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Impact of macroeconomic indicators on housing prices

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Received 17 September 2018
Revised 4 February 2019
Accepted 6 February 2019

Abstract

Purpose – This paper uses statistical analyses to quantify the effects of five major macroeconomic indicators, namely crude oil price, 30-year mortgage interest rate (IR), Consumer Price Index (CPI), Dow Jones Industrial Average (DJIA), and unemployment rate (UR), on housing prices over time.

Design/methodology/approach – Housing price is measured as housing price index (HPI) and is treated as a variable affecting itself. Actual housing sale prices in the Town of Amherst, New York State, USA, 1999-2008, and time-series data of the macroeconomic indicators, 2000-2017, were used in a vector autoregression statistical model to examine the data that show the greatest statistical significance and exert maximum quantitative effects of macroeconomic indicators on housing prices.

Findings – The analyses concluded that the 30-year IR and HPI have statistically significant effects on housing prices. IR has the highest effect, contributing 5.0 per cent of variance in the first month to 8.5 per cent in the twelfth. The UR has the next greatest influence followed by DJIA and CPI. The disturbance from HPI itself causes the greatest variability in future prices: up to 92.7 per cent in variance 1 month ahead and approximately 74.5 per cent 12 months ahead. This result indicates that current changes in house prices heavily influence people's expectation of future prices. The total effect of the error variance of the macroeconomic indicators ranged from 7.3 per cent in the first month to 25.5 per cent in the twelfth.

Originality/value – The conclusions in this paper, along with related tables and figures, will be useful to the housing and real estate communities in planning their business for the next years.

Keywords Housing, Housing market analysis, Real estate, Housing policy, Macroeconomics, Pricing model

Paper type Research paper

1. Introduction

Housing prices are known to reflect local economic conditions. Also, both global economic conditions and the national business cycles influence the local housing markets. In fact, a large number of economic variables affect variation in housing prices over time. For instance, income, mortgage interest rates (IRs), construction costs, labor market variables, stock prices, industrial production, consumer confidence index act as potential predictors (Cho, 1996; Abraham and Hendershott, 1996; Johnes and Hyclak, 1999; and Rapach and

International Journal of Housing Markets and Analysis
Vol. 12 No. 6, 2019
pp. 1055-1071
© Emerald Publishing Limited
1753-8270
DOI 10.1108/IJHMA-09-2018-0070

Strauss, 2007, 2009). The highly volatile crude oil price causes large movements in global economic conditions. These shocks in turn feed into the regional economy.

History shows that over long periods, stock prices and house prices move together. Sutton (2002) presents evidence that a significant part of house price fluctuations can be explained by stock prices in six countries (the USA, the UK, Canada, Ireland, The Netherlands and Australia). With regard to the impact of inflation on the housing sector, different views have been argued. Baffoe-Bonnie (1998) found that shocks to inflation may increase housing prices in the western region of USA. On the other hand, Kearl (1979) indicated that inflation causes nominal housing payments to rise, which results in a lower housing demand, and which in turn lowers housing prices. Baffoe-Bonnie (1998) further reported that recent innovations in the Welsh economy led to the view that the economy of this region is likely to exhibit differential responses to financial and external shocks compared to that of the rest of the UK. He thus concluded that different regions have different responses to the same macroeconomic shock. In addition to the Dow Jones Index Average (DJIA) and inflation, other economic variables, such as mortgage IRs and unemployment rate (UR), can affect both housing prices and the construction of new housing. The mortgage IR is a very important variable influencing the decision of individuals to buy a house. Housing almost always involves mortgage borrowing because of the high purchase price. A rise in mortgage IR increases the cost of home ownership relative to other consumption items. Therefore, people are prevented from buying houses. Therefore, the demand for housing decreases.

The regional UR has also proven to be a predictor of fluctuations in the regional housing prices. The rate of unemployment is an indicator of the local economic conditions. Building activity is stimulated by higher employment growth (Smith and Tesarek, 1991; Sternlieb and Hughes, 1977), whereas Hartzell *et al.* (1993) argued that certain regional employment characteristics play a significant role in investors' decisions and, thus, in the determination of housing prices. Abelson *et al.* (2005) also found that the high UR and the mortgage IR had a negative impact on housing prices. The motivation of this paper is to quantify the effects of major macroeconomic indicators: oil price , 30-year mortgage IR, consumer price index (CPI), Dow Jones Industrial Average (DJIA) and unemployment rate (UR) on the regional housing prices over time. For modeling the impact of macroeconomic indicators on housing prices, the vector autoregressive (VAR) statistical tool has been used to capture the full interaction of the housing sector with the rest of the economy. VAR has proven useful in analyzing the time-series data. The VAR analysis used the time-series data for each of the five macroeconomic indicators and the prices of houses sold in the Town of Amherst, New York, during 1999 to 2008. The various analyses concluded that the 30-year mortgage IR has the highest effect on the housing prices, ranging from 4.97 per cent in the first month to 8.51 per cent in the twelfth month. The regional unemployment rate was next in order, followed by DJIA, and CPI. The total effect of these five macroeconomic indicators ranged from 7.3 per cent in the first month to 25.5 per cent in the twelfth month.

