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Abstract

This paper assessed the effects of housing market shocks on real output in South Africa over the period 1969Q4 – 2014Q4, by emphasizing the real private consumption channel. The agnostic identification procedure employed in this paper has delivered impulse responses that are overall consistent with the existing literature. The paper appropriately identified housing market shocks as non-monetary housing demand shocks. 20% of the variation in house prices are explained by the housing market shocks. The effects of housing demand shocks on real private consumption are short-lived, explaining why real output responded transitorily to these shocks. Housing demand shocks have managed to explain nearly 13% and 14% variations in real private consumption and real output, respectively, over 20-quarters ahead forecast revision.

Keywords: Agnostic Identification, Housing Market Shocks, Real Output, SVAR, South Africa

JEL Codes: C11; C32; E21; E31; R31

1. Introduction

The ever-increasing significance of the housing market in the real economic activity can be summarized by its undoubted role in the recent sub-prime crisis in the US, which spread throughout the world's economies.[2,3] Aside inflation and unemployment, house prices serve as an important leading indicator of business cycles (see Stock and Watson, 2003; Leamer, 2007). The recent empirical literature has established a strong connection between the real economy and the housing market in both advanced and emerging market economies. The general observation is that busts in housing price bubbles culminate in real economic downturns (see, for example,

[2] The topic for the Jackson Hole symposium in 2007 held by the Federal Reserve Bank of Kansas City was the role of the housing market in modern economies (see Mishkin, 2007; Taylor, 2007; Musso *et al.* 2011).

[3] The precise transmission channel through which the housing market shocks generated the recent economic meltdown remains a debatable issue in the literature.

Vargas-Silva, 2008; Pavlidis *et al.*, 2009; Iacoviello and Neri, 2010; Bassanetti and Zollino, 2010; Bulligan, 2010; Ghent and Owyang, 2010; Musso *et al.* 2011).

Although the role of the housing market in the real economy appears empirically straightforward at first glance, the theoretical transmission mechanism is rather ambiguous. In principle, positive shocks to house prices are expected to trigger increases in the wealth of homeowners, which will spur their consumption expenditures. Thereby stimulating production in the economy. This is the so-called *collateral effect*. The collateral effect of house price results because increases in house prices lead to increases in the value of home assets. This enhances the collateral position of homeowners, when they are seeking for new loans. Yet, house price increases are not necessarily transmitted into higher private consumption, and the subsequent increase in production in the economy. The existence of transaction costs, financial constraints, and changes in preferences may ensure that homeowners do not increase their consumption expenditures after house price increments (Engelhardt, 1996; Phang, 2004). The transaction costs result due to the banking and regulatory requirements (such as filing loan forms, queuing in banks, undergoing screening, among others) homeowners must satisfy in order to secure new loans for consumables, despite the rise in the value of their collaterals. The financial constraints stem from the fact that most homeowners are essentially debtors of mortgages. They are constrained by these debts, and will therefore not necessarily increase their consumption expenditures because of their enhanced collateral position. Moreover, relatively older homeowners may have preferences toward other activities (such as medical insurance, saving for retirement and building bequests) to consumption when house prices increase.

This standout theoretical ambiguity of the impact of housing price shocks on the real economy through the private consumption channel has led to burgeoning empirical investigations. There are empirical studies that explore the role of monetary policy, and credit policy shocks on the housing market and the real economy through private consumption and real residential investment channels (see Goodhart and Hofmann, 2008; Jarocinski and Smets, 2008; Iacoviello and Neri, 2010). There are also studies that explore the role of housing price shocks on monetary and credit policies (see Case *et al.*, 2005; Darracq Paries and Notarpietro, 2008; Bjørnland and Jacobsen, 2010; Gupta *et al.*, 2010; Musso *et al.* 2011). These studies have mostly interpreted the role of these shocks on the real economy by first principle. That is, they evaluate the direction of the impact of the housing market shocks (negative or positive) on specific real economic fundamentals and interpret their end products on the real output by appealing to the theory or the conventional wisdom. Whereas these approaches are theoretically consistent, it will be empirically worthwhile to examine the role of these shocks on the real output directly. This is precisely what we do in this paper. We do not pretend that our approach delivers superior results when compared to these other studies. Instead, our paper can be seen as a complement to them.

Our paper utilizes a quarterly dataset covering the period 1969Q4 – 2014Q4 to assess the impact of housing price shocks on the real output in South Africa. Our empirical strategy involves a structural vector autoregression (SVAR), which draws on the agnostic identification scheme proposed in Uhlig (2005), and generalized in Rubio-Ramirez *et al.* (2010) to identify housing market shocks as non-monetary housing demand shocks. With appropriately imposed sign restrictions, the agnostic identification scheme delivers results that are theoretically consistent and obviate the *price puzzle* which short- and long-run identification schemes struggle to handle (see Uhlig, 2005).[4] The identification scheme is agnostic in that the question the policymaker proposes to answer is left agnostically open by virtue of its construction; so that the data will "speak for itself". This distinctive characteristic of the agnostic scheme stands fairly appealing among its worthy competitors, despite the recent criticisms leveled against it. In particular, the identification scheme permits the policymaker to concentrate on identifying the shock of interest, in our case, the housing market shocks. It, therefore, spares the policymaker the burden of identifying other fundamental shocks, which may not necessarily contribute to answering the question at hand.[5]

We recognize the possible influence of regime shifts in parameters due to policy or structural changes.[6] To the extent that this may distort the empirical modeling strategy slightly, the story remains essentially the same. Although we strictly attempt to assess the effects of housing market shocks on the real output, we also take a brief tour around other variables in our empirical model. As pointed out by Uhlig (2005), one must note that these other results are blurred by *a priori* sign restrictions. Having made our position clear, our findings can be summarized as follows. The agnostic identification delivered impulse responses that are overall consistent with the existing literature. The housing market shocks are appropriately identified as non-monetary housing demand. 20% of the variation in house prices are explained by the housing market shocks. The effect of housing demand shocks on real private consumption is short-lived, explaining why real output responded transitorily to these shocks. Housing demand shocks have managed to explain nearly 13% and 14% variations in real private consumption and real output, respectively, over 20-quarters ahead forecast revision.

In the next section, we present the empirical SVAR model and the agnostic scheme proposed in Uhlig (2005), and generalized in Rubio-Ramirez *et al.* (2010). Section 3 presents the data and the results. Section 4 concludes.

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[4] However, the scheme, like the other identification schemes, has its drawbacks. The interested reader may refer to Fry and Pagan (2011), and Moon *et al*. (2013) for detailed criticisms of this identification scheme.

[5] This challenge (of short- and long-run identification schemes) was recognized by studies such as Bernanke and Mihov (1998a, b), Faust (1998), Christiano *et al.* (1999), and Canova and De Nicoló (2002). These authors utilized a block-recursive ordering to concentrate the identification exercise on only a limited set of variables, which interact with the policy shock in order to circumvent this problem (see also Uhlig, 2005; Rubio-Ramirez *et al.* 2010).

