Economics & Finance Research: An Open Access Journal
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/refr20

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Published online: 23 Dec 2013.

To cite this article: John F. McDonald & Houston H. Stokes (2013) Monetary policy, mortgage rates and the housing bubble, Economics & Finance Research: An Open Access Journal, 1:1, 82-91, DOI: 10.1080/21649480.2013.870490

To link to this article: http://dx.doi.org/10.1080/21649480.2013.870490

Economics & Finance Research, 2013
Vol. 1, 82–91, http://dx.doi.org/10.1080/21649480.2013.870490

Monetary policy, mortgage rates and the housing bubble

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The article uses three alternative models and monthly data to investigate whether the Federal Funds Rate or the rate on standard 30 year mortgages in the US for the period 1987 to 2010 impacts an index of housing prices. The results indicate that positive shocks to the Federal Funds Rate are associated with housing price changes in the negative direction and the mortgage rate in the positive direction. Shocks to the mortgage rate have no statistically significant impact on housing prices except when the data are filtered with the Christiano and Fitzgerald (2003) procedure and a vector auto-regression model using 16 lags is estimated.

I. Introduction

While there is general agreement that the bursting of the housing price bubble in the USA led to the financial crisis and deep recession of 2007–2009, there is some disagreement about the causes of the housing price bubble. Roughly speaking, there are four categories of factors that are thought to cause the bubble. One asserts that the financial sector ('Wall Street') created the bubble through unsound lending practices, complex mortgage-backed securities, the shadow banking system that relied on high degrees of financial leverage and short-term borrowing and so on. Others place substantial blame on the Federal government and the Federal Reserve because of deregulation and lax use of existing regulations, an aggressive policy of increasing the rate of home ownership and monetary policy that held the Federal Funds Rate at very low levels during the critical years of 2001–2004. A third argues that a flood of capital from abroad that resulted from the trade deficit pushed up asset prices, and the fourth simply blames a classic asset price bubble that began in the late 1990s and had its own momentum until the inevitable crash.

A recent article by McDonald and Stokes (2013) tested for the effect of the Federal Funds Rate on a popular index of housing prices using monthly data in the period 1987 to 2010/8. This study found evidence that the Federal Funds Rate is a cause of the housing price index in the sense of Granger (1969), and that the housing price had momentum of its own, given the Federal Funds Rate. No other variables were included in the model. A recent study by Miles (2012) using quarterly data in the period 1975 to 2011 was undertaken largely in response to the study by Taylor (2007) and the study by the McDonald and Stokes (2013), both of which did not take account of the possible effect of the mortgage interest rate on housing prices. The basic conclusion of the Miles study is that, during the period 1982 to 2011, '. . .the mortgage rate is highly significant while the Funds Rate exhibits barely any effect'. Miles' (2012) main argument is that both the Taylor (2007) and the McDonald and Stokes (2013) paper suffer from omitted-variable bias and as a result their findings ascribe too much 'guilt' to monetary policy. One shortcoming of the Miles paper is that, while lags of the Federal Funds Rate and the mortgage rate were included on the right-hand side of the models estimated, lags of the dependent variable were not included on the right. Hence, the Miles results cannot be considered as a test of Granger (1969) causality.

The specific goal of the present article is to further the empirical examination of the housing price bubble and crash by analysis using a variety of data transformations and Vector Auto-Regression (VAR) methods of analysis.[1] The research design of this article is very straight forward; using methods of analysis that closely follow the prior two papers, the study by the McDonald and Stokes (2013) is augmented by the inclusion of the 30-year mortgage rate in the model. While McDonald and Stokes (2013) used only log transformed data, in the present article the log data were transformed using both the Hodrick and Prescott (1997) filter and the Christiano and Fitzgerald (2003) filter to be compatible with Miles (2012). The new research finds that the conclusions of the McDonald and Stokes (2013) hold up; shocks from the Federal Funds Rate are causally prior to housing prices in the sense of Granger (1969) although

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[1] There are a number of research designs that might be employed to study this problem. One possibility is the regime-switching approach to access the effect of monetary policy on the housing market as is typified by Chang *et al.* (2011). An alternative is the VAR approach that uses a small-scale VAR model to test for Granger causality. In view of the fact that the main focus of this article is to further investigate the findings of Miles (2012), who used a small-scale model, it is important that his paper's methodology be followed as closely as possible with the objective of investigating the effect on the results of various assumptions.

housing prices have their own momentum in all models.[2] The 30-year mortgage interest rate is found significantly to Granger-cause housing prices only in a model that controls for the lagged Federal Funds Rate, the lagged mortgage rate and lagged housing prices for lags of 16 in a monthly VAR model that uses Christiano and Fitzgerald (2003) filtered data. The Federal Funds Rate is, however, found to be causally prior to the mortgage rate. This finding might be expected since, when the mortgage rate is changed, it takes some time for those with existing mortgages to be able to refinance at the new rate. This suggests that a longer lag VAR model may be needed to pick up the effect.

After a brief discussion of the literature, data descriptions and plots are presented. In view of the fact that a major goal of this article is to determine whether the differences between Miles (2012) and McDonald and Stokes (2013) are due to transforming the data by filtering, we test for unit roots using the Dickey–Fuller (DF) test to determine the effect of filtering. The spectrum plots are used to illustrate the location of the frequencies that were removed. Spectrum plots of all series and DF unit-root tests illustrate the effect of the various transformations on the frequencies left in the data. For example, the Hodrick and Prescott (1997) and Christiano and Fitzgerald (2003) filters are shown to attenuate the low-frequency information in the data. Since McDonald and Stokes (2013) used untransformed log data, while Miles (2012) used filtered data, the objective is to remove the possibility that the differences in the results between the two papers were due to data transformations.

II. Literature

Miles (2012, p. 6) points out that the mortgage interest rate should be included in the model because '. . .the ability of central banks such as the Fed to influence long-term rates is thought to be much less than in years past'. Greenspan (2010, p. 235) argues that long-term rates were drivers of the housing bubble because long-term rates started to fall 6 months before the Fed began to reduce the Federal Funds Rate in 2001, and long-term rates continued to fall after the Fed initiated the increase in the Federal Funds Rate in 2004. Greenspan (2010, p. 236) states that for data from 2002 to 2005:

> Regressing home prices on *both* the fixed-rate mortgage (with an 11-month lead) and the Federal Funds Rate (with an 8-month lead) yields a highly significant t-statistic for the mortgage rate of −5.20, but an insignificant t-statistic for the Federal Funds Rate of −0.51.

Furthermore, Greenspan states (2010, p. 237):

> But the fixed-rate mortgage clearly delinked from the Federal Funds Rate in the early part of this century. The correlation between them fell to an insignificant 0.10 during 2002–05, the period when the bubble was most intense, and as a consequence, the Funds Rate exhibited little, if any, influence on home prices.

Miles (2012) also emphasizes the role of the trade deficit and the resulting influx of foreign capital, but his study does not include a test of this hypothesis. Bergin (2011) provides a summary of the research on this topic.

Another study by Jarocinski and Smets (2008) estimated a VAR model with nine endogenous variables (real Gross Domestic Product (GDP), real consumption, GDP deflator, house prices, commodity prices, money stock, housing investment share of GDP, Federal Funds Rate and the spread between the Federal Funds Rate and the rate on 10-year treasury bonds). The study used data from 1987Q1 to 2007Q2, and found that the impulse response of house prices to the Federal Funds Rate was negative and statistically significant (25 basis point increase resulted in a fall in house prices of 0.5% at 10 quarters). The impulse response of house prices to the interest rate term spread is not statistically significant in this model, but is statistically significantly negative in a model of changes in all of the variables. Note that this study used impulse-response functions rather than Granger causality tests. Also, this study did not include the mortgage rate.

