Monetary Policy Shocks and Housing Bubbles: Is there a relationship?

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We estimate local projection models to investigate the relationship between monetary policy shocks and the probability of housing market bubbles in Australia in the last four decades. We propose a two-stage asset bubble identification process that involves combining recent innovations in asset bubble identification methods and Vector Error Correction Modelling that generate two distinct asset bubble indicators. Applying this two-stage approach to the Australian housing market, we find evidence of two housing bubbles in Australia in the last twenty years. Using two different instruments for monetary policy shocks, the narrative measure as in Bishop and Tulip (2017) and a structural residual series exogenous to house prices, we find evidence that monetary policy shocks affect the probability of housing market bubbles forming. Overall, this study provides new insights on the relationship between monetary policy and housing prices in Australia, with relevant implications for the conduct of monetary policy.

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Contents

1. *Introduction*

Financial crises and economic downturns are frequently preceded by booms and busts in the housing market.[2] To consider just a few examples, the Global Financial Crisis (***the GFC***), the 1991 recessions in Sweden and Finland and the early 90s recession in Australia each erupted after a collapse in housing markets (Jonung, Kiander and Vartia, 2009; Macfarlane, 2006). Moreover, recent research has found that financial crises are usually preceded by asset bubbles and rampant credit growth (Ahamed, 2009). This pattern has led some economists to conclude that asset bubbles play an important role in causing financial crises (Shiller, 1992). To investigate the veracity of this claim, we need to understand asset bubbles. However, there is so much about asset bubbles that we don't know (Fama, 2014; Simon, 2003). Some prominent economists reject the existence of asset bubbles entirely (Fama, 2014), while others attribute their existence to behavioural factors, such as risk aversion (Mishkin, 2016; Siegel JJ, 2003). Alternatively, some argue that bubbles can be explained by rational behaviour (Gali, 2015). However, since the GFC, there has been renewed interest in the role of monetary policy in the formation and evolution of asset bubbles (Bordo and Landon-Lane, 2013; Blot et al, 2017; Taylor, 2015). Taylor (2015) has suggested that excessively expansionary monetary policy can encourage risk taking and inappropriate lending behaviour. Our research attempts to empirically investigates this proposition.

Our objective is to specifically investigate the relationship between monetary policy and housing bubbles in Australia. First, we review recent literature on the identification of monetary policy shocks and on the identification of asset bubbles. Second, we propose a two-stage process that is intended to complement recent innovations in asset identification methods. Third, we select two preferred instruments for monetary policy shocks that will be used in our empirical investigation. Fourth, we apply our two stage approach to the Australian housing market over the last four decades, generating two distinct housing bubble indicators. Finally, we use Jorda's (2005) local projections to investigate the relationship between monetary policy shocks and our two housing bubble indicators.

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[2] More generally speaking, the numerous financial crises of the 20th century have, almost without exception, been preceded by crashing asset prices (Ferguson, 2008; Ahamed, 2009).

This strategy enables us to answer the following questions:

1. Is there evidence of any housing bubbles between 1978 and 2017?

2. What impact, if any, do monetary policy shocks have on housing bubbles?

Briefly, we find evidence of two housing bubbles in the Australian housing market between 1978 and 2017. We find evidence that positive monetary policy shocks have a negative impact on the likelihood of an asset bubble forming and, similarly, we find evidence that expansionary monetary policy shocks may have a positive impact on the likelihood of an asset bubble forming. This suggests that monetary policy and possibly credit controls can be contributing factors to both the formation and dissolution of housing bubbles. We begin our discussion with two literature reviews. The first focuses on monetary policy shocks. We identify Romer and Romer residuals (2004) and residuals from a VAR as our preferred monetary policy shock variables. The second considers recent work on identifying asset bubbles. We discuss the issues that have arisen in identifying asset bubbles and highlight recent breakthroughs using unit root tests for explosive price behaviour. We choose to utilise the method proposed by Phillips, Shi and Yu (2015) as part of our two stage process for identifying asset bubbles. We then present our methodology, empirical application and results. We outline our methodology in detail, discussing the specifics of constructing our preferred monetary policy shocks, the Phillips, Shi and Yu (2015) approach to asset bubbles, and our regression method. We argue that Jorda's Local Projections (2005) are an ideal tool for our research. We then apply our methodology to data from the Australian housing market. Finally, we discuss the limitations of and potential extensions to our research.

2. *Literature Review*

In this section, we discuss the recent literature on the identification of monetary policy shocks and asset bubbles. We begin our discussion with the former.

2.1 Monetary Policy Shocks

A monetary policy shock occurs when the central bank makes an exogenous change to monetary policy (See Ramey (2016) for an excellent discussion of the specific meaning of macroeconomic shocks). However, in order to investigate the impact monetary policy shocks have on the economy, we first need to be able to identify them. Unfortunately, such identification is notoriously difficult (Christiano, Eichenbaum and Evans, 1996; Nakamura and Steinsson, 2018). Deriving causal inference requires identifying 'plausible exogenous variation', which is almost impossible when dealing with macroeconomic variables (Nakamura and Steinsson, 2018, p 59). More specifically, monetary policy is constantly responding to macroeconomic variables, implying that the central bank interest rate is fundamentally endogenous (Cover and Olson, 2013).[3]

The development of the vector autoregression (VAR) constituted a partial solution (Sims, 1980). VARs attempt to capture both the simultaneous and dynamic character of economic relationships (Sims, 1980), which is useful for isolating the exogenous shocks. By regressing the central bank policy rate on multiple lagged variables, the researcher can extract the structural residuals of the central bank policy rate. These residuals, if the VAR is well identified, can generally be treated as monetary policy shocks. This method is currently the most prevalent for identifying exogenous shocks in empirical monetary economics (Bernanke, 1986; Christiano and Eichenbaum, 2005; Nakamura and Steinsson, 2018).[4] In this paper, we attempt to derive a simple measure of monetary policy shocks based on this approach.

However, the VAR still suffers from numerous limitations. Firstly, it is sometimes structured with an inbuilt recursiveness assumption, with the federal funds rate usually ordered last (Cloyne and Hurtgen, 2016).[5] While allowing variables to contemporaneously influence interest rates, this approach assumes

[3] Monetary aggregates suffer from the same problem (Nakamura and Steinsson, 2018).

[4] See Kuttner (2001) and Gali and Gambetti (2015) for further examples.

[5] Please note that the such recursiveness assumptions are not a necessary feature.

interest rates have a lagged effect on other macroeconomic variables. This may be unrealistic given that there tends to be a 'sizable short-term increase in prices in response to a monetary tightening' (Cloyne and Hurtgen, 2016, p77). Nakamura and Steinsson (2018) similarly point out that the 'timing assumption' eliminates important elements from the analysis, such as the possibility of reverse causation when considering the joint determination of output and interest rates (p78). Second, these regressions may be 'structurally fragile', given the quantity of constraints imposed by the method (Rudebusch, 1998). For example, when the attitudes of Federal Open Market Committee (FOMC) evolve with changing membership, the response function guiding the federal funds rate will change (Rudebusch, 1998). However, such structural breaks are not typically or easily accommodated within the VAR approach. Furthermore, there is significant disagreement regarding what variables are present in a correctly specified VAR (Rudebusch, 1998). For example, some have argued that commodity prices are a necessary variable (Christiano et al, 1996a, 1996b), while others suggest more unorthodox variables should be included (Rudebusch, 1998).[6] Hence, it is necessary to turn to alternative approaches to deal with these issues. One such approach is to use the narrative record.

Romer and Romer (1989) were early advocates for isolating exogenous shocks through non-statistical approaches. For example, a change in the central bank response function due to changing personnel or changing preferences would constitute such a shock. Identifying these moments may involve interviewing key decision makers and can be described as exogenous shocks to monetary policy. While useful, this approach is also imperfect. Firstly, it has a poor track record in identifying numerous shocks,[7] exacerbating the risk of omitted variable bias in their analysis (Hoover and Perez, 1994). Second, 'narrative shocks are selected by an inherently opaque process' (Nakamura and Steinsson, 2018, p76).

[6] There is evidence that variables such as the foreign trade deficit, the stance of fiscal policy and measures of 'political pressure' are statistically significant in influencing the federal funds rate, though such variables are rarely included in a standard VAR (Khoury, 1990). Nakamura and Steinsson (2018) highlight the role that sometimes 'idiosyncratic' considerations play in the setting of monetary policy (2018). For example, they list such factors as 'stress in the banking system, … a recent stock market crash, a financial crisis in emerging markets, terrorist attacks… and the Y2K computer glitch' (2018, p77).

[7] Romer and Romer (1989) only specify seven data points.

This raises issues regarding replication, even regarding whether a standard has been consistently applied. Finally, various researchers have raised the problem of endogeneity.[8]

However, Romer and Romer (2004) have derived a new instrument for monetary policy shocks that avoids many of the endogeneity problems associated with the VAR approach while proposing a replicable identification method. Romer and Romer (2004) use quantitative and narrative records to derive the Federal Reserve's intentions for the federal funds rate around FOMC meetings. This series is then 'regressed on the Federal Reserve's internal forecasts to derive a measure free of systematic responses to information about future developments' (p1055).[9] Cloyne and Hurtgen (2016) have used this method in deriving a monetary policy shocks for the UK. Similarly, Bishop and Tulip (2017) have derived an equivalent series of Australian monetary policy shocks. This method has also been used in empirical macroeconomic research (Cover and Olson, 2013). The Romer and Romer measure is not without criticism. Barakchian and Crowe (2013) have argued that it does not take structural breaks in the series into account. For example, Barakchian and Crowe find evidence that US monetary policy has become increasingly forward looking over time. However, no allowance for this is incorporated into the Romer and Romer measure. Nonetheless, given its significant advantages, we have chosen to use the Romer and Romer measure in our analysis.[10] More specifically, we use the narrative series for Australia generated by Bishop and Tulip (2017).

2.2 Asset Bubbles

There are a host of problems faced by any economist attempting identify a bubble, particularly as some argue that asset bubbles do not exist (Siegel JJ, 2003). Even if we accept their existence, the commonly used definition of a bubble is problematic. Brunnermeier (2009) captures this complexity in his purported definition:

1. The bubble consists of excessive variations in price; or

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[8] This is due to the fact that some researchers have found that narrative shocks tend to be predictable. Such a criticism may also be applicable to Romer and Romer's work (Shapiro, 1994; Leeper, 1997), though this does not seem to be a decisive criticism in this case (Romer and Romer, 1997).

[9] See John Cochrane's (2004) NBER EFG discussion for an insightful analysis of the approach.

[10] We also note that the Romer and Romer measure is not a 'universally exogenous' instrument for monetary policy shocks (See Ramey, 2016, page 96).

2. The bubble consists of a consistent departure from the asset's underlying fundamental value.

The first characterisation treats bubbles as 'observable phenomena' (***the statistical approach***). The second defines an asset bubble as a deviation from economic fundamentals (***the theoretical approach***). We will discuss both these approaches in turn.

The statistical approach describes bubbles as empirically observable exuberance. Sudden episodes of explosive price behaviour, or dramatic departures from a long-run trend, can thus be described as an asset bubble. This definition is accepted by several economists (Shiller, 1992; Atkinson, 2012; Borio and Lowe, 2002; Detken and Smets, 2004; Goodhart and Hofmann, 2008; Bordo and Jeanne, 2002; Bordo and Landon-Lane, 2013; Bordo and Wheelock, 2004). There are numerous strategies to apply this approach, such as examining the price to earnings (P/E) ratio (Shiller, 1992), identifying price changes greater than a standard deviation (Blot et al, 2017; Siegel, 2003) or departures from a Hodrick-Prescott filter (Borio and Lowe, 2002; Jorda, 2015), and looking at the speed of price growth relative to the average (Bordo and Jeanne, 2002). Others look for certain patterns in the time series, identifying peaks and troughs in prices as bubble episodes (Bordo and Landon-Lane, 2013; Bordo and Wheelock, 2004). These approaches tend to be easy to apply to time series and are useful in that they usually identify famous bubble episodes as asset bubbles.