2. Data description

The housing price models were formulated using five major macroeconomic indicators:

(1) Oil Price (OIL);

(2) 30-year mortgage IR;

(3) CPI;

(4) (DJIA); and

(5) UR.

Empirical analyses were carried out using monthly time-series data for each of the macroeconomic indicators from 2000 to 2008, which were available from the U.S. Bureau of Labor Statistics, World Bank, New York State Department of Labor and other reliable sources. Figures 1 to 6 show the raw time-series data for each of the five macroeconomic variables, from the period 2000 to 2017; the data from 1999 to 2008 were used in the analyses to match the actual available data of monthly housing sales from the Town of Amherst. Time-series data for the housing price index (HPI), for the same period, have been plotted in Figure 7 to examine the effects of housing prices on the HPI over time. HPI was defined as the median sale price for each time period. Time-series data for each of the macroeconomic variables are described in the following sections.

2.1 Oil price

The crude oil price is measured in US dollars per barrel; the monthly price data are used in the VAR models as the logarithm of the crude oil price (World Bank, 2017). Figure 1 gives the time-series data for US crude oil price for the period 2000-2017. The oil price was $25.31

Source: World Bank (2017)

Figure 1. Time-series data for US crude oil price per barrel, 2000-2017

Source: HSH.com (2017)

Figure 2. Time-series data for 30-year fixed mortgage IR (%), 2000-2016

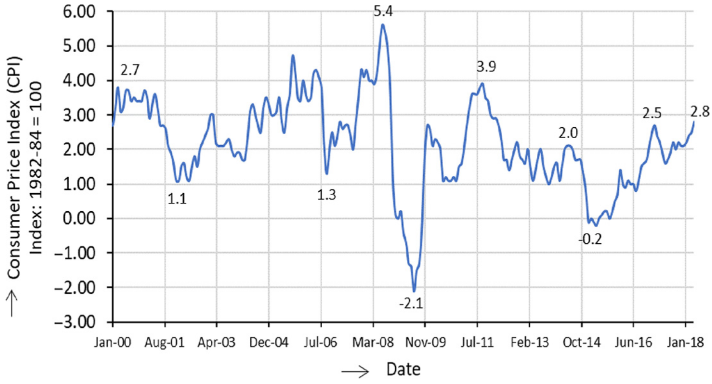


Figure 3.
Time-series data for CPI, 2000-2017

Source: Bureau of Labor Statistics (2017b)

Figure 4.
Time-series data for DJIA, 2000-2017

Source: Willimason (2017)

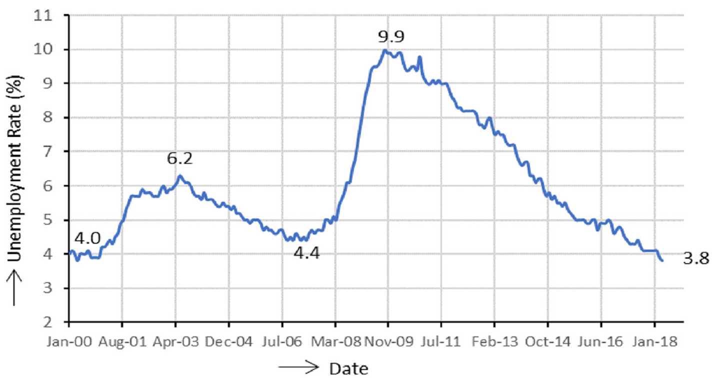
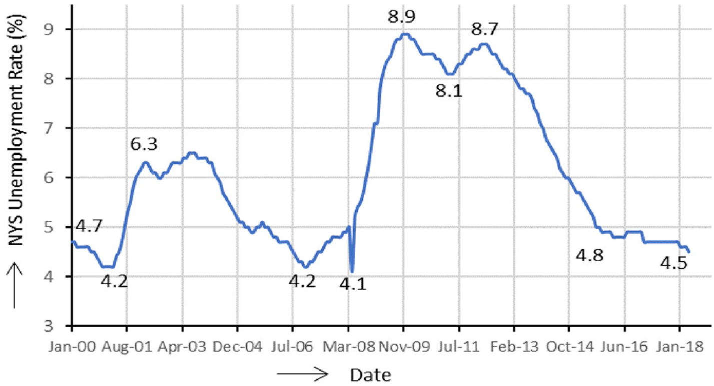


Figure 5.
US time-series data for UR, 2000-2017

Source: Bureau of Labor Statistics (2017a)



Source: New York State Department of Labor (2018)

Figure 6.
New York state (regional) time-Series data for UR, 2000-2017

per barrel in January 2000; it rose to $132.83 in January 2008, and then the price suffered a steep fall to $41.34 per barrel in January 2009. It again rose to $105.23 in January 2011 and stayed at that level for about three years. It has ranged from $45.0 to $55.0 per barrel in the past two years and has risen to $73.43 in June 2018. Oil price, besides the production quotas mandated by OPEC, responds to other economic indicators.