The empirical studies of the impact of monetary policy on house prices do not produce consistent results. Some possible reasons for the inconsistent results are tested in this article.

III. Data

This study makes use of three time-series data sets, the Federal Funds Rate, the S&P/Case–Shiller Home Price Series for 10 major metropolitan areas and the interest rate on standard 30-year mortgages. All data are monthly, and are from to January, 1987 (the first month of the S&P/Case–Shiller series) to August, 2011.

In our study, the Federal Funds Rate was obtained from EconStats (http://www.econstats.com/r/rusa_ew2.htm), and is the market rate for the Friday closest to the end of the month in question. The mortgage rate is the standard variable provided by the Federal Home Loan Bank, and can be found in Federal Reserve Archival System for Economic Research. Graphs of the three variables (levels and natural log levels and two filtered log data series) are shown in Fig. 1.

IV. Model Estimation, Discussion and Testing

While the data plots shown below in Fig. 1 are instructive, they do not allow us to measure the dynamic relationship between the three series. For this we need a model. Fig. 1 shows raw series, log series and log series that have been filtered by either the Hodrick and Prescott (HP) or the Christiano and Fitzgerald (CF) filter. The goal of these filters is to remove the trend (which contains low-frequency information) from the series to avoid spurious regression problems. The DF test reported in Table 1, together with data descriptions and names, shows that there are in fact unit roots in all raw and log series. Except for the HP filtered housing series for which a unit root cannot be rejected, all other filtered series show a significant rejection of a unit root at greater than 99%. Filtering removes the unit-root feature of the raw data, and may lead to spurious results. Details of these

[2] We recognize the controversy over the use of the term Granger causality, which is not true causality, but rather indication that one variable is temporally related to another. As Enders (2004, p. 283) states:
Note that Granger causality is something quite different from a test for exogeneity. For z_t to be exogenous, we would require that it not be affected by the contemporaneous value of y_t. However, Granger causality refers only to the effects of past values of y_t on z_t.
This is one reason why our study includes estimation of VAR models and use of the Choleski decomposition, which achieves identification by positing independent 'innovations' in the variables.

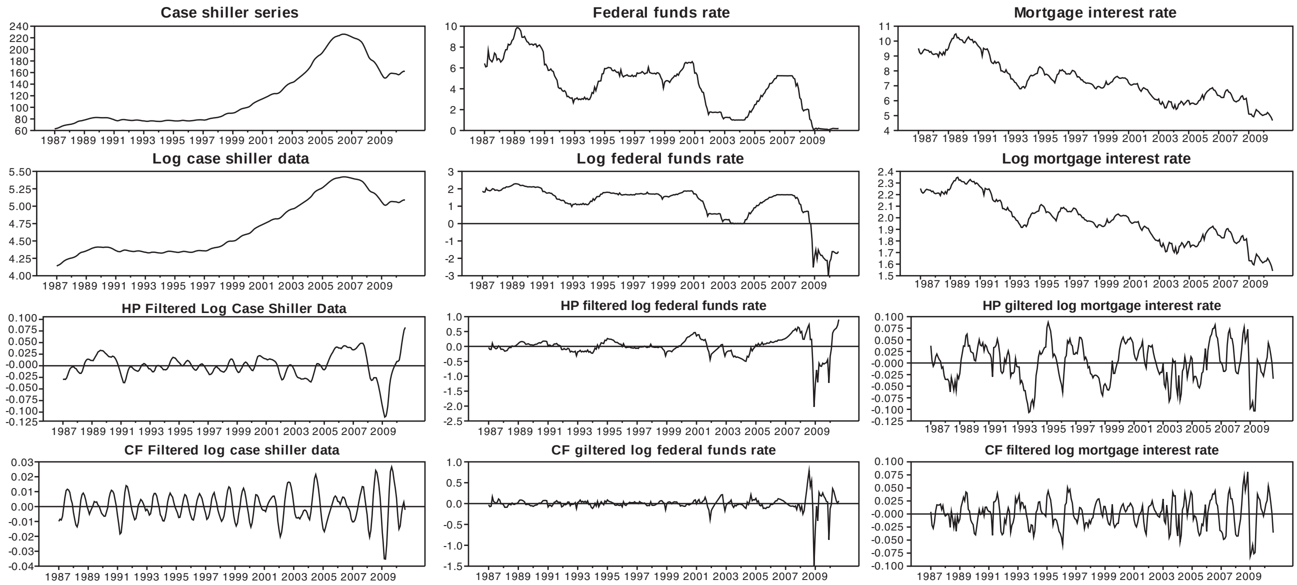

Fig. 1. Case Shiller housing index, Federal Funds Rate and Mortgage Rate

Table 1. Data descriptions for period 1987/1 to 2011/8

Name	Description	Mean	SD	Max	Min	DF
CSXR	Case–Shiller 10 city Composite index	118.656	50.875	226.290	62.82	−.745
FF_RATE	Federal Funds Rate	4.411	2.425	9.850	0.050	−.388
MORT_R	Mortgage Interest Rate	7.364	1.425	10.480	4.670	−.485
LN_CSXR	Log Case–Shiller 10 city Composite index	4.693	0.398	5.422	4.140	−1.444
LNFFRATE	Log Federal Funds Rate	1.166	1.052	2.287	−2.995	−.108
LNMORT_I	Log Mortgage Interest Rate	1.978	0.193	2.349	1.541	−.068
HPLN_CSXR	HP Filtered Log Case–Shiller 10 city index	0.000	0.026	0.083	−0.111	−.705
HPLNFFRATE	HP Filtered Log Federal Funds Rate	0.000	0.311	0.902	−2.028	−4.035
HPLNMORT_I	HP Filtered Log Mortgage Rate	0.000	0.041	0.088	−0.107	−4.327
CFLN_CSXR	CF Filtered Log Case–Shiller 10 city index	0.000	0.009	0.027	−0.035	−4.431
CFLNFFRATE	CF Filtered Log Federal Funds Rate	0.000	0.156	0.786	−1.495	−9.626
CFLNMORT_I	CF Filtered Log Mortgage Rate	0.000	0.027	0.087	−0.081	−6.684

Notes: Hodrick and Prescott (1997) filter (HP) and Christiano and Fitzgerald (2003) filter (CF) were used to detrend log series. DF critical values for 99%, 95% and 90% are −3.45, −2.87 and −2.57, respectively. A value less than a critical value (i.e. a value more negative than −3.45, etc.) indicates rejection of a unit root in the series at a given level. Rejection of a unit root means that running regressions with such data may produce spurious results. See, for example, the textbook by Enders (2004, pp. 170–84).

filters are discussed in an endnote.[3] As noted, the CF filtered series were calculated to be compatible with Miles (2012).

While Sims (1980) used unfiltered series and Sims *et al.* (1990) presented a strong theoretical case for not filtering the data due to low-frequency information loss, Ashley and Verbrugge (2009) urge caution. Their Monte Carlo study found 'VAR in levels estimation models yield poorly sized tests… even when the sample was fairly long such as $N = 400$. HP-filtering of the data and then estimating a VAR model in levels yields even worse results'. In view of this uncertainty, a goal of the present article is to determine to what extent the findings are impacted as a result of using alternative transformations of the data.

This section begins with a short discussion of one-way Granger causality, but quickly moves on to the VAR model that includes feedback effects and complex lag structures. The data used in this study are monthly time-series data that have been assembled to permit the use of the VAR method that can capture shorted lag responses.

