MEANJIN – Arts & Humanities Journal (ISSN: 0025-6293), Vol 6 Issue 3 (2014) PP: 01-08, www.meanjin.xp3.biz

LONG-RUN RELATIONSHIPS AND DYNAMIC INTERACTIONS BETWEEN HOUSING AND STOCK PRICES IN THAILAND

Mansor H. Ibrahim*, Jaharudin Padli and A. H. Baharom

Department of Economics, Faculty of Economics and Management, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

***Corresponding author:** mansorhi@econ.upm.edu.my

ABSTRACT

Economists recognise that macroeconomic and financial variables have an impact on housing prices. In this study, we focus on the relationship between housing prices and stock prices in Thailand using quarterly data from the first quarter (Q1) of 1995 till the last quarter (Q4) of 2006. The analysis is conducted within a multivariate setting that incorporates the Stock Exchange of Thailand Composite Index and housing prices, the real gross domestic product and the consumer price index. In this paper, the autoregressive distributive lags (ARDL) cointegration test is applied to examine the variables' long-run relationships. We then employ the ARDL, DOLS and ML approaches to estimate the long-run parameters and impulse response functions based on a vector autoregression (VAR) framework to explore their dynamic interactions. Our results indicate positive relationships between housing prices and the macroeconomic and financial variables chosen. As regards their dynamic interactions, we note significant responses of housing prices to shocks in the three variables.

Keywords: stock prices, housing prices, long-run relationships, vector autoregression (VAR).

1 .INTRODUCTION

Price fluctuations, particularly those in housing prices, have been much emphasised in recent literature. More specifically, in light of recurring financial crises in many parts of the world, emphasis has been placed on the role played by stock price fluctuations in housing price dynamics. It is generally argued that, being both investment and consumption goods, housing prices may be affected by stock market fluctuations through the well-known wealth effect. Namely, reflecting an increasing share of stocks in investment portfolios, increases in stock prices may motivate households to rebalance their portfolios by investing in or consuming more housing services, which then translates into higher housing prices. Conversely, being a collateralisable asset, property prices are a notably important determinant of household and firm access to financing. This means that, with expanded investment following increases in value of property markets, firms' market values or stock prices may increase. Empirically, pinpointing the relationship between the stock market and the housing market is not only essential for explaining housing price dynamics, but also should provide insight into the noted persistence and boom/bust cycles in the asset markets as well as into their effects on the real sector. However, recent empirical studies have predominantly focused on developed economies or the more advanced Asian economies, including Quan and Titman (1999), Chen (2001), Kakes and Van den End (2004), Kapopoulos and Siokis (2005), and Sim and Chang (2006). These studies, using either linear standard regressions or vector autoregressions, generally find supportive evidence for the significant role of stock prices in accounting for variations in housing prices for many economies. The exception to this finding, however, is the work by Sim and Chang (2006). Looking at South Korea, they provide no evidence pointing to a significant role of stock prices. Instead, housing prices in Korea tend to have a significant influence on the stock market. The present paper extends this line of research to an emerging market, Thailand, the country that was first hit by the Asian crisis. As in other emerging markets, Thailand's stock market exhibits relatively high volatility compared to other advanced markets. Prior to the crisis, the Stock Exchange of Thailand composite index was well over 1000 points. In the face of the Asian crisis, it dropped to its lowest point, 253.8, in the third quarter (Q3) of 1998. In parallel, housing price indices recorded a sharp decline one year later (see Figure 1). Based on this observation, it would be tempting to draw a connection between the stock market and the housing sector. However, to be concrete, a formal analysis is needed to see whether stock prices play any role in the dynamics of the housing market in Thailand or whether there are other factors that might have contributed to the fluctuations in Thai housing prices. In the analysis, we make use of standard time-series econometric techniques to evaluate the long-run relationships and short-run dynamic linkages between housing prices and their determinants. More specifically, we employ an autoregressive distributed lags (ARDL) approach to test for the presence of long-run relationships. We then use various estimators including the ARDL, dynamic ordinary least squares (DOLS), and maximum likelihood (ML) estimators to obtain long-run coefficient estimates. Finally, we simulate impulse response functions from a vector autoregression (VAR) framework to disentangle short-run causal interactions. This empirical approach is outlined in the next section. Section 3 describes the data and presents estimation results. Finally, section 4 concludes with the main findings.EMPIRICAL APPROACH In this analysis, we specify the housing prices (h) in the long run to be determined by two macroeconomic variables – real income (y) and price level (p) – and a financial variable, stock price (s). Writing this relationship in a standard linear form, we have:

$$h_t = \alpha + \beta_1 y_t + \beta_2 s_t + \beta_3 p_t + u_t \,, \tag{1}$$

where all variables are expressed in natural logarithm. Real income or real gross domestic product (GDP) is always included in the housing price equation, whose importance in influencing housing demand and supply is well noted. Stock prices are incorporated to address our main inquiry as to whether stock price fluctuations exert the wealth effect on the housing market and also to provide a potential explanation for boom/bust cycles in housing prices. It should be noted that in existing studies, interest rates are also considered. However, in the case of Thailand, interest rates have been relatively flat and have exhibited little variation during the post-crisis period, which forms a substantial part of our sample. Accordingly, we use the consumer price index instead. The change in the logarithmic consumer price index or inflation, which is later used in dynamic analyses, is normally included in place of the interest rates when the latter is viewed to be repressed. Moreover, the inclusion of the price level is in line with the inflation hedging literature, which substantially focuses on whether real property investment can hedge against inflation. The econometric implementation of model (1) and its dynamic specification begin with the determination of the variables' stochastic properties. To this end, we employ the widely used augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to establish the variables' integration order. Then, the ARDL approach to cointegration, as suggested by Pesaran, Shin and Smith (2001), is utilised to establish their long-run relationship. More specifically, the ARDL cointegration test is based on the following equation:

$$\begin{aligned}\Delta h_t = a + \sum_{i=1}^{n} b_i \Delta h_{t-i} + \sum_{i=1}^{n} c_i \Delta y_{t-i} + \sum_{i=1}^{n} d_i \Delta s_{t-i} + \sum_{i=1}^{n} e_i \Delta p_{t\ \ i} \\ + \varphi_1 h_{t-1} + \varphi_2 y_{t-1} + \varphi_3 s_{t-1} + \varphi_4 p_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

where Δ is the first-difference operator. In model (2), the null hypothesis of no cointegration or no long-run relationship among the variables is:

$$H_0 : \phi_1 = \phi_2 = \phi_3 = \phi_4 = 0 \,.$$

This hypothesis is tested using the F-statistics for the joint coefficient significance of the lagged level variables in (2). In doing so, we first run equation (2) without the lagged-level variables. A variable addition test is then made after adding the lagged-level variable back in the equation. The test statistics is then compared to the critical value bounds provided by Narayan (2005) for small sample sizes. After the integration and cointegration tests, we proceed to the estimation of their long-run relationship using three alternative methods: the ARDL method by Pesaran et al. (2001), the DOLS by Saikkonen (1991) and Stock and Watson (1993), and the ML approach by Johansen (1988) and Johansen and Juselius (1990). These serve as a robustness check on their long-run relationships. The ARDL method is based on the following equation:

$$h_t = \theta_0 + \sum_{i=1}^{n1} \theta_i h_{t-i} + \sum_{i=1}^{n2} \varphi_i y_{t-i} + \sum_{i=1}^{n3} \phi_i s_{t-i} + \sum_{i=1}^{n4} \lambda_i p_{t-i} + \varepsilon_t \,. \qquad (3)$$

From (3), the long-run coefficients in (1) can then be computed as :

$$\alpha = \frac{\theta_0}{1-\sum_{i=1}^{n1}\theta_i}, \beta_1 = \frac{\sum_{i=1}^{n2}\varphi_i}{1-\sum_{i=1}^{n1}\theta_i}, \beta_2 = \frac{\sum_{i=1}^{n3}\phi_i}{1-\sum_{i=1}^{n1}\theta_i}, \beta_3 = \frac{\sum_{i=1}^{n4}\lambda_i}{1-\sum_{i=1}^{n1}\theta_i}\,. \qquad (4)$$