However, the statistical approach can be criticised on the grounds that there is an inherently arbitrary nature as to how the rule is defined. Different researchers provide conflicting definitions of what constitutes a 'sufficient' deviation from the trend, how long the boom needs to be and how large the post-bubble correction must be.[11] Furthermore, the analysis is not based on an underlying theoretical model. Such an investigation without any theoretical underpinning may be quite misleading. Some argue that any test for speculative bubbles must first assume a baseline reference model for equilibrium prices in an efficient market. Otherwise, what appears to be a speculative bubble might be no such thing if the baseline equilibrium-pricing model is itself incorrect (Jones, 2014). Fama argues that asset bubbles

[11] For example, Goodhart and Hofmann (2008), Detken and Smets (2004), Alessi and Detken (2011), Bordo and Jeanne (2002) all offer different measures of deviation from the trend. As Simon (2003) states, 'It seems to come down to personal judgments'

do not exist in asset prices, as we currently lack a systematic method for predicting the 'end' to the bubble (Greenwood, Shleifer and You, 2016; Fama, 2014). As these approaches cannot identify asset bubbles other than in hindsight, it is unclear whether we have a concept that has any 'real world' application (Fama, 2014). Therefore, we need a bubble definition that takes into account economic fundamentals. Consequently, we turn to the theoretical approach.

The theoretical approach generally involves providing a theoretical foundation for how prices should behave based on fundamentals, and identifying asset bubbles as departures from that foundation. This could involve estimating a model of asset prices and treating the residual as the 'bubble element' (Phillips et al, 2015), identifying 'unjustified' discrepancies between related products (DeLong and Schleifer, 1991), assessing the risk-premium (Rappoport and White, 1991), or departures from the theory of rational expectations (Phillips et al, 2015).

The advantages of the theoretical approach are, naturally, consistent with its objectives: The theoretical approach links the researcher's empirical analysis with underlying economic theory, which should be a necessary precondition of an economic analysis. Secondly, the theoretical approach eliminates the problem of arbitrary definitions, as the theoretical argument will impose strict rules on the application of the theory to the data. Finally, advocates of the theoretical approach will argue that this approach will identify 'true' asset bubbles: So long as the theory is correct, an asset bubble will exist if it satisfies the theory.

However, some criticise theoretical models on the grounds of identification failure. Theoretical applications often find that famous historical bubble episodes are not, according to their model, actual asset bubbles, while identifying previously innocuous historical periods to have constituted asset bubbles (Simon, 2003). Secondly, theoretical models regularly produce outcomes inconsistent with other theoretical models.[12] This inconsistency, however, doesn't of itself demonstrate that the theoretical

[12] McGrattan and Prescott (2004) use a theoretical approach to find that the 1929 stock market was not a bubble, but was in fact a period where stocks were undervalued. In contrast, Delong and Shleifer (1991) find that there was a bubble in 1929. Santoni and Dwyer (1990) find that neither the 1929 nor the 1987 asset price booms and busts constituted bubbles. In fact, they find that other time periods, generally understood not to constitute bubble episodes of any kind, to be bubbles.

approach is wrong. Rather, it may simply demonstrate that there is not yet agreement on the appropriate model.

Whether a researcher prefers the statistical or theoretical approach will heavily depend on how they think sound research on asset bubbles should proceed. These competing views can be characterised as follows:

The Statistical Method	***The Theoretical Method***
1. Asset bubbles exist and are empirically observable phenomena that can be visually observed in time series data. 2. A necessary condition of a good model for identifying asset bubbles is that it successfully identifies the most famous bubble episodes in the historical literature as bubbles. 3. Whether the identification method is tied to underlying theory is a secondary concern.	1. Any attempt at identifying at identifying asset bubbles first requires an appropriate theory of what an asset bubble is. 2. This theory can be translated into a model, which in turn can be applied to historical asset price data. 3. An asset bubble will only exist if the model identifies an asset bubble.

We attempt to resolve this tension by recognising that both approaches need to be incorporated into any ideal bubble identification strategy. We start with a defence of the statistical approach by appealing to the justification for our research. Our research into housing bubbles is motivated by economic history, which frequently reveals episodes where sudden explosive house price behaviour is followed by dramatic corrections. These corrections, in turn, are often followed by a recession. We define these historical episodes as housing bubbles and we are interested in exploring how and why these bubbles occur. Hence, any purported identification model that fails to identify the most famous historical bubble episodes will not be considered accurate. Consequently, it is necessary that our identification strategy accounts for the dramatic changes in housing prices observed in the historical record. There is a growing body of empirical research that is consistent with this requirement. One such approach involves identifying asset bubbles in terms of 'explosive price behaviour', which constitutes a departure from the random walk implications of rational market theory (Phillips, Wu and Yu, 2011; Phillips, Shi and Yu, 2015; Hall et al, 1999; Shi and Song, 2014).[13] Phillips, Shi and Yu (2015) have developed a test for identifying asset bubbles (***the PSY test***) that is successful in identifying asset bubbles in Monte Carlo simulations and identifying famous historical asset bubbles in P/E ratio data from the S&P500 over a long time series. We use the PSY test in our the 'firsts-stage' of our bubble identification strategy and will discuss the details of the PSY test in our Methodology.[14]

Nonetheless, we also recognise that explosive price behaviour may simply be an equilibrium response to some exogenous shock. If such a price response can be justified by the fundamentals, then it is inherently inappropriate to describe such price behaviour as a bubble. Thus, in attempting to identify asset bubbles, it is important that we have some model of the asset's underlying value based on the fundamentals of the asset. As discussed above, such an approach has been taken before (for example, De Long and Schleifer, 1991; Jones, 2014). This typically involves modelling an asset price based on fundamentals and then treating the residuals as a 'bubble indicator'. We attempt to utilise this approach in the second stage of our asset bubble identification strategy. Again, we discuss the details of this in our Methodology section below.

[13] One such method involves a 'two-regime Markov-switching unit root' test for identifying such explosive price behaviour (Hall et al, 1999). However, simulation work indicates that this model is may have problems with false detection (Shi, 2013). A more successful method was proposed by Phillips, Wu and Yu (2011), which involved recursively carrying out unit root tests over the sample period. This work was the basis of the Phillips, Wu and Yu (2015) method which we apply in our research.

[14] As will be discussed below, Phillips, Shi and Yu have recently published updates to their approach. This means that our results are different from those found in an earlier version of this report.

3. Methodology

We outline our process for investigating the link between monetary policy shocks and asset bubbles. First, we propose a two-stage approach for identifying asset bubbles. We then provide an intuitive explanation of the PSY test (Phillips, Shi and Yu, 2015), which we use to identify asset bubbles in the first stage.[15] We then explain how we use a Vector Error Correction Model (VECM) to identify a potential model for the 'long-run equilibrium house prices'. We argue that deviations from such a model can be treated as deviations from the fundamental value, and hence as 'bubble behaviour'. We then turn to our measures of monetary policy shocks. We provide an explanation as to how Bishop and Tulip (2017) derived the 'Romer and Romer – equivalent' residuals for Australia. Similarly, we set out how we use a VAR to derive a measure of monetary policy shocks that will be exogenous to house prices (based on the approach taken by Bernanke and Blinder (1992)). Finally, we outline how we use Jorda's Local Projections (2005) to investigate the relationship between asset bubbles and monetary policy shocks.

The PSY test

The PSY test carries out multiple generalised sup Augmented Dickey Fuller tests (GSADF tests), a form of unit root test, over different 'windows' or sub-sets of the time series. This unit root test effectively tests for 'explosive price behaviour' in the time series (Phillips, Shi and Yu, 2015, p 1045). If explosive price behaviour is identified, we identify an asset bubble. The range of the series sub-set being tested gradually expands until covering the final data point, T (the *expanding sample sequence* component). Then, the starting point of the window is moved forward in the series and the test is repeated over the new subset (the *rolling-windows* component). The expanding sample sequence was first proposed by Phillips, Wu and Yu (2011). The PSY test added the 'rolling-windows' component, which enabled the model to more easily identify multiple bubbles in the same series (Phillips, Shi and Yu, 2015). This concept is demonstrated visually in figure 1 below. The SADF Test, on the left, represents the recursive testing process. The GSADF test, on the right, represents the same test with the addition of a rolling windows component.

[15] For the technical details of the method, please see Phillips, Shi and Yu (2015)

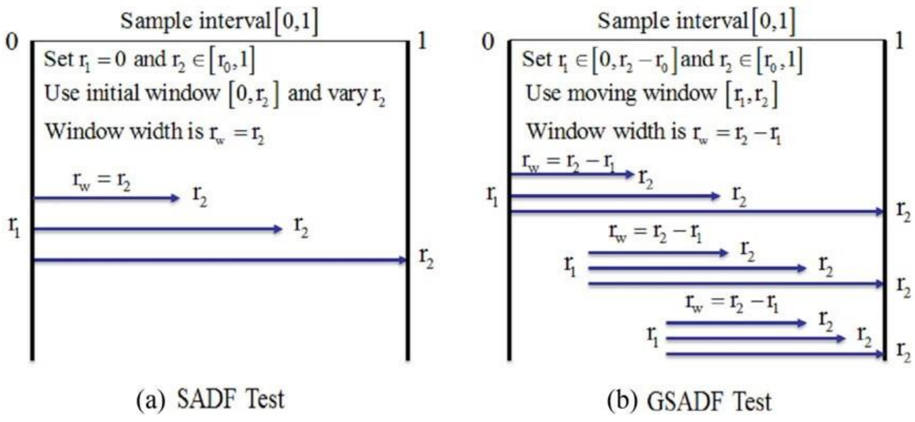

Figure 1, **Source**: **Phillips**, **Shi and Yu**, **2015**, **p1049**

Moreover, in order to identify asset bubbles in real time, rather than just in hindsight, Phillips, Shi and Yu (2015) proposed that this testing process is carried out 'backwards' over the time series: The test commences backwards from the end of the sample period, rather than the beginning. This alternative can be seen visually in figure 2: We see the same process as shown in figure 1, except the test is carried out backwards from the final data point.

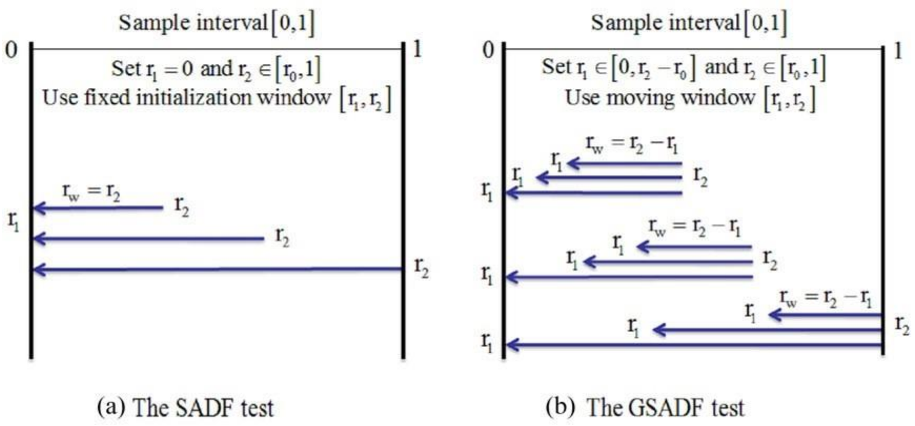

Figure 2, **Source**: **Phillips**, **Shi and Yu**, **2015**, **p1053**

Shuping Shi, one of the creators of the PSY test, has recently updated to the test to include a 'wild bootstrapping'(WBS) component. The WBS element is designed to ensure that the test is not treating one bubble episode as multiple unique bubble episodes. Practically, WBS element has the effect that prices being investigated need to genuinely stagnate or decline before another explosive episode can be identified (comparisons between the PSY test with and without the WBS component are provided in Appendix 1).