[3] The Hodrick and Prescott (1997) filter works as follows. The series y_t from period 1 to period T consists of a trend component denoted by τ_t and a short-term component denoted by c_t, so $c_t = y_t - \tau_t$. The trend component is found by solving the following programming problem to find the values of τ_t that minimize:

$$\left\{\Sigma c_t^2 + \lambda\Sigma[(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2\right\}$$

The summations run from time period 1 to T. The parameter λ is a positive number that penalizes variability in the trend. A higher value for λ produces a smoother trend. We used the recommended value for λ for monthly data of 14 400. The value for λ recommended by Hodrick and Prescott (1997) for quarterly data is 1600. The Christiano and Fitzgerald (2003) filter is of the ideal band pass class that leaves intact the components of the data within a specific band while taking out other components. Christiano and Fitzgerald argue that their filter is "a better approximation to a high pass filter than is" the HP filter. In addition their filter can be more easily adjusted for handling monthly or annual data than the HP filter.

Given that y_t = the log of composite housing price index in period t and x_{1t} = the Federal Funds Rate, and x_{2t} = the 30-year mortgage rate, then x_{jt} will Granger (1969) cause y_t if a model

$$y_t = a + \sum_{i=1}^{m} \gamma_i B^i y_t + \sum_{j=1}^{2} \sum_{i=1}^{m} \delta_{ji} B^i x_{jt} + e_t \tag{1}$$

has a significantly lower error sum of squares than a model that restricts $\delta_{jt} = 0$, for $i = 1, \ldots, m$ where B is the lag operator defined such as $B^i x_{jt} \equiv x_{j,t-i}$ as in Greene (2008, p. 699). In order to use Equation 1 to test for Granger causality, in the case that the series are cointegrated, the lag m should be set sufficiently long so as to remove all significant autocorrelation and cross correlation in the error term e_t. This ensures that the regression residuals are stationary and results are not spurious. See Enders (2004, p. 326) for an example of spurious results. Sims *et al.* (1990, p. 136) make a strong case for not transforming the series to stationary form by filtering such as Miles has done since low-frequency information is removed by the transformation. They note,

> This work shows that the common practice of attempting to transform models to stationary form by difference or cointegration operators whenever it appears likely that the data are integrated is in many cases unnecessary. . . . In particular, individual coefficients in the estimated autoregressive equations are asymptotically normal with the usual limiting variance, unless they are coefficients of a variable which is nonstationary and which does not appear in any of the system's stationary linear combinations.

The present article contains results for both cases – data untransformed and data transformed using both the HP and CF filters. In contrast to Equation 1, Miles (2012) constrained $\gamma_i = 0$ for $i = 1, \ldots, m$.

Given that variables in the model may be inter-related (i.e. all the variables are endogenous), the more defensible approach is to use a VAR model that includes the possibility of feedback from y to x of the form:

$$\Phi(B) \begin{bmatrix} x_{1t} \\ x_{2t} \\ y_t \end{bmatrix} = \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{2}$$

which can be written as

$$\begin{bmatrix} \phi_{11}(B) & \phi_{12}(B) & \phi_{13}(B) \\ \phi_{21}(B) & \phi_{22}(B) & \phi_{23}(B) \\ \phi_{31}(B) & \phi_{32}(B) & \phi_{33}(B) \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \\ y_t \end{bmatrix} = \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{3}$$

where for example, Granger causality from x_{it} to y_t implies that $\phi_{3i}(B) \neq 0$ where $\phi_{ij}(B)$ is a polynomial in the lag operator B with m terms.

Zellner and Palm (1974) have a detailed discussion of the relationship between these alternatives models, both of which have their uses. For example, Equation 1 can be written as

$$\left(1 - \sum_{i=1}^{m} \gamma_i B^i\right) y_t = a + \sum_{i=1}^{m} \delta_{1i} B^i x_{1t} + \sum_{i=1}^{m} \delta_{2t} B^i x_{2t} + e_t \tag{4}$$

which can be simplified to

$$\gamma(B) y_t = \delta_1(B) x_{1t} + \delta_2(B) x_{2t} + e_t \tag{5}$$

Provided that $\gamma(B)$ is invertible ($\sum_{j=1}^{\infty} |\gamma_i| < \infty$), Equation 5 can be expressed as a rational distributed lag or transfer function, as in Box *et al.* (2008); i.e.

$$y_t = \frac{\delta_1(B)}{\gamma(B)} x_{1t} + \frac{\delta_2(B)}{\gamma(B)} x_{2t} + \frac{1}{\gamma(B)} e_t \tag{6}$$

The term $\delta_i(B)/\gamma(B)$ measures the effect of x_{it} on y_t taking into account both the effect of lags of x_{it} on lags of y_t and the direct effects of lags of x_{it} on y_t and is called the impulse-response function by Box *et al.* (2008, p. 13). It is important to stress that Equation 6 implies that there is no feedback from y_t to x_{it} or that $\phi_{ij}(B) \equiv 0$ for $i < j$ in Equation 4.

Since McDonald and Stokes (2013) found feedback from the log housing price, y_t, to the Federal Funds Rate x_{1t}, the specification in Equation 6 is not appropriate for the research design in this current article that adds another variable, the 30-year mortgage rate, to the analysis (The feedback of log housing price to the Federal Funds Rate is found in this study as well.) An alternative estimation approach that does not restrict feedback to zero by assumption is to invert the VAR model in Equation 2 and form the vector moving average (VMA) form of the model which will allow measurement of shocks coming from one equation to impact another equation. A VAR model can be transformed to a VMA model, given $\Phi(B)$ is invertible, or

$$\begin{bmatrix} x_{1t} \\ x_{2t} \\ y_t \end{bmatrix} = \Theta(B) \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{7}$$

where $\Theta(B) \equiv [\Phi(B)]^{-1}$. The terms in $\Theta(B)$ measure the dynamic responses of each of the potentially endogenous variables to a shock to the system. Equation 7 can be expanded to

$$\begin{bmatrix} x_{1t} \\ x_{2t} \\ y_t \end{bmatrix} = \begin{bmatrix} \theta_{11}(B) & \theta_{12}(B) & \theta_{13}(B) \\ \theta_{21}(B) & \theta_{22}(B) & \theta_{23}(B) \\ \theta_{31}(B) & \theta_{32}(B) & \theta_{33}(B) \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{8}$$

Define $\hat{\Sigma}$ as the covariance of the innovations $[e_{1t}, e_{2t}, e_{3t}]'$. Off diagonal terms are consistent with zero period relationships between the variables. To identify the model, restrictions need to be placed on $\hat{\Sigma}$. The usual Choleski decomposition has been used to othogonalize $\hat{\Sigma} = FF'$ where F is lower triangular with positive elements on the diagonal. The Choleski decomposition imposes a semi-structural interpretation on the estimated model by transforming $\Theta(B)$, the VMA form of the model and thus identifies the model, given the ordering of the variables. As discussed by Enders (2004, p. 292), in the Choleski decomposition it is assumed that an innovation in one variable does not have a contemporaneous effect on the other variables. If $\hat{\Sigma}$ was close to a diagonal matrix initially, which would be the case when there was no contemporaneous relationship between the residuals, the Choleski transformation would not be as important. The ordering of the variables might make a difference if $\hat{\Sigma}$ is not diagonal. This possibility is tested later, and found to make no difference in the nature of the results.