[6] See Uhlig (1997), Canova and Gambetti (2004), Cogley and Sargent (2005), Primiceri (2005), Rubio-Ramirez *et al.* (2005), Sims and Zha (2006), Gambetti and Canova (2008), for such treatments.

2. Methodology

In this section, we discuss the econometric technique that is utilized in the paper, namely the sign restricted SVAR. We begin by specifying this SVAR model, and then we discuss briefly how shocks are identified in this model. Further, we explain the agnostic identification procedure that has been proposed in Uhlig (2005)'s influential paper. Finally, we discuss the efficient algorithm proposed in Rubio-Ramirez *et al.* (2010) for solving sign restricted SVARs.

2.1 Model Specification

We follow the lead of Uhlig (2005) and specify a VAR of the following form:

$$Y_t = \beta_{(1)} Y_{t-1} + \beta_{(2)} Y_{t-2} + \cdots + \beta_{(l)} Y_{t-l} + u_t, \quad t = 1, \dots, T, \quad (1)$$

where Y_t is an $m \times 1$ vector of macroeconomic variables at $t = 1 - l, \dots, T$. In this paper, Y_t consists of real output (logGDP), consumer prices (logCPI), real private consumption (logCON), house prices (logHPI), repo rate (REPO), and mortgage rate (MORT). $\beta_{(i)}$ are coefficient matrices of size $m \times m$, and u_t is the one-step ahead prediction error whose variance-covariance matrix is Σ.

Of strong interest to the policymaker is the behavior of u_t, the one-step ahead prediction error. This is the case because forces that result in the variation in u_t are transmitted into the economy. For this reason, a large portion of the VAR literature has been dedicated to decomposing u_t into forms that are economically interpretable. The decomposition of u_t has also been the source of debate in the literature. This stems from the fact that the policymaker's efficacy in assessing the transmission mechanisms of shocks to u_t to the rest of the economy depends on the appropriate decomposition of u_t.

If u_t can be normalized into v_t such that $E[v_t v_t'] = I_m$ (i.e. u_t is normalized to have variance I_m, identity element).[7] Then, there exist a matrix A such that $u_t = A v_t$, whose jth column represents the immediate impact on all variables of the jth fundamental innovation, one standard error in size (see Uhlig, 2005). This also implies that we have a restriction on A, which stems from the form of the variance-covariance matrix:

$$\Sigma = E[u_t u_t'] = AE[v_t v_t']A' = AA'. \quad (2)$$

Eq. (2) indicates that, in specifying A, we have $m(m-1)/2$ degrees of freedom. The current restriction on A is, therefore, not sufficient to identify shocks to u_t. As Uhlig (2005) argues, the literature has proceeded to impose the additional restrictions on A by following one of three ways: (i) by restricting A to be a Cholesky factor of Σ, thus suggesting a recursive ordering of Y_t (see, for example, Sims, 1986); (ii) by drawing information from structural relationships between

[7] Note that u_t is i.i.d.

$v_{ti}, i = 1, \ldots, m$, the fundamental innovations and $u_{ti}, i = 1, \ldots, m$, the one-step ahead prediction errors (see, for example, Bernanke, 1986; Blanchard and Watson, 1986); (iii) by decomposing shocks into permanent and transitory components (see, for example, Blanchard and Quah, 1989). In this paper, we proceed to impose additional restrictions on A in the fashion proposed in Uhlig (2005).

2.2 The Agnostic Identification Scheme

To identify the fundamental shocks of interest, Uhlig (2005) proposed we use sign restrictions on the matrix A. This spares the policymaker the burden of identifying other shocks that may not necessarily help her in answering her policy question. In addition, the above ways of restricting A may not generate impulse responses that have the desired signs (see Rubio-Ramirez *et al.*, 2010). These points were identified by Bernanke and Mihov (1998a, b) and Christiano *et al.* (1999), who utilize a block-recursive ordering to focus their identification exercise on a few sets of covariates which relate with the shock of interest. Other studies such as Faust (1998), and Canova and De Nicoló (2002) also raised these points. This goes without saying that the sign restriction approach has been criticized by Fry and Pagan 2011) for being unable to recover correct elasticities due to its inherent weak information.

This paper uses the sign restriction approach to identify the shocks of interest, namely the housing market shocks. Therefore, we neglect the remaining $m - 1$ fundamental innovations. This means that we will identify a single column $a \in \mathbb{R}^m$ of the matrix A in *Eq.* (2) (see Uhlig, 2005). We impose the restrictions that positive shocks in the housing market lead to an increase in house prices, consumer prices, and mortgage rate. This ensures that such positive shocks are characterized as housing demand shocks. We assume that real private consumption and real output do not react to shocks in the housing market to rule out technology shocks (see Goodhart and Hofmann, 2008; Musso *et al.*, 2011). We qualify positive shocks in the housing market as non-monetary housing demand shocks, if they lead to increase in real house prices, and do not decrease the monetary policy rate (see Jarocinski and Smets, 2008; Iacoviello and Neri, 2010). This is sufficient to rule out expansionary monetary policy shocks. In essence, our identification scheme is constructed such that sign restrictions are imposed on the other variables for a specified period of four quarters, whereas our variables of interest, namely real output, real private consumption, and repo rate are left agnostically open.

To rap up the agnostic identification procedure, a housing market shock will be an impulse response vector, which satisfies the sign restrictions. In this case, a housing market shock is a shock such that the responses of house prices, consumer prices, and mortgage rate are non-negative at all horizons $k = 0, \ldots, K$. Uhlig (2005) proposes two approaches to solving the sign restricted SVAR – the *pure-sign-restriction approach* and *the penalty-function approach*.[8] In this

[8] The interested reader may consult Uhlig (2005) for the technical details of these approaches.

paper, we proceed to use the generalized version of these approaches proposed in Rubio-Ramirez *et al.* (2010) to solve the sign restricted SVAR. This algorithm is discussed in the next section.

2.3 Efficient Algorithm for Solving the Sign Restricted SVAR

It is known that sign restricted SVARs are not locally identified (see Rubio-Ramirez *et al.*, 2010; Fry and Pagan, 2011). That is, for a set of sign restrictions, if there exist a parameter point (A_0, A_+) which satisfies these restrictions, there exist an orthogonal matrix P, arbitrarily close to an identity matrix, such that a parameter point (A_0P, A_+P) also satisfies the sign restrictions (see Rubio-Ramirez *et al.*, 2010).[9] Therefore, sign restricted SVARs are not identified, tasking the policymaker to search for a set of impulse responses that satisfy the same sign restrictions (see Rubio-Ramirez *et al.*, 2010; Fry and Pagan, 2011).[10]

Canova and De Nicoló (2002) developed an algorithm based on grid search to find such a P. The limitation of their algorithm is that it cannot feasibly handle a moderately large (i.e. $n > 4$) SVAR system. Uhlig (2005) developed two algorithms to find that P: the penalty-function approach and the pure-sign-restriction approach. These algorithms search for the orthogonal matrix P recursively column by column. Uhlig's (2005) algorithms are limited in that they may not find the orthogonal matrix P for some draws of (B, Σ) (see Rubio-Ramirez *et al.*, 2010).