We can generate a PSY test statistic series by applying the PSY test to a 'Asset Price to Dividend Ratio' time series. Moreover, we propose that this series can be treated as a 'bubble likelihood indicator' where the larger the test statistic, the more likely there is to be an asset bubble. Therefore, we may be able to use the PSY test statistic series as a dependent variable in a model that analyses the response of a bubble indicator to monetary policy shocks. We proceed on this basis. This constitutes the first stage of our two-stage bubble identification strategy, so we now turn to explaining the second stage.

Using a Vector Error Correction Model (VECM) to identify house price deviations from fundamentals

The VECM is designed to model macroeconomics variables where the variables tend to exhibit a long run underlying relationship. Using the summation operator, we can compactly present the VECM as follows:

$$\underset{(m\times 1)}{\mathrm{dx}_t} = \underset{(m\times 1)}{\mathrm{A}_0} + \prod_{(m\times m)} \underset{(m\times 1)}{\mathrm{x}_{t-1}} + \sum_{j=1}^{p-1} \underset{(m\times m)}{\Gamma_j} \underset{(m\times 1)}{dx_{t-j}} + \underset{(m\times 1)}{\varepsilon_t} \tag{1}$$

Where dx_t is a vector of the variables in first difference form, $\sum_{j=1}^{p-1} \underset{(m\times m)}{\Gamma_j} \underset{(m\times 1)}{dx_{t-j}}$ constitutes the sum of p-1 lags of the variables and $\underset{(m\times 1)}{\varepsilon_t}$ is a vector of errors.[16] It can be shown that $\prod_{(m\times m)} \underset{(m\times 1)}{\mathrm{x}_{t-1}}$ can be rewritten as $\underset{(m\times r)}{\alpha} \underset{(r\times m)}{\beta'} \underset{(m\times 1)}{\mathrm{x}_{t-1}} = \prod_{(m\times m)} \underset{(m\times 1)}{\mathrm{x}_{t-1}}$. It can also be shown that if we define $\underset{(r\times m)}{\beta'} \underset{(m\times 1)}{\mathrm{x}_{t-1}} \equiv \underset{(r\times 1)}{u_{t-1}}$, $\underset{(r\times 1)}{u_{t-1}}$ constitutes a vector of I(0) variables (see Harris and Sollis (2003)). This term is referred to as the 'error correction term', and the series generated by the vector can be treated as 'errors' or 'deviations' from the long run relationship from the variable with a coefficient of one in that particular vector.

[16] Alternatively, a VECM can be described as a VAR in first differences augmented by the term $\prod_{(m\times m)} \underset{(m\times 1)}{\mathrm{x}_{t-1}}$, where $\underset{(m\times 1)}{\mathrm{x}_{t-1}}$ is a vector of the variables in level form, lagged once.

First, we suggest that a VECM can be used to determine whether there is a long run relationship between house prices and a series of identified fundamental variables. Second, assuming that there is a long run relationship, we can define *positive deviations* from that long run relationship as 'bubble' episodes. This constitutes the second stage of our 'two-stage' bubble identification procedure.

Summarising the two-stage bubble identification strategy:

Putting this all together, we propose that we first identify potential housing bubbles using the PSY test. Second, we check whether the potential housing bubbles also coincide with positive deviations *of a sufficient magnitude* from the estimated long run relationship. If the deviations coincide, we tentatively conclude that there is evidence of a housing bubble.[17]

Bishop and Tulip Residuals

Romer and Romer (2004) propose a method of identifying exogenous monetary policy shocks by regressing changes in the central bank interest rate on the central bank's internal forecasts. Bishop and Tulip (2017) apply this method to derive a new monetary policy shock for Australian data, controlling for more than the inflation forecasts. They estimate the following equation:

$$\Delta r_m = \alpha + \varphi\pi_m^F + \gamma y_m^F + \lambda\pi_m^{F\_REVISION} + \theta y_m^{F\_REVISION} + \rho u_m^{NOWCAST} + \beta r_{m-1} + \varepsilon_m \quad (2)$$

This involves regressing the change in the target cash rate announced at Board meeting m (Δr_m) on the current two-quarter-ahead forecasts for inflation and output (π_m^F and y_m^F), as well as the two-quarter-ahead forecasts since the previous forecast round three months ago ($\pi_m^{F\_REVISION}$' and $y_m^{F\_REVISION}$). Bishop and Tulip include the Bank's now-cast of the unemployment rate ($u_m^{NOWCAST}$) for the current quarter, which includes real time data, as well as the cash rate announced at the previous board meeting (r_{m-1}). Bishop and Tulip have deviated slightly from Romer and Romer (2004) by specifying the forecasts 'in terms of year-ended percentage changes' (p. 8). Their sample covers 100 Board meetings

[17] In Appendix 1, we also speculatively consider using deviations from the 'short run equilibrium house price' as a 'third stage' in our testing procedure. This would simply involve extracting the residuals from the fully estimated VECM model and treating them as deviations from the equilibrium house price anticipated by the model. We now turn to our estimated monetary policy shocks.

since 1991. The consequent series is presented in figure 3. The top panel of figure 3 shows the changes in the cash rate announced straight after the Board meeting, along with the fitted values from the above equation. The bottom panel plots the residuals, which constitute the Romer and Romer (2004) monetary policy shocks for Australia. Movements below zero constitute negative shocks, while movements above zero constitute positive shocks. The largest negative shock occurs during 2008-09. We also see a positive shock in December 1994. Bishop and Tulip (2017) explain that at this time that the RBA had adopted inflation targeting and 'inflation expectations remained weakly anchored' (p. 16). A 'more aggressive response' to expected inflation was considered necessary to prevent an increase in inflation (p. 16).

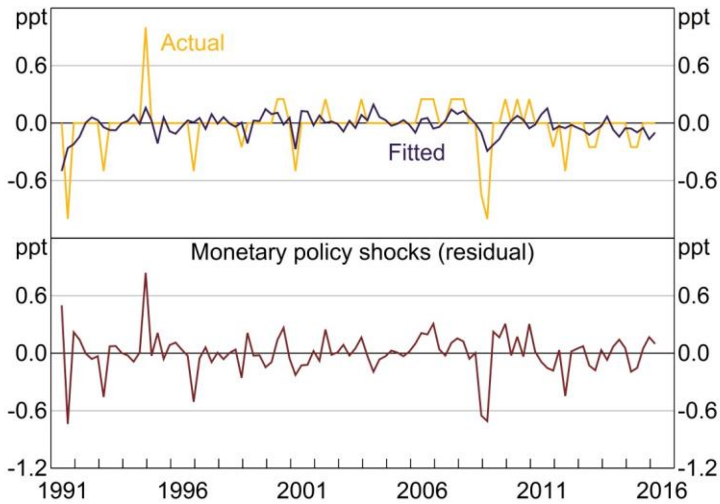

Figure 3, **Source**: **Bishop and Tulip** (**2017**)

However, it may be the case that Bishop and Tulip shocks are not quite appropriate for our purposes. Cochrane (2004) makes the point that Romer and Romer shocks (the basis the Bishop and Tulip shocks) can be described as shocks to output because they are orthogonal to output forecasts. However, we are investigating the impact of Bishop and Tulip shocks on housing bubbles. As house prices are not taken into account in the derivation of the Bishop and Tulip shocks, they may not be truly exogenous and as such not ideal for our purposes. Thus we propose estimating structural residuals from a Vector Autoregression (VAR).

SVAR Residuals

As mentioned in the literature review, VARs constitute a popular tool for estimating purportedly exogenous monetary policy shocks. The m-dimensional reduced form VAR of p lags can be presented in the following form:

$$\underset{(m\times1)}{X_t} = \underset{(m\times1)}{A_0} + \underset{(m\times m)}{A_1}\underset{(m\times1)}{X_{t-1}} + \underset{(m\times m)}{A_2}\underset{(m\times1)}{X_{t-2}} + \cdots + \underset{(m\times m)}{A_p}\underset{(m\times1)}{X_{t-p}} + \underset{(m\times1)}{\varepsilon_t} \tag{3}$$

Where X_t is a vector of m variables, A_0 is a vector of constants and A_p is a matrix of coefficients. To achieve our objective, we will need to include a variable for house prices amongst the m variables chosen. We cannot immediately estimate the structural VAR (SVAR) due to the problems caused by endogeneity bias. However, by making a series of recursiveness assumptions regarding the variables, we can estimate structural residuals for monetary policy shocks. It can be shown the $m \times 1$ vector of structural residuals, u_t, can be derived from

$$S^{-1}u_t = \varepsilon_t. \tag{4}$$

Where S^{-1} is derived from manipulating the Structural VAR such that $SX_t = S_0 + S_1X_{t-1} + S_2X_{t-2} + \cdots + S_pX_{t-p} + u_t$, for which X_t is a vector of contemporaneous variables, X_{t-1} is a vector of variables lagged once, u_t is a vector of contemporaneous errors, and S is a $m \times m$ matrix of coefficients which can be constructed by subtracting the contemporaneous explanatory regressors from both sides of the regression equation.[18] S_1 is a matrix of coefficients for the regressors lagged once and S_p is a matrix of coefficients for the regressors lagged p times. We can use the Cholesky decomposition approach and set S to be lower-triangular matrix to deal with the problem of endogeneity (Harris and Sollis, 2003).

Applying this approach, we estimate a VAR with six variables (m = 6), consisting of House Price Growth (estimated using the OECD real house price index), the unemployment rate and GDP growth (both sourced from the St. Louise Federal Reserve Website), growth in the Australian Commodity Price Index (estimated from data available on the ABS website), the Australian dollar to US dollar exchange rate and the interbank overnight exchange rate (both sourced from the RBA website). We estimated the VAR with four lags, as suggested by the AIC lag length criteria (please see Appendix 1 for the output from this test). We then estimated the Structural Residuals using the Cholesky decomposition. We order our variables as follows: House Price Growth, unemployment rate, GDP growth, Australian Commodity

[18] Let the structural VAR (SVAR) be as follows: $X_t = S_0 + B_1X_t + S_1X_{t-1} + \cdots + S_pX_{t-p} + u_t$.

$$\therefore X_t - B_1X_t = S_0 + S_1X_{t-1} + \cdots + S_pX_{t-p} + u_t$$

It can also be shown that $X_t - B_1X_t = SX_t$ where S is a matrix of coefficients other than on the diagonal, which is populated by ones. Therefore, a SVAR can be manipulated such that $SX_t = S_0 + S_1X_{t-1} + \cdots + S_pX_{t-p} + u_t$.

Price growth, exchange rate, interbank overnight exchange rate. We order our monetary policy variable (the Interbank Overnight Cash Rate) last, meaning that we have assumed that monetary policy responds to the other variables contemporaneously.[19] Regarding the remaining variables, we have attempted to order our variables from least sensitive to contemporaneous shocks to most sensitive to contemporaneous shocks. We have assumed that house price growth is the least sensitive to contemporaneous shocks. Consequently, we should generate a monetary policy shock variable that is exogenous to house prices. Our estimated structural residual shock (***SRS***) series are as follows:

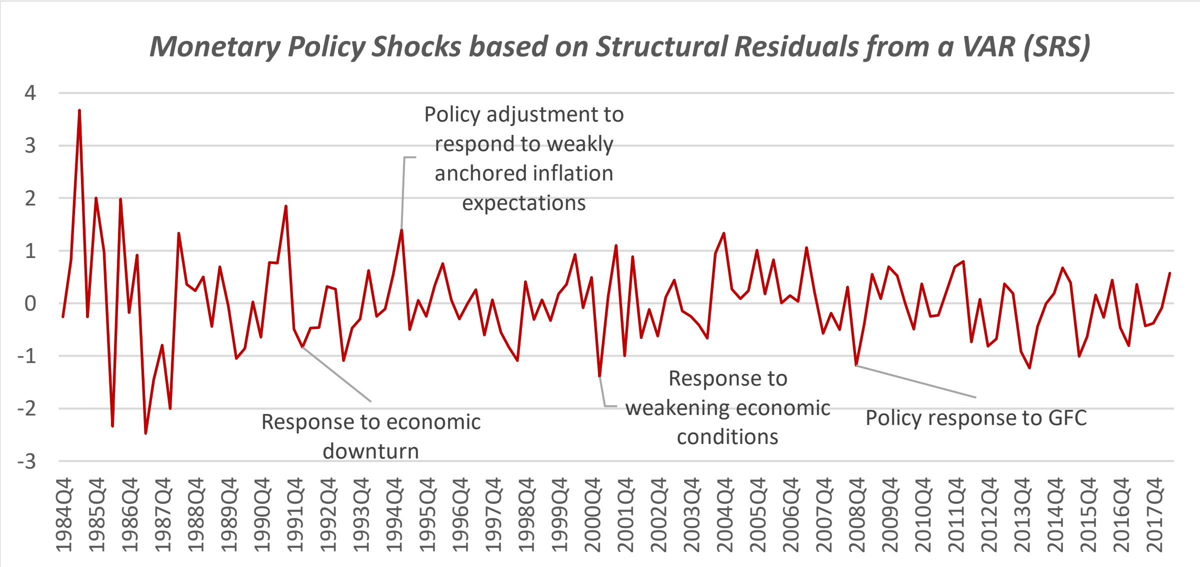

Figure 4, ***Structural Residual Shocks (SRS) series generated from a VAR***.

