as the deviation of market prices from their fundamentals. Some of the recent literature has analyzed bubbles using a signal-based approach, e.g. Jordà et al. (2015) measured bubbles using deviations from a HP filter with a high smoothing parameter, while Greenwood, Shleifer and You (2019) identified bubbles by looking at stock prices of US industries that have increased more than 100% over the last two years. The problem with these approaches is that they are not based on economic theory and can lead to situations where fast but rational price movements are mischaracterized as bubbles. In contrast, we quantify bubbles using the more traditional gap between market prices and fundamentals, which are estimated using discounted dividends for the stock market and discounted rents

for the housing market. Because of the ongoing debate about how exactly one can define and measure bubbles, we test several alternative assumptions and perform a thorough robustness analysis.

Finally, we also provide new evidence to answer less debated research questions, such as the impact of bubbles on the real economy, see for example Miao, Wang and Xu (2015) or Caraiani, Luik and Wesselbaum (2020). The former found that bubbles were dominant both in the dot.com crash and in the Great Recession. The latter showed that bursting bubbles can decrease output due to a drop in investments.

The remaining of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the econometric approach. Section 4 presents the data sample, while Section 5 details the procedure for constructing the bubble proxies. Section 6 presents our main results, while Section 7 evaluates robustness to various methodological choices. Finally, Section 8 discusses the results and Section 9 concludes.

2. Literature Review

There are several dimensions in which we organize the literature review. First, we take a look at the theoretical contributions. Second, we review the main empirical results and contrast our approach with the existing contributions in the literature.

2.1. Theoretical Results

Summarizing the theoretical contributions, Barlevy (2018) noted that there is a mismatch between the views of policymakers about bubbles and those of academic economists, as illustrated by the different theoretical models that they consider. This is because the models used in academic work are sometimes hard to implement in policy-making. Nevertheless, there is some evidence that supports the leaning against the wind approach (LATW, hereafter). In the aftermath of the crisis, Svensson (2014) pointed out that, based on the experience of Swedish Riksbank that used leaning against the wind after 2010, there is evidence of it being able to marginally decrease the risk associated with the household debt to income ratio, while raising the risks associated with inflation and unemployment.

A different view is taken by Gali (2014), who proposed an OLG general equilibrium model featuring bubbles in which raising the interest rate leads to an increase in the size of bubbles. This builds on the older overlapping generations growth models in which there are dynamic inefficiencies. The work by Gali (2014) has been subsequently challenged by Miao, Shen and Wang (2019), who showed that the results are determined by the choice for a particular solution to a backward-looking sunspot method around a stable bubbly steady state. However, when one considers a forward-looking minimum state variable solution around a bubbly steady state, the results are rather conventional. Nevertheless, the argument by Gali (2014) is relevant to infinite horizon bubbles but less to information-based models like those

proposed by Conlon (2015) and Doblas-Madrid and Lansing (2016). In the latter models, the prices are determined by expected discounted values of the expectations of agents over the dividends expected by the other agents.

The literature also provides alternative theoretical approaches, such as a framework based on information frictions where the agents involved in trading have different information, see Barlevy (2018). One can then construct states of the economy where, even if everybody knows an asset has no intrinsic value, they are still willing to trade at a positive price since it is not clear whether everyone is informed. An example is given by Conlon (2015), who analyzed whether central banks should lean against the wind in a finite-horizon model with rational agents, asymmetric information, and short-sales constraint. The policy is considered as leaning against the bubble by revealing information about the scale of overpricing. In such a setting, a central bank can deflate bubbles even if it has no informational advantage, with the caveat that not having such an advantage can make the effects of bubble bursting worse. However, the model by Allen, Barlevy and Gale (2018) addresses some of these issues. Building on the earlier work by Gali (2014), they showed that slightly changing the model (by setting that asset prices are uniquely determined such that the multiple equilibria are eliminated) alters the key result that raising the interest rate leads to an amplified bubble. Furthermore, considering credit-driven bubbles and default costs leads to a rationale for leaning against the wind, as even only a commitment to raise the interest rates for persisting bubbles can increase welfare ex-ante.

Another framework is based on borrowing constraints. Here, the key feature is that agents face an environment characterized by binding constraints. However, if agents can borrow additional funds, the welfare could still increase. Since there are restrictions on borrowing while agents still need to borrow, there is an incentive to trade an asset that has no intrinsic value at a positive value, creating a bubble. In the first contributions, the focus fell on the household side, see Bewley (1980) or Santos and Woodford (1997), while latter contributions target the firms' side, see Martin and Ventura (2012) or Miao and Wang (2018).

More recent theoretical research analyzed the link between credit booms and bubbles. Illing, Ono and Schlegl (2018) found that credit or asset booms can mask aggregate demand deficiencies, which depress spending in the long run. This affects mostly deregulated economies and has implications for the leaning against the wind hypothesis. Biswas, Phan and Hanson (2020) linked bubbly phenomena with stagnation episodes. The emergence of risky bubbles can lead to excessive investment booms, followed by inefficient busts. Since risky bubbles can lead to a lower welfare, there is a rationale for leaning against the wind, bubble policies that could potentially address boom-bust trade-offs.

Recent work also addressed the possibility of managing the credit bubbles, see Martin and Ventura (2016). In their approach, the credit is limited by insufficient collateral, resulting in lower levels for output and investments. However, positive shocks to expectations lead to credit cycles, which in this

model result in an expansion in the credit not backed by fundamentals but by credit itself. A so-called credit management agency can optimize the bubble size and maximize output and investments.

Doblas-Madrid and Lansing (2016) developed a model of credit-fuelled bubbles which is based on lenders accepting risky assets as collateral. If there is a boom in asset prices, lenders can allow for further lending, leading to higher prices that further fuel a bubble. The mechanism is based on the greater fool idea, with asymmetrically informed investors trying to profit as much as possible from the bubble acceleration. In the burst phase, unlucky investors will incur losses. The model allows for a positive role for monetary policy which can tame the bubble, in contradiction to the results in Gali (2014).

Finally, Asriyan, Fornaro, Martin and Ventura (2020) proposed a model of bubbles, credit, and money. Here, bubble growth and burst can lead to fluctuations in output and investment. They identify a new channel for monetary policy which emerges when bubble growth is evaluated in nominal terms. There is also a limit on managing bubbles for monetary policy given by the zero lower bound.

2.2. Empirical Results

On the empirical side, the research focused on the relationship between monetary policy shocks and stock market bubbles. Some recent examples include Gali and Gambetti (2015), who build on the theoretical model in

Gali (2014) and provide evidence that monetary policy shocks lead to an increase in bubble size. However, Caraiani and Călin (2018) found that when the shadow interest rate is used, asset prices respond negatively while the response of bubbles is much weaker, though still positive. Another approach was taken by Beckers and Bernoth (2016), who decompose the asset prices into a fundamental component, a risk premium, and a mispricing component. According to them, the mispricing component determines the ultimate impact of monetary policy shocks on excessive stock prices, although they do not identify the sources of mispricing, attributing it to either a violation of the transversality conditions due to subjective expectations or to false expectations of irrational investors about future dividends.

An alternative view is provided by Blot, Hubert and Labondance (2017), who use principal component analysis to construct measures of bubbles based on competing approaches, i.e. statistical, structural, and econometric ones. Their main finding is that the bubble reacts to monetary policy shocks only in the United States, for which the reaction is positive. Blot, Hubert and Labondance (2020) contribute by testing an interesting extension pointing to asymmetric responses of bubbles to expansionary or restrictive monetary policy shocks.

There is also some related work that, although not directly discussing the bubbles in either market, does study the impact of monetary policy shocks either on the stock market, on the housing market, or both. Paul (2020) combines high-frequency monetary policy surprises with the usual selection

of macroeconomic variables in a time-varying VAR framework, finding weaker responses of stock market and housing market prices before the 2007-2009 financial crisis. Furlanetto, Ravazzolo and Sarferaz (2017) focus, on one hand, on identifying the impact of financial shocks on real activity and stock market prices, and, on the other hand, on understanding the composition of such financial shocks. Their results point towards a significant role for financial shocks in driving output and the stock market during the Great Moderation, and also a significant role for financial shocks stemming from the housing market.

Some work has also been done concerning the impact of monetary policy shocks on housing market bubbles. André et al. (2018) use the empirical approach outlined in Gali and Gambetti (2015) to study the time-varying impact of monetary policy shocks on the housing market prices and bubbles in Canada, the United Kingdom, and the United States, finding that both housing prices and bubbles respond negatively to a more restrictive monetary policy. However, there are costs associated with this leaning against the wind policy. Caraianni and Calin (2020b) obtain similar results on a much larger, generalized data sample. The latter paper also studies the comovement of housing market bubbles and monetary policy shocks, identifying that there is not only a common global bubble factor but also regional factors pertaining to more stable or more speculative housing markets.

Our paper differs from the above-mentioned ones in several dimensions. First, our baseline approach is a constant-VAR coefficient, where the focus is

on the mixed-frequency of the data (we discuss the motivation for choosing this particular approach in the next section). However, we also consider subsample analysis and a rolling-window, time-varying approach. Second, this paper also innovates through the simultaneous inclusion of stock and housing market bubbles, while most previous papers focused on one or another. This allows us to analyze how both bubbles react to a monetary policy shock, how bubbles in different markets interact with each other, or the impact of co-bubbles on the real economy, especially the GDP.

3. The MF-VAR model

The econometric framework is based on the mixed frequency (S)VAR approach as proposed in the recent literature by Ghysels (2016). Although there are alternative approaches that deal with the presence of mixed frequencies in VAR models, the approach by Ghysels (2016) does not require the use of filtering. A major advantage of MF-VAR modeling is that it allows for a heterogeneous impact from high-frequency variables on the low-frequency ones. Thus, we are able to combine the usual quarterly frequency series for macroeconomic data with higher-frequency, monthly data available for the stock and housing markets.

3.1. A Single-Frequency SVAR

For comparison, we first consider the standard single-frequency framework. We denote by t each quarter and include in our VAR the quarterly

stock market bubble, denoted by s_t^q , the quarterly housing market bubble, h_t^q , the quarterly GDP, y_t , prices π_t , credit d_t and the interest rate r_t . Besides interest rates, all variables are log differentiated to assure stationarity. We estimate separate models using only the stock market bubbles, only the housing market bubble, or both at the same time. The latter, complete model can be represented as follows (K stands for the lag order):

$$A_c \begin{pmatrix} s_t^q \\ h_t^q \\ r_t \\ \pi_t \\ y_t \\ d_t \end{pmatrix} = \sum_{k=1}^K \begin{pmatrix} a_{11,k} & a_{12,k} & a_{13,k} & a_{14,k} & a_{15,k} & a_{16,k} \\ a_{21,k} & a_{22,k} & a_{23,k} & a_{24,k} & a_{25,k} & a_{26,k} \\ a_{31,k} & a_{32,k} & a_{33,k} & a_{34,k} & a_{35,k} & a_{36,k} \\ a_{41,k} & a_{42,k} & a_{43,k} & a_{44,k} & a_{45,k} & a_{46,k} \\ a_{51,k} & a_{52,k} & a_{53,k} & a_{54,k} & a_{55,k} & a_{56,k} \\ a_{61,k} & a_{62,k} & a_{63,k} & a_{64,k} & a_{65,k} & a_{66,k} \end{pmatrix} \begin{pmatrix} s_{t-k}^q \\ h_{t-k}^q \\ r_{t-k} \\ \pi_{t-k} \\ y_{t-k} \\ d_{t-k} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \\ \epsilon_{5,t} \\ \epsilon_{6,t} \end{pmatrix}$$

The ordering of the variables in this model as well as in the MF-VAR model follows Ghysels (2016), who suggested using the order in which they are publicly announced (see Section 6.1 for details). Here the matrix A_c is a lower triangular matrix that is used to derive the structural shocks.

3.2. A Mixed-Frequency SVAR

In the MF-(S)VAR, we allow a monthly frequency for the two bubbles. This exploits the additional information available in the data. The rest of the variables remain at a quarterly frequency. We denote by s_{jt} the level of the bubble in the stock market in the $j - th$ month of quarter t , with $j = 1, 2, 3$. We proceed similarly for h_{jt} , the bubble in the housing market. Following Ghysels (2016), or the application in Motegi and Sadahiro (2018), the MF-VAR model containing, for brevity, only the stock market bubble can be represented as follows (K stands for the lag order):

$$A_c \begin{pmatrix} s_{1t} \\ s_{2t} \\ s_{3t} \\ r_t \\ \pi_t \\ y_t \\ d_t \end{pmatrix} = \sum_{k=1}^K \begin{pmatrix} a_{11,k} & a_{12,k} & a_{13,k} & a_{14,k} & a_{15,k} & a_{16,k} & a_{17,k} \\ a_{21,k} & a_{22,k} & a_{23,k} & a_{24,k} & a_{25,k} & a_{26,k} & a_{27,k} \\ a_{31,k} & a_{32,k} & a_{33,k} & a_{34,k} & a_{35,k} & a_{36,k} & a_{37,k} \\ a_{41,k} & a_{42,k} & a_{43,k} & a_{44,k} & a_{45,k} & a_{46,k} & a_{47,k} \\ a_{51,k} & a_{52,k} & a_{53,k} & a_{54,k} & a_{55,k} & a_{56,k} & a_{57,k} \\ a_{61,k} & a_{62,k} & a_{63,k} & a_{64,k} & a_{65,k} & a_{66,k} & a_{67,k} \\ a_{71,k} & a_{72,k} & a_{73,k} & a_{74,k} & a_{75,k} & a_{76,k} & a_{77,k} \end{pmatrix} \begin{pmatrix} s_{1,t-k} \\ s_{2,t-k} \\ s_{3,t-k} \\ r_{t-k} \\ \pi_{t-k} \\ y_{t-k} \\ d_{t-k} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \\ \epsilon_{5,t} \\ \epsilon_{6,t} \\ \epsilon_{7,t} \end{pmatrix}$$

Again, this is the structural form, with A_c being used to identify the structural shocks. In the context of the MF-VAR, it is also important to use a structural VAR approach to symmetrically account for the way the high-frequency variables influence each other.² When doing the actual estimation, we use the following unstructured form:

$$\begin{pmatrix} s_{1t} \\ s_{2t} \\ s_{3t} \\ r_t \\ \pi_t \\ y_t \\ d_t \end{pmatrix} = A_c^{-1} \sum_{k=1}^K \begin{pmatrix} a_{11,k} & a_{12,k} & a_{13,k} & a_{14,k} & a_{15,k} & a_{16,k} & a_{17,k} \\ a_{21,k} & a_{22,k} & a_{23,k} & a_{24,k} & a_{25,k} & a_{26,k} & a_{27,k} \\ a_{31,k} & a_{32,k} & a_{33,k} & a_{34,k} & a_{35,k} & a_{36,k} & a_{37,k} \\ a_{41,k} & a_{42,k} & a_{43,k} & a_{44,k} & a_{45,k} & a_{46,k} & a_{47,k} \\ a_{51,k} & a_{52,k} & a_{53,k} & a_{54,k} & a_{55,k} & a_{56,k} & a_{57,k} \\ a_{61,k} & a_{62,k} & a_{63,k} & a_{64,k} & a_{65,k} & a_{66,k} & a_{67,k} \\ a_{71,k} & a_{72,k} & a_{73,k} & a_{74,k} & a_{75,k} & a_{76,k} & a_{77,k} \end{pmatrix} \begin{pmatrix} s_{1,t-k} \\ s_{2,t-k} \\ s_{3,t-k} \\ r_{t-k} \\ \pi_{t-k} \\ y_{t-k} \\ d_{t-k} \end{pmatrix} + A_c^{-1} \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \\ \epsilon_{5,t} \\ \epsilon_{6,t} \\ \epsilon_{7,t} \end{pmatrix}$$

In the case of the MF-VAR model for the housing market, we replace the three components representing the stock market bubbles with those representing the housing market bubbles. In the complete model, which we consider as the baseline specification, we include all components for both bubbles.