Meanwhile, the DOLS methods extend equation (1) to include leads and lags of first-differenced non-stationary variables as:

$$h_t = \alpha + \beta_1 y_t + \beta_2 s_t + \beta_3 p_t + \sum_{i=+m}^{-m} \vartheta_i X_{t-i} + u_t \,, \qquad (5)$$

where X is a vector of included non-stationary variables.1 Finally, the ML estimation of the long-run relationships is readily available from the now well-known Johansen-Juselius procedure. We use Microfit for the ARDL implementation and EVIEWS for the latter two procedures.Finally, we cast the analysis in a VAR framework[1]. The VAR framework has distinct advantages in that it allows all variables to be potentially endogenous and imposes minimal restrictions on the ways in which the variables interact. In this way, it enables the evaluation of the variables' causal interactions. This is appealing because from an economic point of view, it is readily acceptable that the concerned variables may be linked through various causal patterns and not merely from the housing price determinants of the housing prices. As a basis for inferences, we simulate impulse response functions (IRF) from the estimated VAR. Essentially, the IRF traces the temporal responses of a variable to a one-standard-deviation shock in other variables. From the functions, we can assess the direction, magnitude and persistence of the responses of, say, housing prices to stock price shocks and vice versa.

It should be noted that the simulated IRF can be sensitive to the variables' ordering under Sims' (1980) shock identification scheme, i.e., the Cholesky orthogonalisation. Indeed, the ordering becomes important when the contemporaneous correlation among the shocks in the VAR is high (Enders, 1995). Alternatively, the IRF can be simulated based on Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) known as the generalised impulse response functions. Under this approach, historical patterns of correlations among different shocks are fully incorporated, making the impulse response functions unique and hence invariant to alternative orderings of the variables. Thus, with the possibility that the asset markets can be contemporaneously correlated, we adopt the generalised impulse response functions in our case.

2. DATA AND RESULTS

2.1. Data Preliminaries

We use quarterly data spanning from Q1 to Q4, the period of which is dictated by data availability. In the present analysis, we use two alternative housing price indices, the semi-detached houses with land (hd) and the townhouses with land (ht) price indices, which are published by the Bank of Thailand. For stock prices, we use the Stock Exchange of Thailand Composite Index (s). Meanwhile, real gross domestic product and consumer price index represent real income (y) and the general price level (p), respectively. Given obvious seasonal patterns in real income, it is seasonally adjusted using the X12 census procedure. All data except for the consumer price index are sourced from Bank of Thailand website (Bank of Thailand, 2009). The consumer price index is taken from the International Financial Statistics (CD-ROM) (IMF, 2008). As noted early, these data are expressed in natural logarithm. The time series plots of the data are provided in Figure 1.

1 The ARDL cointegration test is to verify whether there exists a long-run relationship among the variables and does not indicate their causal interactions. iven that the variables utilised can be dynamically linked, it is more appropriate to cast the analysis in a vector autoregression setting. Indeed, it is not necessary that a one-equation-based cointegration test such as the ARDL test needs to be followed by one-equation-based error correction modelling. Indeed, the latter will be valid only if the right-hand-side variables are weakly exogenous. Among recent papers that proceed from the ARDL cointegration test to VAR modelling including Shyh-Wei (2007), Shahbaz, Ahmed and Ali (2008) and Feridun (2009).

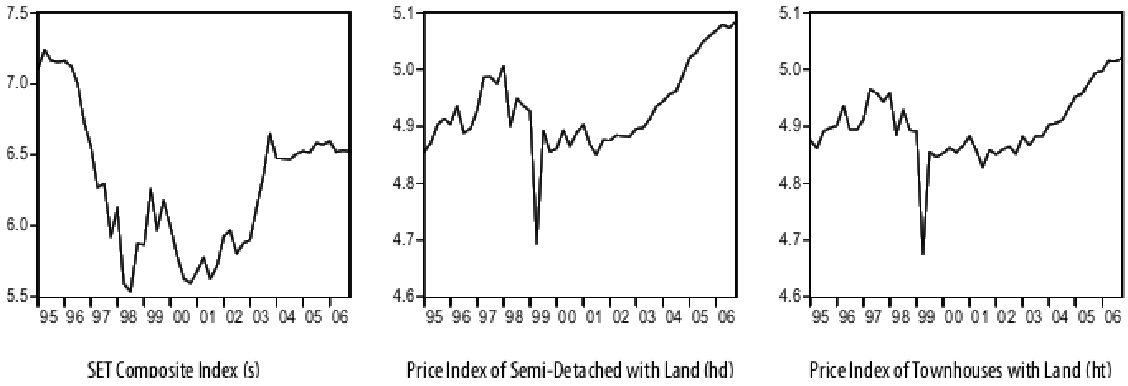

Figure 1. Time series plots of the data.