While this particular measure of monetary policy shocks should be exogenous to house prices, it does involve series of restrictive recursiveness assumptions. As mentioned in the Literature Review, such recursiveness assumptions have been criticised by numerous researchers (for example, Nakamura (2018)), while others have pointed out the problematic and somewhat arbitrary nature of the restrictions (Ramey, 2016). Consequently, we believe it is worthwhile to investigate the impact of both measures of monetary policy shocks on our housing bubble indicators.

Jorda's Local Projections

Macroeconomic investigation into impulse response functions typically involves the use of VARS, developed by Christopher Sims (1980). However, there is evidence that the VAR may be a 'significantly mis-specified representation of the data generating process (DGP) (Jorda, 2005, p161; Zellner and Palm,

[19] This approach was first taken by Bernanke and Blinder (1992) (Ramey, 2016).

1974; Wallis, 1977; Cooley and Dwyer, 1998). Jorda (2005) proposes an alternative method of generating impulse responses and variance decompositions without the researcher needing to specify and estimate the whole macroeconomic system. Local Projections incorporates direct forecasting models that are re-estimated for each forecast horizon. This involves projecting y_{t+h} onto the linear space generated by $(y_{t-1}, y_{t-2}, \dots, y_{t-p})'$. This gives us

$$y_{t+s} = \alpha_{t+s} + \delta_{t+s}x_t + \sum_{k=1}^{m}\sum_{i=1}^{p}\beta_{k,t-i}\gamma_{k,t-i} + u_{t+s}^{s} \tag{5}$$

where $(s = 0, 1, 2, \dots, h)$, α^s is the constant at horizon $t+s$, x_t is our shock variable and δ_{t+s} is our coefficient of interest at horizon $t+h$. $\sum_{k=1}^{m}\sum_{i=1}^{p}\beta_{k,t-i}\gamma_{k,t-i}$ is the sum of m control variables with up to p lags. $\gamma_{k,t-i}$ is the control variable k at lagged i times and $\beta_{k,t-i}$ is the corresponding coefficient. We can then plot the δ_{t+s} over h horizons (See Jorda, 2005 for further details). This method allows impulse responses to be estimated by least squares, enables inference testing without needing asymptotic delta-method approximations or numerical techniques for calculation, and is robust to misspecification of the DGP. It also easily accommodate experimentation with highly non-linear specifications that are impractical or infeasible in a multivariate context. Finally, in terms of forecasting, local projections generally outperform impulse responses from a VAR.[20]

We use Jorda's local projections method to generate impulse response functions that show the impact of our two monetary policy shocks on both our asset bubble indicators: the PSY test statistic series and the deviations from the long run relationship. Assuming we have two valid indicators of asset bubbles, we will consequently be able to see the impact of monetary policy shocks on the likelihood of an asset bubble forming.[21]

[20] The VAR impulse response is a function of forecasts at increasingly distant horizons. Therefore, there is a significant risk of a compounding effect if there are any errors in the original specification. On the other hand, Jorda's method involves using projections 'local to each forecast horizon', which eliminates this compounding problem (Jorda, 2005, p162). Moreover, there is strong evidence that such direct forecasting performs well relative to numerous models and consistently outperforms autoregressive models where the lag length is too short (Cox, 1961; Weiss, 1991; Tsay, 1993; Lin and Tsay, 1966; Bhansali, 1996, 1997; Ing, 2003; Bhansali, 2002). Jorda's paper contains Monte Carlo evidence demonstrating the consistency and efficiency properties of local projections relative to fixed parameter VARs and time-varying Bayesian VARs.

[21] Our analysis involves the use of monetary policy shock variables that have been estimated from other regressions, otherwise known as generated regressors. Generated regressors can pose some problems for our analysis due to sampling bias (Pagan, 1984). These problems are also applicable to our strategy for generating impulse responses (Jorda, 2005). It is important to note that this may cause some sampling bias in our results (Pagan, 1984).

4. *Application and Results*

In this section, we apply our two-stage bubble identification strategy to data from the Australian housing market. Our tests generate time series which are treated as 'bubble likelihood indicators'. Following this, we also present, compare and discuss the two instruments for monetary policy shocks that are used in our research. Finally, we use the previously generated bubble likelihood indicators to estimate local projections investigating the relationship between monetary policy shocks and housing bubbles.

4.1 Identifying Housing Bubbles

In this part, we inspect our relevant time series and apply our two-stage bubble identification strategy to the Australian housing market.

Inspecting the data

Below in figure 5, we can see the real house prices index, collected from the OECD data base, ranging from the first quarter of 1970 to the first quarter of 2018. As we are primarily interested in housing bubbles, it is interesting to look at this series first. We notice the significant acceleration in housing prices that commenced in roughly the first quarter of 1988. This just preceded the Australian recession of the 1990s. We can see the slow down and correction that occurred in the third quarter of 1989 and the first quarter of 1990. This follows the classic boom-bust pattern that often precedes recessions. This could potentially constitute a housing bubble. We also note the acceleration in house prices that took place between 2001 and seems to have peaked in late 2004 and stagnated in 2005. This could also potentially constitute a housing bubble. However, this period was not followed by an economic downturn. There is a downturn in house prices roughly at the same time as the GFC, another downturn in the first quarter of 2012. Finally, we see the housing boom of recent times, from the third quarter of 2013 to 2017. In this period there has some media speculation about the cause and nature of this housing boom. Thus, in our inspection of the series, we identify three periods that could constitute housing bubbles.

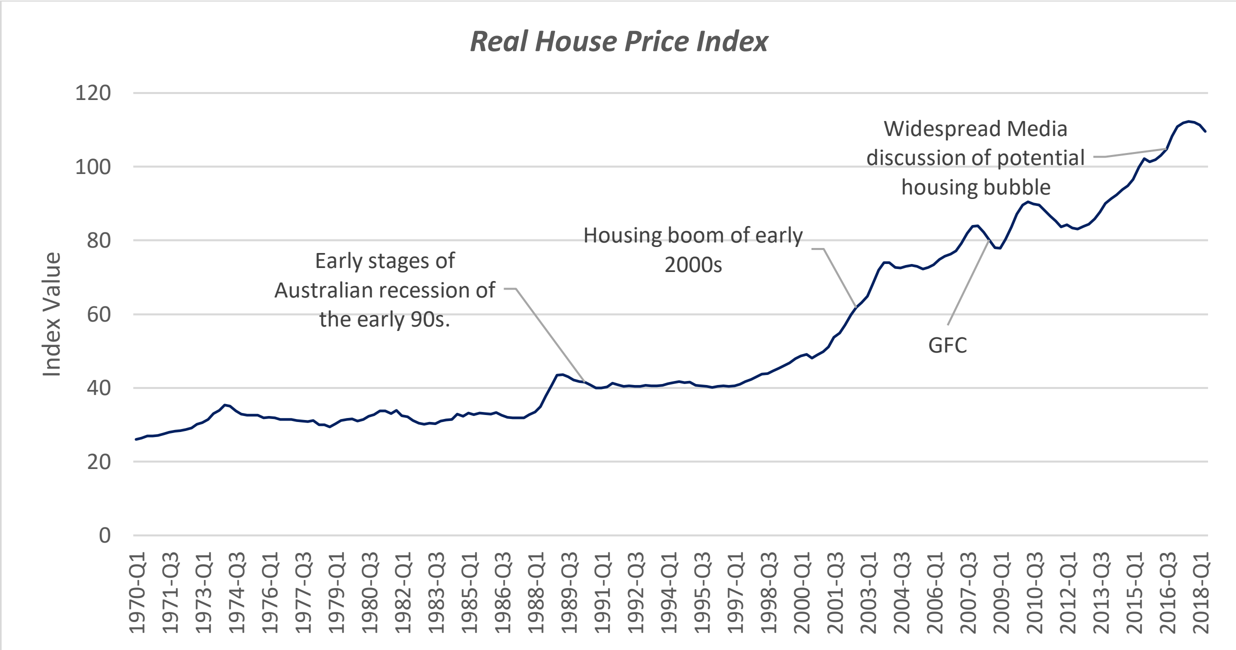

Figure 5: ***Real House Price Index data collected from the OECD database***

However, looking at the house price index alone may be a very misleading starting point, especially if house prices are simply responding to fundamentals. We next turn to the house price to income ratio shown in figure 6 below (and also available from the OECD database). While this certainly doesn't capture all the fundamentals, it will give us better guidance on whether house prices deviating from fundamentals, which is an important component of our definition of a housing bubble. We first note that this series seems to have less of a deterministic trend than the real house price index series. We again see the explosive episode that took place prior to the early 90s recession. Interestingly, the housing boom between 2002 and late 2004/early 2005 is actually far more dramatic when we take into account income. Similarly, the boom of recent times seems far steadier and gradual when we take into account income growth, though there is a clear upward trend. We now turn to applying the PSY Test to our data.

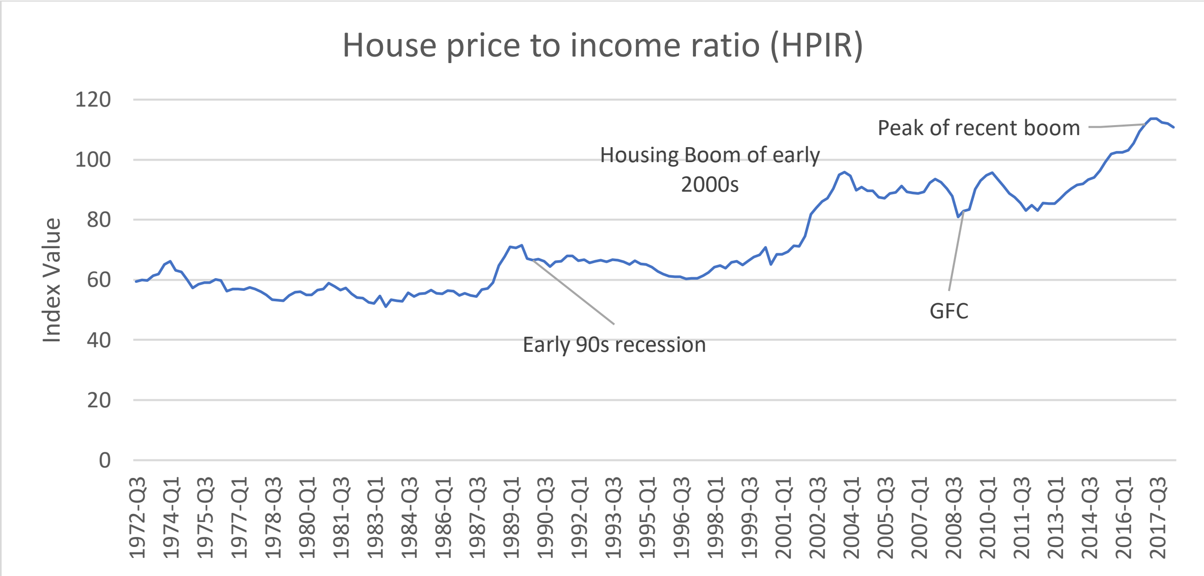

Figure 6*: House Price to Income Ratio, collected from the OECD database*

Identifying explosive episodes: Stage one

Given our earlier discussion, it is inherently better to evaluate the likely hood of housing bubbles based on whether house prices are deviating from the underlying fundamentals, and as such we will apply the PSY test procedure to the House Price to Income Ratio (***HPIR***). As noted in our Methodology, we will apply the test with Shuping Shi's recent updates to the testing procedure, which involves incorporating a Wild Bootstrapping component to the test.[22] Inspecting figure 7 below, the blue line represents the PSY test statistic series and the dark red flat line represents the 90% critical value. Thus, when the blue line crosses the dark line, we identify *explosive house price behaviour* with 90% confidence. The lighter red line constitutes the 95% critical value.