While additional data could be used at monthly frequencies, we only

²We thank a referee for pointing out the inherent difficulties of working with mixed-frequency VARs and taking into account properly the impact of high-frequency variables on each other. In other words, the first displayed equation, the dependence of $s_{2,t}$ on $s_{1,t}$, and so on, is encoded in the lower off-diagonal elements of the matrix A_c , but when we move to the second of those displayed equations, that dependence winds up getting encoded in the Cholesky decomposition.

consider the bubble variables for several reasons. First, they reflect fast-moving series that could also be available at higher frequencies (e.g., daily for stock prices). Second, while credit or interest rates are also available at monthly frequencies, including them as such would excessively increase the number of parameters to be estimated. Third, we consider the usual frequencies for the other series (this could be argued for most macroeconomic series, including the interest rate and credit).

4. Data

We apply the MF-VAR on a combined dataset of monthly and quarterly variables compiled from public sources for the case of the United States. The primary sample spans from December 1959 (1959Q4) to March 2021 (2021Q1). A secondary sample that goes back to December 1926 is used for constructing bubble proxies (see Section 5). Unless otherwise stated, all of the data is collected from the Federal Reserve Bank of St. Louis (hereafter FRED). To construct monthly stock market bubbles, we collect inflation-adjusted (real) stock prices, represented by the S&P500 index, and corresponding real dividends from Robert Shiller.³ For the housing market bubble estimates, we collect also from Robert Shiller⁴ the S&P CoreLogic Case-Shiller Home Price index, which proxies real house prices, while for rents we use the Consumer Price Index for All Urban Consumers: Rent

³http://www.econ.yale.edu/~shiller/data/ie_data.xls (accessed November 2021).

⁴<http://www.econ.yale.edu/~shiller/data/Fig3-1.xls> (accessed November 2021).

of primary residence (FRED: CUUR0000SEHA). To assure comparability between the series, we convert the index values into dollar amounts. The house price index is converted into 2019 US dollars by matching the 2019Q2 value of the index to the 2019 Median Sales Price of Houses Sold in the United States (FRED: MSPUS).⁵ Similarly, the rent index is converted into nominal dollars using the Median gross rent reported by the U.S. Census Bureau for 2019⁶ and the resulting series is then expressed in real terms by reconvertng it into 2019 US dollars using the CPI.

All of the other data series used in the MF-VAR are quarterly. In the baseline model, we proxy monetary policy using the end of quarter value for the long-term interest rate, namely the 10-Year Treasury Constant Maturity Rate (FRED: GS10). The choice is based on the necessity of taking into account the recent period of zero lower bound. For robustness, we alternatively use the shadow Fed Funds rate, which is collected from Jing Cynthia Wu’s website.⁷ Inflation is based on the Consumer Price Index for All Urban Consumers: All Items (FRED: CPIAUCSL). Total output is proxied by the Real

⁵The conversion rate used is 322,500 USD for an index value of 175.9713, corresponding for the values observed at the end of the second quarter of 2019. The formula used for the conversion is thus $P_t^r = I_t^r \times 322,500USD \div 174.4389$, where P_t^r is the dollar house price and I_t^r is the house price index, both expressed in real terms.

⁶Data is available from The Institute for Policy & Social Research at <http://www.ipsr.ku.edu/ksdata/ksah/housing/4house10.pdf> (accessed November 2021). The conversion rate is 1,097 USD for an index value of 307.7435 (which represents the median index value for the 12 months of 2019) and the procedure follows the one used for house prices.

⁷<https://sites.google.com/view/jingcynthiawu/shadow-rates> (accessed November 2021).

Gross Domestic Product (FRED: GDPC1), while credit is proxied by Total Credit to Private Non-Financial Sector, Adjusted for Breaks (FRED: QUS-PAM770A).⁸ In the robustness analysis, we alternatively consider the Bank Credit (FRED: QUSNAMUSDA) to Bank Deposits (FRED:SAVINGSL before 2020Q1 and FRED:MDLM after) ratio, which is selected based on the findings of Mathonnat and Minea (2018).

Table 1: Summary statistics for variables included in the baseline MF-VAR model

Statistic \ Variable	s_{1t}	h_{1t}	s_{2t}	h_{2t}	s_{3t}	h_{3t}	r_t	π_t	y_t	d_t
Min	-142.69	-194.06	-101.29	-158.37	-165.62	-145.91	0.68	-15.96	-37.45	-7.18
Max	108.02	134.67	113.46	151.48	187.42	179.96	15.32	17.35	29.11	16.03
Average	0.03	-1.62	1.27	-0.74	-0.86	-0.23	5.96	3.62	2.91	1.28
Std Dev	34.49	25.34	32.69	23.29	36.92	23.3	2.95	3.65	4.49	3.22
Skewness	-0.36	-1.88	0.22	-0.57	0.32	0.56	0.7	0.02	-2.29	0.3
Kurtosis	4.63	21.39	3.58	20.31	7.6	24.59	3.29	6.82	33.34	4.41

Note: $s_{it}, i = 1..3$ denotes the annualized month-on-month log difference in the stock market bubble, estimated as described in Section 5. $h_{it}, i = 1..3$ denotes the annualized month-on-month log difference in the housing market bubble, estimated as described in Section 5. r_t is the interest rate on 10-year government bonds. π_t denotes inflation, the annualized quarter-on-quarter log difference in CPI. y_t denotes economic growth, the annualized quarter-on-quarter log difference in real GDP. d_t denotes credit growth, the annualized quarter-on-quarter log difference in Credit.

With the exception of interest rates, all of the data series are log differentiated, i.e. converted into growth rates, and expressed in annual terms. Specifically, for every level variable X , we compute and use in the MF-VAR model $x_t = (\ln X_t - \ln X_{t-1}) \times N \times 100$, where $N = 12$ for monthly data and $N = 4$ for quarterly data.⁹ This adjustment shifts the first observation in

⁸Our main credit proxy is a measure of the outstanding amount of credit (loans and debt securities) owed by non-financial corporations, households, and non-profit institutions serving households to US domestic banks, all other sectors of the economy, and non-residents.

⁹In an earlier version of the paper we used YoY growth rates, i.e. $x_t = (\ln X_t - \ln X_{t-N}) \times 100$, as it handles for any seasonality in the data. However, this approach has the disadvantage of potentially introducing spurious correlation into the analysis. Nevertheless, we note that using YoY rates leads to more stable impulse responses in the

our sample to 1960Q1. Table 1 reports summary statistics and describes the variables used to estimate the baseline MF-VAR model.

5. Estimating bubbles

In this Section we detail our treatment of bubbles. Although several interpretations exist for bubbles in the literature, including restricted ones such as in Phillips, Wu and Yu (2011) or Greenwood et al. (2019), there is no generally accepted definition. Here, we follow Gali and Gambetti (2015) and decompose real asset prices (denoted P) into a *fundamental* component (denoted F) and a *bubble* component (denoted B). However, to model the effects of monetary policy on both stock and housing market bubbles we choose to use the ratio between market prices and fundamentals, $B_t = P_t/F_t$, which provides a relative measure of the bubble component, as opposed to the absolute difference, $P_t - F_t$. We do this for two reasons. First, it allows for log-differencing (the bubble series that we incorporate in the MF-VAR model is $b_t = (\ln B_t - \ln B_{t-1}) \times N \times 100$, see Section 4). This would not have been possible if using the absolute difference in cases where prices are lower than fundamentals (for negative mispricings). Second, and more importantly, it results in a comparable measure for the bubble component on both the stock and housing markets. These are both incorporated in our baseline

MF-VAR model, but the results are qualitatively very close to the ones that are reported herein, i.e. the responses generally have the same sign and statistical significance. More importantly, the conclusions derived from the analysis are qualitatively similar with YoY rates.

model and using different scales for them would have biased the results. As a consequence, we implicitly loosely define a *bubble* as either positive or negative relative mispricing.

The main difficulty associated with using this interpretation of bubbles is estimating the fundamental value component, which is the theoretical, intrinsic value of the asset.¹⁰ Several approaches exist, each with its own advantages and drawbacks. For example, Shiller (1981) uses a simple backward recursive algorithm, but imposes strict conditions on the price and cash flow processes (e.g., a deterministic trend), while also using ex-post observed data to obtain estimates. This latter step implicitly assumes investors anticipate cash flows with perfect foresight, which, as discussed by Kleidon (1986), is not realistic and should be rather understood as resulting in an *omniscient* estimate for the fundamental value component, which is smoother relative to prices.¹¹ Based on the work of Cochrane (2005), a log-linearized backwards recursive algorithm can be alternatively used, this handling for some of the aforementioned issues. However, this approach also comes with its own drawbacks as, e.g., it assumes a constant long term dividend yield (a stationary yield process), it still requires an arbitrary terminal condition (an assumption

¹⁰In an earlier version we used the expression "rational value". However, bubbles can emerge even if all agents are rational. To be more precise, for both OLG models and the more recent information-based models, the price does not necessarily equal the fundamental value, even if all agents are rational. We thank a referee for highlighting this.

¹¹More specifically, real-world investors constantly revise their opinions about the future as they update their information set through news, whereas for omniscient-type investors there are no news and no revisions, making their *omniscient* fundamental value much smoother. We thank one referee for pointing this out.

on the level of mispricing at the end of the sample), and, most importantly, it is not immune to hindsight bias if applied using ex-post observed data.

Our approach sticks with the classical discounted cash flow (DCF) principle but take steps to handle for the perfect foresight, omniscient value critique. The DCF model states that the fundamental value of an asset is the sum of all future cash-flows, discounted using an appropriate rate of return:

$$F_t = D_t + \mathbb{E}_t \left[\sum_{k>0} \frac{D_{t+k}}{\prod_{i=1}^k (1 + r_{t+i})} \right] = D_t + \mathbb{E}_t \left[\sum_{k=1}^K \frac{D_{t+k}}{\prod_{i=1}^k (1 + r_{t+i})} + \frac{F_{t+K+1}}{\prod_{i=1}^{K+1} (1 + r_{t+i})} \right], \quad (1)$$

where D_{t+k} denotes the cash-flow obtained k periods into the future¹², r_{t+i} denotes the discount rate applicable to the cash flows obtained in the period $(t + i - 1) \rightarrow (t + i)$, and all values are conditionally expected on the information available at time t . The main question is how to estimate future expected cash-flows $\hat{D}_{t+k} \equiv \mathbb{E}_t[D_{t+k}]$ and discount rates $\hat{r}_{t+k} \equiv \mathbb{E}_t[r_{t+k}]$, at each moment in time, in a way that minimizes or eliminates hindsight bias.

5.1. Baseline approach

Our baseline approach borrows from a broad literature (e.g., Bernanke and Kuttner (2005), Brunnermeier and Julliard (2008), Campbell, Giglio and Polk (2013), Beckers and Bernoth (2016)), and is based on obtaining estimates from an auxiliary VAR model that only uses data that is contemporaneously available to investors. Specifically, for each t in the sample, we

¹²Note that D_{t+k} is the cash-flow accrued in the period $(t + k - 1) \rightarrow (t + k)$.

fit the following VAR model using historically observed data:

$$Y_t = A + \sum_{l=1}^L B_l Y_{t-l} + u_t \quad (2)$$

where Y is a vector of endogenous variables, A is a vector of intercepts, B is a matrix of coefficients, L is the lag length, and u represents i.i.d. errors. We use two distinct auxiliary VARs for the stock and housing markets, respectively. To the set of endogenous variables in each VAR we first add the log prices and log cash flows (dividends for the stock market and rents for the housing market). For the stock market VAR, we follow Campbell et al. (2013) and consider as additional predictors the log price-earnings ratio (where the earnings data are smoothened using a ten-year trailing moving average), the term yield spread, the small-stock value spread, and the default spread.¹³ For the housing market VAR, we follow Brunnermeier and Julliard (2008) and include the log price-rent ratio (where the rent data are smoothened using a ten-year trailing moving average), a one year moving average on the log rent growth rate, and a one year exponentially smoothed moving average of inflation. To this we add the Monthly Supply of Houses in the United States (FRED: MSACSR) to account for liquidity in the housing market.¹⁴

¹³See Campbell et al. (2013) for details on how the variables are constructed.

¹⁴We thank one referee for suggesting this improvement and pointing out that illiquidity is a major challenge for properly assessing fundamental values in the housing market and also that this may partially explain the lack of empirical literature on housing bubbles. We also note that other liquidity measures could have been used, such as the time on the market (TOM), i.e. the number of days between listing a property and selling a property. However, Famiglietti, Garriga and Hedlund (2020) report that they obtain similar results

We apply the auxiliary VARs starting in 1959Q4 using a quarterly data sample that begins in 1926Q4.¹⁵ As we advance through the quarters, newly available data is added to this initial sample. Some variables are missing in the early years, e.g., MSACSR is available from FRED only after 1964. Because of this, at each moment in time we disregard variables that do not meet a minimum requirement of 13 available (historical) observations. Each time we estimate the VARs we choose the optimum lag length $1 \leq L \leq 4$ using the BIC. Finally, because of stability issues, we actually estimate the VARs using differentiated variables and then reconstruct level prices and cash flows from the estimated growth rates.

Crucially, the set of endogenous variables considered in each auxiliary VAR includes prices and cash flows. This allows us to use the model and forecast future occurrences of these quantities K periods into the future:

$$\hat{Y}_{t+k} = A + \sum_{l=1}^L B_l \hat{Y}_{t+k-l}, \forall 1 \leq k \leq K \quad (3)$$

The resulting expected cash flow and price series help estimate the funda-

when using either TOM or MSACSR.

¹⁵A quarterly frequency is preferred because some important variables, such as dividends, are only reported on a quarterly basis. To compute monthly bubbles, we use monthly fundamental values that are obtained via linear interpolation from the quarterly series.

mental value using:

$$\hat{F}_t = D_t + \sum_{k=1}^K \frac{\hat{D}_{t+k}}{\prod_{i=1}^k (1 + \hat{r}_{t+i})} + \frac{\hat{P}_{t+K}}{\prod_{i=1}^K (1 + \hat{r}_{t+i})}, \quad (4)$$

or

$$\hat{F}_t^* = D_t + \sum_{k=1}^K \frac{\hat{D}_{t+k}}{(1 + \bar{r})^k} + \frac{\hat{P}_{t+K}}{(1 + \bar{r})^K}, \quad (5)$$

where $\hat{P}_{t+K}$ is the *terminal value*, i.e. the estimated price of the asset at $t + K$, $\hat{r}_{t+i} = \frac{\hat{D}_{t+i} + \hat{P}_{t+i} - \hat{P}_{t+i-1}}{\hat{P}_{t+i-1}}$ is the time-varying discount rate, and $\bar{r} = \sqrt[K]{\prod_{i=1}^K (1 + \hat{r}_{t+i})} - 1$ is the geometric mean discount rate in the forecast period. For small forecast horizons, the fundamental value estimates are sensitive to the type of discount rate used (constant or time-varying). However, when the forecasting horizon is large, Equations (4) and (5) provide identical results. Choosing $K = 400$, representing 100 years of quarterly forecasts, eliminates the sensibility and falls within the second category.