2.2 Thirty-year fixed mortgage annual interest rate

This economic indicator is measured in annual percent rate of the borrowed amount (HSH.com, 2017) and captures the cost of borrowing for house purchase. The 30-year fixed mortgage annual IR has seen wide variations in the past 16 years, from 6.89 per cent in January 2000 to 3.58 per cent at the end of 2017 (Figure 2). Its highest value was 8.7 per cent in October 2000 and has been trending downward in a roller coaster fashion since. As expected, IR data-series values have been inversely proportional to HPI, shown in Figure 7. While the IR has halved from 6.89 per cent in January 1999 to 3.58 per cent in December 2017, the HPI has about doubled from $100.00 in January 2000 to 198.86 in December 2017 (Figure 7).

2.3 Consumer price index

For CPI computations, the number 100 is assigned to the base period 1982-1984 (Bureau of Labor Statistics, 2017b). Time-eries data for CPI for the period 2000-2017 are shown in Figure 3. CPI was 2.7 in January 2000 and 2.8 in June 2018. It has remained around 3.0 with minor variations over the past 18 years, except in August 2008 when it reached its highest value of 5.4 and then dipped to its lowest value of −2.1 in July 2009. These extreme values are rare in the US economy. The raw CPI data were transformed into a logarithm of the CPI data for VAR analysis.

2.4 Dow Jones industrial average

The DJIA represents the US stock price index, which is plotted in Figure 4 for the period January 2000 to July 2017 and beyond. The closing prices at day's end are taken to represent this index. The raw DJIA data were used in a logarithm format in the VAR data analysis (Willimason, 2017).

The DJIA is the direct indicator of the US economy. As shown in Figure 4, DJIA has a positive slope in the long run, except for short humps and valleys showing the booms and recessions in the economy, respectively. Its value was 11,358 in January 2000, which reached a low of 7,423 in the last quarter of 2002 and 6,547 in March 2009. Its highest value of 26,393 was in the last month of 2017 and dipped to 24,283 in June 2018.

2.5 Unemployment rate

The UR is expressed in percentage of people unemployed relative to the total work force. The goal of this research is to measure the impact of macroeconomic indicators on housing prices; thus, it was assumed that the regional UR should more directly affect housing prices. Therefore, the raw data for the national and regional (New York state) URs were plotted for the years 2000-2017 (Figures 5 and 6). The two time-series plots follow similar trends, but some of the values are slightly different. In January 2000, the national UR was 4.0 per cent against New York's at 4.7 per cent, and in May 2018, the national UR was 3.8 vs 4.7 per cent for New York. The national UR was the highest in November 2009, at 9.9 per cent, and the regional rate then was 8.9 per cent. Unemployment in both statistics took a dip in March 2007 to 4.2 and 4.4 per cent.

In summary, in both cases, the trend of the data was similar except for minor percent differences, indicating that the national trend is essentially the same as the regional trend. Also, as VAR analysis measures changes per month (or per lag length), and the Bureau of Labor Statistics more accurately computes national URs than regional (New York state) URs, the time-series data for the national UR have been used in plotting the response of HPI to unemployment (Figure 12) and for computing forecast error variance decomposition (FEVD) of HPI (Table IV) .

2.6 Housing price index (HPI)

The FHWA HPI is a broad measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales median price index, which serves as a timely, accurate indicator of house price trends at various geographic levels. The data set, used in estimation and testing in this research, consists of monthly median sale prices of single-family houses from the records of the Town of Amherst, New York, for the period January 1999 to December 2008, as given in the time-series data for nominal HPI, 1999-2008, in Figure 7. The housing price indices have increased considerably during the sample period and only begun to decline after 2008. The HPI was 115 in January 1999,

Figure 7.
Time-series data for nominal HPI, 1999-2008

rose to 178 in January 2004 and stayed around that level until March 2008. It then dropped to 117 in the middle of January 2008.

The HPI data have been transformed to the logarithmic form for VAR analysis.

3. Data analysis

3.1 Vector autoregression method

Traditionally, researchers have used models which impose *a priori* restrictions on the coefficients; however, VAR is a dynamic model for time-series data analysis that allows the data, rather than the researcher, to specify the dynamic structure of the model. VAR was therefore used to analyze the time variation of the housing prices, over time, and their interaction with the macroeconomic indicators.

VAR is a set of symmetric equations in which each variable is described by a set of its own lagged values and the current and past lagged values of all other variables in the system. The lagged value of a variable is simply the value that the variable took to define this method in a previous period. For example, the value of Y_t, lagged one period is written as Y_{t-1}. Following Baffoe-Bonnie (1998), an n-variable VAR system can be written as in equation (1):

$$\Gamma(\phi)X_t = I - \Gamma_1\phi - \Gamma_2\phi^2 - \cdots - \Gamma_n\phi^n \tag{1}$$

where X_t is an $n \times 1$ vector of variables; Γ is an $n \times 1$ vector of constants; V_t is an $n \times 1$ vector of random variables, each of which is serially uncorrelated with constant variance and zero mean.

Equation (1) is an $n \times n$ matrix of a normalized polynomial in the lag operator $\phi(\phi^k X_t = X_{t-1})$, with the first entry of each polynomial on Γs being unity. The ordinary least squares (OLS) method is used for the estimation.