[22] Please see the Appendix for an application of this test to the HPIR without the Wild Bootstrapping Component, as well as an application to the alternative series; the House Price to Rent Ratio (HPRR).

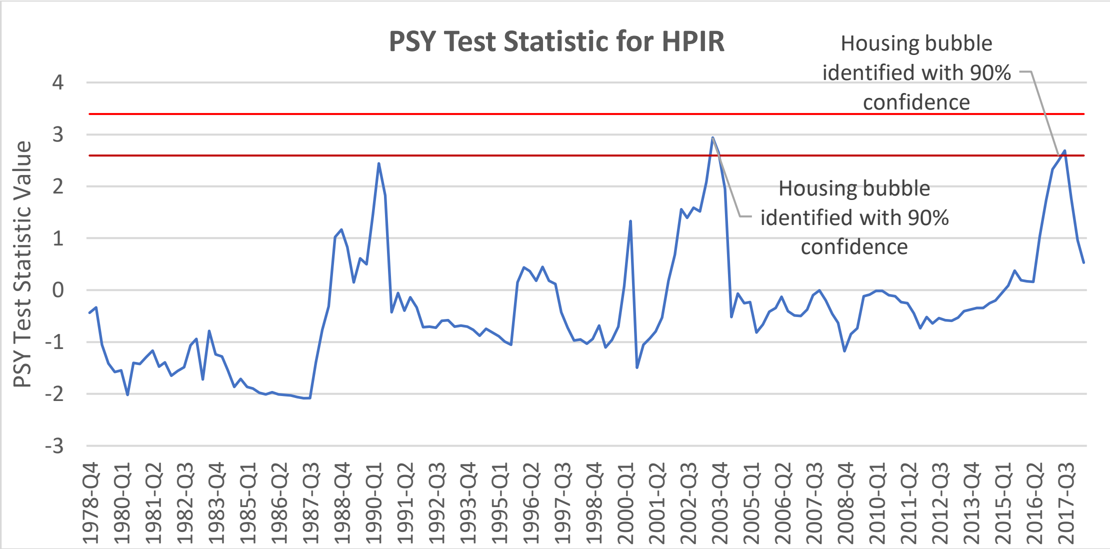

Figure 7*: PSY Test Statistic Series, where test is applied to the HPIR with wild bootstrapping*

As can be in figure 7, we identify no explosive house price episodes at the 95% confidence level. However, we do identify two such episodes at the 90% confidence level. We find the strongest evidence for the presence of an explosive episode in the period constituting the housing boom of the early 2000s. The second episode is identified as peaking in 2017, confirming our earlier speculation that this could constitute an explosive period. We also note that the test comes quite close to identifying an earlier explosive episode in the late 80s. This is also consistent with our earlier discussion of the boom-bust behaviour of house prices in this period. Thus we have carried out the first stage of our two stage bubble identification process, identifying two explosive episodes with 90% confidence. We now must ensure that these periods also coincide with house prices deviating from their underlying equilibrium behaviour.

Identifying Deviations from the Long Run Equilibrium House Prices

Data used to estimate the VECM

We estimated a VECM model with the following variables: the OECD real house price index, the OECD real rent index, Consumer Price Index data from the St. Louis Federal Reserve website, Real GDP data from the St. Louis Federal Reserve website, the Australian dollar to US dollar exchange rate data collected from the Reserve Bank of Australia (***RBA***) website, the interbank overnight cash rate collected from the RBA website, the Housing Input Index collected from the Australian Bureau of Statistics (***ABS***) website, quantity of new houses completed data from the ABS website, unemployment rate data collected from the St. Louis Federal Reserve website, estimated population growth data from the ABS website and Household Debt to GDP data collected from the *Trading Economics* website.[23] More specifically, the Housing Input Index constitutes a weighted average of price indices of multiple commodities that are commonly used in the construction of houses.[24] We would submit that these variables constitute proxies for the crucial underlying fundamentals of house prices.

Estimating the VECM

First, we estimate a VAR for the purposes of choosing the appropriate lag length. After estimating the VAR, we carry out a Lag Order Selection Criteria test (please see Appendix 1 for the output from this test). The AIC suggests using six lags, the BIC suggests using one lag and the HQ suggests using two lags. We are wary of the limited size of our data set, with only roughly 130 observations, depending on the lag length. Consequently, we choose to go with the HQ suggested lag length of two.

We then estimated a VECM with an intercept inside the cointegrating term and an intercept in the VAR. This is appropriate as most of the data series used in our analysis seem to demonstrate both deterministic as well as stochastic trends. After producing an initial estimation, we carry out a Johansen Cointegration test to identify if there are any cointegrating vectors (the output is included in Appendix 1). The Trace test identifies seven cointegrating equations at the 0.05 level, while the Maximum Eigenvalue test identifies four cointegrating vectors at the 0.05 level. However, we choose to estimate three cointegrating vectors for two reasons: First, we want to estimate the most accurate equilibrium long run model of house prices we can. If we estimate four cointegrating vectors, the cointegrating vector for real house prices will not include the house price input index. As this index is our only measure of construction costs, we think it is important that it is included in our long run equilibrium model. Second, if we chose to use an alternative ordering of our variables so that the input index was guaranteed to be included in our cointegrating vector, this would mean that our model would purport to explain long run

[23] Trading Economics, Australian Household Debt to GDP, https://tradingeconomics.com/australia/households-debt-to-gdp

[24] Please see the ABS website at < http://www.abs.gov.au/AUSSTATS/abs@.nsf/second+level+view?ReadForm&prodno=6427.0&viewtitle=Producer%20Price%20Indexes,%20Australia~Dec%202018~Latest~01/02/2019&tabname=Notes&prodno=6427.0&issue=Dec%202018&num=&view=&>, Series 6427.0 - Producer Price Indexes, Australia, Dec 2018.

macroeconomic variables, such as GDP and estimated population growth, in terms of variables tied to house prices. As such cointegrating vectors would not make much sense in theory, we would suggest that it is most appropriate to estimate three cointegrating vectors.

As the focus of our paper is on identifying deviations from long-run equilibrium house prices, we only report the first cointegrating vector here. For full output from the estimated VECM, and evidence that each data series used is I(1), please see Appendix 1. The long run estimated I(0) process is estimated as follows:

$$HP - \underset{\substack{(1.39777)\\ [-1.17711]}}{1.645329}(ii) - \underset{\substack{(0.00024)\\ [-1.06776]}}{0.000257}(GDP) + \underset{\substack{(1.77183)\\ [2.63334]}}{4.665845}(cpi) + \underset{\substack{(1.53677)\\ [4.11051]}}{6.316932}(iocr) - \underset{\substack{(18.0972)\\ [-4.22313]}}{76.42684}(erpg) -$$

$$\underset{\substack{(26.7197)\\ [-2.86526]}}{76.55911}(xr) - \underset{\substack{(0.40098)\\ [-1.89124]}}{0.758350}(hdgdp) - \underset{\substack{(2.91734)\\ [-0.05519]}}{0.161005}(ur) - 34.51857 \sim I(0) \qquad (6)$$

Where *HP* represents the real house price index, *ii* represents the housing input index, *GDP* represents gross domestic, cpi represents the consumer price index, iocr represents the interbank overnight cash rate, erpg represents the estimated population growth, *xr* represents the Australian dollar to US dollar exchange rate, *hdgdp* represents the household debt to GDP ratio and *ur* represents the unemployment rate. This equation represents an *I(0)* process, and we argue that where this relationship generates a positive number, real house prices are greater than their underlying fundamentals would suggest. We provide this series graphically in figure 8 below.

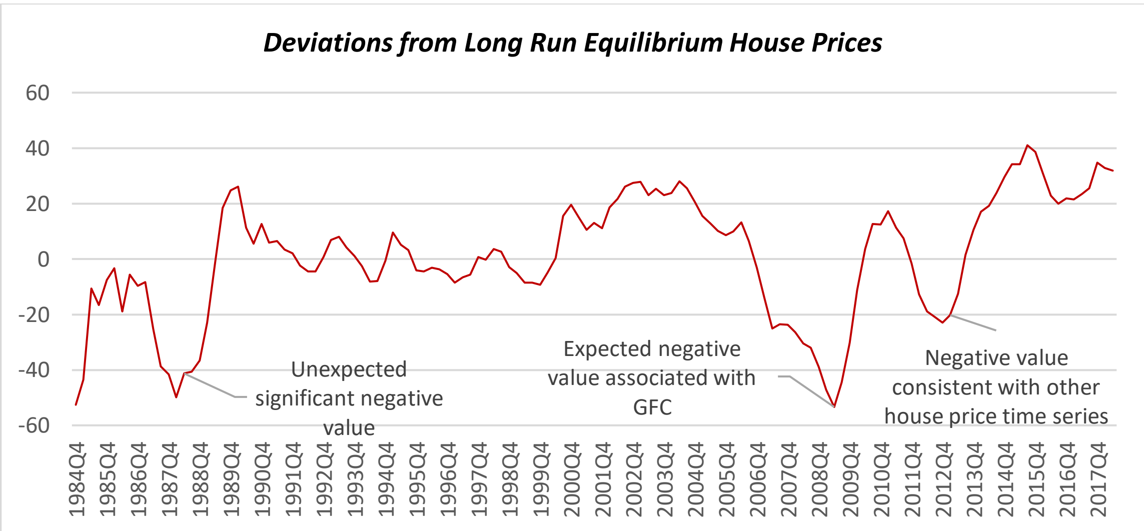

Figure 8: ***Deviations from the long run equilibrium house price based on chosen fundamentals***

We can see a significant negative deviation in late 1987 and a significant decline at roughly the same time as the GFC was setting in. We also see a negative value towards the end of 2012 or beginning of 2013. The negative value around the GFC is unsurprising given global economic conditions at that time. We also note that the downturn towards the end of 2012 is consistent with the real house price series and real house price to income series presented above. However, the negative value in late 1987 is somewhat surprising as the real house price series and HPIR series do not show negative dips at that time. This seems to suggest that at least part of the increase in house prices between 1988 and 1990 was justified by the fundamentals.

It is insufficient to simply define every data point in the series with a value greater than zero as a housing bubble, as it is inevitable that the series will fluctuate around zero. Rather, we reproduce the same series below with the addition of a horizontal line blue line. This line is equal to the value of one standard deviation above the mean. Thus, any value that is greater than one standard deviation away from the mean can be considered as an episode where *house prices were higher than could be justified based on underlying fundamentals*. Only these periods can be treated as potential bubble episodes.