5.2. Alternative approaches

The resulting procedure estimates fundamental values at each moment in time with negligible hindsight bias. As a robustness check, we compare the results with several alternative approaches. The baseline fundamental value estimate (denoted *DCF*) and all following alternatives are plotted in Figure 1. The associated series of relative bubble proxies, $\hat{B}_t = P_t / \hat{F}_t$, are plotted in Figure 2, while Table 2 reports summary statistics on them.

First, similar to Bernanke and Kuttner (2005), we estimate a single VAR

Figure 1: Fundamental Value Proxies ($\hat{F}$) vs. Prices (P)

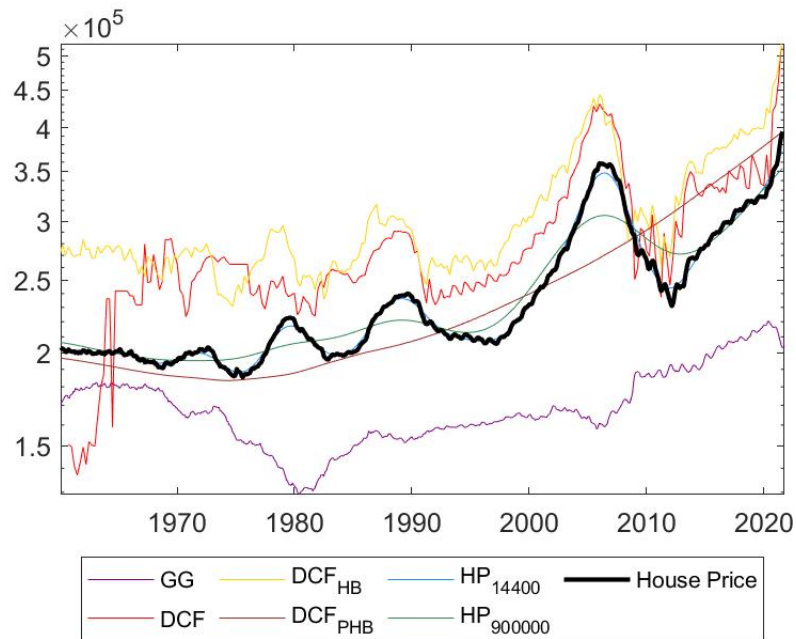
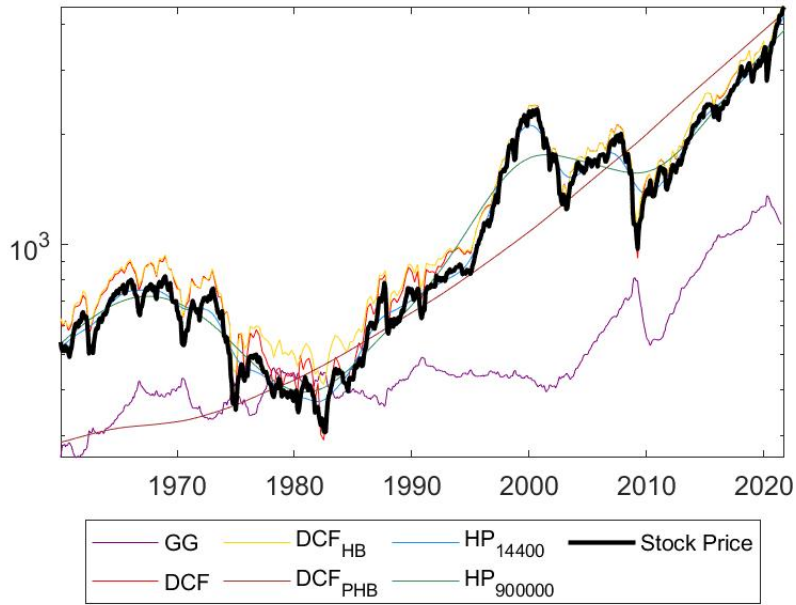


Figure 2: Bubble Proxies ($\hat{B}$)

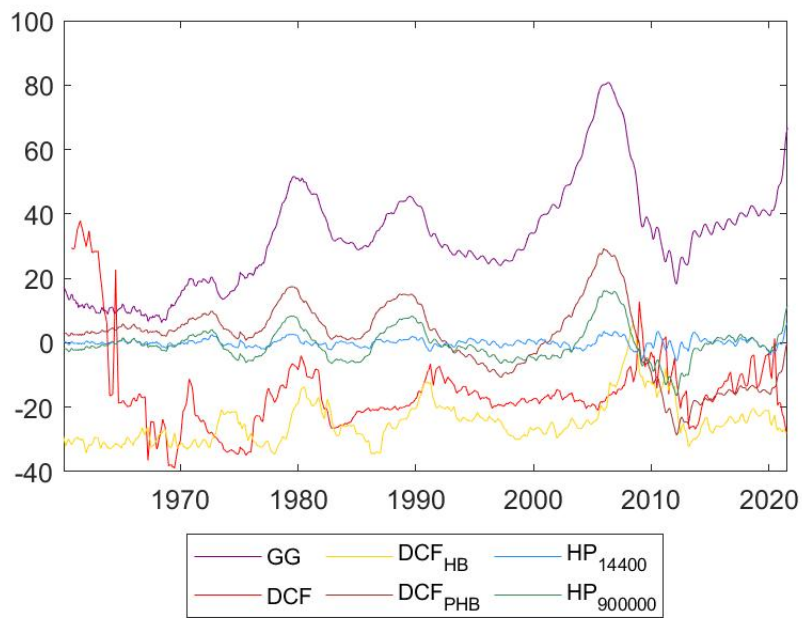
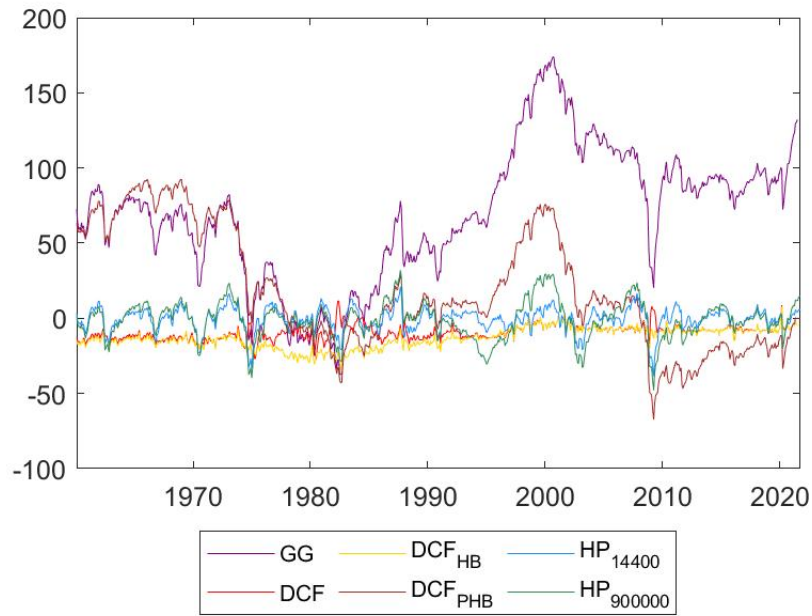


Table 2: Summary statistics for bubble proxies ($100 \times \log$ price-to-fundamental ratio)

Panel A: Stock market bubble proxies									
Variable	Min	Average	Max	StDev	Skewness	Kurtosis	P_{25}	Median	P_{75}
GG	-37.45	69.26	174.05	44.00	-0.10	2.78	42.54	71.79	94.83
DCF	-27.24	-9.45	11.71	4.89	0.32	4.66	-12.82	-9.39	-6.71
DCF_{HB}	-35.55	-13.01	7.76	6.59	-0.35	2.77	-17.09	-12.92	-7.84
DCF_{PHB}	-67.42	18.16	92.69	38.83	0.37	1.99	-12.62	9.85	56.67
HP_{14400}	-38.52	-0.50	20.85	7.81	-1.07	5.45	-4.10	0.35	4.42
HP_{900000}	-47.93	-1.24	32.03	12.51	-0.26	3.60	-8.12	-0.64	6.05

Panel B: Housing market bubble proxies									
Variable	Min	Average	Max	StDev	Skewness	Kurtosis	P_{25}	Median	P_{75}
GG	6.22	32.72	80.80	16.39	0.71	3.55	20.25	31.99	41.16
DCF	-38.96	-15.26	37.89	12.78	1.93	8.35	-20.73	-17.29	-11.75
DCF_{HB}	-34.64	-24.67	5.84	6.79	1.43	5.89	-29.68	-25.90	-21.65
DCF_{PHB}	-28.68	1.28	29.27	11.45	-0.19	2.93	-6.31	3.00	7.86
HP_{14400}	-5.67	-0.04	6.07	1.38	-0.02	5.00	-0.74	-0.04	0.63
HP_{900000}	-16.42	-0.41	16.29	5.30	0.65	4.34	-4.02	-1.02	1.86

Panel C: Correlation matrix of bubble proxies

Stock market							Housing market						
	GG	DCF	DCF_{HB}	DCF_{PHB}	HP_{14400}	HP_{900000}		GG	DCF	DCF_{HB}	DCF_{PHB}	HP_{14400}	HP_{900000}
GG	1.000						GG	1.000					
DCF	0.295	1.000					DCF	-0.034	1.000				
DCF_{HB}	0.922	0.456	1.000				DCF_{HB}	0.515	0.137	1.000			
DCF_{PHB}	0.249	-0.334	0.068	1.000			DCF_{PHB}	0.369	-0.072	0.031	1.000		
HP_{14400}	0.282	0.021	0.241	0.253	1.000		HP_{14400}	0.251	-0.065	-0.089	0.308	1.000	
HP_{900000}	0.376	0.075	0.285	0.421	0.790	1.000	HP_{900000}	0.582	-0.011	0.137	0.719	0.591	1.000

Note: GG denotes the fundamental value/bubble proxy estimated using the Gordon Growth model with no hindsight bias. DCF denotes the (baseline) fundamental value/bubble proxy estimated using an auxiliary VAR model, whose parameters are re-estimated at each moment in time using only historically available data. DCF_{HB} denotes the fundamental value/bubble proxy estimated using an auxiliary VAR model, whose parameters are estimated only once using all available information. DCF_{PHB} denotes the (omniscient) fundamental value/bubble proxy estimated following Shiller (1981). HP_{14400} denotes fundamental value/bubble proxy estimated using a Hodrick-Prescott filter with a small smoothing parameter, $\lambda = 14400$. HP_{900000} denotes fundamental value/bubble proxy estimated using a Hodrick-Prescott filter with a large smoothing parameter, $\lambda = 900000$. See text for detailed explanations.

model using the entire data sample and then apply this model to estimate fundamental values (denoted DCF_{HB}) at each historical moment in time. This approach is computationally more efficient but suffers from some hindsight bias, as forecasts at the beginning of the sample are based on a model whose coefficients are estimated using yet unobservable information. Figure

1 indeed shows that the results are different in the early years, especially before 1990, but are afterwards fairly close to the baseline. However, as observed in Figure 2 and in Table 2, this alternative leads to a higher average (negative) bubble compared to the baseline.

Second, we compare our baseline with a perfect foresight alternative (denoted DCF_{PHB}) that is based on Shiller (1981), but without assuming a deterministic trends for the price and cash flow processes. Specifically, we set $\hat{F}_T = P_T$ and then compute $\hat{F}_t = \frac{D_t + \hat{F}_t}{(1 + \bar{r})}, \forall t < T$, where P_T is the price observed at the end of the sample, D_t are ex-post observed dividends, and $\bar{r}$ is the full-sample geometric mean total return for stocks/houses. Figure 1 shows that this proxy is much smoother compared to the baseline, while Figure 2 and Table 2 show that the associated bubble proxy is on average larger (positive) and more volatile compared to the previous two alternatives.

Third, recognizing that our baseline model still suffers from minor hindsight bias—as the VAR model was only available to investors after being introduced by Sims (1980)—we estimate a simpler, yet possibly naïve version based on the Gordon growth model:

$$\hat{F}_t = \frac{D_t(1 + \bar{g})}{(\bar{r} - \bar{g})} \quad (6)$$

where the constant dividend growth ($\bar{g}$) and discount ($\bar{r}$) rates are estimated at each moment in time t using the geometric mean of historically observed values (up to t). The resulting bias-free proxy tends to underestimate the

fundamental value component and overestimate the bubble component, the latter in this case also being the most volatile among all alternatives.

Finally, we also make a comparison with the alternative definition of fundamental values based on the Hodrick-Prescott filtering methods (see, e.g., Jordà et al. (2015)). We estimate two versions, one with a small smoothing parameter, $\lambda = 14400$ (denoted HP_{14400}) and another with a high smoothing parameter, $\lambda = 900000$ (denoted HP_{900000}). These proxies closely follow the price series and indicate the lowest average mispricing among the alternatives. They are also much smoother compared to the other proxies and prices, which is not surprising, since *filtering* basically means *smoothing* by definition. However, we note that all fundamental value proxies are smoother compared to prices, this presumably occurring because real investors are responding to information shocks not observed by the economist.

Overall, our analysis shows that different choices lead to different proxies for both stock and housing fundamentals. This highlights the many complications and uncertainties associated with empirical studies of fundamental values and bubbles, which may partially explain why consensus is so difficult to reach in the literature. Nevertheless, the analysis also reveals that the different proxies significantly correlate with each other in some cases and, interestingly, tend to identify similar important bubble episodes.

6. MF-VAR results

6.1. Identification

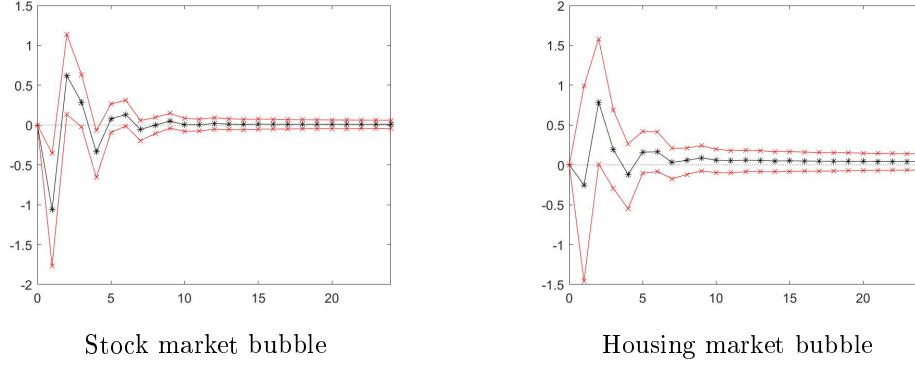
While studies like the one by Gali and Gambetti (2015) identify interest rate shocks using a traditional setup based on the Cholesky ordering of the variables, here we follow the setting proposed by Ghysels (2016). According to his approach, the Cholesky ordering of the variables should be done according to the "time-stamp" or the order in which they are announced. That is, high-frequency variables should stand first, followed by the quarterly ones. For quarterly variables, the timing of announcements should also decide their order. In the end, for the low-frequency VAR the following order is used: $s_t^q \rightarrow h_t^q \rightarrow r_t \rightarrow \pi_t \rightarrow y_t \rightarrow d_t$. For the MF-VAR we use: $s_1 \rightarrow h_1 \rightarrow s_2 \rightarrow h_2 \rightarrow s_3 \rightarrow h_3 \rightarrow r_t \rightarrow \pi_t \rightarrow y_t \rightarrow d_t$.