Due to the limitations of these algorithms for solving sign restricted SVAR models, Rubio-Ramirez *et al.* (2010) developed a new algorithm, based on the Householder-transformation methodology.[11] This algorithm is referred popularly as the Rubio-Ramirez *et al.* (2010)' rejection method. Their algorithm can be outlined as follows:

Let (A_0, A_+) be any given value of the unrestricted structural parameters.

- Step 1: Draw an independent standard normal $n \times n$ matrix $\tilde{X}$ and let $\tilde{X} = \tilde{Q}\tilde{R}$ be the QR decomposition of $\tilde{X}$ with the diagonal of $\tilde{R}$ normalized to be positive.
- Step 2: Let $P = \tilde{Q}$ and generate impulse responses from A_0P and $B = A_+A_0^{-1}$.

[9] Rubio-Ramirez *et al.* (2010) formulates a compact form of the SVAR as $y_t'A_0 = x_t'A_+ + \varepsilon_t'$ and a reduced-form as $y_t' = x_t'B + u_t'$, so that $B = A_+A_0^{-1}$, $u_t' = \varepsilon_t'A_0^{-1}$, and $E[u_tu_t'] = \Sigma = (A_0A_0')^{-1}$. The reduced-form parameters are thus (B, Σ). Two parameter points are observationally equivalent if and only if they have the same reduced-form representation (B, Σ). Therefore, parameter points (A_0, A_+) and $(\tilde{A}_0, \tilde{A}_+)$ have the same reduced-form representation (B, Σ), if and only there exists an orthogonal matrix P such that $A_0 = \tilde{A}_0P$ and $A_+ = \tilde{A}_+P$ (see Rubio-Ramirez *et al.*, 2010).

[10] Numerically, the policymaker must bear the computational burden of locating a set of Ps such that the parameter point (A_0P, A_+P) satisfies the sign restrictions.

[11] See Rubio-Ramirez *et al.* (2010) for the distinction between their algorithm and the ones proposed in Uhlig (2005). In particular, this algorithm has a sizeable efficiency gain if more than one shock is to be identified.

- Step 3: If these impulse responses do not satisfy the sign restrictions, return to Step 1.[12]

3. Data and Results

This section describes the data and presents the key empirical results. We begin by describing the data. Then we discuss the impulse responses stemming from the popular identification scheme based on Cholesky decomposition. This identification scheme is frequently used in the literature as the baseline with which to compare competing SVAR approaches (see for example, Canova and De Nicoló, 2002; Uhlig, 2005;). We add to this by discussing the impulse responses based on the agnostic identification scheme. Then, we discuss the forecast error variance decomposition. We take the results further by reporting the results based on alternative measures of house prices. This constitutes our sensitivity analysis.

3.1 Data

Our dataset is quarterly and covers the period 1969Q4 – 2014Q4. The real output (logGDP) consumer prices (logCPI), repo rate (REPO), and mortgage rate (MORT) are taken from the IMF's International Financial Statistics (IFS). The real output is the logarithm of the GDP at constant 2005 prices denoted in national currency. The consumer prices are measured by the logarithm of the headline consumer price index. The repo rate is the Central Bank policy rate (EOP). The mortgage rate is the lending rate percent per annum. We used the lending rate to measure the mortgage rate because historical data on mortgage rate in South Africa is only available from the 1990s. The lending rate is the most closely related interest rate to the mortgage rate; therefore it is the most appropriate proxy of the mortgage rate. The real private consumption (logCON) is taken from the South African Reserve Bank's Economic and Financial Data for South Africa. It is the logarithm of the seasonally adjusted final consumption expenditure by households in 2005 constant prices. The house prices (logHPI) are sourced from Quantec, a private macroeconomic data provider in South Africa. We used three measures of house prices: (i) the logarithm of affordable houses, all sizes, new and old purchase prices; (ii) the logarithm of middle class houses, all sizes, new and old purchase prices; and (iii) the logarithm of luxury houses, all sizes, new and old purchase prices (smooth rand). Throughout the empirical exercise, we used the variables in their levels. This is consistent with Uhlig (2005), who argues in favour of levels as against first differences in order that the restrictions are imposed directly on the impulse responses and not the cumulative impulse responses. It turns out that the results are invariant regardless of whether the variables are demeaned, differenced, or detrended.[13]

[12] Rubio-Ramirez *et al.* (2010) set a maximum of 100,000 iterations for Steps 2 – 3 to be repeated. If the maximum is reached, the algorithm moves to Step 1 to draw another orthogonal matrix $\tilde{Q}$.

[13] These results are withheld for the sake of concision. They are freely available upon request.

3.2 Impulse Responses Generated from Cholesky Decomposition

We begin our empirical analysis by reporting the results based on Cholesky decomposition. Figure 1 reports these results. Here, the prior restriction on (B, Σ) is a flat Normal inverted-Wishart prior.[14] The conventional Cholesky decomposition requires that we impose lower triangularity on A in *Eq.* (2). The ordering in the Cholesky decomposition corresponds to the ordering of the variables in Y, and also the choice of the covariate whose innovations are denominated as the housing market shocks. In this paper, we ordered the variables as follows:

$$Y = [logCPI, logGDP, logCON, logHPI, REPO, MORT]. \quad (3)$$

Our ordering is consistent with Musso *et al.* (2011) who placed $logCPI$ first, and Uhlig (2005) who placed the variable of interest fourth. Ordered this way, we identify housing market shocks as innovations of $logHPI$. The impulse responses are generated using 1000 Markov Chain Monte Carlo (MCMC) replications, 4 lags, and a horizon of 20-quarters ahead. The size of the shock is one standard deviation, thereby constraining the impulse responses to the median, 16% and the 84% quantiles.

A shock in the housing market produces mostly consistent responses for all the variables, except for consumer prices. Real house prices rose and peaked around 6 quarters, then declined after that but remained positive over the forecast horizon. Real private consumption and real output rose initially, peaked after 4 quarters, and declined thereafter to hit negative around 7.5 to 8 quarters. The repo and mortgage rates rose as well, and peaked around the 5^{th} quarter. These rates declined after the 5^{th} quarter and eventually turned negative after 9 quarters. Consumer prices responded rather unusually after the housing demand shock. Consumer prices began from zero and turned negative after just 2 quarters. As pointed out by Uhlig (2005), the standout limitation of identification based on Cholesky decomposition is its failure to replicate theoretically consistent impulse responses. Consequently, we will not focus on discussing these impulse responses.

3.3 Impulse Responses Generated from the Agnostic Identification Scheme

Figure 2 shows the impulse responses generated from the benchmark identification scheme, namely the agnostic identification scheme. Here, we maintain the recursive ordering in Section 3.2, meaning that the housing market shock is the innovations in the fourth variable, house prices. We iterate the impulse responses using the Rubio-Ramirez *et al.* (2010) rejection algorithm, and report them based on the Fry and Pagan (2011) median target method.[15] The size of the shock is one standard deviation, thereby constraining the impulse responses to the median, 16% and the 84% quantiles. It turns out that a maximum of 1000 MCMC draws meet the

[14] Canova (2007) provides technical details on this prior restriction.