Before testing for cointegration by using the ARDL bounds testing procedure, the order of integration for all of the variables are determined. Table 1 shows the results of the ADF and PP unit root tests for the order of integration of the variables under investigation. In the tests, we include both the trend and the intercept terms for the variables in level and only the intercept term for the variables in first difference. The autoregressive order of the ADF test equation is determined by the Schwatz information criterion (SIC), which is known to be parsimonious in its lag selection[2]. The test statistics are compared to the critical values provided by MacKinnon (1996). For the level variables, the 10%, 5% and 1% critical values are, respectively, –3.184, –3.508 and –4.166. The corresponding values for testing the first-differenced variable are –2.601, –2.925 and –3.578. Both tests clearly indicate that all of the variables under consideration are difference stationary. As may be observed from the table, the unit-root null hypothesis cannot be rejected at conventional levels of significance for any variables expressed in level form. However, the test statistics soundly reject the null once they are first-differenced. In other words, they belong to an I(1) process. Note: The intercept term and time trend are included in testing the level variables. Meanwhile, only the intercept term is included in testing the first-difference of the variables. The lag order of right-hand-side first-differenced terms is based on the Schwatz information criterion. * denotes significance at the 1% significance level. Having noted that all series are of the same order of integration, we proceed to the ARDL cointegration test. Given our rather small sample size, we again utilise the SIC for selecting the lag order up to the maximum lag of 4. The lag order of 3 is determined to be optimal. In the test equation, we experiment whether the results are sensitive to the inclusion of the Asian crisis dummy variable, defined to be equal to 1 from July 1997 to December 1998 and 0 otherwise. The test results are tabulated in Table 2. From the table, the null hypothesis of no cointegration can be clearly rejected for both housing price indices regardless of the crisis dummy variable. As a confirmatory check, we also apply the VAR-based cointegration test advanced by Johansen (1988) and Johansen and Juselius (1990). After adjusting the test statistics for small sample bias as suggested by Reinsel and Ahn (1992), we are pleased to note the presence of a unique cointegrating vector for both systems. Thus, there are long-run relationships between housing prices (in this case, semi-detached houses with land and terrace houses with land), stock prices, real income, and the price level.

Table 1: ADF and PP unit root tests.

	Level		First Difference	
Variables	ADF	PP	ADF	PP
hd	–1.446	–2.571	–11.11*	–11.34*
ht	–1.457	–2.219	–11.15*	–11.92*
y	–1.618	–1.209	–3.696*	–3.734*
s	–1.527	–1.528	–7.500*	–7.456*
p	–2.054	–2.557	–5.339*	–5.350*

Table2: ARDL cointegration tests.

		F-statistics	
Equations	Lags	Without crisis dummy	With crisis dummy
hd	3	6.606	9.962
ht	3	9.190	10.47
Lower and Upper Bound Critical Values			
	10%	5%	1%
	[2.873 3.973]	[3.500 4.700]	[4.865 6.560]

Note: The critical values are from Narayan (2005), case III: unrestricted intercept and no trend with n = 50 (p. 1988).

[2] [3]It is well-known that the SIC is parsimonious in selecting the lag length as compared to the AIC.This is crucial in our analysis with small sample size, as it preserves degrees of freedom. See, for instance, Ito (2009).

