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Housing Prices, Stock Prices and the U.S. Economy

by

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Abstract. This paper studies the relationship between housing prices, stock prices, interest rates and aggregate output in the U.S. using monthly data from 1993 to 2014. Evidence from causality tests and a variance decomposition procedure suggest that stock prices have a much larger effect on aggregate output in the U.S. economy than do either housing prices or interest rates. Instead, the wealth effect created by changes in stock prices has a relatively large impact on U.S. aggregate output. Separate estimations and variance decompositions for the sample periods 1993 - 2001, 2002 – 2008 and 2009 – 2014 show that the impact of housing prices relative to stock prices has been waning over time.

Keywords: housing prices; stock prices; U.S. economy; Granger causality; vector error correction model
***JEL* Classifications:** E20, E32, G00

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I. Introduction and Background

Housing is, and has traditionally been, an important sector of the U.S. economy. The historical data indicate that the contribution of housing to U.S. GDP is about 17 percent, of which approximately one-third comes from residential and fixed investment and around two-thirds comes from housing services (National Association of Home Builders, 2014). Construction of new houses not only generates additional construction employment, it also adds to employment in the intermediate goods-supplying sectors of the economy, such as lumber, concrete, heating and cooling equipment, electric lighting fixtures and others. In addition to these benefits, construction activity generates greater employment in professional services, such as architecture, engineering, accounting, law and real estate, all of which provide services to home builders, home buyers and remodelers (Emrath, 2014). According to 2014 data provided by the National Association of Home Builders (nahb.org), the building of an average new single-family home creates 2.97 jobs and results in an additional $110,957 in taxes, while the building of an average rental apartment creates 1.13 jobs and $42,383 in new tax receipts.[1] Lastly, $100,000 spent on remodeling creates 0.89 jobs and $29,799 in additional taxes. Clearly, construction of new houses, as well as remodeling of existing houses, is important for an economy as it creates employment, generates income and provides tax revenues to government.

The housing market also impacts the economy through changes in home prices. A rise in home prices increases household net worth, which is an important element of one's consumption function (Friedman, 1957; Papadimitrious, Hannsgen and Zezza, 2007). With the rise in home prices, consumers often use home equity credit lines when they lack cash or find it otherwise difficult to borrow. Estimates by Menegatti and Roubini (2007) suggest that each dollar of additional housing

[1]Any potential issue regarding the credibility NAHB-provided data is duly noted.

wealth increases the propensity to consume anywhere from 4.5 cents to 16 cents. They also estimate that one dollar of home equity withdrawal generates additional consumption spending that ranges from 10 cents to 50 cents. Given the current tax deductibility of mortgage interest payments (including home equity interest) in the U.S., consumers often purchase consumer durables, such as autos and home appliances, with these proceeds. Moreover, households also tend to use these proceeds for improvements, as well as to pay off other debts (e.g., non-mortgage debts). Greenspan and Kennedy (2007) argue that once such expenditures are included, the impact of a dollar in home-equity withdrawal is multiplied over several times (Papadimitriou et al., 2007). This increase in consumer spending, which occurs as a result of increases in housing prices, generates additional aggregate demand, which provides a boost to the economy.

Many financial economists argue that housing prices and stock prices are related (Chen, 2001; Sutton, 2002; Abelson et al., 2005; McMillan, 2011). Although housing is often considered to be a consumer good, it can also be viewed as an investment alternative to other financial assets, including stocks. It is possible that the wealth effect that arises from an increase in home prices may lead a household to increase the share of its financial portfolio represented by stocks. Likewise, an unexpected increase in stock prices may motivate a household to rebalance its portfolio by consuming more housing. Although the causality can run in either direction, the essence of this discussion is that housing markets and stock markets are interrelated.

Standard macroeconomic theory indicates that an increase in stock prices (as well as housing prices) creates wealth, which, in turn, increases aggregate demand, leading to an increase in output. Conventional wisdom suggests that any increase or decrease in housing prices creates economic fluctuations in the U.S. economy (Leamer, 2007). The remaining question relates to the significance, or lack thereof, of the housing market's relationship to the overall economy. Although historical evidence may point to the conclusion that the housing market is a key economic variable, particularly in the case of assisting the economy during recessions, its importance may have waxed or waned in recent time periods given the changes that have occurred in the structure of the U.S. economy (Leamer, 2007).