[15] The discussion of this method is beyond the scope of this paper. The interested reader may consult Fry and Pagan (2011) for sufficient treatment of this method.

imposed sign restrictions. A total of 500 MCMC replications, and 500 sub-replications over the rejection routine were more than sufficient for convergence.

The impulse responses delivered by the agnostic identification are generally consistent with the observed pattern brought forth in the literature. All the restricted variables, namely house prices, consumer prices, and the mortgage rate, responded according to the restrictions. Therefore, the housing market shock is appropriately identified as a non-monetary demand shock.[16] Concentrating on the main responses of interest, real house prices reacted to the housing demand shock and increased to peak at 1% after just 2 quarters, then started to return to its original level. The impact of the housing demand shock on real house prices only disappeared after 15[th] quarters. Real private consumption and real output rose by nearly the same magnitude and peaked at 0.2% around the 4[th] quarter, following the housing demand shock. In principle, the temporary increase in real private consumption may be explained by the collateral effect pointed out earlier. The rise in house prices enhances the value of home assets, thereby improving the collateral position of homeowners (see Aoki, 2002; Muellbauer and Murphy, 2008; André *et al.*, 2012). These homeowners may now stand higher chances of securing loans for private consumption. South Africa has a relatively developed real estate market, which enable homeowners to react strongly towards consumption, after such housing demand shocks. Rising private consumption leads to shortages of goods and services; this pushes consumer prices up. The end result will be increases in the production of goods and services in the economy to meet the surge in demand. Another source of the rise in real private consumption stems from the contemporaneous rise in mortgage rate (6%) beyond consumer prices (0.4%). This shot up the real cost of financing mortgages, thereby discouraging renters to save in prospect to becoming homeowners. The decline in real private consumption and real output could also be due to the contemporaneous rise in the repo rate and consumer prices, which may have offset the collateral effect. That aside, homeowners who are retirees or nearing retirement may be austere by shifting their preferences towards precautionary savings and health related activities (see Banks *et al.*, 1998; Disney *et al.*, 2002).[17] This may have offset the initial rise in real private consumption. An equally plausible reason why the housing demand shock on real private consumption and real output is short-lived may be due to the very weak impact of the shock on house prices which appeared to wane off drastically over the forecast horizon. Generally, real private consumption and real output are sensitive to permanent shocks than transitory ones. This appears to be the case here. Our findings are qualitatively similar to those of Simo-Kengne *et al.* (2013), who found private consumption in South Africa to react to housing demand shocks in this fashion.

Looking at the other results, consumer prices increased by nearly 0.4% and remained the same for more than 20 quarters after the housing demand shock. The housing demand shock had

[16] Recall that shocks in the housing market are non-monetary housing demand shocks, if they lead to increase in real house prices, and do not decrease the monetary policy rate (see Jarocinski and Smets, 2008; Iacoviello and Neri, 2010).
[17] This is the so-called retirement savings puzzle in the literature.

lasting impact on consumer prices, and this may be due to the strong causal effect of house prices on rents – an important component of the consumer price index in South Africa. Recent homeowners may be eager to cut their costs by renting out their apartments at higher prices. This shift in the incidence of house price hike to renters in the form of high rents translates into higher consumer prices. Besides, the South African housing market is not a perfect one. Therefore house prices are sticky downwards. This means that the temporary increase in nominal house prices takes longer time to adjust, thereby ensuring that the increase in rent persists. This keeps the consumer price index high over a considerable period of time, after the housing demand shock. In addition, if the collateral effect resulting from the housing demand shock is strong, the increase in house prices promotes real private consumption and real demand for goods and services. Temporary shortages of goods and services will trigger inflationary pressures. This will enhance the impact of high rents on the consumer price index indefinitely.

The mortgage and the repo rates reacted positively, following the housing demand shock. They increased by almost the same magnitude, and peaked at 6% after 5 quarters. These rates declined thereafter and turned negative after nearly 14 quarters, following the housing demand shock. The monetary authority in South Africa appeared to have reacted to the permanent rise in consumer prices by increasing its repo rate. In principle, the monetary authority's reaction to inflation using the repo rate is transmitted via three channels, namely: the credit channel, the interest rate channel, and the exchange rate channel. Through the credit channel, the South African Reserve Bank (SARB) can moderate the rising consumer prices by raising the interest rates on reserve funds to commercial banks and other financial intermediaries. This will force commercial banks and other financial intermediaries to decrease their lending capacity. Households will therefore find it more difficult to borrow money for private consumption, which will ease the pressure on consumer prices. The SARB may moderate the rise in consumer prices using the interest rate channel by inducing homeowners to invest in interest-bearing assets. If the SARB increases its repo rate, the interest rates on other assets will increase as well, inducing homeowners to invest in high-return assets, leading to a reduction in private consumption. Besides, the increase in interest rates means that existing loans (including home loans) now cost more in terms of interest payments, forcing borrowers to cut down consumption. The increase in interest rates also implies that the price of both financial and real assets falls because the present value of future returns falls. Therefore the SARB can offset the collateral effect of house price increase by increasing its repo rate. The SARB may also moderate the rise in consumer prices by increasing the repo rate, to stimulate capital inflows. This leads to increases in the demand for the South African rand, and the appreciation of the exchange rate. Since most capital inputs are imported, appreciation in the rand reduces the costs of these capital inputs and production, which translates into lower consumer prices in the economy. In the current empirical exercise, the repo rate appeared to have been increased to mitigate the rise in consumer prices. It appears that the increment in the repo rate was not long-lasting because the monetary authority saw the rise in the consumer prices to be sustainable after the 5^{th} quarter (see Figure 2).

3.4 Forecast Error Variance Decomposition

In this section, we assessed the amount of the variation in real private consumption and real output that is explained by the housing demand shocks. A technical way to put it is: what proportion of the variance of the k-step ahead forecast revision $E_t[Y_{t+k}] - E_{t-1}[Y_{t+k}]$ in real private consumption, and real output is due to the housing demand shock? Figures 3 and 4 report the proportion of the variance of the 20-step ahead forecast revision of the variables in our empirical exercise. Let us concentrate on Figure 4 because it shows the forecast error variance decomposition of the sign restricted SVAR. It shows that, within the first five quarters, housing demand shocks accounted for 22% and 17% variations in real output and real private consumption, respectively. From the 5th to the 20th quarter, housing demand shocks are responsible for nearly 13% and 14% variations in real private consumption and real output, respectively. This confirms the results from the impulse response analysis presented above, which shows that housing demand shocks led to increases in real private consumption and real output within the first five quarters but this influence wane off thereafter. Starting from 5% in the first quarter ahead, housing demand shocks have consistently accounted for 10% variation in consumer prices, further buttressing the source of consumer price persistence found earlier. Quite surprisingly, it appears that housing demand shocks explained nearly 13% of the variations in the repo rate and the mortgage rate beyond the 5th quarter, than they do prior to that. Perhaps, the monetary authority found itself in a quandary between bringing down consumer prices and reducing the cost of mortgage loans. To wit, the monetary authority raised the repo rate in response to the increasing consumer prices but soon realized that the level of consumer prices was sustainable and therefore decided to undercut the repo rate in order to reduce the mortgage rate. Overall, the housing demand shocks explained larger proportion of the variation in the real house prices (20%) than any of the other variables. This is as expected: after all, those were housing demand shocks.