3.2 Preliminary testing and analysis

Before the VAR analysis on data, two preliminary diagnostic tests are commonly used:

- unit root tests; and
- cointegration tests.

These preliminary diagnostic tests are discussed in the following sections.

3.2.1 Unit root tests. In practice, most economic time series are non-stationary. A stationary time series is significant to a regression analysis because useful information or characteristics are difficult to identify in a non-stationary time series. Moreover, it is well established that OLS produces spurious results when applied to non-stationary data. By differentiating the data, non-stationary time series can be induced to be stationary. Useful information can then be recognized in the data. All macroeconomic indicators were tested for unit-root non-stationary time series by using the augmented Dicky–Fuller (ADF) test (Dickey and Fuller, 1979) at the level form and at their first differential of data series. The result of the ADF test showed that when first differentials were used, non-stationarity was rejected at the 1 per cent and 5 per cent significance levels, strongly supporting that all data series were stationary after their first differential.

Then, VAR equations can be written as:

$$\Delta OIL_t = \alpha_{10} + \sum_{i=1}^{3} \beta_{11i}\Delta OIL_{t-i} + \sum_{i=1}^{3} \beta_{12i}\Delta IR_{t-i} + \sum_{i=1}^{3} \beta_{13i}\Delta CPI_{t-i} + \sum_{i=1}^{3} \beta_{14}\Delta DJIA_{t-i} + \sum_{i=1}^{3} \beta_{15}\Delta UR_{t-i} + \sum_{i=1}^{3} \beta_{16}\Delta HPI_{t-i} + e_t \tag{2}$$

$$\Delta IR_t = \alpha_{20} + \sum_{i=1}^{3} \beta_{21i}\Delta OIL_{t-i} + \sum_{i=1}^{3} \beta_{22i}\Delta IR_{t-i} + \sum_{i=1}^{3} \beta_{23i}\Delta CPI_{t-i} + \sum_{i=1}^{3} \beta_{24}\Delta DJIA_{t-i} + \sum_{i=1}^{3} \beta_{25}\Delta UR_{t-i} + \sum_{i=1}^{3} \beta_{26}\Delta HPI_{t-i} + e_t \tag{3}$$

$$\Delta CPI_t = \alpha_{30} + \sum_{i=1}^{3} \beta_{31i}\Delta OIL_{t-i} + \sum_{i=1}^{3} \beta_{32i}\Delta IR_{t-i} + \sum_{i=1}^{3} \beta_{33i}\Delta CPI_{t-i} + \sum_{i=1}^{3} \beta_{34}\Delta DJIA_{t-i} + \sum_{i=1}^{3} \beta_{35}\Delta UR_{t-i} + \sum_{i=1}^{3} \beta_{36}\Delta HPI_{t-i} + e_t \tag{4}$$

$$\Delta DJIA_t = \alpha_{40} + \sum_{i=1}^{3} \beta_{41i}\Delta OIL_{t-i} + \sum_{i=1}^{3} \beta_{42i}\Delta IR_{t-i} + \sum_{i=1}^{3} \beta_{43i}\Delta CPI_{t-i} + \sum_{i=1}^{3} \beta_{44}\Delta DJIA_{t-i} + \sum_{i=1}^{3} \beta_{45}\Delta UR_{t-i} + \sum_{i=1}^{3} \beta_{46}\Delta HPI_{t-i} + e_t \tag{5}$$

$$\Delta UR_t = \alpha_{50} + \sum_{i=1}^{3} \beta_{51i}\Delta OIL_{t-i} + \sum_{i=1}^{3} \beta_{52i}\Delta IR_{t-i} + \sum_{i=1}^{3} \beta_{53i}\Delta CPI_{t-i} + \sum_{i=1}^{3} \beta_{54}\Delta DJIA_{t-i} + \sum_{i=1}^{3} \beta_{55}\Delta UR_{t-i} + \sum_{i=1}^{3} \beta_{56}\Delta HPI_{t-i} + e_t \tag{6}$$

$$\Delta HPI_t = \alpha_{60} + \sum_{i=1}^{3} \beta_{61i}\Delta OIL_{t-i} + \sum_{i=1}^{3} \beta_{62i}\Delta IR_{t-i} + \sum_{i=1}^{3} \beta_{63i}\Delta CPI_{t-i} + \sum_{i=1}^{3} \beta_{64}\Delta DJIA_{t-i} + \sum_{i=1}^{3} \beta_{65}\Delta UR_{t-i} + \sum_{i=1}^{3} \beta_{66}\Delta HPI_{t-i} + e_t \tag{7}$$

In the above VAR equations:

- ΔOIL_t, ΔIR_t, ΔCPI_t, $\Delta DJIA_t$, ΔUR_t and ΔHPI_t are the first differentials of the natural log of the crude *OIL*, 30-year mortgage *IR*, *CPI*, *DJIA*, (*UR*) and Nominal HPI, respectively, at month *t*;

- ΔOIL_{t-i}, is the first differential of the natural log of the crude OIL *one* month ago;
- α_{10}, α_{20}, α_{30}, α_{40}, α_{50} and α_{60} are intercepts; and
- all Greek symbols, β_{ij}, are parameters.