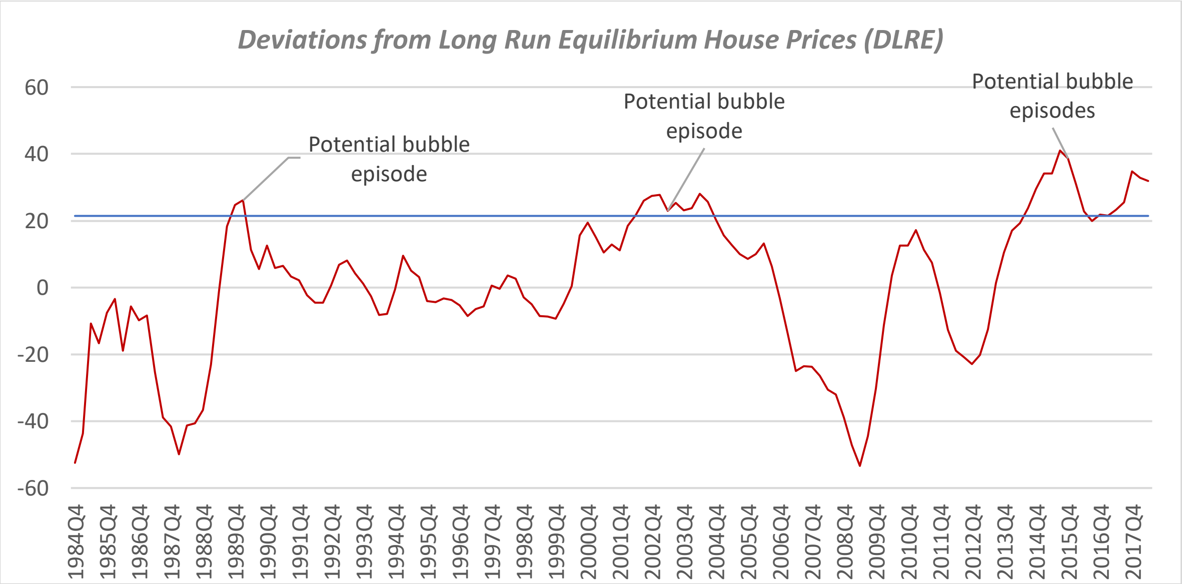

Figure 9*: I(0) series generated from first cointegrating vector of estimated VECM*

As can be seen in figure 9, we can see three potential periods of time which could constitute housing bubbles. A brief period ranging from 1989 to early 1990, a more extended period from 2001 to late 2004 or early 2005 and a seemingly interrupted period from early 2014 to late 2017. We now have set up for the second stage of our bubble identification strategy: In figure 10 below, we combine the PSY test statistic generated earlier with the DLRE series. We note that the spikes in PSY test statistic series generally coincide with higher positive values in the DLRE series. The correlation between the two series is 0.47. Both the PSY test statistic and the DLRE series must identify the same period as a bubble in order that it can be considered as a housing bubble. Consequently, the increase in house prices just before 1990 cannot be considered a housing bubble, even though it is identified as a potential bubble episode in figure 9 and corresponds with a spike in the PSY test statistic series.

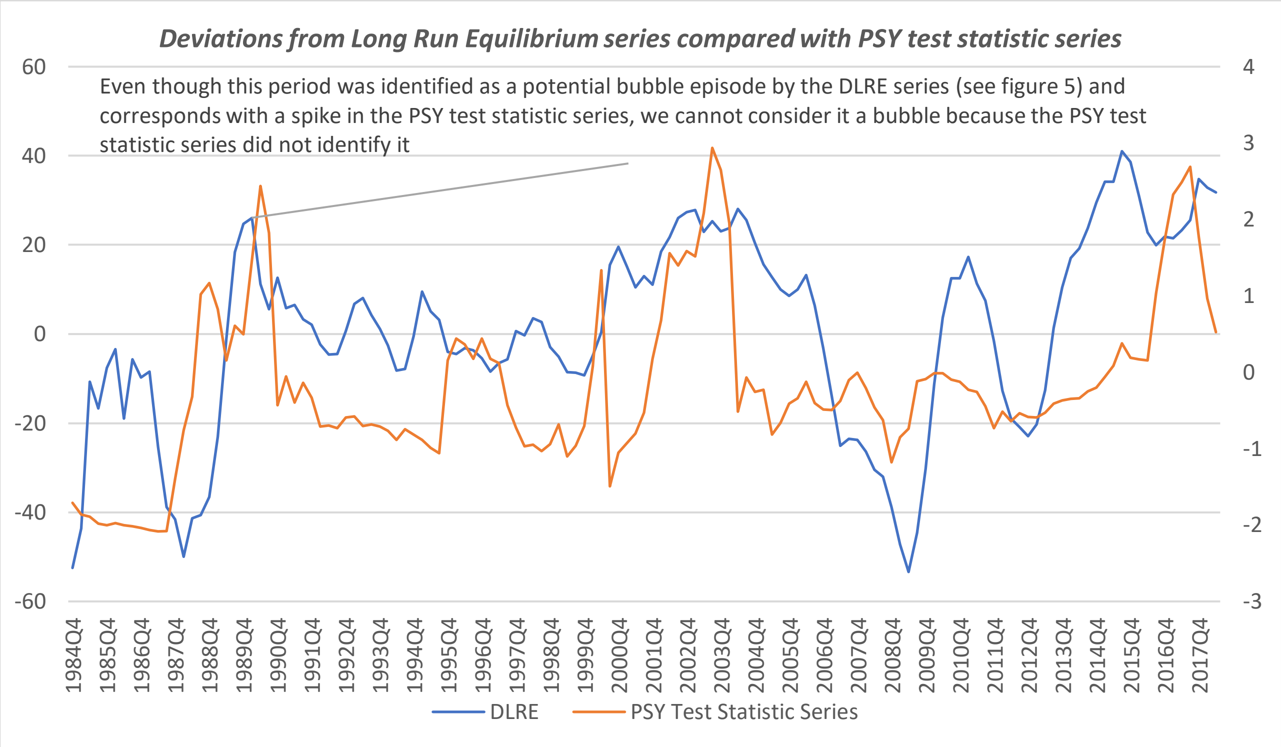

Figure 10*: **Combining both series in one graph. Our strategy involves identifying overlapping periods where both series identify a potential housing bubble.***

In figure 11 below, we reproduce figure 10 with the addition of the standard deviation line from the DLRE series. Thus, we can tentatively identify housing bubbles as periods where the DLRE series (the blue line) is greater than one standard deviation from zero (the black) line, *and* this period aligns with an episode of explosive price behaviour as identified by the PSY test statistic series. Consequently, we identify two housing bubbles in the last forty years. The first lasted from roughly the second quarter of 2003 to the second quarter of 2004. The second lasted from the fourth quarter of 2016 to the fourth quarter of 2017.

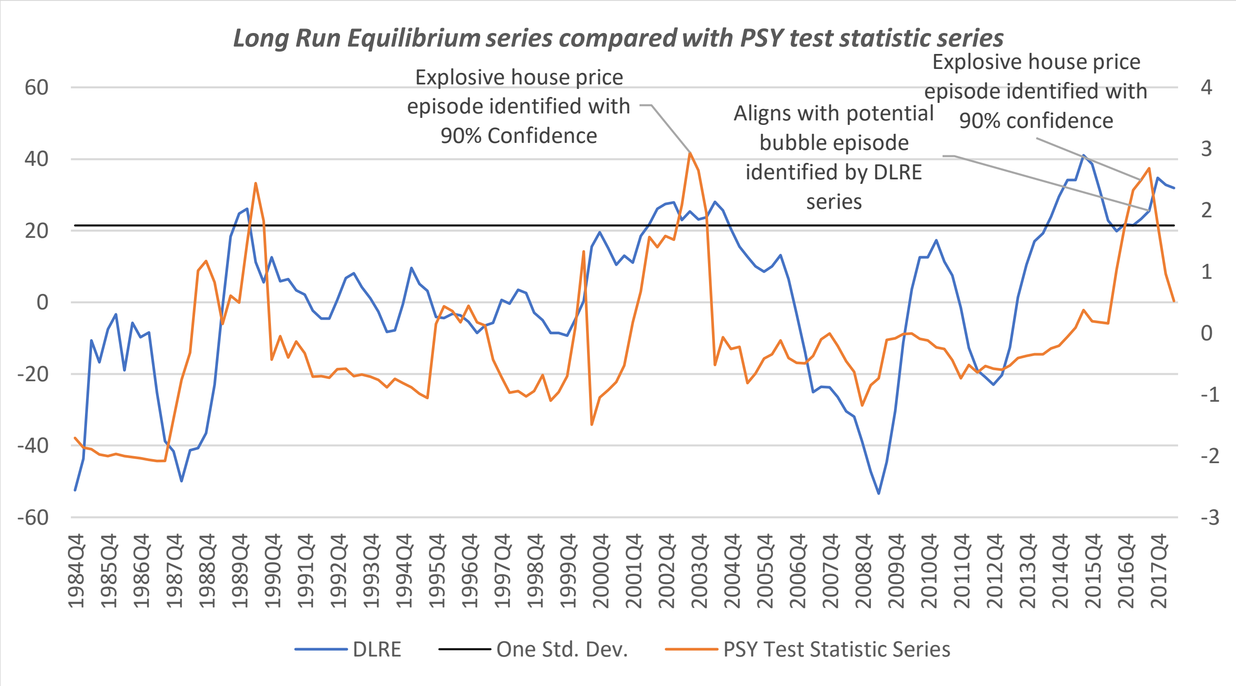

Figure 11*: **DLRE and PSY Test Statistic series are again presented on the same graph with the DLRE standard deviation included as the black line**.*

In summary, we have applied our two stage approach to identifying asset bubbles to the Australian housing market, and have identified two housing bubble episodes. We now turn to setting out the two monetary policy shocks discussed in the Methodology.

4.2 Monetary Policy Shocks

We discuss two instruments used for monetary policy shocks. We start with the Bishop and Tulip shocks (***BTS***) and then turn to structural residual shocks (***SRS***).

Bishop and Tulip Shocks

We obtained BTS data for Australia from the RBA website. This is monthly data and spans from January 1990 to April 2016, constituting 316 observations. In order to apply the shocks to quarterly variables, we treated the average of the three month period for each quarter as the value of the shock for that quarter.

The series is reproduced in figure 12 below.

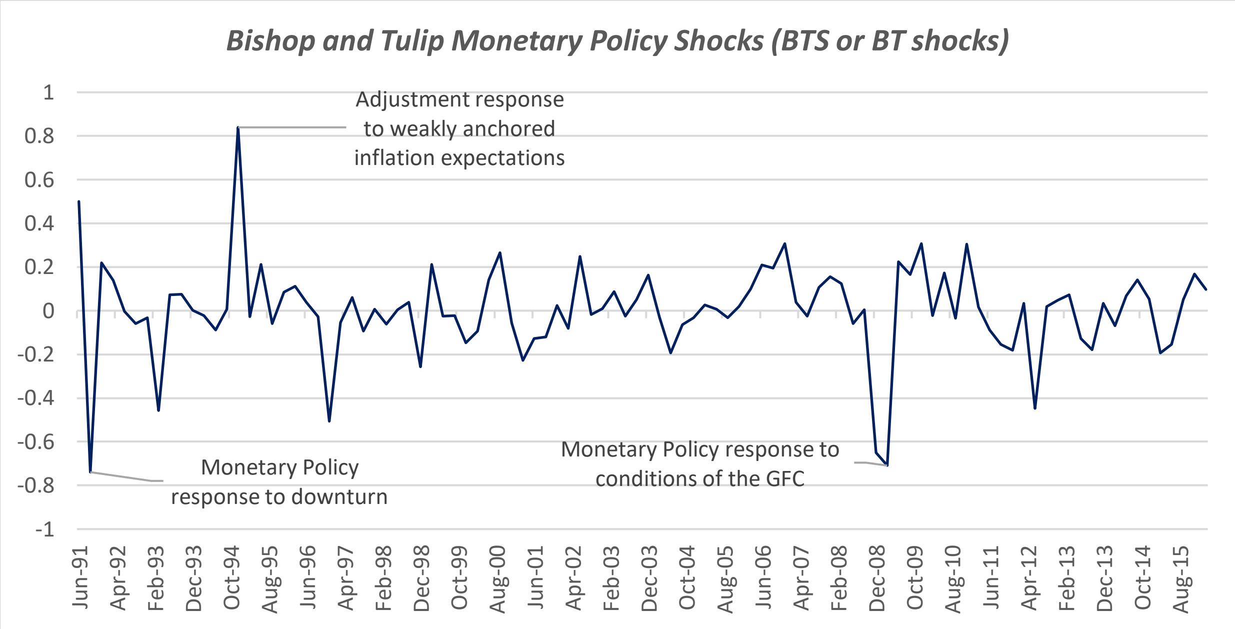

Figure 12*: BTS series, sourced from the RBA website (Bishop and Tulip, 2017)*

Structural Residual Shocks (SRS)

The details of the construction of the SRS are contained in the Methodology section (Please see above). We reproduce the series below in figure 13 below. We also compare the two differing monetary policy shock variables in figure 14. There are numerous interesting elements for comparison. First, both series respond in a similar fashion to the downturn of the GFC, as well as the weakening of economic conditions in 2001. Similarly, both series show positive results around 1994 to 1995 as the Reserve Bank attempted to strengthen its response to weakly anchored inflation expectations (See Bishop and Tulip, 2017). However, there are very significant differences. The SRS series demonstrates far greater variance than the BTS series. Looking particularly at recent history (from 2010 to the first quarter of 2016), the SRS series registers many negative shocks compared to the BTS series, which is relatively stable in this period. Finally, there is complete divergence in the two series at roughly the second or third quarter of 1991 (the very beginning of the series). The BTS series identifies a negative policy shock, while the SRS series identifies a large positive policy shock. This is likely to be a consequence of the additional variables that are incorporated into the construction of the SRS series, such as house price growth.