Significance bounds on the VMA coefficients can be obtained using Monte Carlo integration. Rats software Pro version 8.20 routine @mcgraphirf, Doan (2010, p. 495), is used to calculate using Monte Carlo integration 95% bounds for $\theta_{ij}(B)$ for all the nine possible cases of the three variable VAR model. Sims and Zha (1999) provide a detailed discussion of alternative methods for obtaining VMA coefficient bounds. An advantage of their suggested method, which has been used in this research, is that the estimated confidence bounds of the VMA form of the model are not assumed to be symmetric, as would be the case if bootstrap methods were attempted. An additional advantage of Monte Carlo integration is that it does not suffer from bias amplification that can occur with bootstrap methods, as noted by Sims and Zha (1999, p. 1125).

In general, the number of lags in the VAR model m is not the number of lags in $\theta_{ij}(B)$ which we will call q. In the results reported later, both $m = 12$ and 16 and $q = 20$ were used. The lag length m was selected using both the M statistic suggested by Tiao and Box (1981) and inspection of the cross correlations. B34S version 8.11F was been used to calculate these tests reported in the paper.

If x_{1t} is the log of the Federal Funds Rate, x_{2t} is the 30-year mortgage rate and y_t is the log of the housing price series, the term $\theta_{31}(B)$, suitably transformed by the Cholesky factorization, measures the effect of shocks in the log Federal funds market on the log housing price and $\theta_{32}(B)$ measures the effect of shocks in the mortgage market on the log housing price index. If $\theta_{ij}(B) = 0$ for $i \neq j$, then each endogenous variable is not impacted from shocks coming from the other endogenous variables.

Theory would suggest that shocks from the interest side would have a negative effect on housing prices, resulting in $\theta_{31}(B) < 0$, and positive shocks coming from the housing market would tend to bid up interest rates, resulting in $\theta_{13}(B) > 0$. And theory suggests that an increase in the mortgage rate would have a negative effect on housing prices; $\theta_{32}(B) < 0$. These hypotheses will be investigated in the results section of this article.

In contrast to the log of the Federal Funds Rate (LNFFRATE) that had a coefficient of variation of 0.9022, the coefficient of variation of the log mortgage rate (LNMORT_I) was 0.0975. While Miles (2012) asserted that a Granger (1969) causality approach such as was used by Friedman and Kuttner (1992) was used, in fact lags of the left-hand variables were not placed on the right. As noted, in terms of Equation 1 this means that $\gamma_i = 0$ by assumption or in words that the model is not measuring conditional expectation. In his words '. . . we regress the filtered FHFA index on four lags of the filtered FFR and the filtered thirty-year mortgage rate . . .' In comparing the results of the two papers, it is important to determine whether it was the model used, the housing data series used, the transformations applied to the data or the frequency of the data that makes a difference.

The equation that Miles (2012) used can be written in terms of the VAR model notation. Consider the last row of Equation 3 which can be written as

$$\phi_{31}(B)x_{1t} + \phi_{32}(B)x_{2t} + \phi_{33}(B)y_t = e_{3t} \qquad (9)$$

By moving terms to the right and dividing by $\phi_{33}(B)$ we obtain

$$y_t = -\frac{\phi_{31}(B)}{\phi_{33}(B)}x_{1t} - \frac{\phi_{32}(B)}{\phi_{33}(B)}x_{2t} + \frac{e_{3t}}{\phi_{33}(B)} \qquad (10)$$

which is what Miles (2012) used with the addition of a constant. While the Granger (1969) methodology consists of testing whether $\phi_{3j}(B) = 0$ for $j \neq 3$ this is not the same as testing if $\phi_{3j}(B)/\phi_{33}(B) = 0$ for $j \neq 3$ which Miles is doing implicitly. Since we cannot assume that $\phi_{33}(B) = 1$, these are not equivalent tests. While Miles thinks he is testing whether x_{it} is a significant variable, the test he used is contaminated by the effect of the implicit lags of y_t that are contained in $\phi_{33}(B)$.

The data in Fig. 1 suggest that the home price index and the Federal Funds Rate were uncorrelated from 1987 through 1997 as the home price index changed very little and the Federal Funds Rate moved sharply down after 1989 and then up in 1994. During this same period, the mortgage rate appears to move with the Federal Funds Rate. The Federal Funds Rate increased in 1999 and 2000, and mortgage rate increased in 1999 and remained roughly constant in 2000. The mortgage rate began the year 2000 at 7.45% on January, reached a high point of 7.63% in April, and ended the year at 7.40% in December. The Federal Funds Rate began its sharp decline in January, 2001, and the mortgage rate followed – falling to 6.79% at the end of 2001, 6.04% at the end of 2002, and 5.59% at the end of 2003 (with low point of 5.48% in January, 2004). The mortgage rate moved up 54 basis points during 2004 as the Federal Reserve increased the Federal Funds Rate aggressively. The mortgage rate hovered between 5.75% and 6.03% during the first 10 months of 2005 as the Fed continued to increase the Federal Funds Rate sharply, so there is a basis to suggest that there was a disconnect between the two rates during this year. But then the mortgage rate increased in late 2005 and early 2006, reaching 6.87% in August, 2006. Mortgage rates trended downward from this high point to 4.67% in August, 2010. This cursory examination of the raw data does indeed suggest that the correlation between the Federal Funds Rate and the mortgage rate decreased in the first decade of the new century, but that a positive correlation continues to exist.[4] The housing price index reached its peak in June, 2006 – 2 years after the Fed began to increase the Federal Funds Rate and 2 months prior to the peak in the mortgage rate. The housing price index crashed during the next 2½ years. The Federal Funds Rate was held steady through July, 2007 and moved sharply downward during the second half of 2007 and 2008. As noted, the mortgage rate declined during this period.

V. Empirical Results

This section reports a series of Granger causality tests for alternative versions of the model based on Equation 3. The results conclude with the presentation of impulse-response functions. The spectra displayed in Fig. 2 show the amount of information centred at each frequency. The spectra, which were estimated using WinRats Pro 8.2 using the default flat window, show that the CF filter takes out the most low-frequency information from the series. The HP filter series takes out the next most. Thus using filtered data alters the interpretation of any findings in that the detection of any low-frequency relationships is biased downward.

Table 2 reports a three VAR(16) Granger (1969) tests using log data, HP filtered log series and CF filtered log series, respectively, for the Federal Funds Rate, the mortgage rate and Case–Shiller housing price data. Summary results for both 12 lag and 16 lag variants and a subset model with only the mortgage rate and the housing series are shown in Table 3. Turning first to the detailed results in Table 2 for the 16 lag model, we find that the Federal Funds Rate is causally prior to the housing price series for the log model, the HP filtered model and the CF filtered model with significance of 99.7598%, 98.6347% and 100%, respectively. The mortgage rate was found significantly to Granger cause the housing series only for the CF filtered data at 99.4147%. For the log data and HP models, the significance was 77.06% and 45.517%, respectively.

[4] This brief examination of the raw data suggests that there may have been a structural change in the relationship among the variables. See McDonald and Stokes (2013) for tests pertaining to the relationship between the Federal Funds Rate and the housing price index series. These tests show a weaker relationship between the two variables for the 1987–1999 period compared to the 2000–2010 period. However, the main results presented by McDonald and Stokes (2013) pertain to the entire 1987–2010 period, so the current study utilizes data from the entire 1987–2011 period. Miles (2012) also tests for and finds evidence of structural change.