3.2.2 Cointegration tests. The results from the unit-root test showed that all variables are stationary at the first differential. The possibility of cointegration among these variables was examined next, for which a VAR model was postulated to obtain a long-run relationship. Cointegration means that each of the macroeconomic indicators shares the same stochastic trend, so that they can be combined together in the long run. Even though economic indicators deviate from each other in the short run, they tend to come back to a similar trend in the long run. If variables are cointegrated and the corresponding cointegration vector is not used in the VAR model, the model with only first differenced data will be unspecified. The methodology of the Johansen cointegration test (Johansen, 1991, 1995; Johansen and Juselius, 1990) was used to determine the existence of cointegration and, specifically, the number of cointegrating vectors. The Johansen cointegration test results indicated that there is no long-run relationship in the VAR model. In other words, a simple VAR model is accepted.

3.3 Vector autoregression analysis results

Based on the unit-root and cointegration test results, the first differentials of the data series were used in the VAR model. The six VAR equations, developed in this research [equations (2)-(7)], were used to examine two aspects of the data that tested the statistical significance and assessed the quantitative effect of each of the macroeconomic indicators on the housing prices. The two aspects of the data included:

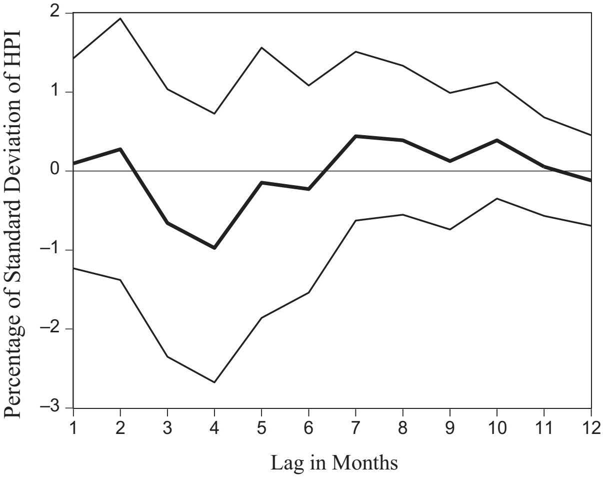
(1) impulse response functions; and
(2) FEVD.

Empirical results achieved using these two aspects are briefly discussed below.

3.3.1 Impulse response functions. In applied work, it is often of interest to know the response of one variable to a shock in another variable, impulse response function plots a picture of how the variable in question (HPI in this context) responds to one standard deviation increase in the current value of one of the macroeconomic indicators over several periods. It indicates whether the impact is positive or negative, or whether it is a temporary jump or a long-run persistence. In this research, the impulse response functions have been used to predict the responses of HPI to a shock in each of the five macroeconomic indicators and also because of a shock in HPI itself, over a period between 1 and 12 months. The response of a stationary variable to a one-time shock should eventually dampen out to zero over time.

Confidence intervals for impulse response functions give the time-path for a variable explained in the VAR model, when one of the variables in the model is shocked. Whether a response to a shock is statistically different from zero is assessed by constructing 95 per cent confidence intervals around a variable's time-path. In line with classical hypothesis testing, a variable's response is considered statistically significant if at least one of the confidence interval lines crosses the zero line.

In this paper, the estimates of the parameters are not reported, as the goal of VAR analysis, in this research, was to determine the dynamic interrelations among variables, not the parameter estimates. Figures 8 to 13 depict the impulse response functions for *HPI* in response to the changes in:



Note: *Thick line is impulse response of HPI and thin lines represent the 95% confidence intervals

Figure 8.
Response of HPI to OIL*

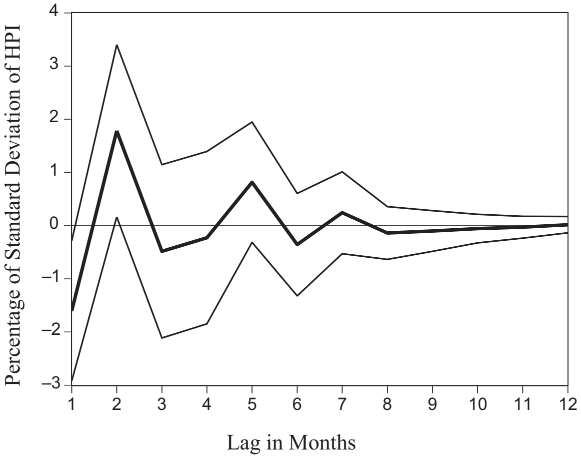


Figure 9.
Response of HPI to IR

- crude *OIL*;
- mortgage *IR*;
- *CPI*;
- stock price index (*DJIA*);
- local unemployment rate (*UR*); and
- HPI.