Based on the information criteria, we use 2 lags for the low-frequency VAR and the MF-VAR with stock or housing market bubbles. However, using a different number of lags does not significantly change the results.

6.2. Baseline Results

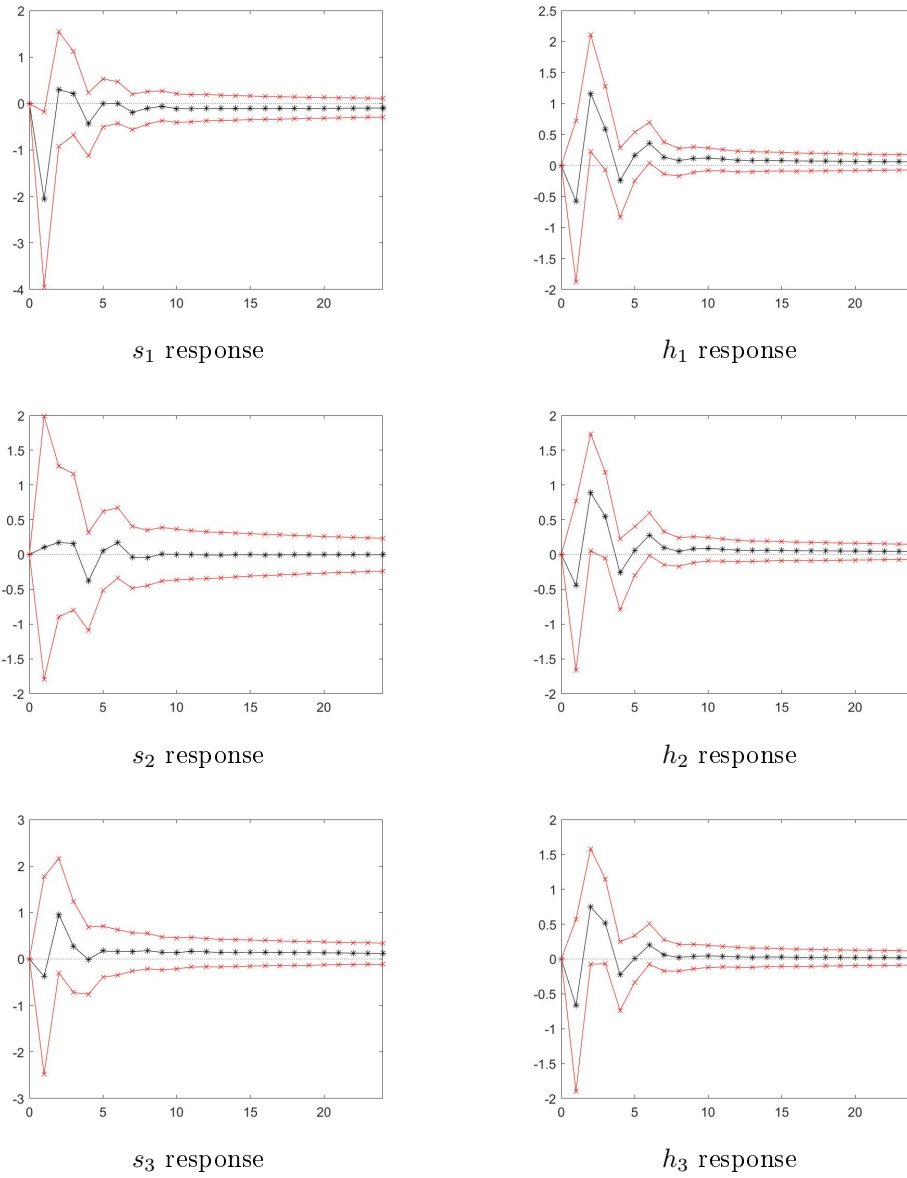
Our main focus rests on the reaction of stock and housing market bubbles to monetary policy shocks. We consider interest rate shocks amounting to 25 basis points and make inferences following standard approaches in the literature. The main results are reported in Figure 3 for the low-frequency VAR and Figure 4 for the MF-VAR.

Figure 3: Bubble responses to interest rate shock, Low-frequency VAR



Two results are worth outlining. First, both the low-frequency VAR and the MF-VAR indicate a negative response of stock market bubble but a positive response by housing market bubble to an increase in the interest rates. Stock market bubble responses are immediate and strong but are less persistent. In contrast, housing market bubbles have a more persistent response, reacting also immediately but weaker and positively to monetary policy shocks. In terms of magnitude (using the MF-VAR model), the peak response of the stock market bubble is about -2% after 1 quarter, while for the housing market bubble is over 1% after 2 quarters. Second, we find that the results differ in the MF-VAR compared to the low-frequency VAR, this echoing the results in Ghysels (2016). When the MF-VAR model is considered, the peaks of the two bubble responses are significantly stronger. This implies that the traditional low-frequency VAR framework underestimates the impact of monetary policy shocks on bubbles in the stock and housing

Figure 4: Bubble responses to interest rate shock, (High-frequency) MF-VAR



markets (the effects if -2% versus -1% for the stock market bubble and of 1.2% versus 0.8% for the housing market bubble).

6.3. Further Results

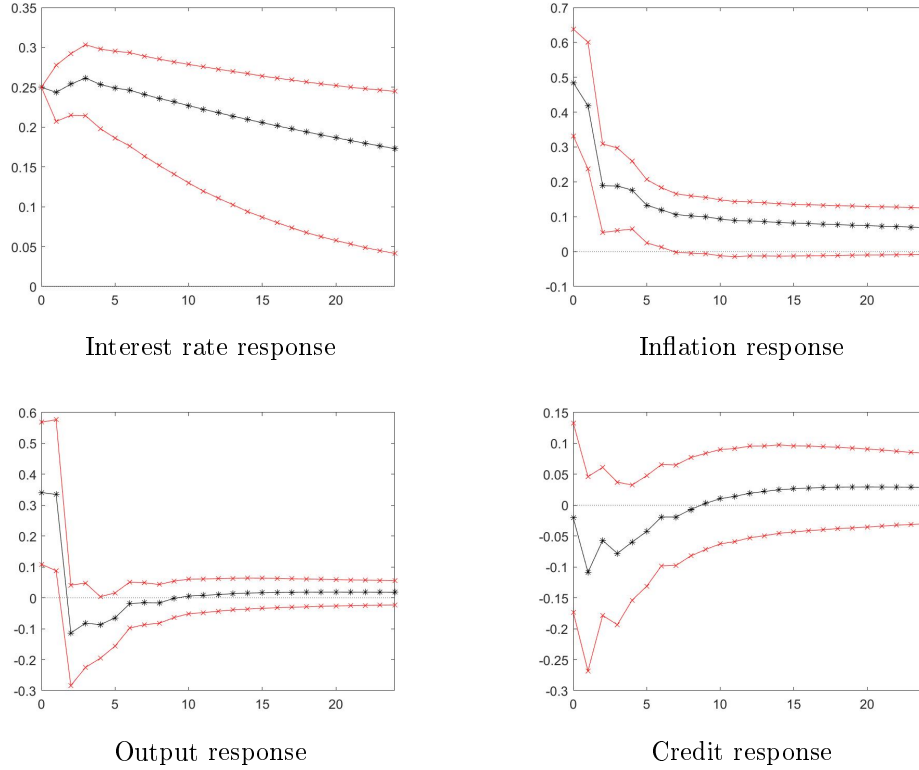
We extend the analysis by looking at other relevant results in terms of impulse response functions, which are constructed by considering a 1% shock for all variables apart from interest rates. All additional results are reported in the Internet Appendix. First, we compare the impact that housing and stock market bubbles have on each other, see Appendix A for the low-frequency VAR and Appendix B and Appendix C for the mixed frequency VAR. For the low-frequency VAR, we find that stock and housing market bubbles do not influence each other in a statistically significant manner, but that they display mean-reverting autoregressive behavior: shocks in either bubble tend to partially revert in the following periods. The evidence from the MF-VAR model supports this latter finding, but not the former one. Specifically, it points to a positive and significant responses of the stock market bubble to the housing counterpart, with a peak impact of about 1% (significant at the 5% level).

Second, we analyze the impact of bubbles on GDP, see Appendix D. The evidence is mixed in this regard, in that both bubbles lead to predominantly negative responses that are not however very persistent. The peak impacts are about 0.05 to 0.15 percentage points.

Third, we also analyze the impact of credit on the two bubbles, see Appendix E. We find no significant impact in the baseline model, although when changing the credit proxy in the robustness analysis (see Section 7.6), the results become stronger for the response of housing bubbles as compared to

the baseline case.

Figure 5: Other variable responses to interest rate shock in MF-VAR



Finally, we take a look at the responses of the other variables to monetary policy shocks. The results are reported in Figure 5 and show that inflation reacts initially positive, which is related to the price puzzle, typical for structural VARs. Although there is a surprising first positive response by output, this quickly and rather persistently goes in the negative territory. The reaction of credit is negative in the short run but not statistically significant. Although the results show some limitations of the framework used

here (for example, in the case of inflation), our main purpose is to focus on the analysis of bubbles. This is in the spirit of Gali and Gambetti (2015), who obtain similar results for their responses of macroeconomic variables to monetary policy shocks.

7. Robustness

We test the robustness of bubble responses by re-estimating the MF-VAR model with different methodological choices, namely using alternative bubble proxies, changing the identification approach (i.e. varying the order of the variables), directly using fundamental values (and prices) as endogenous variables, taking only one bubble at a time, considering a different interest rate, using a different credit variable, or a combination of the above. We also check for potential asymmetric and time-varying responses of the two bubbles. In the following subsections, we only refer to the most noteworthy results.

7.1. *Using Different Bubble Proxies*

As discussed in Section 5, fundamental value and bubble proxies are sensitive to various methodological assumptions. Would the results change when using other definitions? Here, we present three alternatives. The first is an *omniscient* measure, which uses ex-post observed data to estimate fundamentals. The second is an hindsight bias-free measure, relying on contemporaneously available data and methods (the Gordon Growth model) to

estimate fundamentals. The third is based on the HP filter with $\lambda = 900,000$ and is similar to the one in Jordà et al. (2015). The results are reported in Appendix F, Appendix G, and Appendix H, respectively.

For all alternatives we find the same negative and significant short-term response of stock market bubbles to interest rates, this even being more pronounced (having a peak of almost -4%) in the case of the naïve proxy. In contrast, changing the proxy points to a positive and insignificant short-term response of housing market bubbles to interest rates, but to negative and sometimes significant responses in the medium term. Nevertheless, the peak negative responses are relatively small (-0.2% at best).

7.2. Using a Different Variable Order

Up until now, we have implemented identification following the approach outlined by Ghysels (2016), with variables ordered according to their time stamp or the order of announcement. In this subsection, we consider a more conventional ordering, adapted from the standard in macroeconomics, namely: $s_1 \rightarrow h_1 \rightarrow s_2 \rightarrow h_2 \rightarrow s_3 \rightarrow h_3 \rightarrow d_t \rightarrow y_t \rightarrow \pi_t \rightarrow r_t$. Also, we test an ordering adapted from the approach of Gali and Gambetti (2015), namely: $y_t \rightarrow \pi_t \rightarrow r_t \rightarrow d_t \rightarrow s_1 \rightarrow h_1 \rightarrow s_2 \rightarrow h_2 \rightarrow s_3 \rightarrow h_3 \rightarrow$.¹⁶

The variables remain the same as in the baseline case, while the econometric framework is the MF-VAR model with 2 lags. We find that the results,

¹⁶While the ordering exactly follows Gali and Gambetti (2015), the variables slightly differ. Specifically, Gali and Gambetti (2015) additionally incorporate the log difference in commodity prices, while we consider a credit variable.

which are shown in Appendix I and Appendix J, respectively, do not significantly change. The main difference is that the negative responses of the stock market bubbles are now stronger in the second identification strategy, with a peak around -2.5%. The housing market bubble reacts again positively and statistically significant for the first ordering, while it remains positive although borderline significant for the second ordering.

The results imply that the partial differences between our results and the ones reported in Gali and Gambetti (2015) cannot be explained by variable orderings, but instead should be due to the difference in how bubbles are treated in the model. At the same time, we point that the two methodologies (ours and the one in Gali and Gambetti (2015)) are not fully compatible by default in terms of bubble measurement (though we tried to make them as close as possible). It is not our intention to derive a perfect comparison to the work of Gali and Gambetti (2015), as there are both common points (determining the fundamental value based on dividends and the bubble from comparing prices and fundamentals) and differences (we measure the bubble before estimating the VAR model, while they measure only the implicit response of bubbles to IRFs as the difference between the response to asset prices to monetary policy shocks and the response of the fundamental value to the monetary policy shocks).

7.3. Adding Fundamental Values to the Model

Some recent papers on the impact of monetary policy on asset mispricing directly use price, dividend, and/or fundamental variables in the model to infer the response of bubbles to monetary policy (e.g., Gali and Gambetti (2015), Beckers and Bernoth (2016)). As a result, we also test if the results change when including the fundamental value variable in the MF-VAR model or when further using real market prices instead of the bubble variable.

The results obtained when adding fundamental values to the MF-VAR model are presented in Appendix K, showing that the responses of the stock bubble is quantitatively very similar (the peak response is of about -2.5%) and has similar persistence, while the response of the housing bubble is even stronger (the peak response is now closer to 1.5%) and more persistent. The results obtained when also substituting bubbles with prices are presented in Appendix L, showing that the influence of monetary policy on prices is similar to the response of bubbles in the case of the stock market, though stronger and more persistent, but becomes negative for the housing market.

Taken together, the results imply that (1) stock prices are more sensitive to interest rates compared to stock fundamentals, and (2) housing prices are less sensitive to interest rates compared to house fundamentals. In other words, bubbles tend to arise from the overreaction of stock prices and the underreaction of house prices to monetary policy decisions.

7.4. Taking Bubbles Separately

In the baseline model we considered the two bubbles together. However, we also estimate a MF-VAR model with the same setting but including only one type of bubble at a time. The results, shown in Appendix M, do not substantially differ: The magnitudes are similar, with a peak response of about -2% and 1% for the stock and housing markets, respectively.

7.5. Using a Different Interest Rate Measure

As previously noted, we also consider the shadow interest rate as proposed by Wu and Xia (2016). This interest rate measures the actual stance of the Fed when the nominal interest rate hits the zero lower bound. However, in normal times, its value is very close to that of the federal funds rate.

The results obtained when substituting GS10 with the shadow rate are shown in Appendix N, and are generally in line with the baseline results. *For the low-frequency VAR (not reported), the results are similar for both the stock market bubble response (the peak slightly drops to less than -2.0%) and housing market bubble response (the peak is similar, although not statistically significant).* In the MF-VAR case, the responses remain about the same for the stock market bubbles (the peak response is significant at about 2%), while for the housing market bubbles are not statistically significant anymore.

7.6. Using Alternative Measures for Credit

The work by Jordà et al. (2015) and others has put in focus the fact that credit variables are a good signal for the occurrence of speculation booms

that are followed by financial crises. Reviews of the literature regarding financial development, the level of credit in the economy, and the occurrence of financial crises can be found in Jordà et al. (2015) or Mathonnat and Minea (2018). Here, we draw attention to the findings in Mathonnat and Minea (2018) who, using a large dataset combining multiple countries and various variables reflecting the credit level in the economy, found, in contrast to previous studies, that it is the level of bank's credit over GDP that provides a very strong signal for the probability of crisis occurrence. To test whether changing the measurement of credit stance in the economy matters, we run the baseline MF-VAR model but replace the credit variable using the ratio of credit to deposit for banks.