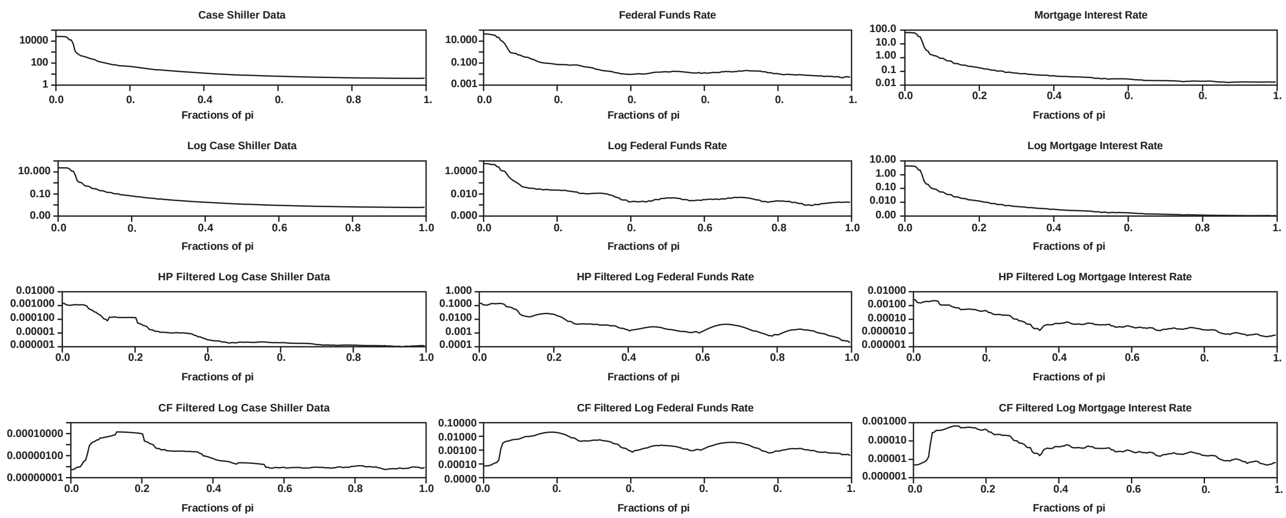

Fig. 2. Spectra of series

Table 2. Granger causality tests for alternative VAR(16) models

	Model using log data		
Granger causality $F(i,j)$			
	Fed funds	Mortgage R	Case–Shiller
Fed funds	164.433	0.691330	4.17756
Mortgage rate	1.98950	221.264	0.666269
Case–Shiller	2.40641	1.25379	149,183
Significance of $F(i,j)$			
	Fed funds	Mortgage R	Case–Shiller
Fed funds	1.00000	0.198748	1.00000
Mortgage rate	0.985107	1.00000	0.174648
Case–Shiller	0.997598	0.770604	1.00000
	Model using HP filtered log data		
Granger causality $F(i,j)$			
	Fed funds	Mortgage R	Case–Shiller
Fed funds	22.0912	0.771090	5.02237
Mortgage rate	1.67415	38.6411	0.865557
Case–Shiller	2.01012	0.921888	1018.03
Significance of $F(i,j)$			
	Fed funds	Mortgage R	Case–Shiller
Fed funds	1.00000	0.282693	1.00000
Mortgage rate	0.946883	1.00000	0.390324
Case–Shiller	0.986347	0.455170	1.00000
	Model using CF filtered log data		
Granger causality $F(i,j)$			
	Fed funds	Mortgage R	Case–Shiller
Fed funds	15.1924	1.73628	4.85856
Mortgage rate	2.16322	18.5917	0.775258
Case–Shiller	7.06101	2.20663	302.419
Significance of $F(i,j)$			
	Fed funds	Mortgage R	Case–Shiller
Fed funds	1.00000	0.958257	1.00000
Mortgage rate	0.992924	1.00000	0.287314
Case–Shiller	1.00000	0.994147	1.00000

Note: $F(i,j)$ tests whether jth series Granger causes ith series.

The Federal Funds Rate was found to be causally prior to the mortgage rate for all three models with significance of 98.51%, 94.69% and 99.29% for the log, HP and CF models, respectively. There is feedback from the housing series to the Federal Funds Rate of 100% for all these models. For the mortgage rate, there was no feedback since the significance was 17.46%, 39.03% and 28.73%, respectively. Only for the CF model was the mortgage rate causally prior to the Federal Funds Rate (95.83%); for the log and HP models the significance was 19.87% and 28.27%, respectively.

Table 3 repeats the significance values of Table 2 for the 16 lag model and reports results for the 12 lag model. For the 12 lag model, the mortgage rate is not causally prior to the housing series. In addition, a sub-model containing only the mortgage rate and the housing data was attempted. Only for the log model do we find that the mortgage rate is causally prior to the housing series (98.62% for VAR(16) model and 99.96% for VAR(12) model). A possible economic argument might be that this model includes the most low-frequency information. The filtered models remove this information. Of concern is that this model is not specified correctly, since the Federal Funds Rate is not included, and the effect found is in fact due to this omission.

Table 4 presents results of estimates of a model that is similar to the form estimated by Miles (2012) where LN_CSXR is on the left but is not lagged on the right-hand side. Except for the period used and the housing variable used, this equation is as close as possible to that setup. The lag was initially assumed to be 12 since monthly data were used. Miles (2012) used quarterly data and used a lag = 4. As noted above, this is not a Granger model. Using this functional form suggested by Miles form and assuming lag = 12 LNMORT_I and LNFFRATE are significant for both log and CF filtered data. If the lag length is 16 and CF filtered data are used both the filtered mortgage rate series and the Federal Funds Rate series remain significant. However, for the 16 lag log model, the Federal Funds Rate is no longer significant while the mortgage rate remains significant. However, as shown in Exhibits 4 and 5, when lags of LN_CSXR are in the model on the right-hand side, LNMORT_I is not statistically significant except when the data is filtered by the CF procedure and a VAR(16) model is estimated. The Federal Funds Rate is always significant. The take away is that the Miles (2012) results appear not to be due to the fact that he used quarterly data or a different period.

VI. Impulse-Response Results

In order better to understand the dynamics of the three variables a VAR model as in Equation 8 and the impulse-response functions

Table 3. Granger causality tests for complete and subset VAR models significance of terms for complete model

Type of model	FFR to CS	MORTR to CS	MORTR FFR	FFR to MORTR	CS to FFR	CS to MORTR
VAR(16) log	.9976	.7706	.1987	.9851	1.0000	.1746
VAR(16) HP-Log	.9863	.4552	.2827	.9469	1.0000	.3903
VAR(16) CF-Log	1.0000	.9941	.9583	.9929	1.0000	.2873
VAR(12) log	.9992	.7088	.5015	.9927	.9999	.4604
VAR(12) HP-Log	.9932	.3278	.5727	.9675	1.0000	.5894
VAR(12) CF-Log	.9972	.4134	.8195	.9976	.9999	.8683
Significance of terms for sub-model of MORTR and CS						
Type of model	MORTR to CS	CS to MORTR				
VAR(16) log	.9862	.6316				
VAR(16) HP-Log	.7732	.9231				
VAR(16)	CF-Log .5794	.7553				
VAR(12) log	.9996	.6448				
VAR(12) HP-Log	.5955	.8613				
VAR(12) CF-Log	.4316	.9608				

Notes: FFR, Federal Funds Rate; CS, Case–Shiller house price index; MORTR, mortgage rate.