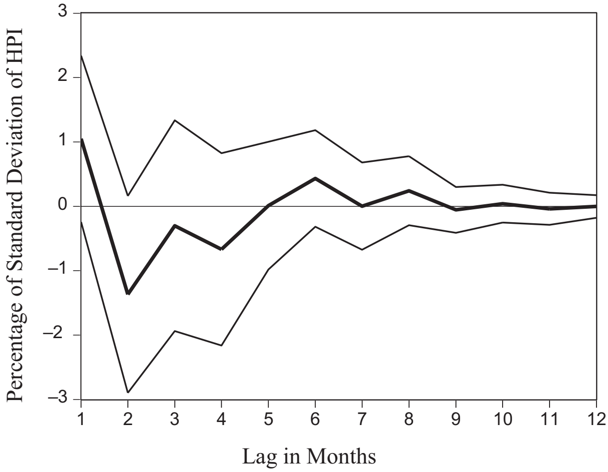


Figure 10.
Response of HPI to CPI

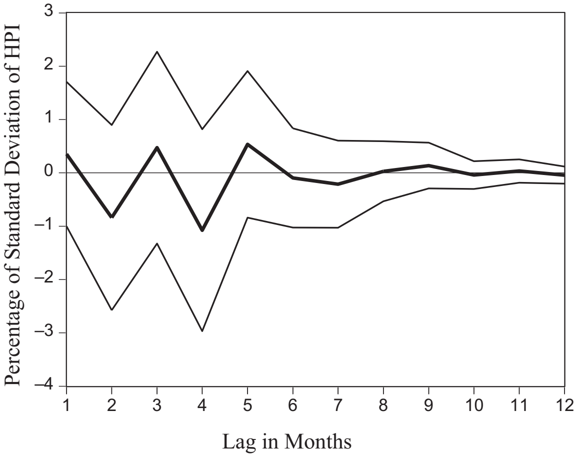


Figure 11.
Response of HPI to DJIA

The time horizon chosen for the impulse response functions is 12 months. The *y*-axis shows the movement trend of HPI. The impulse response of HPI is assumed as zero at time $t = 0$, and each macroeconomic indicator is assumed to receive a one positive unit standard deviation shock at time $t = 0$. Figures 8 to 13 trace the response of HPI to shock at times $t =$ 1, 2,. . . 12 months to each of the macroeconomic indicators. The thinner lines shown in Figures 8 to 13 represent ± 2 standard deviation bands, which yield an approximate 95 per cent confidence interval. According to Sims and Zha (1999), these standard error bands give a more accurate summary of the central tendency of the response. The positive symbol means a favorable effect on housing prices' growth, and a negative symbol means an adverse effect. In addition, the values shown on the *y*-axis indicate a change in the housing prices' movement trend.

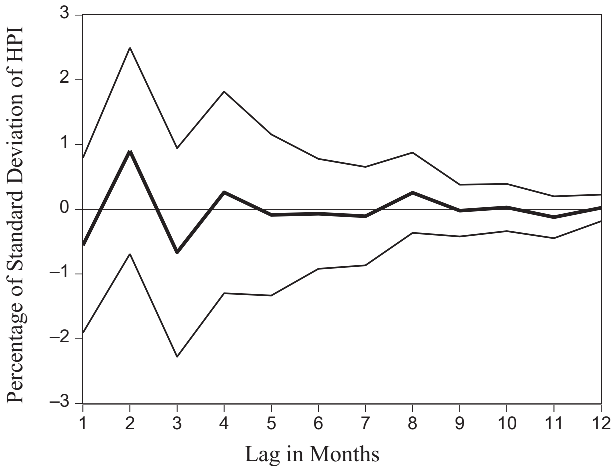


Figure 12.
Response of HPI to UR

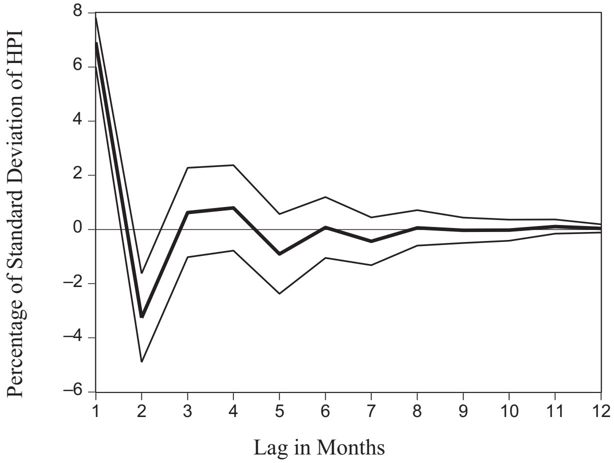


Figure 13.
Response of HPI to HPI

The responses of HPI are shown below in Figures 8 to 13.

3.3.1.1 Response of housing price index to change in crude oil price. Figure 8 shows the response of *HPI* to one standard deviation shock in crude OIL. An increase in the crude OIL slightly pushes housing prices up (shown as a thick line) during the first two months and then goes into adversely affecting the HPI for the next four months. During these four months, the most severe decrease in HPI occurs at the end of the fourth month, −1 per cent standard deviation of the HPI. The HPI then recovers to start having a favorable effect after six months, stays positive within +0.5 per cent standard deviation of HPI and ends in 0 per cent effect at the end of 12 months. As none of the 95 per cent confidence intervals for the response cross over the zero line, the impact of the shock in OIL is not significantly different from zero.