The results, presented in Appendix O, do not drastically change compared to the baseline. However, we notice that housing market bubbles react in a stronger manner now, the peak response being close to 1.5%.

7.7. The Role of Asymmetries

In this subsection, we investigate possible asymmetries in the transmission of monetary policy shocks to bubbles. Some recent work has suggested that monetary policy has an asymmetric role depending on if one considers positive or negative shocks, or state-dependent effects with respect to the position within the business cycles, for example. A study outlining the state-dependent effects of monetary policy shocks is due to Tenreyro and Thwaites (2016), while Blot et al. (2020) analyzed the asymmetric impact of monetary

policy shock on stock market bubbles. As in Blot et al. (2020) and the related literature, we test for asymmetries (i.e. for differences in the magnitude of responses) using a local projection approach specified as:

$$s_{t+h} = \alpha_h + \beta_h * \epsilon_t^+ + \gamma_h * h_t + \delta * X_t^c + \eta_{t+h} \quad (7)$$

for positive monetary policy shocks (implying an contractionary policy, defined as $\epsilon_t^+ = \max\{\epsilon_t, 0\}$) and:

$$s_{t+h} = \alpha_h + \beta_h * \epsilon_t^- + \gamma_h * h_t + \delta * X_t^c + \eta_{t+h} \quad (8)$$

for negative monetary policy shocks (implying an expansionary policy, $\epsilon_t^- = \min\{\epsilon_t, 0\}$) on stock bubbles; with a similar specification being used for housing bubbles, h_{t+h} .¹⁷ Here, ϵ_t are the monetary policy shocks derived on the basis of the baseline MF-VAR, while X_t^c is a vector of controls consisting in inflation, GDP and a credit measure. We consider robust standard errors and a horizon for impulse response functions of 24 periods. The effects of shocks are cumulative. The results are shown in Appendix P.

When distinguishing between contractionary (positive) and expansionary (negative) monetary policy shocks, we find different behaviors. On one hand, even though it follows the general pattern, the response of housing market bubbles is more persistent following an expansionary shock. Also, the behav-

¹⁷Blot et al. (2020) also include interaction terms in the model. However, following this particular specification does not significantly alter the results in our case.

ior of the house market bubbles is reversed with respect to sign when shocks are restrictive vs. expansionary. On the other hand, stock market bubbles respond somewhat differently in terms of magnitude to the different types of shocks. Specifically, our decomposition reveals an asymmetric response according to the sign of the shocks: Negative response of stock market bubbles for expansionary monetary policy shocks in the shorter run but negative responses for restrictive shocks in the longer run.

7.8. Time-Varying Effects

We finally examine possible time-varying bubble responses to interest rate shocks. First, we split the sample into three parts and estimate the baseline MF-VAR on each. The first sub-sample spans from 1960 to 1979 and represents a period of relatively positive mispricing in both the stock and housing markets. The second sub-sample spans from 1980 to 1999 and represents a period of largely negative mispricing in both markets. The last sub-sample is from 2000 to 2018 and includes the dot.com bubble in the stock market and the housing market bubble that preceded the financial crisis in 2007. It also includes the gradual Fed policy shift to inflation targeting, which became explicit in 2012. The responses of the bubbles to monetary policy in each sub-sample are reported in Appendix Q.¹⁸ For the stock market bubble, we find a negative response in the first sub-sample, this being stronger (peak of -4%) compared to the baseline result. However, the magnitude of

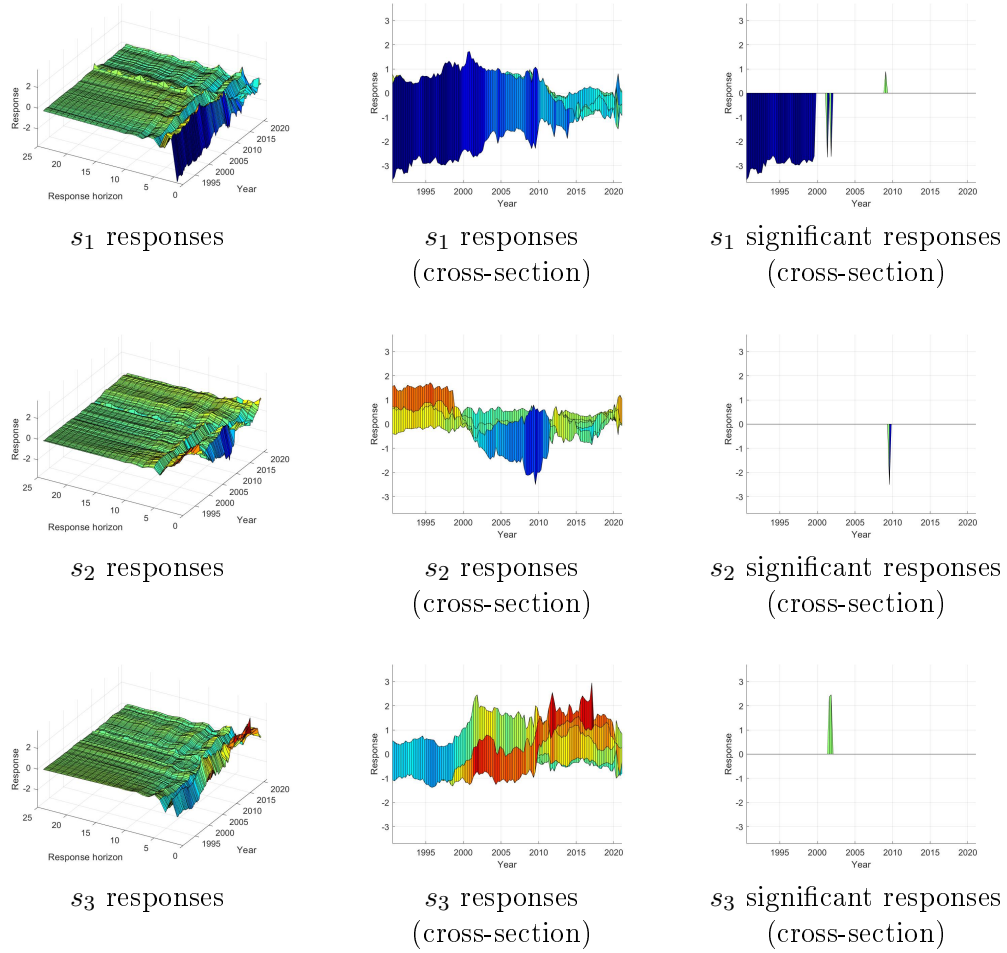
¹⁸For brevity, we only report the first monthly components, s_1 and h_1 .

the response gradually decreases in the following sub-samples. The results are rather statistically insignificant over the sub-samples. For the housing market bubble, there is no significant response in the first sub-sample, a negative significant response (peak of -0.5% after 4 quarters) in the second, and a positive significant response (peak of almost 4% after 2 quarters) in the third.

Second, we perform 30-year rolling-window estimations of the model for each consecutive quarter starting in 1990Q1 (we also check 20- and 40-year windows but the results point toward a similar conclusion). Each quarter, we estimate the baseline MF-VAR model and record the 24-quarters-ahead estimated responses of the two bubbles to 25 bps monetary policy shocks. Figures 6 and 7 show the time-varying responses, as well as the cross-section of responses and the cross-section of statistically significant responses.¹⁹ For the stock market bubble, we find that the first component responded consistently negative to interest rate shocks throughout the sample, but the magnitude and significance of the response has continuously declined over time. The second (third) component had a mainly positive (mixed) response before 2000 and a negative (positive) response afterwards, but these were overwhelmingly not statistically significant. For the housing market bubble, we find that the responses of all components had a tendency to decrease until

¹⁹The cross section of responses at one moment in time is obtained by superimposing the responses for the 24 quarters on the same 2D plot. Statistically significant responses are just the responses when they are significant at the 5% level, and zero otherwise.

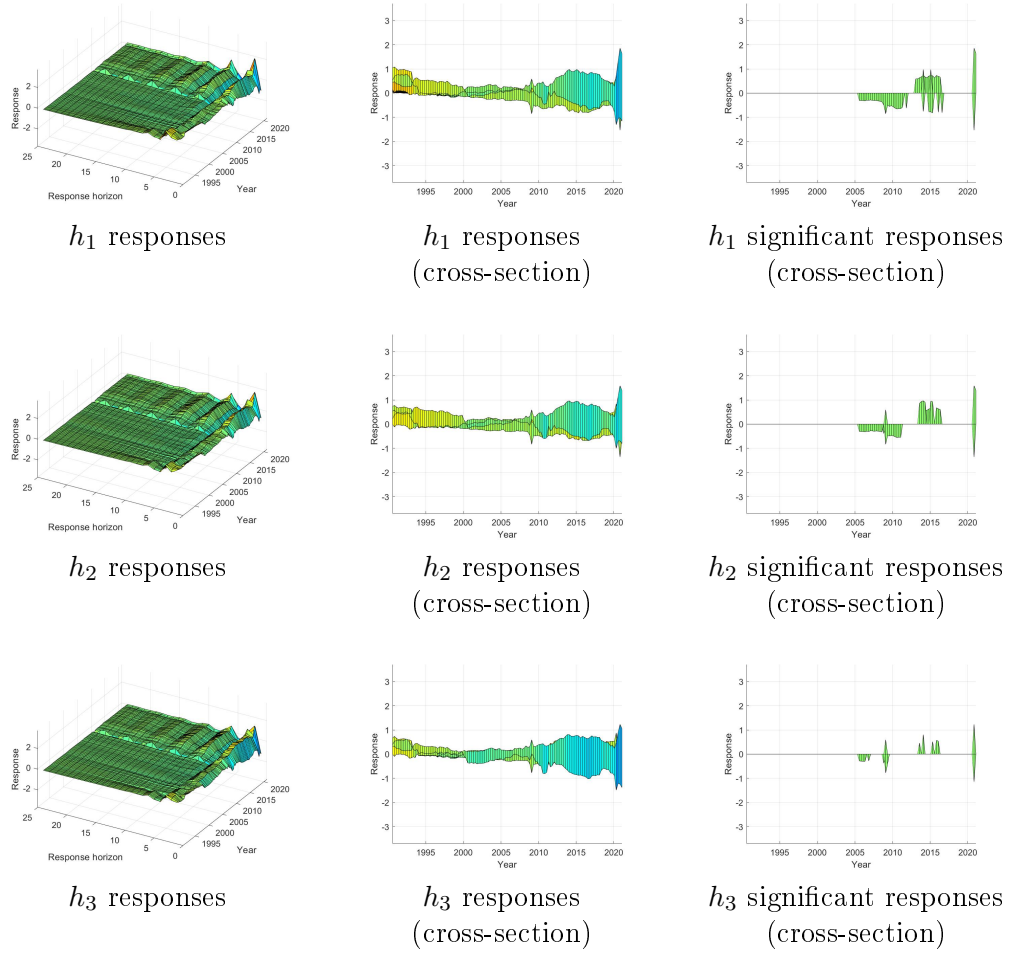
Figure 6: Time-varying response of stock market bubble to interest rate shock



roughly 2012, but then slightly increased and became more volatile. In terms of statistical significance, the housing market bubbles responses became significant only after 2005.

Overall, the results in this section show that bubbles have a time-varying response to monetary policy decisions. They also lead to some very interest-

Figure 7: Time-varying response of housing market bubble to interest rate shock



ing conclusions. On the one hand, monetary policy decisions seem to have a predominantly negative impact on stock market bubbles, but the magnitude of the impact has decreased over time to the point that it is no longer significant after the year 2000. On the other hand, bubbles in the housing market were not responsive to monetary policy decisions in early years (actually,

responses were predominantly positive but were not statistically significant), but have become so after 2005. Surprisingly, statistically significant responses were negative from 2005 to 2012, turned predominantly positive from 2012 to 2017, and have reappeared in both directions in the last few quarters of our sample, which coincide with the COVID-19 pandemic-related crisis.

The results imply that both recent changes in monetary policy regimes (e.g., the explicit shift to inflation targeting) and market behavior (e.g., shifts in market efficiency, as reported, among others, by Bajgrowicz and Olivier (2012)) have influenced the way bubbles respond to monetary policy decisions. We note that the detected time variation may also explain the differences observed between our results and the ones reported in Gali and Gambetti (2015), although we largely attribute this to the fact that they do not measure the actual historical bubbles, but rather derive their conclusions directly from the impulse-response analysis. At the same time, with respect to time-variation, the results are similar to those in Gali and Gambetti (2015): there is a decreasing negative response, with a slight tendency to become positive towards the end of the sample (rather for the housing market bubbles). We can also add that some of the statistical non-significance might come from the fact that the later years include observations from the Great Moderation, when the interest rate (and, potentially, the other variables in the model) varied less, implying less precise estimates of the responses, and so, fewer significant terms. This latter explanation is supported by the spike in significant house bubble responses once the COVID-19 pandemic hit and

volatility increased.

8. Discussion

Our findings contribute to the ongoing debate regarding the leaning against the wind policy. Our results point to the ability of the Federal Reserve to directly counter bubbles in the stock market in the early years of our sample (until about 2000). However, the impact on the housing market bubbles was positive in more recent years (starting in 2005). Moreover, because of the positive feedback between them (the stock market bubble is influenced by its housing market counterpart), policy decisions targeting the bubble in one market may also have had an undesired indirect effect on the bubble in the other. There is however a caveat, namely that the effects in recent years are overall weaker (stock market) or mixed (housing market). This is in line with recent research outlining a weak transmission mechanism before the Great Recession of 2007-2009, see Jannsen, Potjagailo and Wolters (2019) or Paul (2020), or after it, see again Jannsen et al. (2019). At the same time, even if the Fed might have actively intervened to counter bubbles, there would have been real costs associated with these interventions, since both bubbles have a direct impact on the GDP, in line with findings in Svensson (2014).

Additionally, our results show the necessity of improving the current generation of bubble models, see also Barlevy (2018). Not only do they highlight an interdependence between the two bubbles, but they also suggest that there is a difference between the responses of stock and housing market bubbles—in

terms of magnitude, sign and persistence—following monetary policy shocks. Moreover, they show that frequency matters. Specifically, the results in the MF-VAR somewhat differ compared to the standard low frequency (LF) approach, suggesting that the MF-VAR is relevant in this application. For the most part, a LF specification tends to underestimate the influence of monetary policy decisions on bubbles, while not capturing the inter-dependence between bubbles in the two markets.

As for the transmission channels of monetary policy, we mention two that we implicitly test for, i.e. the interest rate channel and the credit channel. A review of these can be found in Mishkin (1995) and Boivin, Kiley and Mishkin (2010), while here we analyze them in light of our MF-VAR results. First, the interest rate channel seems more effective in the sense that a rise in the Fed’s rate is capable to influence the bubbles in the stock and housing markets, although with some limitations. Second, we also allow for the presence of a credit channel by controlling for different measures of credit. What measure of credit is used matters for the response of the bubbles in the two markets.

9. Conclusions

In this paper, we bring fresh evidence regarding the impact of monetary policy shocks on bubbles, by combining quarterly macroeconomic data with monthly data for both the stock and housing markets. We find that methodological choices influence the results. However, these are generally consistent in pointing toward the same conclusions. In a nutshell, the main takeaways

are as follows. First, we find a negative impact of contractionary monetary policy shocks on stock market bubbles, but this has weakened over time to the point that monetary policy decisions are not longer effective after the .com episode. Second, we find a mostly positive impact on housing market bubbles, but this was not statistically significant before the Great Recession and seems unstable after (the signs of statistically significant responses are mixed). Third, similar to the recent literature concerning the use of a mixed-frequency approach, we find that it matters: Using a low-frequency approach underestimates the magnitude and statistical significance of the interactions between bubbles and other economic variables.