Table 4. Single equation models of the form LN_CSXR = f (lags(LNFFRATE), lags(LNMORT_I)) for Log and CF filtered data

Null hypothesis: the following coefficients are zero	
LNFFRATE	Lags 1–12 $F(12, 247) = 2.11687$ significance 98.4%
LNMORT_I	Lags 1–12 $F(12, 247) = 27.04804$ significance 100%
CFLNFFRATE	Lags 1–12 $F(12, 247) = 5.75932$ significance 100%
CFLNMORT_I	Lags 1–12 $F(12, 247) = 4.56264$ significance 100%
LNFFRATE	Lags 1–16 $F(16, 235) = 1.18618$ significance 72%
LNMORT_I	Lags 1–16 $F(16, 235) = 16.72771$ significance 100%
CFLNFFRATE	Lags 1–16 $F(16, 235) = 5.94923$ significance 100%
CFLNMORT_I	Lags 1–16 $F(16, 235) = 5.98848$ significance 100%

were calculated using the data displayed in Fig. 1. The lags were set at 16 months so as to remove all significant autocorrelations and cross correlations in the estimated VAR residuals, although the results are not very sensitive to this parameter. The impulse-response functions for the models are shown in Figs 3–5. The Figures show the two SD bounds set by Monte Carlo integration.

Fig. 3 shows that both the mortgage rate and the housing price index respond to shocks to the Federal Funds Rate in the expected directions, and that these responses are statistically significant. The maximum response of the housing price index of −0.016 at 19 months to an impulse of 1% to the Federal Funds Rate is very similar to the response found by McDonald and Stokes (2013). The maximum response of the mortgage rate to the Federal Funds Rate is 0.017 at 15 months. The housing price index does not respond to shocks to the mortgage rate. All three variables respond to own shocks. The patterns for the Federal Funds Rate and the housing price index are virtually identical to those found by McDonald and Stokes (2013). Shocks to the housing price index have a statistically significant positive effect on the Federal Funds Rate at 3–5 months. The Taylor rule (2007) states that the Federal Funds Rate should be a function of two variables; the inflation rate and the extent to which GDP falls short of potential GDP. Housing prices are a component of inflation. However, Taylor (2007) shows that the Taylor rule was not being followed during the first half of the 2000–2010 decade. Fig. 3 shows a feedback effect of the housing price index on the Federal Funds Rate for the entire 1987–2011 period. This effect also was found in the McDonald and Stokes (2013) study.

The results of this exercise are clear; the shocks to the Federal Funds Rate move the housing price index and the mortgage rate in the expected directions, but shocks to the mortgage rate do not move the housing price index given that the Federal Funds Rate and the housing price index are included in the model.

Fig. 4 displays results for estimates of the model shown in Fig. 3 with the addition that all log series have been transformed using the Hodrick and Prescott (1997) filter. Plots of these data are shown in the next to bottom row of Fig. 1. The HP filter is used to separate short-term fluctuations from longer-term trends.

The results in Fig. 4 support those reported in Fig. 3. Shocks in the filtered log mortgage rate significantly positively impact the filtered log housing price series (see the plot in the 3,2 position) for the first three periods. It is hard to think of a reason why this might be the case since the expected sign was negative. The filtered log Federal fund rate does impact the filtered log housing price series in a manner similar to what was found in Fig. 3 (see the plot in position 3,1) in the expected negative direction. This finding suggests that the effects of the Federal Funds Rate on the housing price series are not only at lower frequency since, when this frequency component of the series was removed by the HP filter, the effects are still present. Some feedback effect of the housing price series on the Federal Funds Rate (in the positive direction) appears in Fig. 4 as well as in Fig. 3. In results not reported but investigated, the series ordering of the two interest rates were reversed with little effect seen. This finding is consistent with $\hat{\Sigma}$ being nearly diagonal.

Fig. 5 uses the CF filtered data. Federal Funds Rate shocks are found initially to positively impact the housing price series, then negatively impact the price series substantially and finally, after a lag of 12 months, positively impact housing prices (see position 3,1). Except for the final positive effect, these results may be due to the fact that, as the economy picks up and the Federal Funds Rate is increased, housing prices first rise but are later choked off by the Federal Funds Rate shock. This pattern is observed also for the mortgage rate. However, from period 12 on, the effect of a shock in either rate series is positive, which was not expected. Comparison between Figs 4 and 5 suggest that this final effect pattern may be due