2.2. Long-Run Relationships

With the finding of cointegration, the interest would thus be in the parameter estimates of the housing price equation, i.e., equation (1). To this end, we use three alternative estimators – the ARDL approach by Pesaran et al. (2001), the DOLS approach by Saikkonen (1991) and Stock and Watson (1993), and the maximum-likelihood (ML) approach by Johansen (1988). We set the lag order for the ARDL to 3 and lead-lag order for the DOLS to 2 on the basis of SIC. In the case of the ML approach, we follow the suggestion by Hall (1989) and Johansen (1992) by setting the lag order such that the error terms are serially uncorrelated, which we find to be 3. Table 3 presents the estimates of the long-run parameters from these three approaches. The results from DOLS and ML are consistent, while those from ARDL differ in sign from the others for the coefficients of stock prices and consumer prices. We tend to believe that the ambiguity in the results from the ARDL approach may be due to regressor endogeneity. Indeed, from the maximum likelihood approach, we note that stock prices and consumer prices are not weakly exogenous, rendering a single-equation ARDL approach questionable. The DOLS, however, controls for regressor endogeneity by adding leads and lags of the first difference of the regressors to equation (1). Although the estimates from the Johansen procedure can sometimes be different, as it tends to exhibit larger variations compared to single-equation approaches in small samples (Maddala & Kim, 1998), we are pleased to note that in our case, the coefficient estimates from the ML largely conform to DOLS estimates. Based on these, we rely on both DOLS and ML approaches for inferences of the long-run relationships between housing prices and other included macroeconomic variables.

Table3: Long-run coefficients

	Semi-detached houses			Townhouses		
Variable	ARDL	DOLS	ML	ARDL	DOLS	ML
y	1.156	0.334	0.143	0.452	0.430	0.205
	(0.076)	(0.024)	(0.108)	(0.053)	(0.003)	(0.027)
s	−0.163	0.057	0.080	−0.051	0.025	0.046
	(0.180)	(0.047)	(0.000)	(0.278)	(0.357)	(0.014)
p	−0.670	0.371	0.561	−0.132	0.017	0.260
	(0.336)	(0.031)	(0.000)	(0.633)	(0.909)	(0.022)

Note: Numbers in parentheses are p-values.

Based on the DOLS and ML results, we note positive relationships between housing prices and three variables – real output, stock prices and consumer prices. Indeed, for real income, the result remains similar under the ARDL approach. This should be expected, as real income or output affects both demand for and supply of housing. While positive, the magnitude of long-run stock price coefficient is small. While this lends support to the stock market wealth effect, the fundamental factor (i.e., real output) presumes importance in housing prices in the long run. With positive coefficients of consumer prices, the housing sector also possesses an inflation-hedging ability. However, it is not complete. The coefficient estimates for consumer prices are found to be significantly less than unity.

2.3. Impulse Response Analysis

For further analysis, we estimate a VAR model for each system and generate the generalised impulse response functions to disentangle their dynamic interactions. The VAR lag order is set to 3 for both systems, which we find sufficient to render the error terms serially uncorrelated. The impulse response functions for the semi-detached house system and the townhouse system are respectively plotted in Figures 2 and 3. Looking across the two figures, we may note strikingly similar dynamic interactions among the variables. Overall, they suggest substantial dynamic interactions among the variables. In line with the long-run relationship, we note significant responses of housing prices to shocks in the three variables. While the responses of housing prices to consumer price shocks seem contemporaneous, they become significant after five quarters following shocks in real output and stock prices. At the same time, we also note significant causal influences running from housing prices to consumer prices. Apart from these results, we also document bi-directional causality between stock prices and real output and also between real output and consumer prices, and we find unidirectional causality from stock prices to consumer prices. These results are comforting, as they are in line with various conventional views. First, stock price shocks do anticipate future variations in real economic activity, and the stock prices also respond to fundamental shocks as captured by shock in real output. Second, we note that real activity contracts following consumer price shocks. This conforms to the view that positive shocks in consumer prices bring together inflation uncertainty, which may retard private investment and, consequently, output. Meanwhile, the significant lagged responses of consumer prices to output shocks reflect price rigidity and increasing inflationary pressure during the boom period. Finally, reflecting the wealth effect, the stock market leads to an increase in the future price level through output stimulation.