Our findings could be used in further studies that would take a more detailed look at how much the high-frequency components matter in the transmission of monetary policy shocks, since using the series at their original (higher) frequency in a mixed frequency approach can uncover dynamics and effects not visible with aggregated series. Further research could also be undertaken at an international level. For example, it could build on the contribution by Mallick and Sousa (2013), who provide a methodology to measure the credit bubble through the loan-to-GDP ratio that allows for a comparison across countries (and which is also shown to have implications for the housing market).

Acknowledgement

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Monetary Policy Shocks vs. Bubbles in the Stock and Housing Markets

– *Supplementary Materials* –

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Abstract

This document reports additional impulse response functions estimated and discussed in the main analysis (Section 6.3 of the paper) and in the robustness analysis (Section 7 of the paper).

JEL Classification: E5

Keywords: Bubbles, Stock market, Housing market, Mixed-Frequency VAR, Monetary policy

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Appendix A. Low-frequency VAR: the impact of bubbles on each other

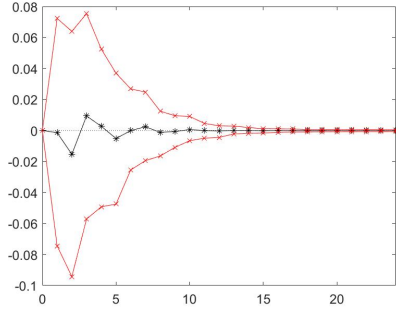


Figure A.1: Baseline model: stock market response to housing market bubbles

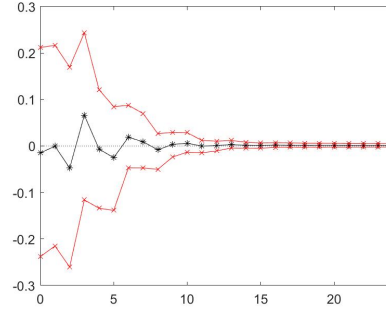


Figure A.2: Baseline model: housing market response to stock market bubbles

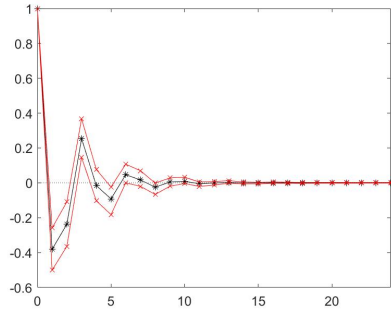


Figure A.3: Baseline model: stock market bubble autoregressive response

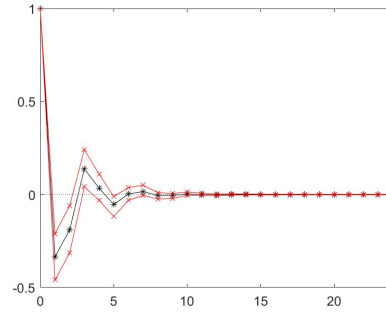


Figure A.4: Baseline model: housing market bubble autoregressive response

Appendix B. Mixed-Frequency VAR: the impact of housing market bubbles on stock market bubbles

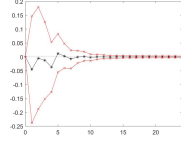


Figure B.1: s_1 response to h_1

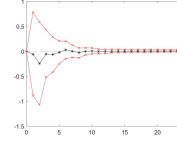


Figure B.2: s_1 response to h_2

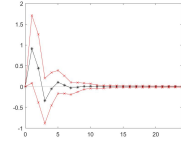


Figure B.3: s_1 response to h_3

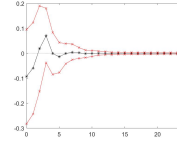


Figure B.4: s_2 response to h_1

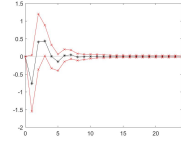


Figure B.5: s_2 response to h_2

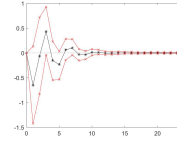


Figure B.6: s_2 response to h_3 response

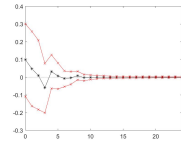


Figure B.7: s_3 response to h_1

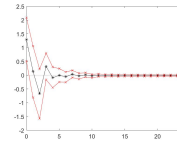


Figure B.8: s_3 response to h_2

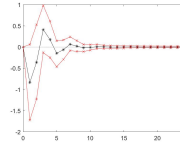


Figure B.9: s_3 response to h_3

Appendix C. Mixed-Frequency VAR: the impact of stock market bubbles on housing market bubbles

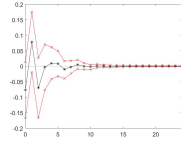


Figure C.1: h_1 response to s_1

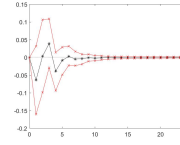


Figure C.2: h_1 response to s_2

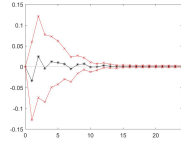


Figure C.3: h_1 response to s_3

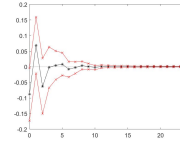


Figure C.4: h_2 response to s_1

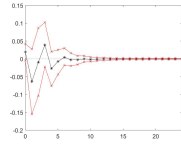


Figure C.5: h_2 response to s_2

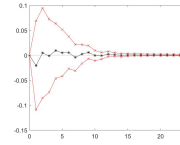


Figure C.6: h_2 response to s_3

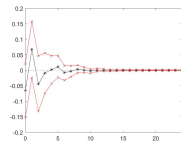


Figure C.7: h_3 response to s_1

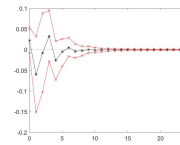


Figure C.8: h_3 response to s_2

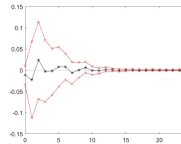


Figure C.9: h_3 response to s_3

Appendix D. Mixed-Frequency VAR: the impact of bubbles on GDP

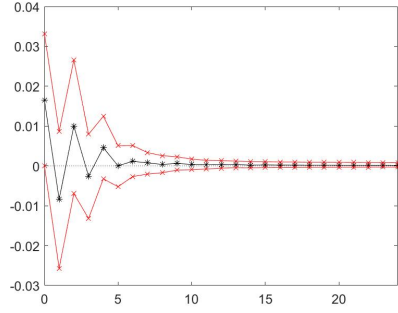


Figure D.1: GDP response to s_1

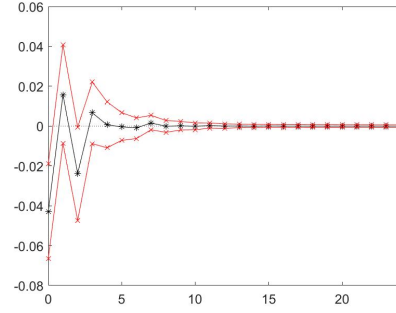


Figure D.2: GDP response to h_1

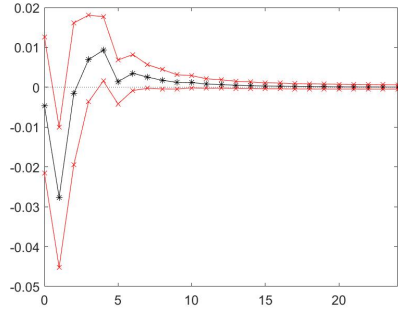


Figure D.3: GDP response to s_2

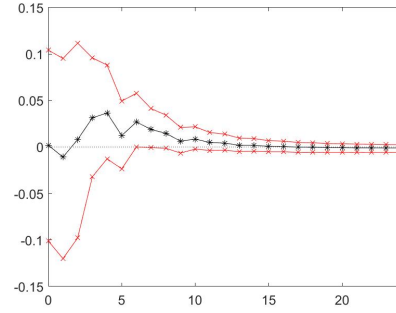


Figure D.4: GDP response to h_2

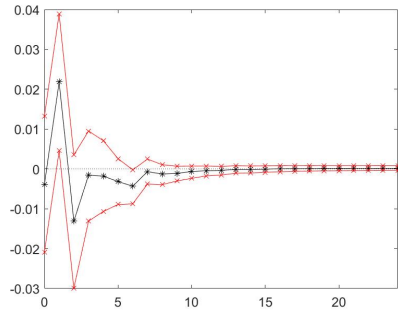


Figure D.5: GDP response to s_3

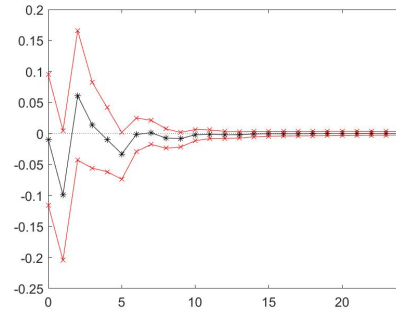


Figure D.6: GDP response to h_3

Appendix E. Mixed-Frequency VAR: the impact of credit on bubbles

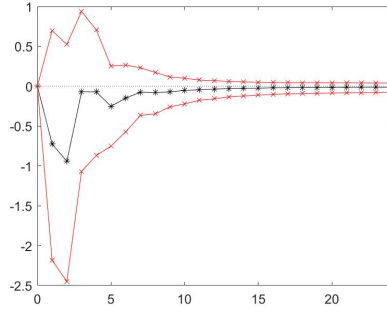


Figure E.1: s_1 response to credit

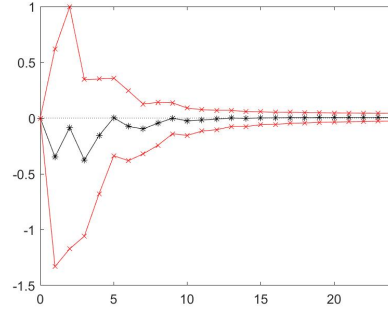


Figure E.2: h_1 response to credit

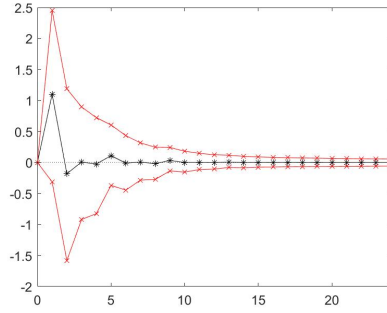


Figure E.3: s_2 response to credit

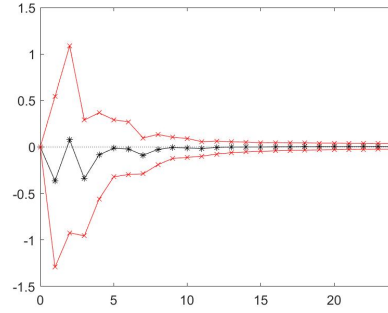


Figure E.4: h_2 response to credit

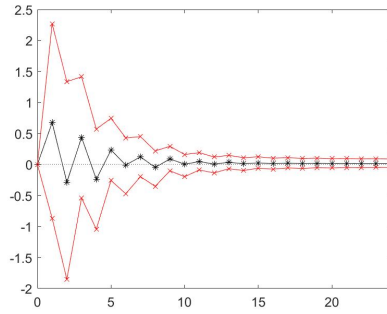


Figure E.5: s_3 response to credit

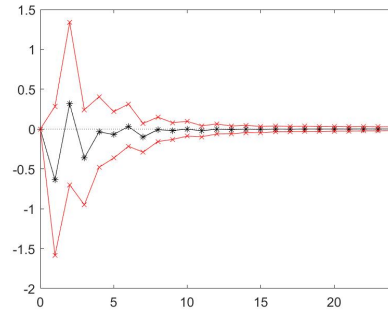


Figure E.6: h_3 response to credit

Appendix F. Robustness - alternative bubble measure (omniscient proxy): the impact of interest rates on bubbles

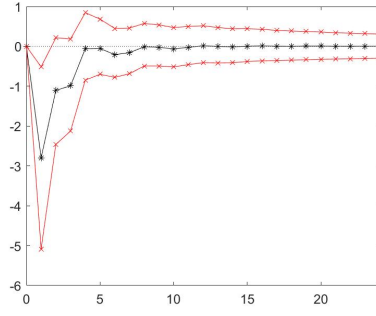


Figure F.1: s_1 response to interest rate

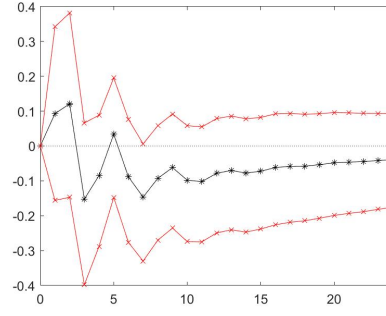


Figure F.2: h_1 response to interest rate

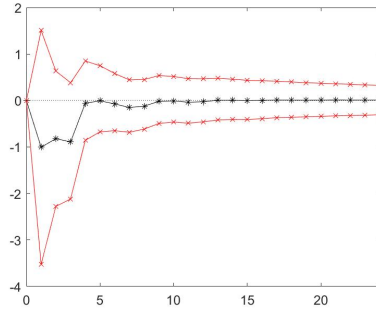


Figure F.3: s_2 response to interest rate

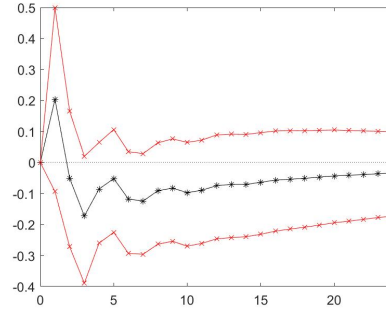


Figure F.4: h_2 response to interest rate

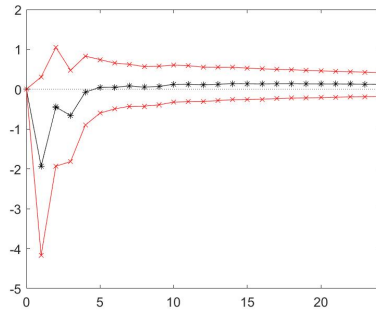


Figure F.5: s_3 response to interest rate

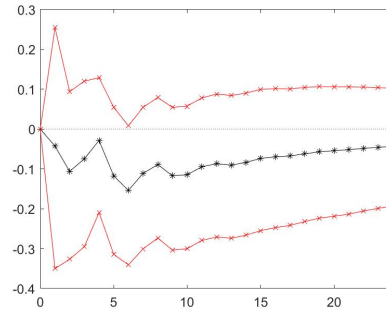


Figure F.6: h_3 response to interest rate

Appendix G. Robustness - alternative bubble measure (naïve proxy): the impact of interest rates on bubbles