3.5 Sensitivity of Impulse Responses to Alternative Measures of House Prices

In this section, we attempt to answer the following question. Are the effects of the housing demand shocks on real private consumption and real output invariant when real house prices are measured differently? A successful response to this question constitutes our sensitivity any analysis.

Until this point, our measure of real house prices is the logarithm of middle class houses, all sizes, new and old purchase prices. So we will replace this measure with two alternative measures, namely: (i) the logarithm of affordable houses, all sizes, new and old purchase prices; and (ii) the logarithm of luxury houses, all sizes, new and old purchase prices (smooth rand), to see whether our results above remain unaffected. For the sake of convenience and space, we generate the impulse responses here based on only the agnostic identification procedure and the exact specifications used in the empirical exercise of Section 3.3. The results are reported as Figures 5 and 6. It appears that the measure of real house prices based on the logarithm of affordable houses, all sizes, new and old purchase prices generated impulse responses that are nearly the same as our baseline measure, within the 20-quarters ahead forecast horizon. However, the impulse responses generated using the logarithm of luxury houses, all sizes, new and old purchase prices behaved differently (see Figure 6). Unlike the former results, the effect of housing demand shocks on real private consumption and real output dies down after nearly 25 quarters, in this case![18] Nevertheless, the story remains the same: housing demand shocks influence real private consumption and real output positively after a specified period of quarters and wane off thereafter, in the case of South Africa – the transmission mechanism being slightly complex.

4. Conclusion

This paper assessed the effects of housing market shocks on real output in South Africa over the period 1969Q4 – 2014Q4, by emphasizing the real private consumption channel. This is important because majority of the existing studies both on South Africa and other economies have concentrated on the impact of these shocks on specific real economic fundamentals and interpreted the impact of these shocks on the real output by appealing to the theory. These studies are theoretically justified. However, it will be empirically worthwhile to examine the role of these shocks on the real output directly. We did precisely that in this paper. Our attempt should not be viewed as a proposal to replace these other studies. Instead, it should be seen as a complement to the growing literature. The agnostic identification procedure employed in this paper delivered impulse responses that are overall consistent with the existing literature. It turned out that the housing market shocks were appropriately identified as non-monetary housing demand shocks. 20% of the variation in house prices were explained by the housing market shocks. The effects of housing demand shocks on real private consumption were short-lived, explaining why real output responded transitorily to these shocks. Housing demand shocks have managed to explain nearly 14% and 13% variations in real output and real private consumption, respectively, over 20-quarters ahead forecast revision.

[18] This part is not shown in the empirical exercise but it is very straightforward to show.

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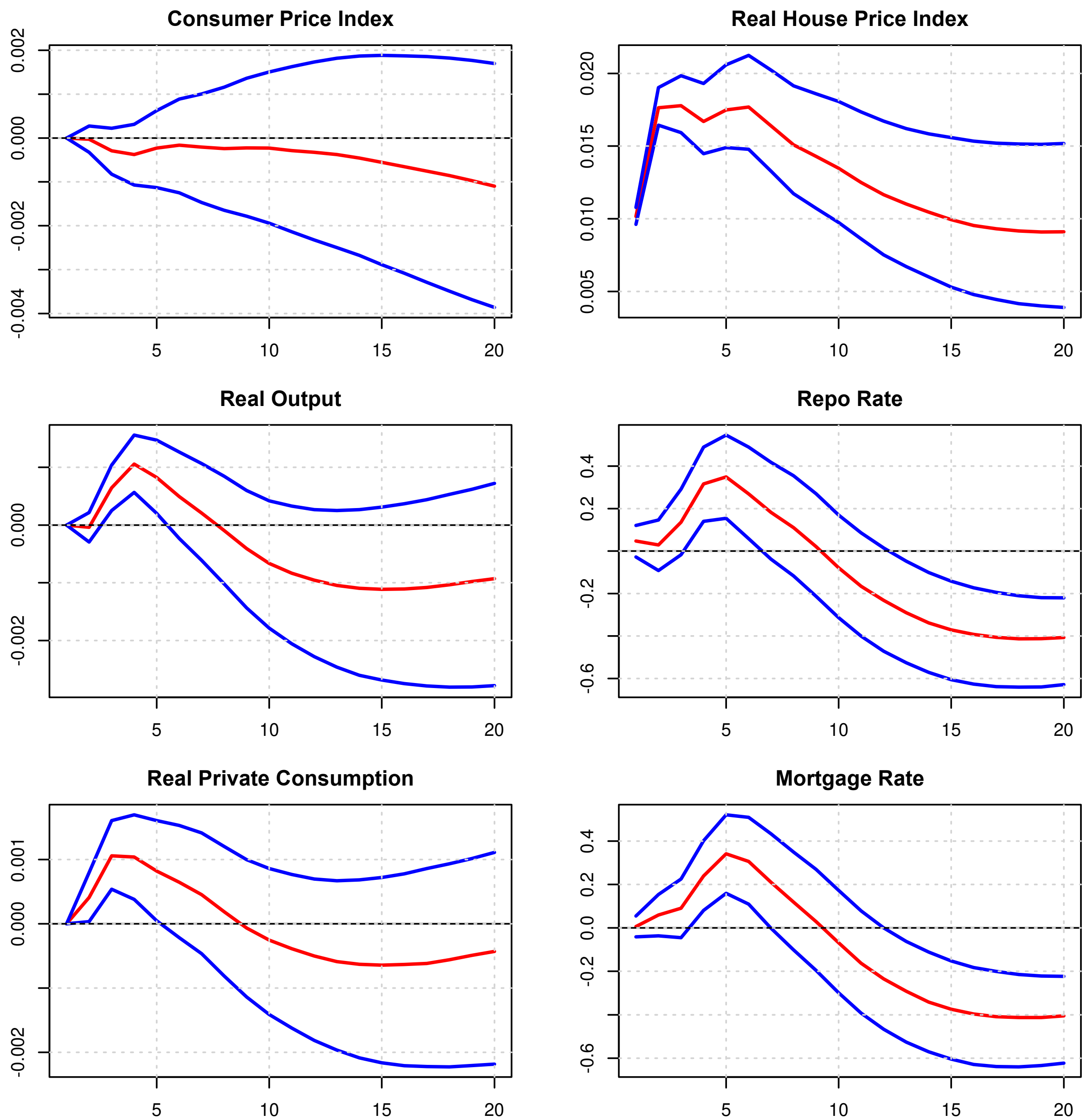

Figure 1: Impulse responses to a housing market shock one standard deviation in size, which is identified as the innovation in the house price index, ordered fourth in Cholesky decomposition before the repo rate and the mortgage rate. The three lines denote the 16% quantile, the median and the 84% quantile of the posterior distribution.