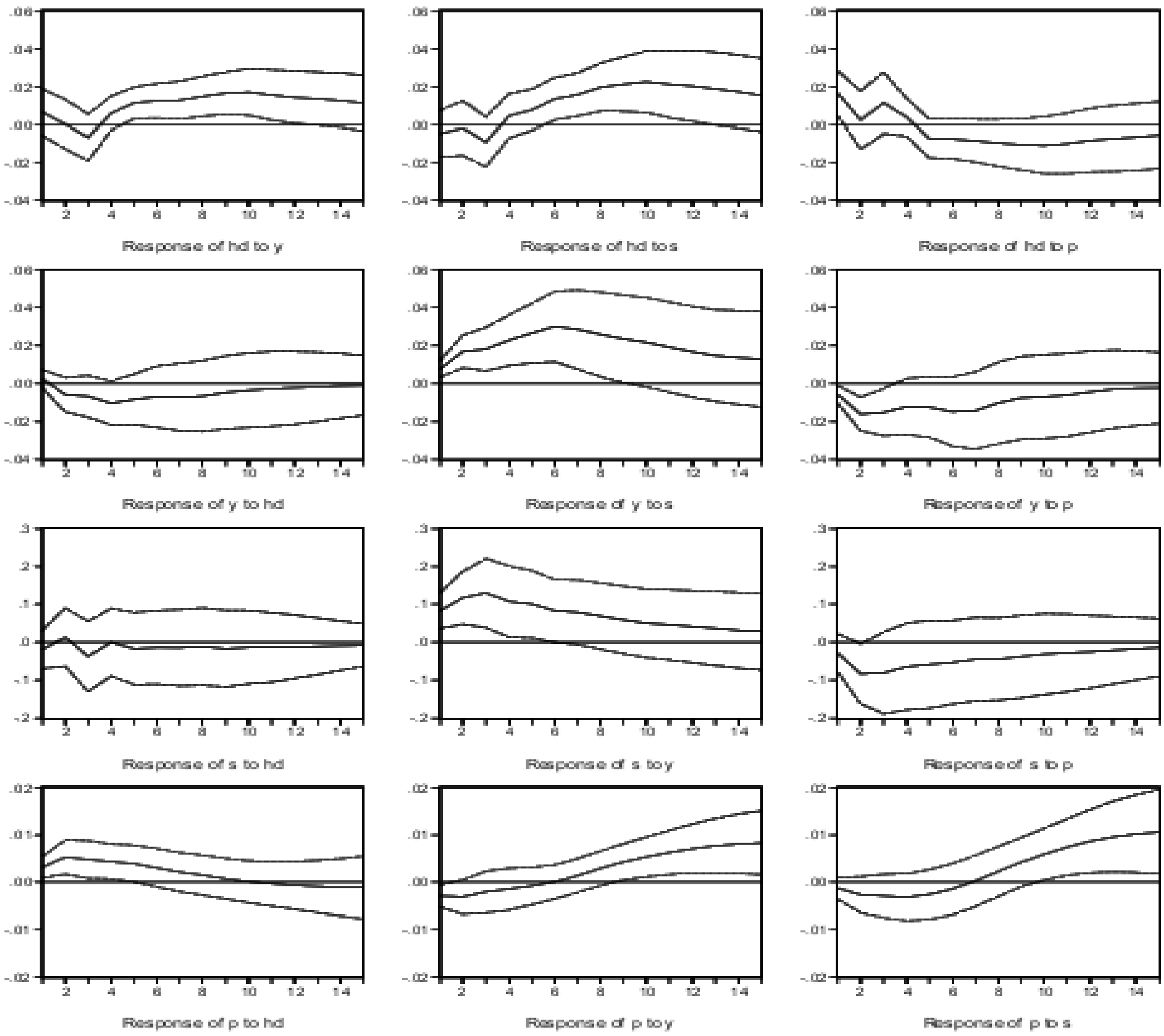

Figure 2. Impulse response functions – semi-detached house system.