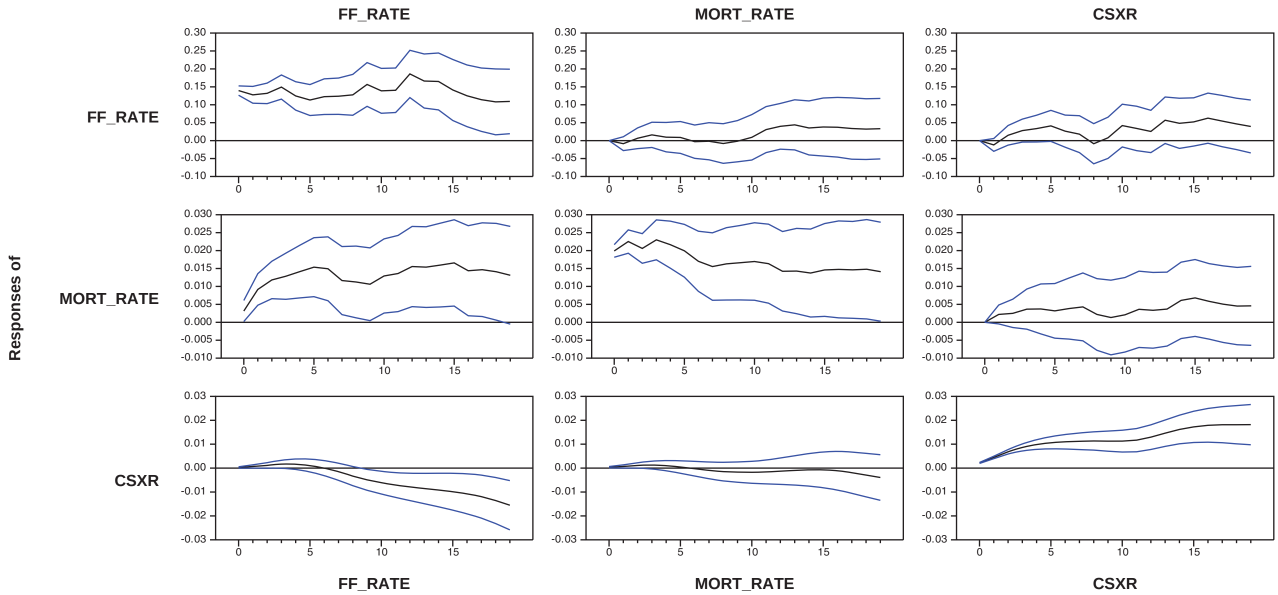

Fig. 3. Impulse-response functions for log VAR(16) model

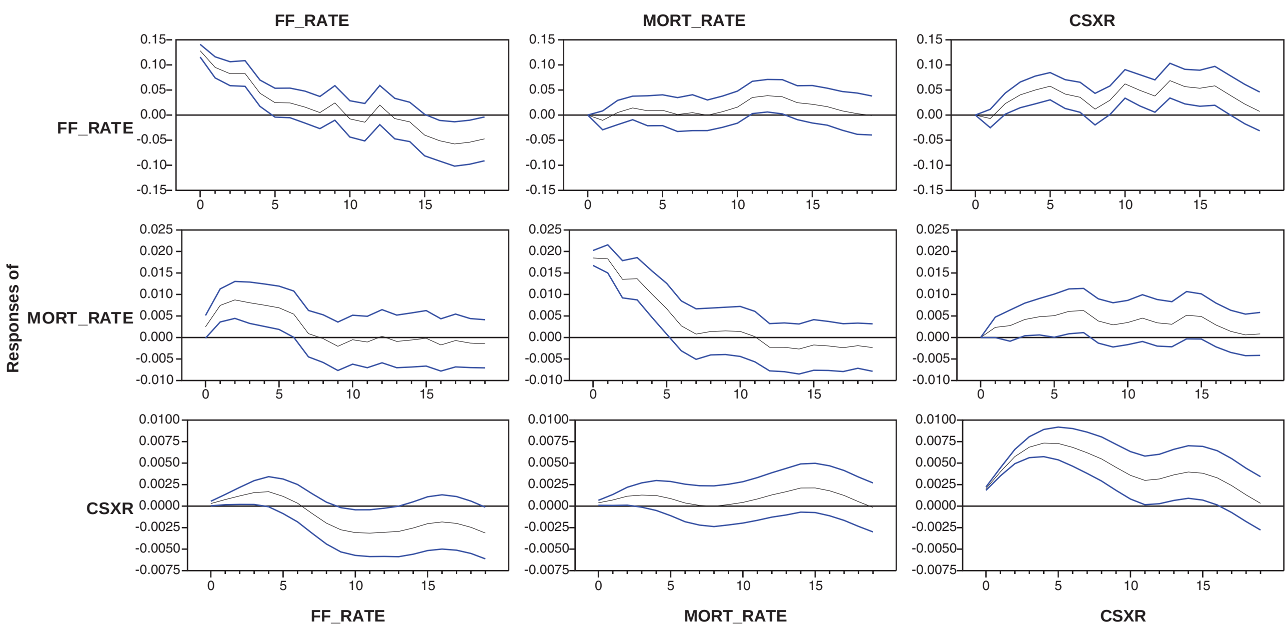

Fig. 4. Impulse-response functions HP filtered log VAR(16) model

to the HP and CF filtering altering the structure of the series as can be seen by the data plots in Fig. 1 and the spectrums in Fig. 2. For the unfiltered log series, the initial positive, then negative effect of the Federal Funds Rate is observed without the final positive effect.

VII. Short Run Dynamics as Measured by an Error Correction Representation

Table 1 reports DF tests of −1.444, −.108 and .705 for LN_CSXR, LNFFRATE and LNMORT_I, respectively, that fail to reject a unit root since the critical values at the 10%, 5% and 1% level are −2.5722, −2.8718 and −3.4550, respectively. Since all series have unit roots, cointegration or a linear relationship between the series that is stationary is required for the estimated model to be correct. For simplified notation assume that $\text{LNFFRATE}_t = x_{1t}$, $\text{LNMORT\_I}_t = x_{2t}$ and $\text{LNCSXR}_t = y_t$. Cointegration requires that

$$\beta_1 x_{1t} + \beta_2 y_t + \beta_3 x_{2t} + \alpha = \varepsilon_t \tag{11}$$

A finding that the series are not cointegrated, which would be the case if ε_t is not stationary implies, that there is no long-run relationship or equilibrium between the variables. If all series are not integrated of the same order, then there cannot be a long-run relationship between these series. The Johansen likelihood ratio method of detecting, if there is cointegration using the Rats procedure JOHMLE, is reported in Exhibit 10 for VAR(12) and VAR(16) models. For the largest eigenvalue λ_{trace} values of 42.1626 and 35.8932 were found to be larger than the 95% critical value of 35.07 indicating that there was one cointegrating vector which has been reported and is remarkably similar for the two VAR models tested. Note that

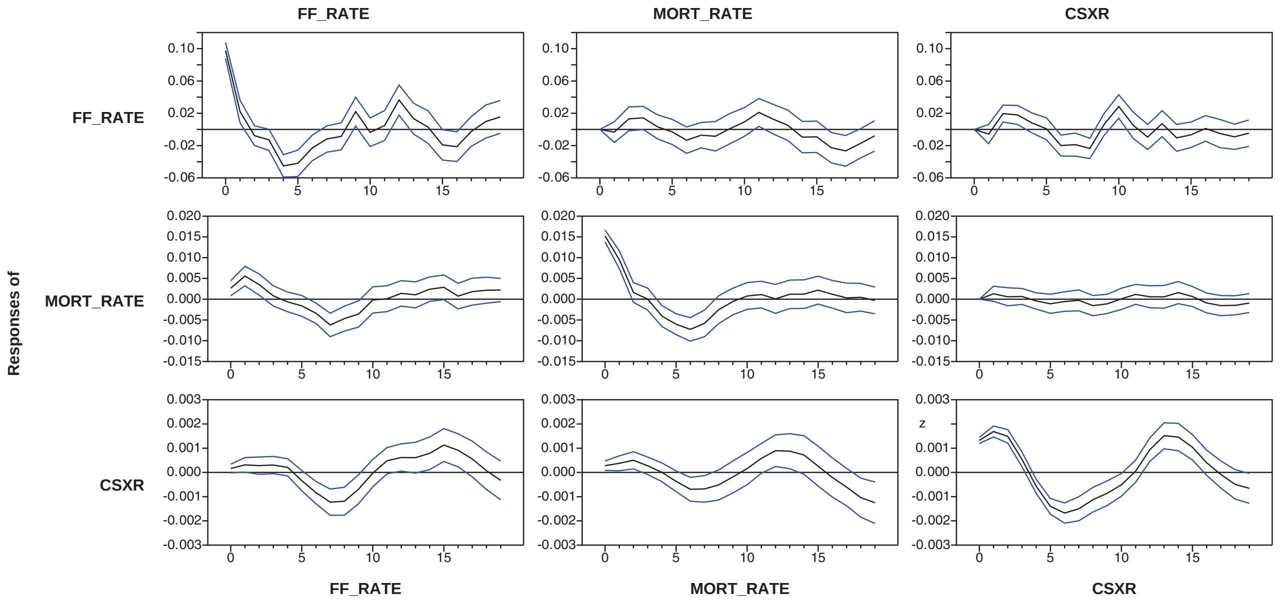

Fig. 5. Impulse-response functions CF filtered log VAR(16) model

Table 5. Johansen test for 12 lag model

Rank	EigVal	λ Max	λ Trace	Trace-95%	LogL
0					2135.0456
1	0.1012	29.0361	42.1626	35.0700	2149.5636
2	0.0396	10.9884	13.1265	20.1600	2155.0578
3	0.0078	2.1381	2.1381	9.1400	2156.1268
Cointegrating vector for largest eigenvalue					
LNFFRATE	LN_CSXR	LNMORT_I	Constant		
−1.111966	−3.646605	−2.891158	23.836971		
Error correction term	Variable	Value	*t*-Value		
α_{x1}	LNFFRATE	−0.190	−1.767		
α_{x2}	LNMORT_I	.00201	1.351		
α_y	LN_CSXR	−.0006	3.438		
Johansen test for 16 lag model					
Rank	EigVal	λ Max	λ Trace	Trace-95%	LogL
0					2147.9621
1	0.0822	22.9842	35.8932	35.0700	2159.4542
2	0.0395	10.7904	12.9090	20.1600	2164.8494
3	0.0079	2.1186	2.1186	9.1400	2165.9087
Cointegrating vector for largest eigenvalue					
LNFFRATE	LN_CSXR	LNMORT_I	Constant		
−1.549215	−4.965297	−3.981037	32.645792		
Error correction term	Variable	Value	*t*-Value		
α_{x1}	LNFFRATE	−.0312	−2.108		
α_{x2}	LNMORT_I	.00144	.668		
α_y	LN_CSXR	−.0006	−2.698		

β_1, β_2 and β_3 are all the same sign which is consistent with theory that argues that a movement down in LNFFRATE can be countered by an increase in LN_CSXR.