3.3.1.2 Response of housing price index to change in mortgage interest rate . In Figure 9, a positive shock to the mortgage IR produces sharp cycles in HPI. The profound dynamic changes indicate that housing prices are influenced by mortgage rates or are sensitive to the mortgage market. An increase in the mortgage rate generates an immediate negative response in housing prices and the house prices fall in the first month. A plausible explanation of this relationship may be that as the cost of financing a house (mortgage rate) rises, the demand for housing declines, and housing prices are likely to fall. The house prices then recover and peak at the end of the second month, and then roller coaster to reach a no-change state at the end of the eighth month. The house prices then stay around the zero line until the end of the twelfth month. The negative confidence interval line crosses the zero line, which indicates that the response of HPI to mortgage IR is statistically significant.

3.3.1.3 Response of housing price index to change in consumer price index. A shock to CPI(inflation) causes dynamic responses in housing prices (Figure 10). A shock to inflation seems to have a positive effect in the first month. The HPI then dips to below the zero line to a minimum of -1.3 per cent at the end of the second month, rising gradually to cross the positive region after five months. The HPI then stays around zero for the next seven months. Because the confidence interval lines never cross the zero line, it appears that the HPI does not significantly respond to CPI.

3.3.1.4 Response of housing price index to change in stock price index. An inspection of Figure 11 shows that a positive shock to stock price index (DJIA) leads to higher housing prices, as expected, in the immediate time horizon. The HPI then undulates in one-month cycles for six months. The speed of adjustment is fast and it reaches the steady-state level after six months from the occurrence of the shock. The HPI then stays around the zero for the next seven months, showing no changes during that period. Because the confidence interval lines never cross the zero line, HPI does not significantly respond to the stock price index (DJIA).

3.3.1.5 Response of housing price index to change in unemployment rate. Inspection of Figure 12 reveals that a positive shock to unemployment rate tends to immediately lower housing prices. In other words, a growth in the unemployment level may discourage individuals to purchase houses, and this decrease in demand seems to slightly decrease housing prices. The negative response quickly dies off, increasing the HPI to $+1$ per cent of the standard deviation at the end of the second month. The housing prices then undulate for the next three months and reach the steady state after five months from the occurrence of the shock. The change in HPI is not significantly different from zero for most of the forecast horizon, as the 95 per cent confidence interval lines do not cross the zero line.

3.3.1.6 Response of housing price index to change in current housing prices. In response to a 1 standard deviation positive disturbance in current housing price itself (Figure 13), the housing prices increase steeply in the first month. The prices decrease in the secondmonth to below the zero line and then enter into the positive region at the end of third month. Housing prices stay higher for one month and then roller coaster for two months. These variations die out after six months, implying that the current housing price change has a favorable impact on the next month's housing price, rather than over a longer-term horizon. The positive confidence interval line crosses the zero line, which indicates that the response of HPI to a rise in housing prices is statistically significant.

3.3.2 Forecast error variance decomposition. In econometrics and other applications of multivariate time-series analysis, an FEVD is used to aid in the interpretation of a VAR model, once it has been fitted. To indicate the relative importance of the shocks requires variance decomposition of the forecast errors for each macroeconomic indicator. The variance decomposition of the forecast error is the percentage of the variance of the error made in forecasting. Thus, the forecast variance decomposition is like a partial R^2 for the forecast error. The larger the percentage of forecast error attributed to the one variable, the more important that variable is in explaining or predicting the target variable. Of key interest here is what percentage of the deviation in HPI is caused by changes in each of the macroeconomic indicators. If, for example, mortgage IR accounts for a high percentage of the forecast error variance in HPI, this could be interpreted as evidence that mortgage IR strongly helps in predicting the HPI.

Given that the main focus of this paper is to investigate the influence of each of the macroeconomic indicators on housing prices, Table I presents the forecast er18.ror variance decompositions for each of the indicators, for 1-12 months. To calculate these variance decompositions, shocks are identified by imposing an ordering in which the *OIL* is placed first, followed by *IR*, *CPI*, *DJIA*, *UR* and *HPI*. Table I, an output of the VAR analysis, gives the variances in *HPI* which are explained by random shocks in the five macroeconomic indicators and the HPI, from 1 to 12 months. In practice, this decomposition is computed and reported in percentage terms, so that the total amount of variation in one variable due to another can be compared. The first column in Table I lists the steps in the forecast, with each step corresponding to one month. The total forecast horizon covers one year. Column 2, labeled "S.E" is the forecast standard error of the variable at the given forecast horizon. The next six columns in the table report the percentage of forecast variance in the *HPI* as explained by *OIL*, *IR*, *CPI*, *DJIA*, *UR* and HPI. Because the VAR accounts for all forecast variances, each row sums to 100 per cent.

The results of the FEVD, given in Table 1, indicate that the disturbance originating from the HPI itself causes the greatest variability to future housing prices; it contributes up to 92.7 per cent of the variance one month ahead and gradually reduces to 74.5 per cent after 12 months. This result indicates that current changes in house prices heavily influence people's expectations of future price changes in housing.