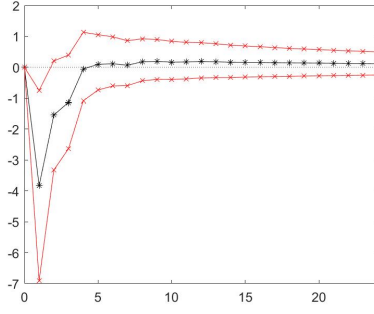


Figure G.1: s_1 response to interest rate

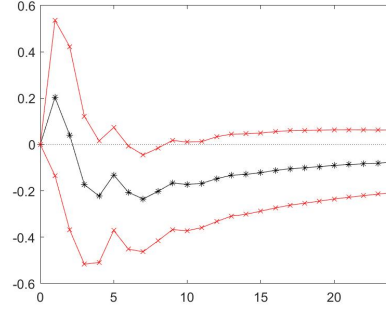


Figure G.2: h_1 response to interest rate

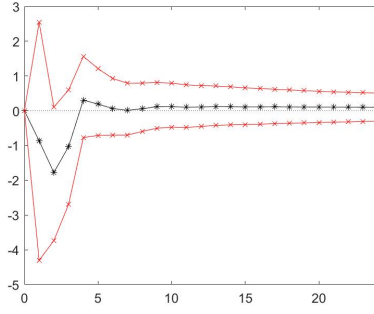


Figure G.3: s_2 response to interest rate

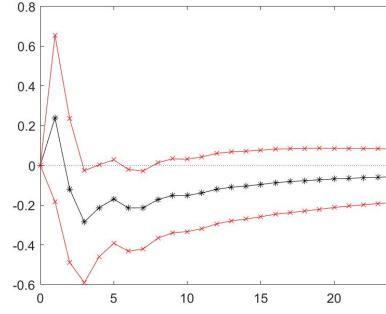


Figure G.4: h_2 response to interest rate

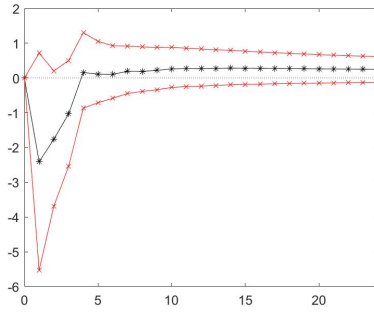


Figure G.5: s_3 response to interest rate

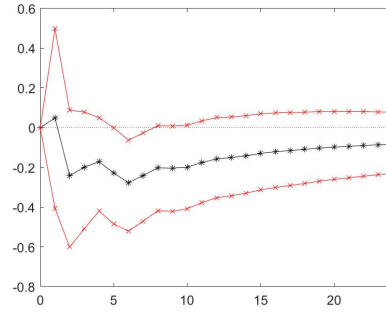


Figure G.6: h_3 response to interest rate

Appendix H. Robustness - alternative bubble measure (HP based measure, $\lambda = 900,000$): the impact of interest rates on bubbles

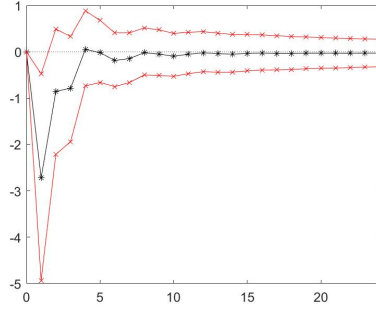


Figure H.1: s_1 response to interest rate

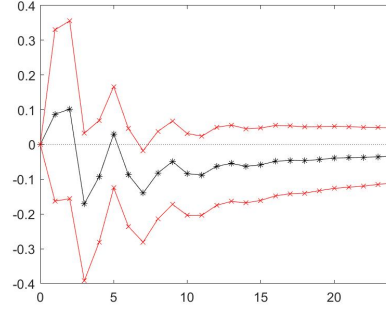


Figure H.2: h_1 response to interest rate

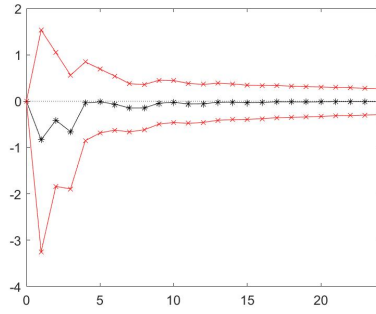


Figure H.3: s_2 response to interest rate

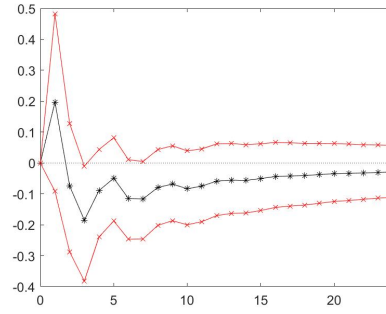


Figure H.4: h_2 response to interest rate

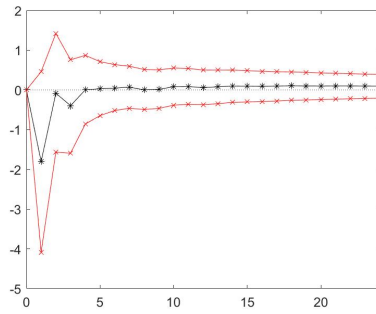


Figure H.5: s_3 response to interest rate

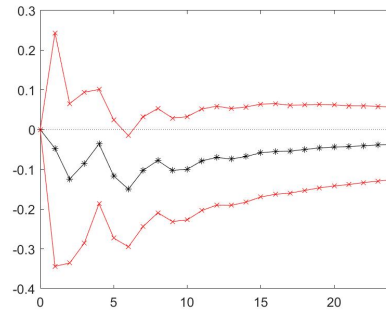


Figure H.6: h_3 response to interest rate

Appendix I. Robustness - standard identification strategy: the impact of interest rates on bubbles

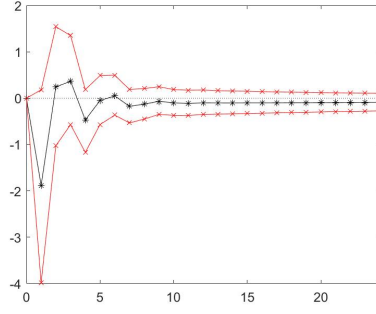


Figure I.1: s_1 response to interest rate

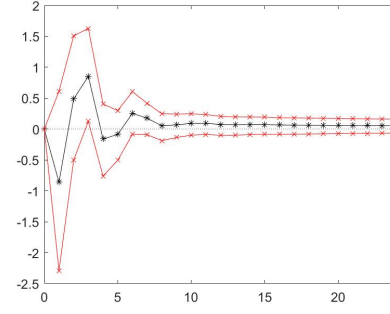


Figure I.2: h_1 response to interest rate

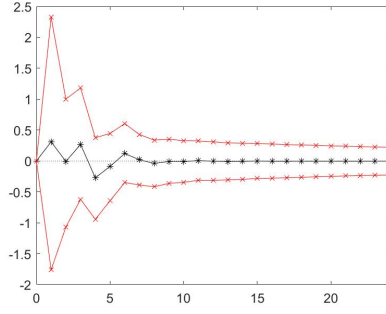


Figure I.3: s_2 response to interest rate

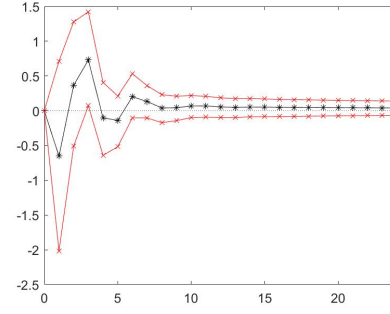


Figure I.4: h_2 response to interest rate

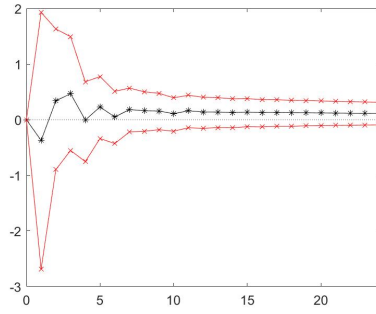


Figure I.5: s_3 response to interest rate

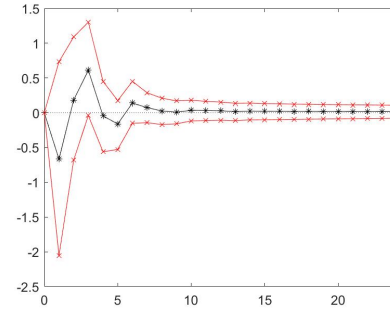


Figure I.6: h_3 response to interest rate

Appendix J. Robustness - identification strategy of γ : the impact of interest rates on bubbles

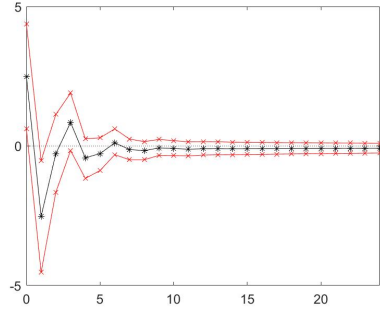


Figure J.1: s_1 response to interest rate

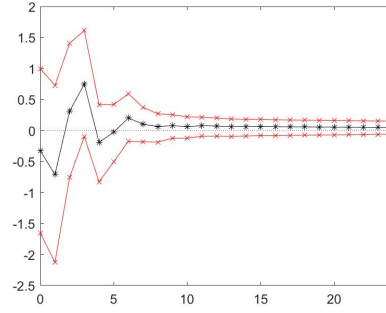


Figure J.2: h_1 response to interest rate

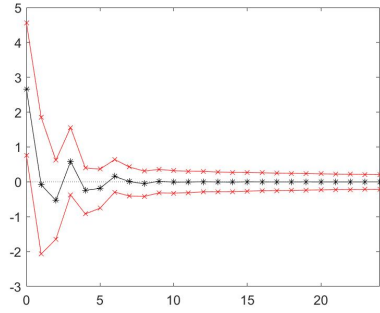


Figure J.3: s_2 response to interest rate

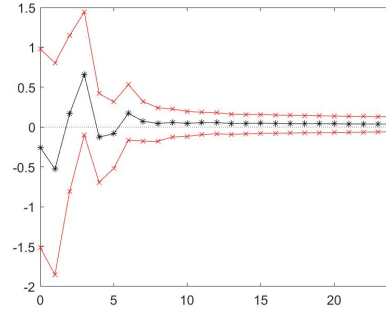


Figure J.4: h_2 response to interest rate

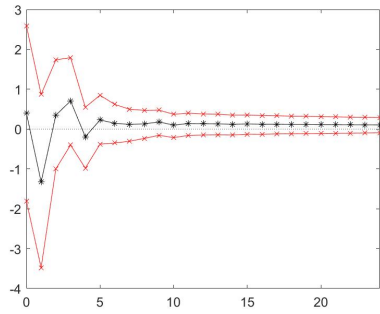


Figure J.5: s_3 response to interest rate

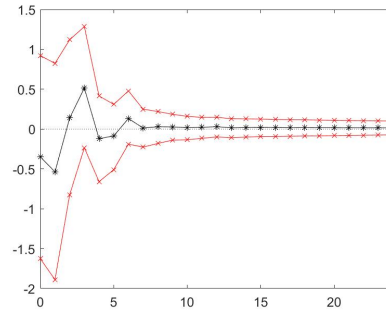


Figure J.6: h_3 response to interest rate

Appendix K. Robustness - adding fundamental values to the model: the impact of interest rates on bubbles

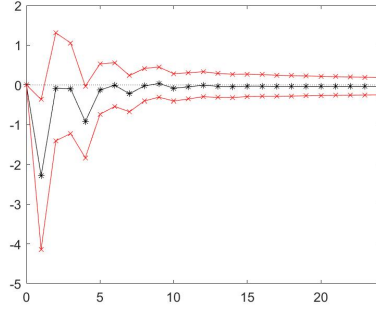


Figure K.1: s_1 response to interest rate

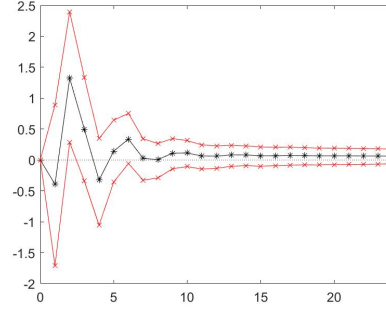


Figure K.2: h_1 response to interest rate

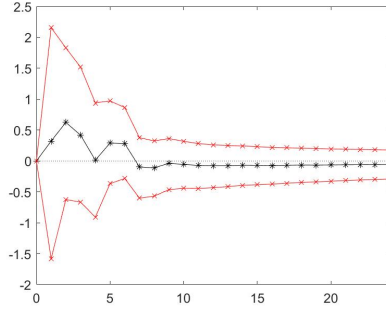


Figure K.3: s_2 response to interest rate

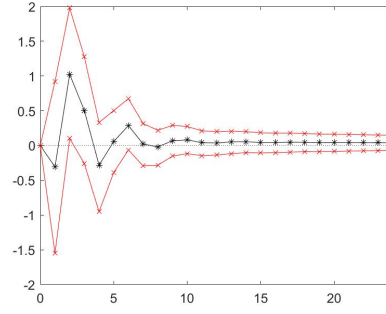


Figure K.4: h_2 response to interest rate

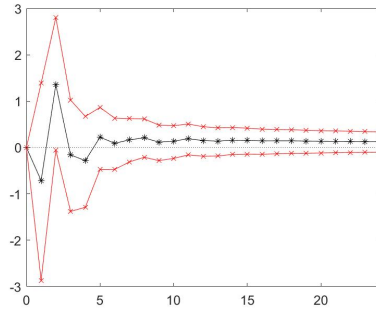


Figure K.5: s_3 response to interest rate

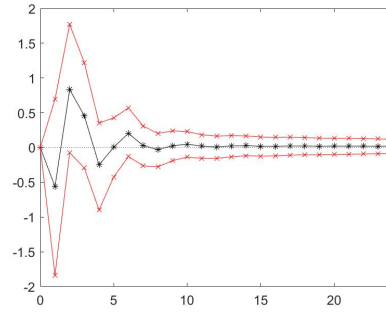


Figure K.6: h_3 response to interest rate

Appendix L. Robustness - adding fundamental values and replacing bubbles with prices: the impact of interest rates on prices

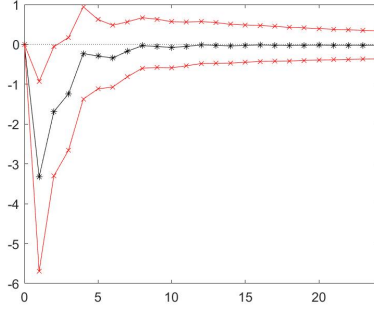


Figure L.1: ps_1 response to interest rate

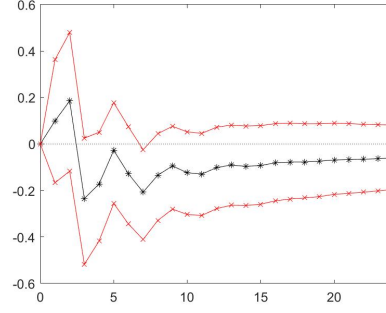


Figure L.2: ph_1 response to interest rate

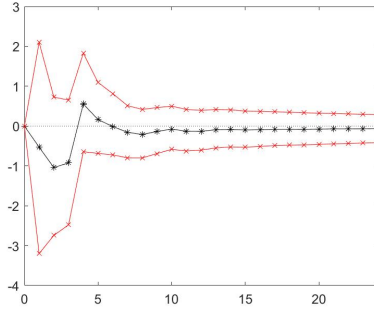


Figure L.3: ps_2 response to interest rate

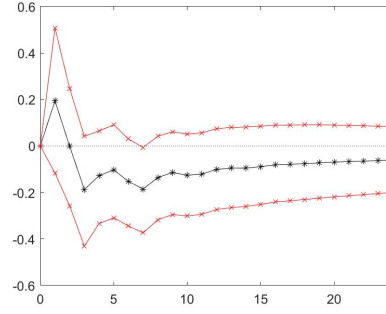


Figure L.4: ph_2 response to interest rate

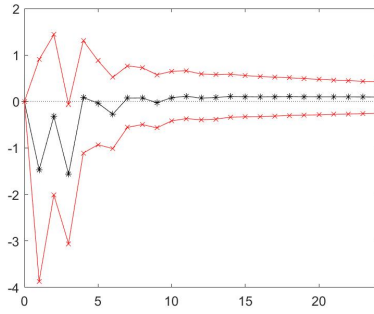


Figure L.5: ps_3 response to interest rate

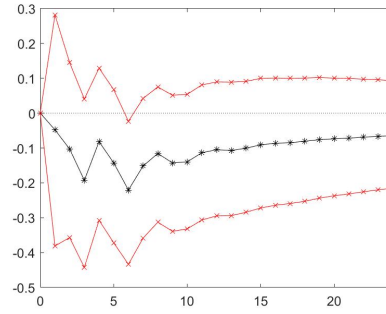


Figure L.6: ph_3 response to interest rate

Appendix M. Robustness - only one bubble at once: the impact of interest rates on bubbles