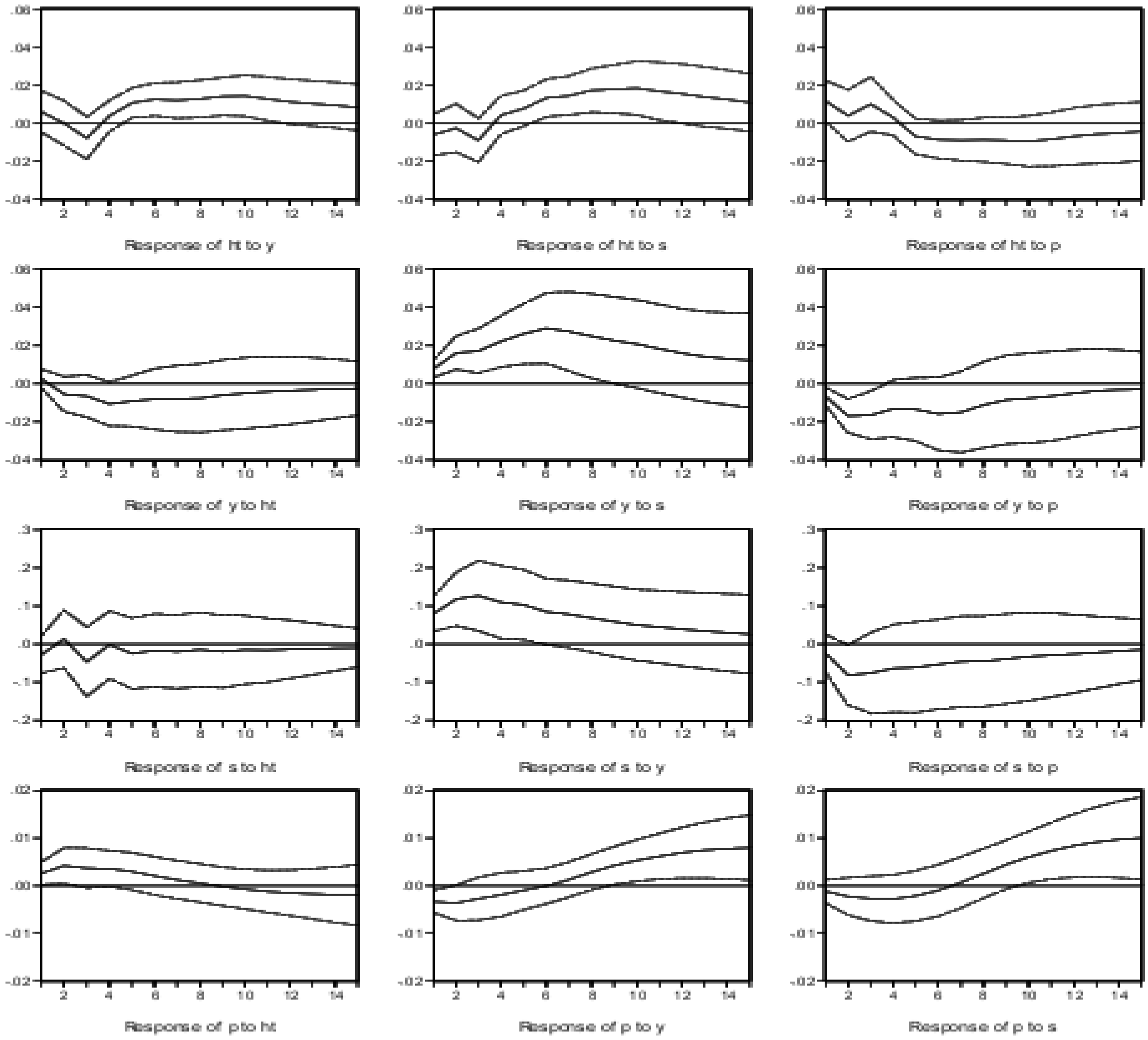

Figure 3. Impulse response functions – townhouse system.

3. CONCLUSION

Motivated by the noted fluctuations and boom/bust cycles, particularly in housing prices, the present paper makes an attempt to examine the relationships between housing prices and stock prices in a multivariate setting for the case of Thailand. We define housing price equations to depend on the real GDP or output, the aggregate price level and stock prices. The paper makes use of the ARDL cointegration test to establish long-run relationships between housing prices and other included variables. Then, with the finding of cointegration among them, the ARDL, DOLS and ML approaches to estimating the long-run parameters are employed. Finally, as a further analysis, the paper simulates generalised impulse response functions to disentangle dynamic causal interactions among the variables under consideration. The results from the analysis may be summarised as follows. First, in the long run, the behaviour of housing prices is governed by its relationships to stock prices, real output and consumer prices. Second, the three variables have a positive association with housing prices. The long-run estimates seem to be robust for the case of real output. Indeed, the magnitude of coefficient estimates seem to indicate that in the long run, housing prices in Thailand are driven more by a macroeconomic fundamental factor or real output. Finally, we note substantial short-run interactions between the variables under study. To our interest, the three macroeconomic and financial variables exert short-run causal influences on housing prices. Thus, central to our theme, the role of stock prices in the dynamics of housing prices should not be sidelined. At the same time, variations in housing prices do exert positive influences on the price level and accordingly may have predictive ability for future inflation. It is also comforting to note that the interaction patterns among the macroeconomic and financial variables conform to established theories.