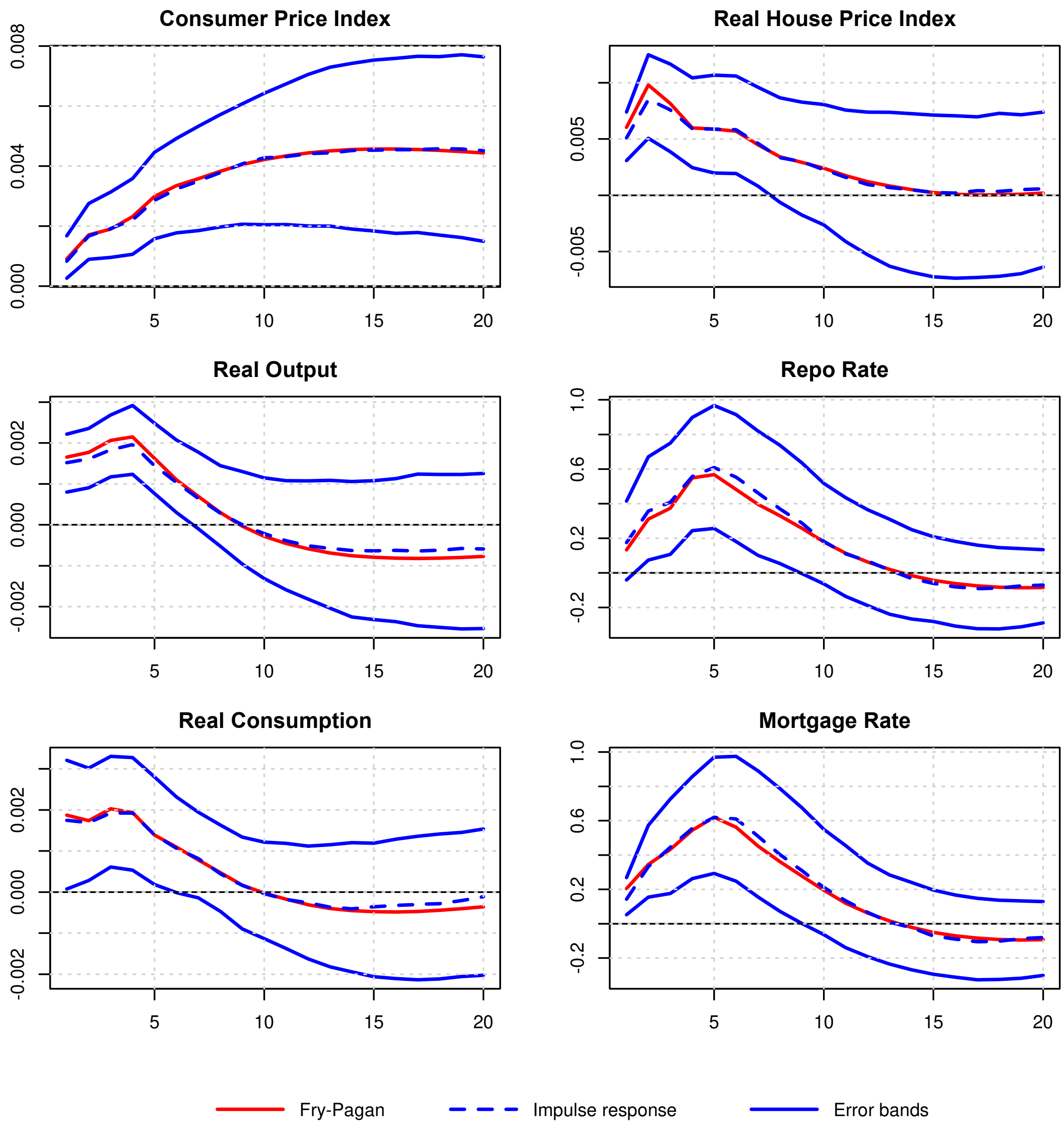

Figure 2: Impulse responses to a housing market shock one standard deviation in size, using the Rubio-Ramirez *et al.* (2010) rejection method with K=5. Impulse responses correspond to the Fry and Pagan (2011) median target method. The three lines denote the 16% quantile, the median and the 84% quantile of the posterior distribution. Responses of real house prices, consumer prices, and mortgage rate are restricted to be positive for quarters k, $k = 0, \ldots, 5$, after the housing market shock.