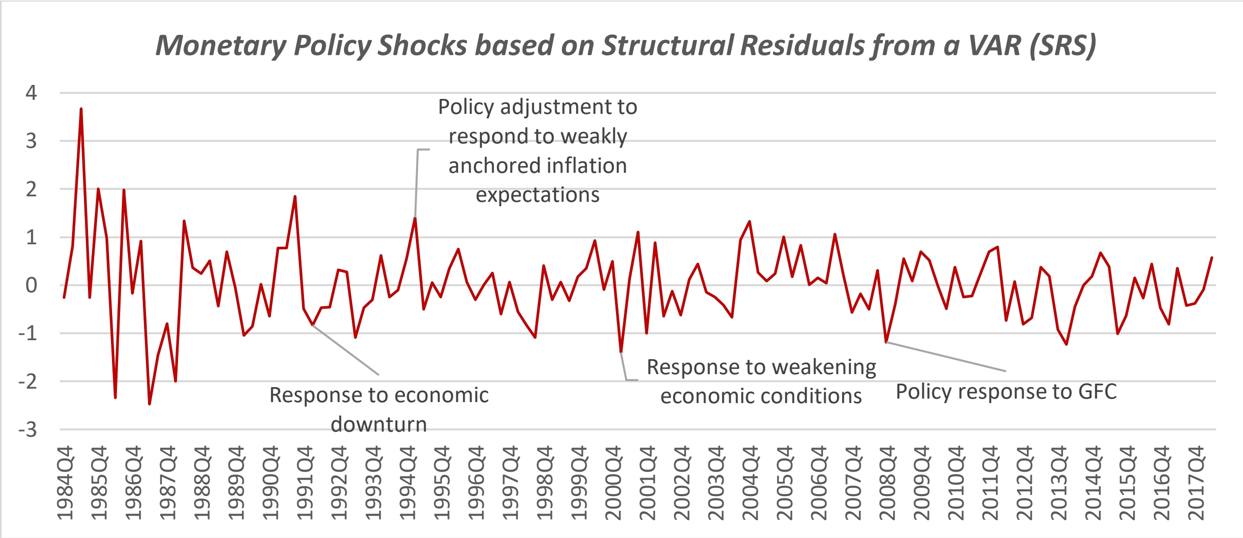

Figure 13: ***SRS series. Please see the methodology section for details of their construction.***

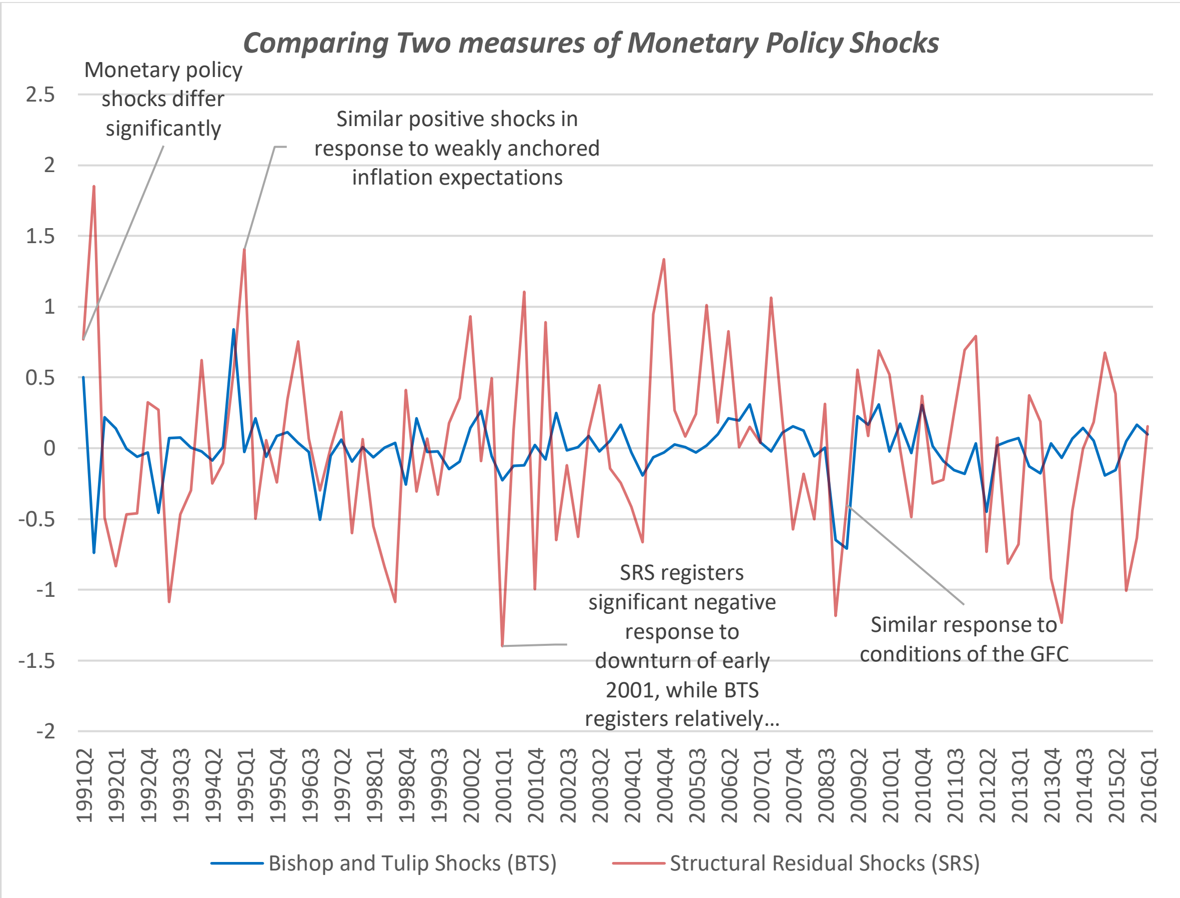

Figure 1: ***Comparing the SRS series with the BTS series. While the move together for quite a few significant events, the SRS has far greater variance and both series diverge at some interesting times.***

4.3 Using Local Projections to investigate the impact of Monetary Policy shocks on Housing Bubble Indicators

We generate Local Projections using the method proposed by Jorda (2005), estimating the following model:

$$B_{t+h}^{k} = \alpha_{t+h} MPS_t^j + \sum_{i=1}^{n} \gamma_{1,t-i} GDPG_{t-i} + \sum_{i=1}^{n} \gamma_{2,t-i} UR_{t-i} + \sum_{i=1}^{n} \gamma_{3,t-i} \pi_{t-i} + \sum_{i=1}^{n} \gamma_{4,t-i} X_{t-i} + \sum_{i=1}^{n} \gamma_{2,t-i} UR_{t-i} + u_{t+h} \quad (7)$$

Where B_{t+h}^{k} is the k bubble indicator at h horizons after time t, $\alpha_{t+h} MPS_t^j$ is the j monetary policy shock, *GDPG* is real GDP growth, *UR* represents the unemployment rate, π represents the inflation rate and X represents the Australian Dollar to US dollar exchange rate. We estimated local projections with n lags ranging from one to four, for both measures of bubble indicators and monetary policy shocks. We then select the optimal lag length for each horizon, h, based on the AIC selection criterion. The AIC tables are presented in the Appendix 2, where the lowest AIC value is highlighted. The local projections for the monetary policy shock coefficient (α_{t+h}) are graphed against the horizon with 90% and 95% confidence intervals. The tables of projected coefficient values can also be found in Appendix 2. As an important note, as the SRS series is a generated regressor, there may be some estimation bias in results (Pagan, 1984). We will return to this point below. We first consider the impact of the SRS series on the PSY test statistic indicator.

Monetary Policy shocks and the PSY Test Statistic Series

In the local projections presented below, the estimated impulse response function is the dark blue line. The outer red line represents the 95% confidence bounds, while the darker red line represents the 90% confidence bounds.

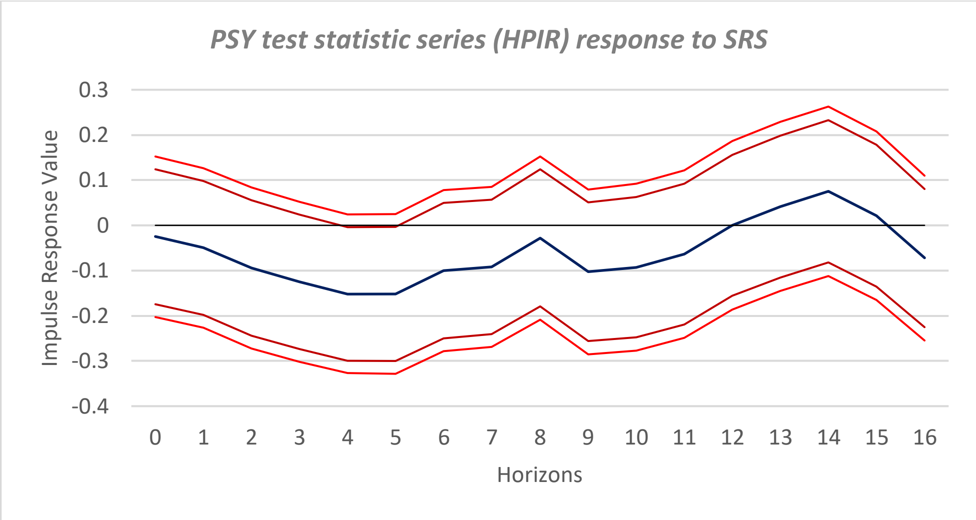

Figure 15*: **We project the response of the PSY test statistic to a positive monetary policy shock, using the SRS as our instrument. We find weak evidence of a negative relationship between monetary policy shocks and the likelihood of a housing bubble**.*

The response is generally negative, with a statistically significant negative effect at the 90% critical value at horizons four and five. The remaining results are largely statistically insignificant. This provides weak evidence that positive monetary policy shocks have a negative effect on the likelihood of a housing bubble forming. Similarly, it provides weak evidence that a negative monetary policy shock will have a positive effect on the likelihood of a housing bubble forming. More specifically, it seems that there is some weak evidence that a positive monetary policy shock will have a negative effect on the likelihood of explosive house price behaviour, and vice versa. We now consider the effect of the BTS series on the same housing bubble indicator.