REFERENCES

Bank of Thailand. (2009). Statistics: Economic and financial. Retrieved 10 June, from http://www.bot.or.th/English/Statistics/EconomicAndFinancial/Pages/index1.aspx.

Chen, N. K. (2001). Asset price fluctuations in Taiwan: Evidence from stock and real estate prices 1973 to 1992. Journal of Asian Economics, 12, 215–235.

Enders, W. (1998). Applied Econometric Time Series. New York: Wiley.

Feridun, M. (2009). Determinants of exchange market pressure in Turkey: An

econometric investigation. Emerging Markets Finance and Trade, 45(2), 65–81. Kakes, J., & Van den End, J. W. (2004). Do stock prices affect house prices? Evidence for the Netherlands. Applied Economics Letters, 11, 741–744.

Kapopoulos, P. & Siokis, F. (2005). Stock and real estate prices in Greece: Wealth versus 'credit-price' effect. Applied Economics Letters, 12, 125–128.

Hall, S. G. (1989). Maximum likelihood estimation of cointegration vectors: An example of the Johansen procedure. Oxford Bulletin of Economics and Statistics, 51, 213–218.

International Monetary Funds (IMF). (2008). International Financial Statistics [CD]. Washington DC: IMF.

Ito, K. (2009). The Russian economy and the oil price: A cointegrated VAR approach. Transition Studies Review, 16(1), 220–227.

Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12, 231–254.

. (1992). Testing weak exogeneity and the order of cointegration in UK money demand data. Journal of Policy Modeling, 14, 313–334.

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration: With applications to the demand for money. Oxford Bulletin of Economics and Statistics, 52(2), 169–210.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74, 119–147.

Maddala, G., & Kim, I. (1998). Unit Roots, Cointegration, and Structural Change. Cambridge: Cambridge University Press.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics, 11, 601–618.

Narayan, P. K. (2005). The saving and investment nexus for China: Evidence from cointegration tests. Applied Economics, 37(17), 1979–1990.

Pesaran, M. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58, 17–29.

Pesaran, M. H., Shin, Y., & R. Smith, J. (2001). Bounds testing approaches to the analysis of level relationship. Journal of Applied Econometrics, 16, 289–326.

Quan, D. C., & Titman, S. (1999). Do real estate prices and stock prices move together? An international analysis. Real Estate Economics, 27(2), 183–207.

Reinsel, G. C., & Ahn, S. K. (1992). Vector autoregressive models with unit roots and reduced rank structure: estimation, likelihood ratio test, and forecasting. Journal of Time Series Analysis, 13, 353–375.

Saikkonen, P. (1991). Asymptotically efficient estimation of cointegrating regressions. Econometric Theory, 7, 1–21.

Shahbaz, M., Ahmed, N., & Ali, L. (2008). Stock market development and economic growth: ARDL causality in Pakistan. International Research Journal of Finance and Economics, 14, 182–195.

Shyh-Wei, C. (2007). Exactly what is the link between export and growth in Taiwan? New evidence from the Granger causality test. Economic Bulletin, 6(7), 1–10.

Sim, S. H., & Chang, B. K. (2006). Stock and real estate markets in Korea: Wealth or credit-price effect. Journal of Economic Research, 11, 99–122.

Sims, C. (1980). Comparison of interwar and postwar business cycles: Monetarism reconsidered. American Economic Review: Papers and Proceedings, 70, 250– 257.

Stock, J., & Watson, M. (1993). A simple estimator of cointegrating vectors in higher order integrated system. Econometrica, 61(4), 783–820.