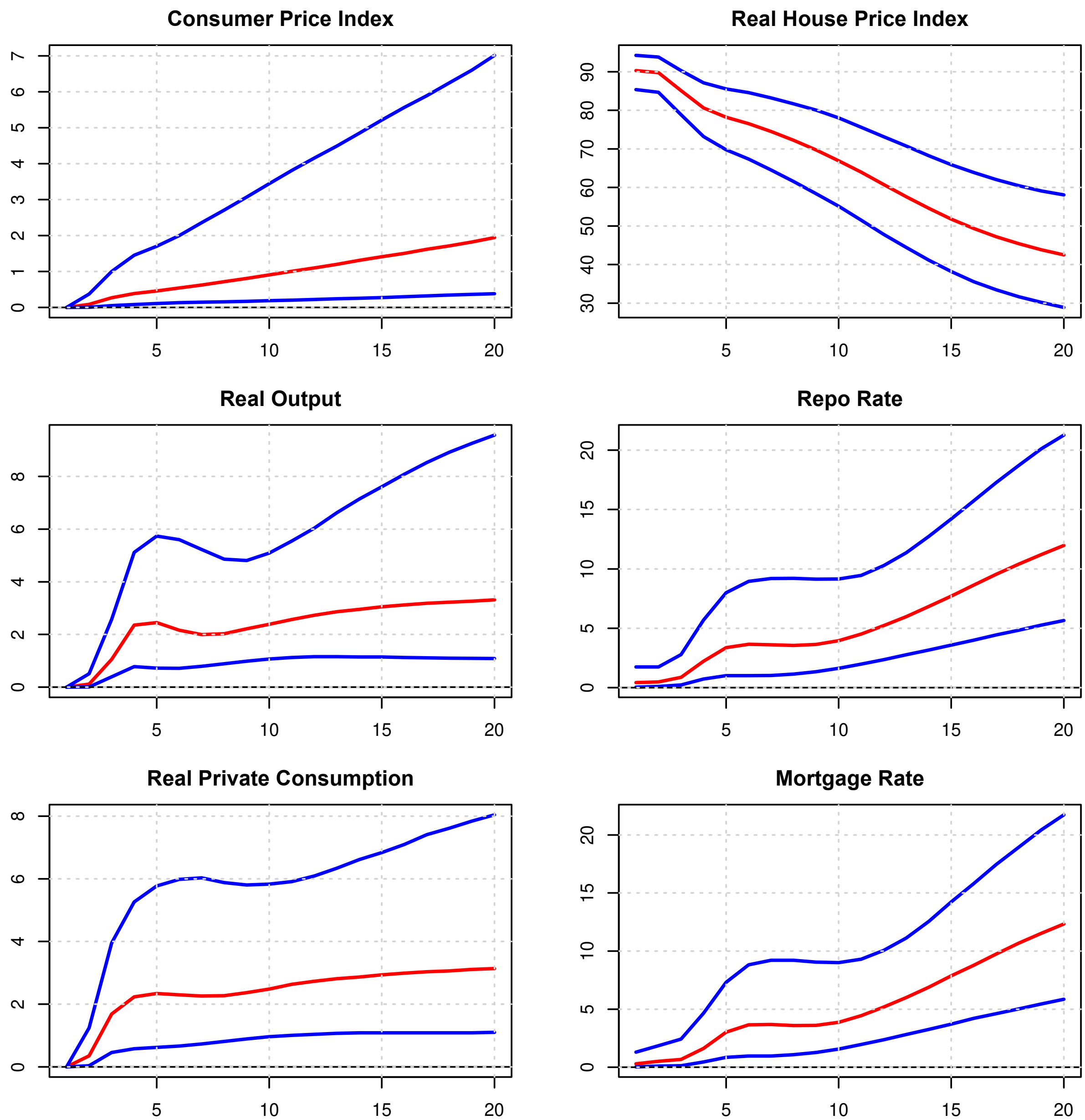

Figure 3: FEVDs due to a housing market shock one standard deviation in size, which is identified as the innovation in the house price index, ordered fourth in Cholesky decomposition before the repo rate and the mortgage rate. The three lines denote the 16% quantile, the median and the 84% quantile of the posterior distribution.

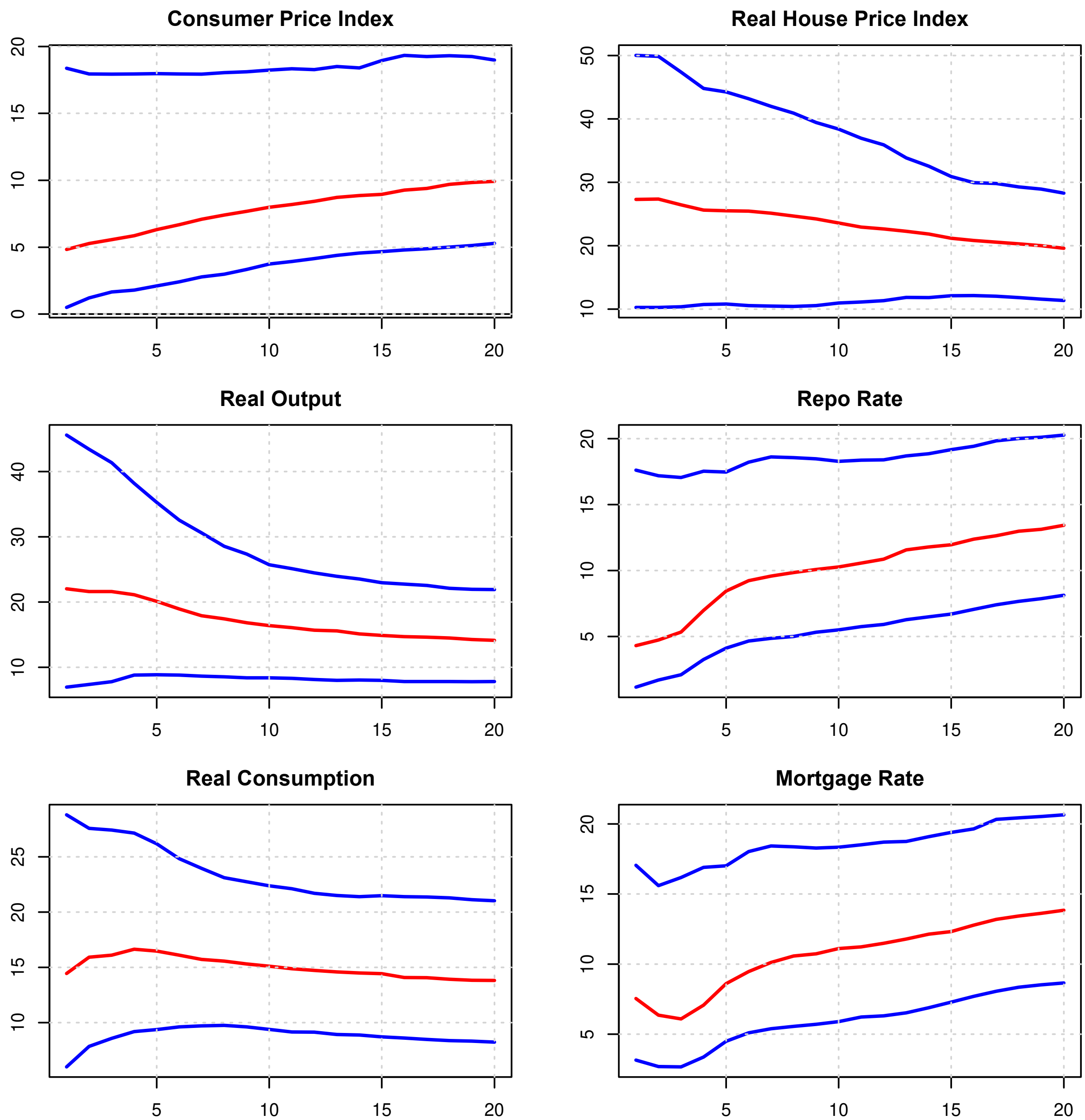

Figure 4: FEVDs due to a housing market shock one standard deviation in size, using the Rubio-Ramirez et al. (2010) rejection method with K=5. The three lines denote the 16% quantile, the median and the 84% quantile of the posterior distribution. Responses of real house prices, consumer prices, and mortgage rate are restricted to be positive for quarters k, k= 0,…,5, after the housing market shock.