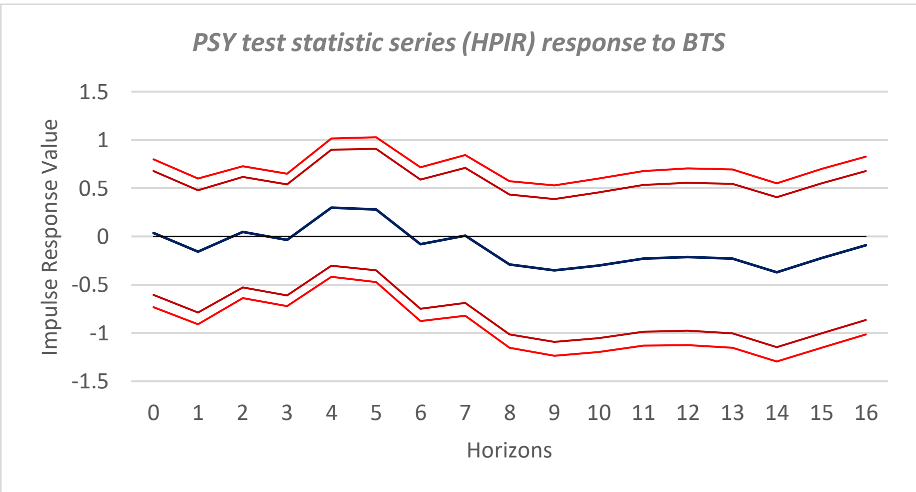

Figure 16*: **We project the impact of monetary policy shocks (using the BTS series) on the PSY test statistic series. We find no statistically significant evidence of a relationship**.*

From inspecting the results for local projection, we can see that the BTS has a statistically insignificant effect on the likelihood of a housing bubble forming. If there is any relationship at all, it seems that it is generally negative. This test seems to suggest that monetary policy shocks have no effect on the likelihood of a housing bubble forming. Focusing on the nature of the PSY test statistic series, this test suggests that monetary policy shocks have no statistically significant effect on the likelihood of house prices exhibiting explosive price behaviour.

Monetary Policy Shocks and deviations from the equilibrium long run house prices

We now treat the DLRE, which indicates deviations from the long run house prices based on underlying fundamentals, as a bubble indicator. We first consider the effect of the SRS as an instrument for monetary policy shocks.

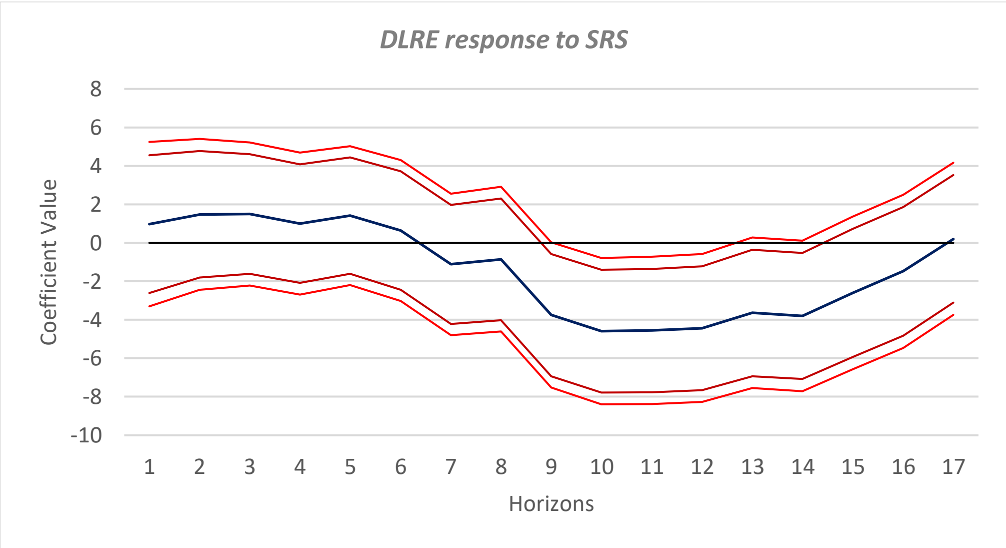

Figure 17: ***We project the effect of monetary policy shocks on the DLRE series using the SRS as our instrument. We find a statistically significant negative impact at the 95% confidence level.***

We then use the DLRE as a bubble indicator. We find that, in the short run, monetary policy shock has no effect on the DLRE. However, in the medium term, we find statistically significant evidence at the 95% confidence level that positive monetary policy shocks have a negative impact on the DLRE. Likewise, we find that negative monetary policy shocks will have a positive effect on the DLRE. This provides evidence that negative or expansionary monetary policy shocks can increase the likelihood of a housing bubble forming. Specific to our bubble indicator in question, we find evidence that negative monetary policy shocks increase the likelihood that house prices will move above their price level justified by the underlying fundamentals. We now repeat this analysis, instead using the BTS as our instrument for monetary policy shocks.

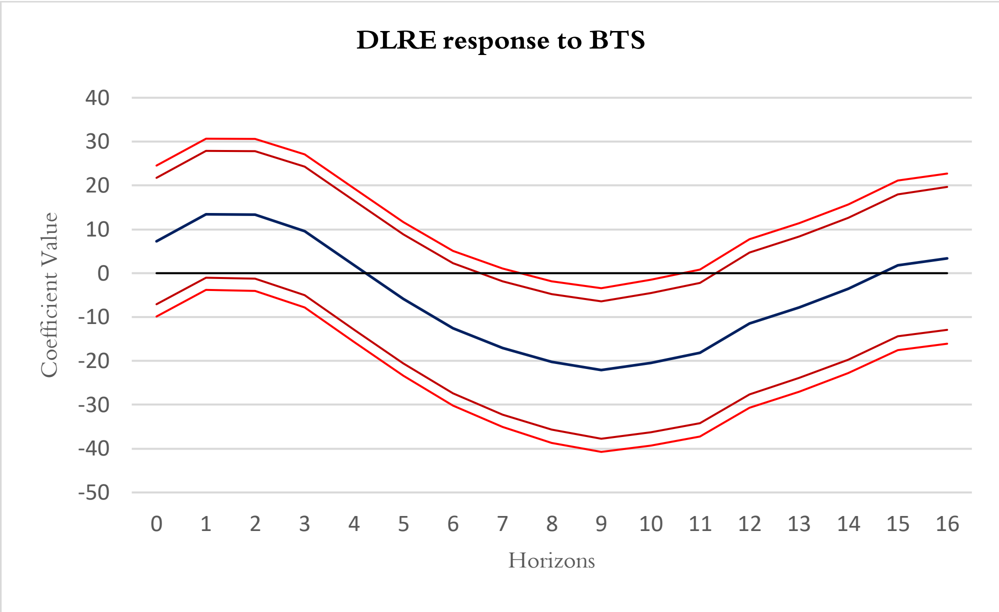

Figure 18: ***Using the BTS as an instrument for monetary policy shocks, we find that monetary policy shocks have a statistically significant negative impact on the DLRE. This is very similar to our findings in Figure 17.***

Interestingly, we get an almost identical outcome when we use the BTS as our instrument for monetary policy shocks rather than the SRS. While there is no statistically significant impact in the short run, we find evidence that, in the medium term, a positive monetary policy shock will have a statistically significant negative effect the likelihood of there being a housing bubble. Speaking to the nature of the DLRE series directly, we find evidence that a negative monetary policy shock will increase the likelihood that house prices will move above the price level expected based on their underlying fundamentals.

Unlike the PSY test statistic series, the DLRE exhibits a remarkably similar response to both measure of monetary policy shocks, even though both measures of monetary policy shocks are quite different. While the magnitude of the response is smaller for the SRS instrument than for the BTS instrument, this can be explained by the larger variance exhibited by the SRS instrument generally.

Summary of results

We find weak evidence of a negative relationship between monetary policy shocks and explosive house price behaviour, depending on which monetary policy shock instrument is used. We find statistically significant evidence at the 95% confidence level that there is also a negative relationship between monetary policy shocks and positive results in the DLRE series. This provides some support for the proposition that negative monetary policy shocks will increase the likelihood that house prices will move above their equilibrium level. In other words, a negative monetary policy shock may increase the likelihood that house prices would be higher than would otherwise be justified by their underlying fundamentals. Looking at these results more broadly, we find evidence that negative monetary policy shocks will increase the likelihood of a housing bubble forming and vice versa.[25]

Policy Implications

The policy implications from these findings are quite clear: it offers support for the argument that central bank policy makers could potentially constrain housing bubbles through monetary policy (Brunnermeier and Schnabel, 2014). It also offers some support for the argument that 'overly expansionary' monetary policy may contribute to or possible even cause the formation of housing bubbles (Taylor, 2015; Garrison, 2001). More specifically, it also offers support to the argument that prudential regulators can manage housing bubbles through the strategic use of credit controls. These results will hopefully be useful for Australian policy makers in light of the recent behaviour of Australian house prices and ongoing housing affordability concerns.

[25] For contrary evidence, see Gali and Gambetti (2016).

5. *Limitations and Extensions*

There are several limitations to our research. We first recognise that the size of our data set and thus the quality of our results would be enhanced by utilising monthly rather than quarterly data. More specifically though, there are a number of potential problems with the application of our procedure.

First, there may be some specification issues with our VECM. As discussed in the Appendix, there is some danger that one of our variables, estimated population growth, may not be an I(1) process, which is problematic for the estimation of our cointegrating vectors and long run relationships (Harris and Sollis, 2003). Furthermore, we chose to estimate a VECM with three cointegrating vectors rather than the seven suggested by the Trace Test, or the four suggested by the Maximum Eigenvalue test. Thus our long run relationship may have been mis-specified, despite our arguments otherwise. Alternatively, given we were specifically interested in the long run relationship between house prices and their underlying fundamentals, it may have been more appropriate to only estimate one cointegrating vector. These alternative specifications would constitute useful checks on the robustness of our findings.

Second, the SRS series was generated using a relatively simplistic method. The methods for the identification of monetary policy shocks have advanced significantly over the last two decades, thus our analysis may have been improved by using a more up to date approach to identifying monetary policy shocks that were exogenous to house prices (See Nakamura and Steinnson, 2018; Ramey, 2016; Stock and Watson, 2018). Finally, as the SRS is a generated regressor, it may suffer from some estimation bias (Pagan, 1984). While some strategies have been developed to deal with this problem (Gauger, 1989), such strategies were not applied here. It may be appropriate to apply such strategies in future research.

Third, our two-stage approach to identifying housing bubbles was relatively informal. It could be possible that strategy of looking for episodes that demonstrate both explosive price behaviour and deviations from fundamental could be better achieved through some form of Principal Component Analysis. This similarly constitutes what could be a useful extension to our research.

Finally, we note that a range of similar tests were carried out on alternative PSY statistic series that were generated from alternative house price indicators. Moreover, we also carried out a slightly different version of the PSY test without using the Wild Bootstrapping component. These results are included in Appendix 1. We also speculatively considered a 'third-stage' for our bubble identification strategy, where we looked at the House price residuals from the estimated VECM. These residuals would have constituted 'short-run' deviations from equilibrium house prices. A bubble episode could only be identified if the 'short-run' deviations were positive over the same period. Furthermore, we carried out some additional local projections with the alternative bubble indicators. These are all included in Appendix 1.

6. *Conclusion*

In this paper, we have attempted to investigate monetary policy shocks and strategies for identifying housing bubbles. We used two different instruments for monetary policy shocks, one constructed for the purpose of this research, and attempted to apply a two-stage bubble identification strategy to the Australian housing market. Finally, we have sought to explore what impacts our monetary policy shock instruments have on housing bubble indicators. We found some evidence that there have been two housing bubbles in Australia in the last four decades; the first in the early 2000s, and the second in the last few years. Furthermore, we found some evidence that monetary policy shocks will have a negative relationship with the likelihood that house prices are higher than they would be based on their underlying fundamentals. We found weak evidence that positive monetary policy shocks have a negative impact on the likelihood of explosive price behaviour. We briefly touched on the implications this could have for public policy and discussed the limitations and possible extensions to our research.

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