An error correction model first calculates ε_{t-1} from Equation 11, then adds ε_{t-1} to a VAR in first differences of all the variables in Equation 8.

$$\Delta x_{1t} = \alpha_{10} + \alpha_{x1}(\varepsilon_{t-1}) + \sum_{i=1}^{m} \delta_{11i}\Delta x_{1t-i} + \sum_{j=1}^{m} \delta_{12j}\Delta x_{2t-j} + \sum_{j=1}^{m} \delta_{13j}\Delta y_{t-j} + e_{1t}$$

$$\Delta x_{2t} = \alpha_{20} + \alpha_{x2}(\varepsilon_{t-1}) + \sum_{i=1}^{m} \delta_{21i}\Delta x_{1t-i} + \sum_{j=1}^{m} \delta_{22j}\Delta x_{2t-j} + \sum_{j=1}^{m} \delta_{13j}\Delta y_{t-j} + e_{2t}$$

$$\Delta y_{t} = \alpha_{30} + \alpha_{y}(\varepsilon_{t-1}) + \sum_{i=1}^{m} \delta_{31i}\Delta x_{1t-i} + \sum_{j=1}^{m} \delta_{32j}\Delta x_{2t-j} + \sum_{j=1}^{m} \delta_{33j}\Delta y_{t-j} + e_{3t} \qquad (12)$$

If all the error correction terms, $\alpha_{x1}, \alpha_{x2}, \alpha_y$, are not significant there are problems since the model will not adjust to long-run equilibrium in the short run. In the results reported in Table 5 where only the error correction terms are shown, however, we note that in both VAR(12) and VAR(16) models α_y is negative and significant with t-values of -3.438 and -2.698, respectively. This indicates that the log housing price is adjusting to shocks. In the VAR(16) model, in addition, α_{x1} is significant that indicates that the log of the Federal Funds Rate will also adjust. These results are consistent with the Granger representation theorem that states that error correction and cointegration are equivalent representations. As noted in Enders (2004, p. 370) 'cointegration necessitates coefficient restrictions in a VAR model . . . it is inappropriate to estimate a VAR of cointegrated variables using only first differences'. The fact that the log mortgage rate error correction coefficient α_{x2} was not significant in either the VAR(12) or VAR(16) models suggests that this rate does not adjust and is thus what is called weakly exogenous Enders (2004, p. 371).

VIII. Conclusion

Shocks to the log housing price index tend to move the log housing price index in the positive direction (momentum), shocks to the log Federal Funds Rate move the log housing price index in the negative direction as expected by theory. Shocks to the log mortgage rate do not move the housing price index except when CF filtered data are used and a VAR(16) model is estimated. Rather, the mortgage rate is moved by shocks to the Federal Funds Rate. The finding that, given the interest rate variables, housing prices have their own momentum is suggestive (but not conclusive) evidence of a housing price 'bubble'. What can account for the discrepancy in results between Miles (2012) and the current study? The evidence provided by Greenspan (2010) concerning the relationships between housing prices and interest rates pertains only to the years 2002–2005, so it would seem that more data from a longer period of time might produce different findings. Miles (2012) both used data from a longer-time period (1982 to 2011) and employed econometric procedures that differ from those in McDonald and Stokes (2013) in that he did not lag the dependent variables in his estimated equations and only used CF filtered data. The present article finds

- The results differ depending on whether filtered data or nonfiltered data are used.
- The number of lags in the VAR makes a difference.
- Whether the lags of the left-hand side variable are in the model impacts the findings. We have been able to replicate Miles results when using his form of the model that did not have these lags.

To gain added insight the VAR impulse-response functions are presented that answered a number of questions but suggested more research is warranted. What is clear is that both the Federal Funds Rate and the mortgage rate should be in the model.

Our findings suggest that the removal of some of the trends in the data may remove important facts to be explained, especially at the low-frequency end. However, the discrepancy in the results of the study by Miles (2012) and this study does not appear to stem from the de-trending procedure Miles employed since we report results of estimating our model with de-trended data with little effect on our prior results. Our results indicate that lagged values of the housing price index should be included in the model. Models estimated without these lags were shown to show questionable results that disappear when a true Granger model is estimated. Finally, the lack of impulse-response functions in Miles (2012) is not a likely source of the difference in results because they largely replicate the Granger causality findings. Since the log form of the model showed unit roots in the three series used, an error correction model was estimated that showed significant coefficients for the error correction coefficients for the log housing price series in VAR(12) and VAR(16) models in differences. This finding calls into question models that are just first differences without error correction terms. These observations are meant only to stimulate further research on this important topic.

References

Ashley, R. and Verbrugge, R. (2009) To difference or not to difference: A Monte Carlo investigation of inference in vector auto regression models, *International Journal of Data Analysis, Techniques and Strategies*, **1**, 242–74.

Bergin, P. (2011) Asset booms and current account deficits, *Federal Reserve Bank of San Francisco Economic Letter*, **2011-37**, December.

Box, G., Jenkins, G. and Reinsel, G. (2008) *Time Series Analysis: Forecasting and Control*, 4th edn, John Wiley & Sons, Hoboken, NJ.

Chang, K., Chen, N. and Leung, C. (2011) Monetary policy, term structure and real estate return: Comparing REIT, housing and stock, *Journal of Real Estate Finance and Economics*, **43**, 221–57.

Christiano, L. and Fitzgerald, T. (2003) The band-pass filter, *International Economic Review*, **44**, 435–65.

Doan, T. (2010) *Rats User's Manual: Version 8.0*, Estima, Evanston, IL.

Enders, W. (2004) *Applied Econometric Time Series*, 2nd edn, John Wiley & Sons, Hoboken, NJ.

Friedman, B. and Kuttner, K. (1992) Money, income, prices and interest rates, *American Economic Review*, **28**, 472–92.

Granger, C. (1969) Investigating causal relations by econometric models and cross-spectral methods, *Econometrica*, **37**, 424–38.

Greene, W. (2008) *Econometric Analysis*, 6th edn, Pearson/Prentice-Hall, Upper Saddle River, NJ.

Greenspan, A. (2010) The crisis, *Brookings Papers on Economic Activity*, Spring, 201–62.

Hodrick, R. and Prescott, E. (1997) Postwar business cycles, *Journal of Money, Credit and Banking*, **29**, 1–16.

Jarocinski, M. and Smets, F. (2008) House prices and the stance of monetary policy, *Federal Reserve Bank of St. Louis Review*, **90**, 339–66.

McDonald, J. and Stokes, H. (2013) Monetary policy and the housing bubble, *Journal of Real Estate Finance and Economics*, **46**, 437–51.

Miles, W. (2012) The housing bubble: How much blame does the fed really deserve? *Journal of Real Estate Research*, forthcoming.

Sims, C. (1980) Macroeconomics and reality, *Econometrica*, **48**, 1–48.

Sims, C. and Zha, T. (1999) Error bounds for impulse responses, *Econometrica*, **67**, 1113–55.

Sims, C., Stock, J. and Watson, M. (1990) Inference in linear time series models with some unit roots, *Econometrica*, **58**, 114–44.

Taylor, J. (2007) Housing and monetary policy, National Bureau of Economic Research Working Paper 13682, NBER, New York.

Tiao, G. and Box, G. (1981) Modeling multiple time series with applications, *Journal of the American Statistical Association*, **76**, 802–16.

Zellner, A. and Palm, F. (1974) Time series analysis and simultaneous econometric models, *Journal of Econometrics*, **2**, 17–54.