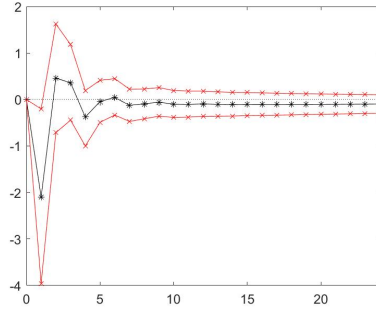


Figure M.1: s_1 response to interest rate

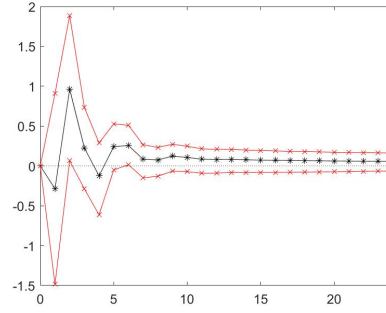


Figure M.2: h_1 response to interest rate

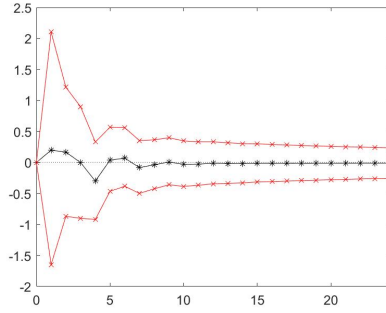


Figure M.3: s_2 response to interest rate

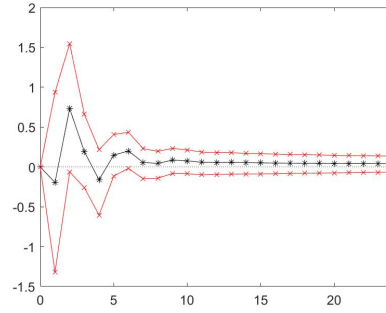


Figure M.4: h_2 response to interest rate

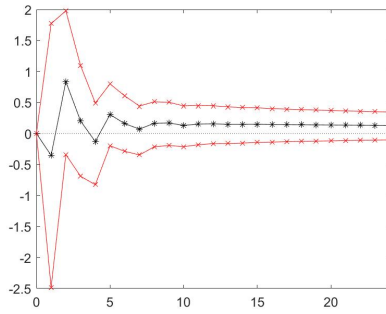


Figure M.5: s_3 response to interest rate

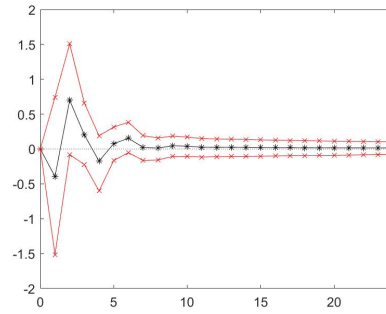


Figure M.6: h_3 response to interest rate

Appendix N. Robustness - using shadow interest rate: the impact of interest rates on bubbles

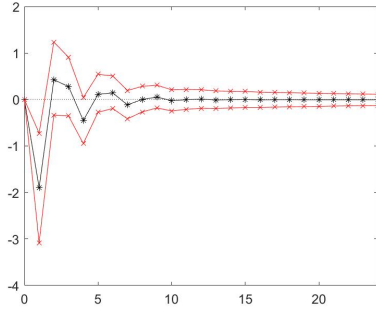


Figure N.1: s_1 response to interest rate

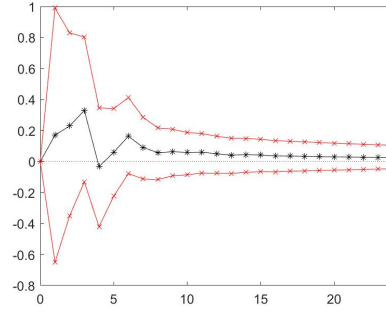


Figure N.2: h_1 response to interest rate

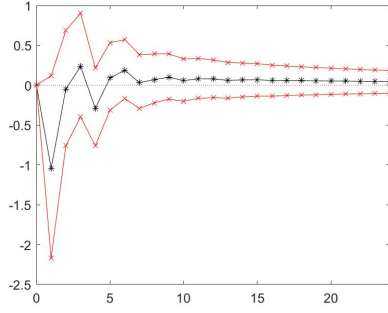


Figure N.3: s_2 response to interest rate

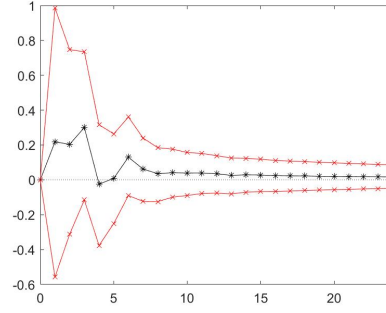


Figure N.4: h_2 response to interest rate

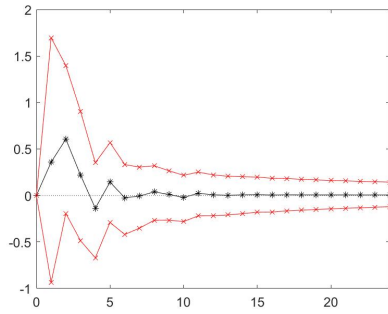


Figure N.5: s_3 response to interest rate

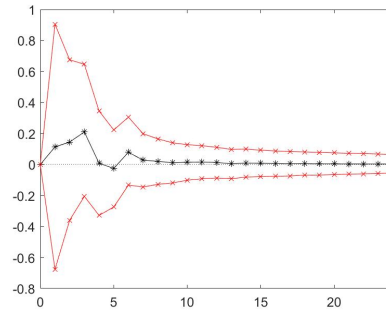


Figure N.6: h_3 response to interest rate

Appendix O. Robustness - using credit over deposit ratio: the impact of interest rates on bubbles

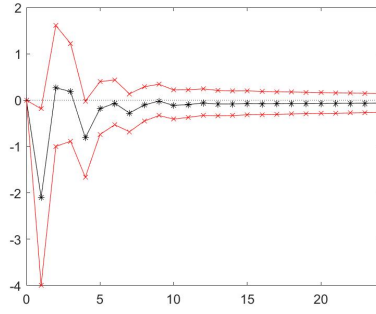


Figure O.1: s_1 response to interest rate

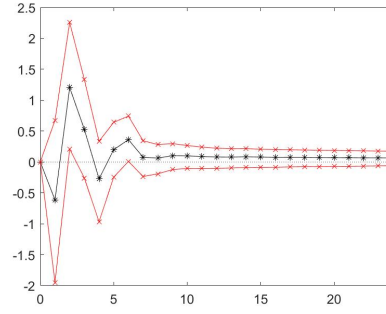


Figure O.2: h_1 response to interest rate

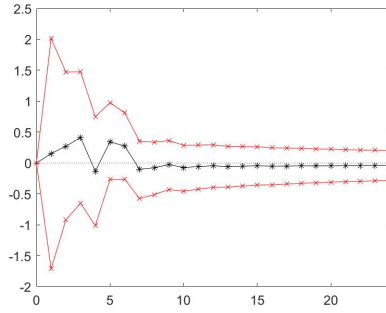


Figure O.3: s_2 response to interest rate

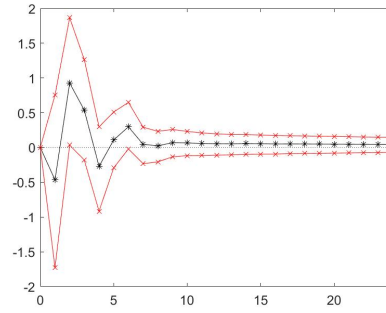


Figure O.4: h_2 response to interest rate

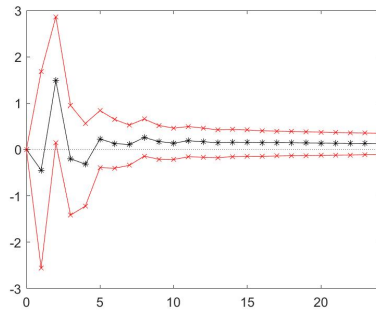


Figure O.5: s_3 response to interest rate

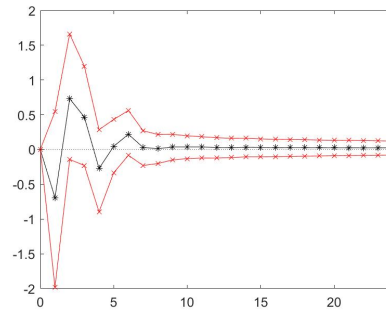


Figure O.6: h_3 response to interest rate

Appendix P. Robustness - asymmetric effects trough local projections: the impact of interest rates on bubbles

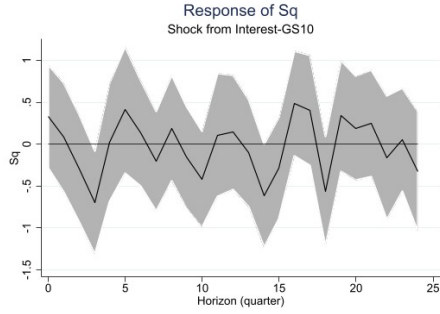


Figure P.1: s_q response

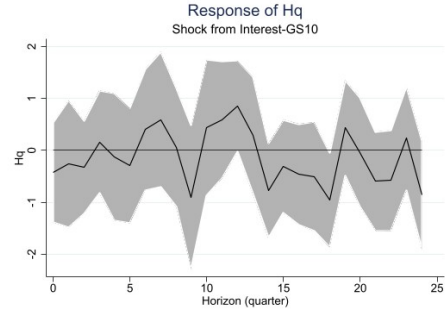


Figure P.2: h_q response

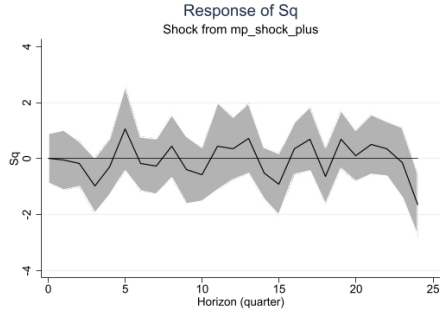


Figure P.3: s_q response to restrictive shocks

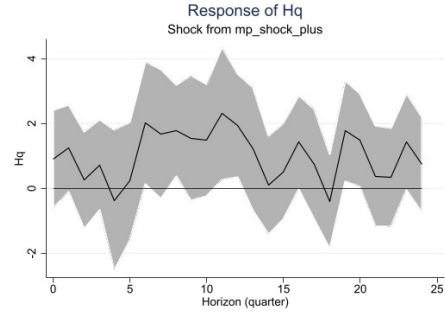


Figure P.4: h_q response to restrictive shocks

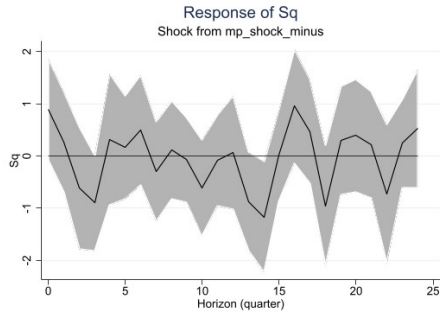


Figure P.5: s_q response to expansionary shocks

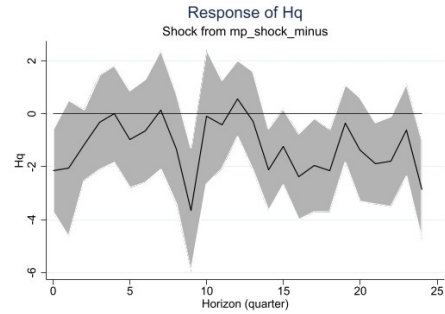


Figure P.6: h_q response to expansionary shocks

Appendix Q. Robustness - time-varying effects trough subsample tests: the impact of interest rates on bubbles

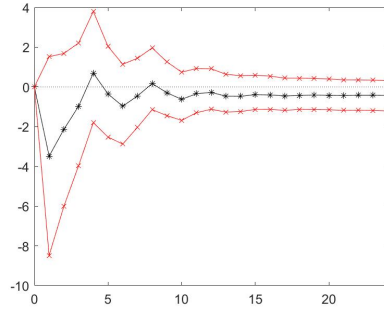


Figure Q.1: s_1 response (1960-1979)

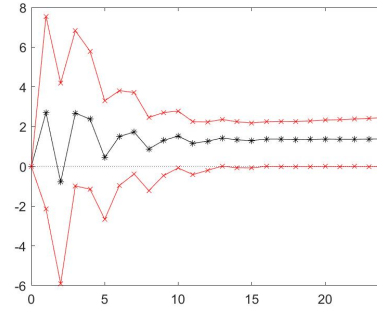


Figure Q.2: h_1 response (1960-1979)

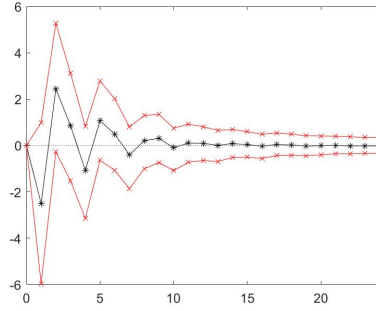


Figure Q.3: s_1 response (1980-1999)

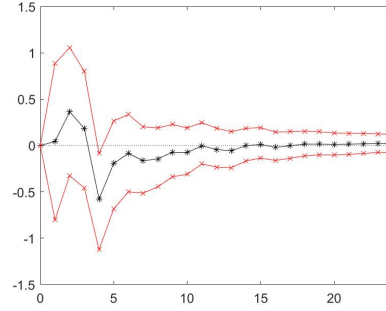


Figure Q.4: h_1 response (1980-1999)

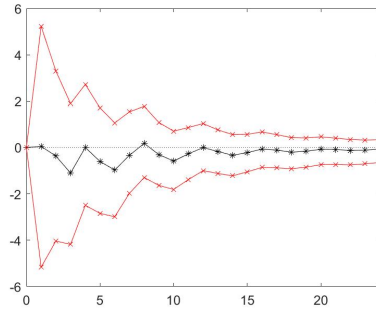


Figure Q.5: s_1 response (2000-2021)

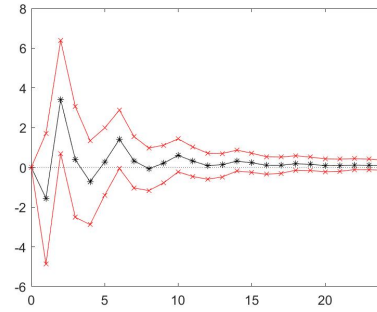


Figure Q.6: h_1 response (2000-2021)