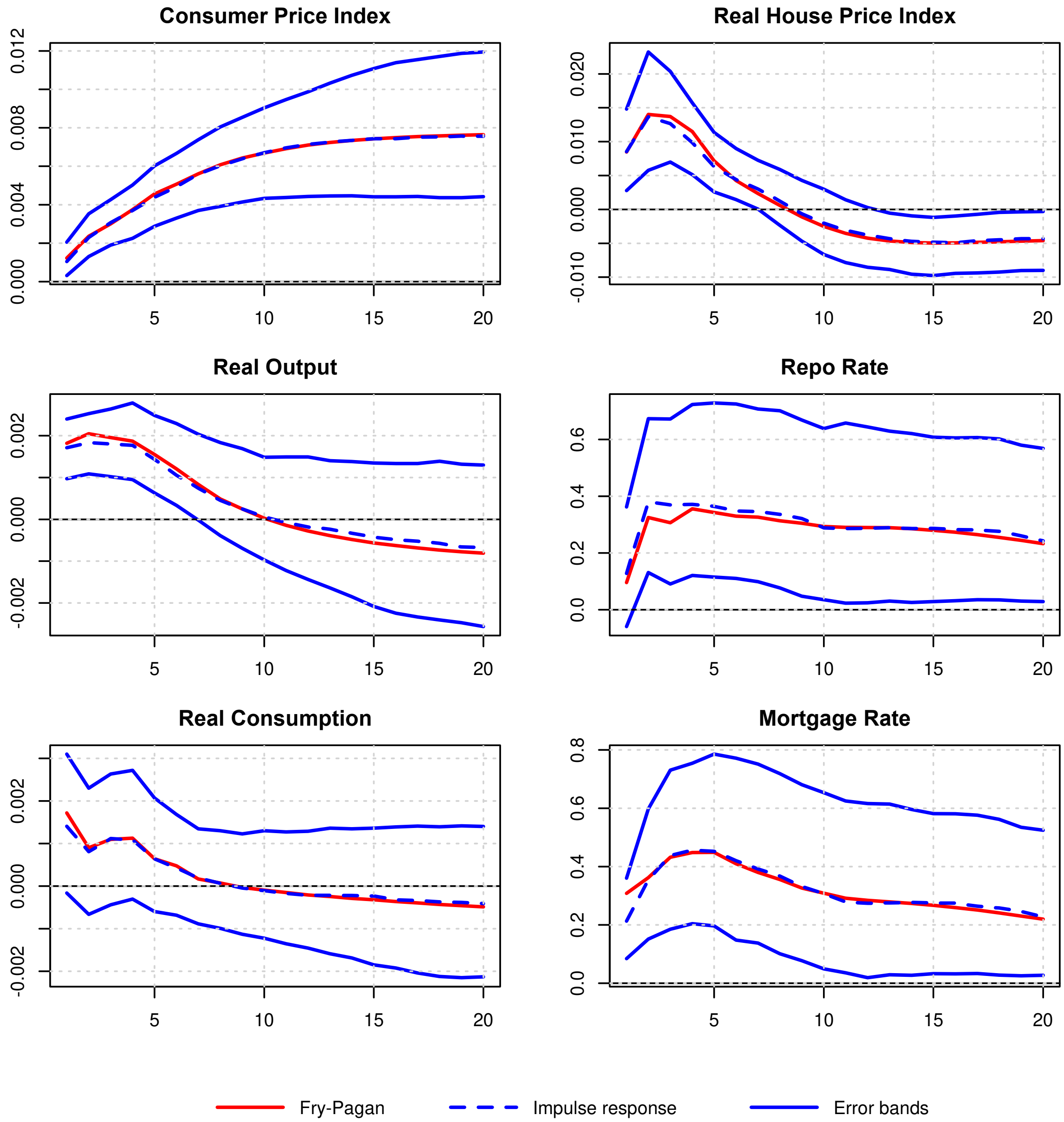

Figure 5: Impulse responses to a housing market shock one standard deviation in size, using the Rubio-Ramirez *et al.* (2010) rejection method with K=5. Impulse responses correspond to the Fry and Pagan (2011) median target method. The three lines denote the 16% quantile, the median and the 84% quantile of the posterior distribution. Responses of real house prices (affordable houses), consumer prices, and mortgage rate are restricted to be positive for quarters k, $k = 0, \ldots, 5$, after the housing market shock.

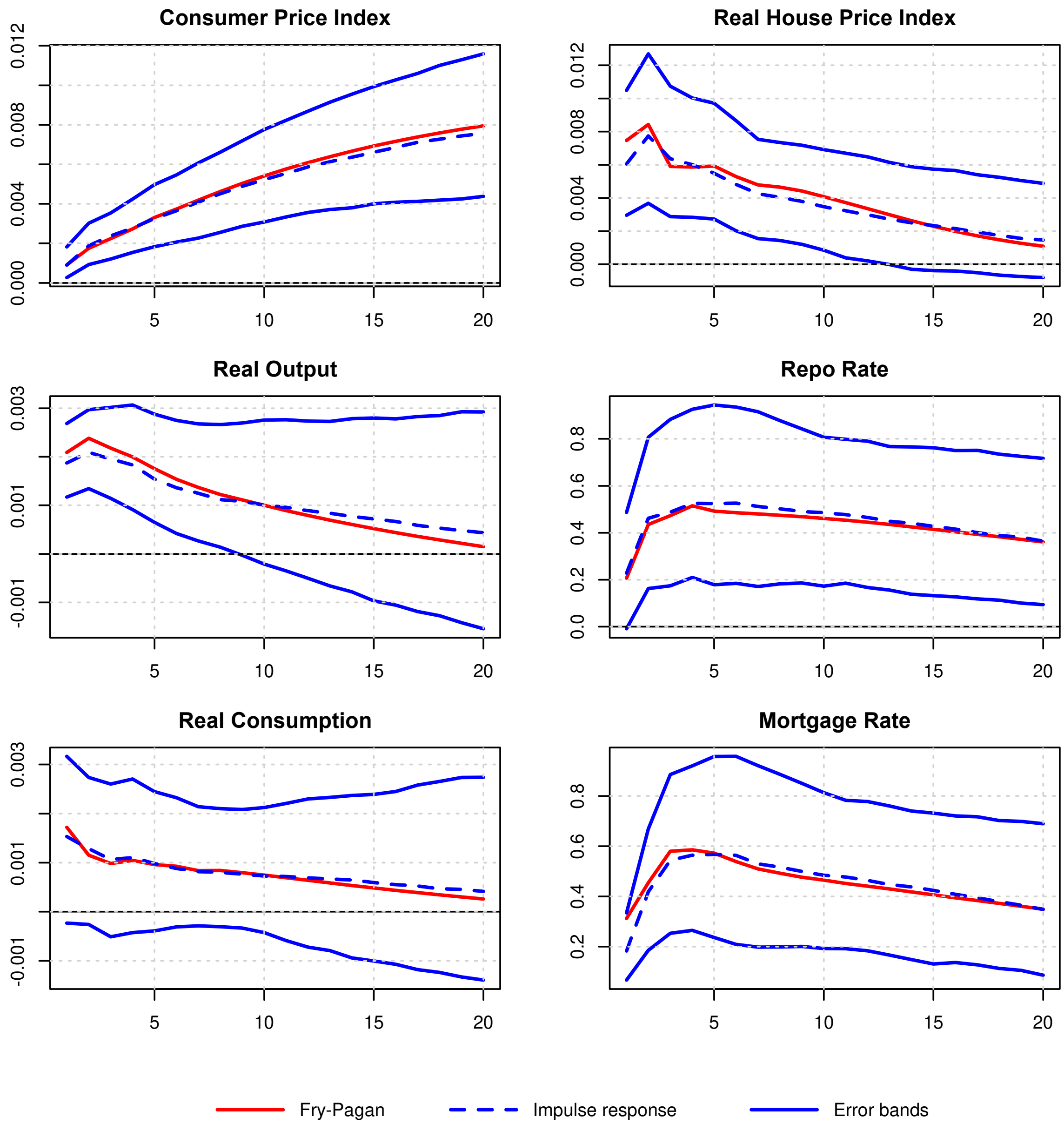

Figure 6: Impulse responses to a housing market shock one standard deviation in size, using the Rubio-Ramirez *et al.* (2010) rejection method with K=5. Impulse responses correspond to the Fry and Pagan (2011) median target method. The three lines denote the 16% quantile, the median and the 84% quantile of the posterior distribution. Responses of real house prices (luxury houses), consumer prices, and mortgage rate are restricted to be positive for quarters k, $k = 0, \ldots, 5$, after the housing market shock.