Besides a 74.5 per cent variance contributed by current housing price changes after one year, there remains 25.5 per cent of the variance, which is explained by the other five macroeconomic indicators. The FEVD results suggest that shocks to the mortgage rate and UR account for more variance in housing prices than variances produced by shocks to crude OIL, CPI and stock price index. Mortgage IR prevails over other four house price determinants in influencing house prices. A shock to the mortgage IR explains about 5.0 per cent of the variance in the first month to 8.5 per cent at the end of the twelfth month. It

Step (month)	S.E.	OIL	IR	CPI	DJIA	UR	HPI
1	0.0718	0.0253	4.9741	2.1302	0.1110	0.0992	92.6602
2	0.0830	0.0263	8.3370	4.3142	0.5601	1.8951	84.8673
3	0.0856	0.2920	8.1602	4.1813	1.0233	5.9923	80.3508
4	0.0885	1.6670	7.6913	4.4793	4.5885	5.6841	75.8898
5	0.0894	1.6344	8.3738	4.3917	4.5127	5.6652	75.4222
6	0.0898	1.6622	8.4581	4.5847	4.7731	5.7622	74.7596
7	0.0900	1.6675	8.5018	4.5690	4.7627	5.7588	74.7402
8	0.0901	1.6814	8.5072	4.6312	4.7931	5.8016	74.5855
9	0.0901	1.7051	8.5110	4.6302	4.8225	5.8217	74.5096
10	0.0901	1.7105	8.5130	4.6313	4.8284	5.8212	74.4956
11	0.0901	1.7104	8.5113	4.6316	4.8323	5.8292	74.4851
12	0.0901	1.7108	8.5104	4.6309	4.83393	5.8386	74.4754

Table I.
Forecast FEVD of HPI (%)

accounts for approximately 33 per cent of the total variance contributed by the five macroeconomic indicators.

The second largest source of house price variance appears to be UR. A shock to UR explains 0.1 per cent of the variance in housing prices after one month and 5.8 per cent of the variation after 12 months, accounting for approximately 23 per cent of the total variance contributed by the five macroeconomic indicators.

Apart from these two variables, the three remaining variables account for approximately 11 per cent of housing price variance at the end of 12 months. The corresponding variances in housing prices caused by a shock in CPI and stock price index are 4.63 per cent and 4.83 per cent, respectively, after 12 months. Crude OIL contributes 1.7 per cent of the total variance after 12 months.

4. Summary and conclusions

The two main objectives of this research were:

(1) To quantify and compare the effects of the five major macroeconomic indicators on housing prices. The macroeconomic indicators included were: OIL, 30-year mortgage IR, CPI, DJIA, UR and also the current HPI.

(2) To understand the monthly dynamic responses of housing prices due to a shock in each of the five macroeconomic indicators, and also because of a shock in the HPI itself, over a period of 1 month to 12 months.

The various analyses used the time-series data for the five macroeconomic indicators, for the period from 2000 to 2008, and monthly housing sales data for the Town of Amherst, New York, USA, for the period 1999-2008. The VAR statistical tool was used to analyze these time-series data. The analyses resulted in the following conclusions:

- Disturbance originating from the HPI itself causes the greatest variability to future housing prices; it contributes up to 92.7 per cent of the variance one month ahead and gradually reduces to 74.5 per cent at the end of twelfth month. This result indicates that current changes in house prices heavily influence people's expectation of future price changes.
- Changes in mortgage IR and UR combined account for more variance in housing prices than variances produced by crude OIL, CPI and stock price index. Mortgage IR prevails over other four macroeconomic indicators in influencing housing prices. A shock to the mortgage IR explains about 5.0 per cent of the variance in the first month to 8.5 per cent in the twelfth month. It accounts for approximately 33 per cent of the total variance contributed by the five macroeconomic indicators.
- The second largest source of house price variance appeared to be UR. A shock to UR explains 0.1 per cent of the variance after 1month and 5.8 per cent of the variation in housing prices after 12 months, accounting for approximately 23 per cent of the total variance contributed by the five macroeconomic indicators.
- The three remaining variables: OIL, CPI, and DJIA account for approximately 2.3 per cent of the variance after 1 month and 11 per cent of housing price variance at the end of 12 months. The corresponding variances in housing prices due to a shock in CPI and stock price index are 4.63 per cent and 4.83 per cent, respectively, after 12 months. Crude OIL contributes 1.7 per cent of the total variance after 12 months.

The results arrived in this research have practical application because they show which of the macroeconomic indicators are critical, and which are not, in influencing housing prices over time. The study found that a focus on immediate past house pricing, and the trend in mortgage IRs, are critical in predicting future sale prices. These results, along with several related tables and figures, will be useful to the housing community and real estate companies in developing business models.

The VAR analyses in this research are based on the housing sales data from the Town of Amherst, with a population of about 125,000, and a median annual income of $74,000; the results are therefore directly applicable to similar towns. Readers desirous of assessing impacts in their own region may write to the corresponding author of this paper for statistical designs not detailed in this paper.

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