We are not aware of any published literature that has studied the changing effectiveness of the housing market in boosting the U.S. economy over a period of time. This study fills the void in the literature by presenting empirical estimates and analysis of the relationships between housing prices, stock prices and growth in the U.S. economy from 1993 to 2014. This particular period is instructive because it includes high-tech boom of the 1990s, the housing boom that started in early 2000 and that busted in 2008, leading to the financial crisis. We first look at the relative importance of housing and stock markets on the U.S. economy for the period beginning in 1993 and ending in 2014. We further decompose this sample into three sub-samples representing the high-tech boom (1993-2001), housing boom (2002-2008) and monetary boom (2009-2014), thus adding to the novelty of this particular study. It is expected that the findings of this study will help to better understand the relationship between housing prices and the U.S. economy, particularly with the changing structure of the U.S. economy. Such an improved understanding will provide important insights to policymakers.

II. THEORETICAL BACKGROUND, METHODOLOGY AND DATA

In order to estimate the relationship between the output (Y), housing prices (HP) and stock prices (DJ), the following equation is used:

$$Y = f(HP, DJ, R) \qquad (1)$$

where,

Y = output level (index of industrial production),

HP = housing price index,

DJ = Dow Jones industrial Average index (i.e., stock prices),

R = the 10-year U.S. Treasury yield,

In the absence of monthly data on real GDP, the index of industrial production is used for total output. All of the variables, with the exception of R, are in logarithmic form, while R is in percentage form.

As discussed above, an increase in housing prices boosts a household's net worth. Given that a household's consumption is, at least in part, a function of its overall wealth, an increase in housing prices increases aggregate demand, leading to an increase economic output. An increase in economic output leads to an increase in household income, which, in turn, further increases the demand for housing in the economy. In other words, a two-way causality exists between the housing prices and output in the economy. Likewise, an increase in stock prices creates a wealth effect and increases consumer confidence. This, in turn, leads to an increase in aggregate demand and, subsequently, economic output. The resulting economic expansion combines with the prospect of future economic growth to further increase investment demand. A rise in investment demand increases the demand for stocks, and, as a result, stock prices also rise. Therefore, one also expects to observe two-way causality between stock prices and economic output.

Given that investment demand is a negative function of the interest rate, an increase in the interest rate decreases the level of investment while a decrease in the interest rate increases the level of investment. As a result, any increase in the interest rate lowers aggregate demand, as well as overall output, while a decrease in the interest rate increases aggregate demand and aggregate output. At the same time, however, an increase in aggregate output and household income increases the overall level of saving in the economy, leading to an additional increase in the level of investment. This, in turn, may work to increase the interest rate, which is a result supporting the existence of two-way causality between the interest rate and overall output. Finally, given that a rational investor will distribute his or her wealth into different group of assets depending on their risks and potential returns, we assume that housing prices, stock prices and the interest rate are not only related to overall output (i.e., real GDP), they are also related to each other. In other words, a two-way causality exists between each pair of variables in this particular set.

The theoretical issues discussed above suggest that housing prices, stock prices and output (i.e., real GDP) exhibit two-way relationships. Additionally, the interest rate also affects stock prices, housing prices and aggregate output, with these relationships also pointed in both directions. As such, we first develop an unrestricted vector autoregressive model (VAR) in order to capture the expected relationships between these variables.

Using the VAR model, we attempt to identify the causal relationships – in the Granger (1969 and 1980) sense – among the variables.[2] Lastly, as indicated earlier this study employs monthly time series data from 1993 to 2014. Given the absence of monthly data for real GDP, however, the index of industrial output, which is collected from the Federal Reserve Bank of St. Louis, is used for aggregate output (Y). The data for R, which is represented by the 10-year U.S. Treasury yield, is also collected from the Federal Reserve Bank of St. Louis.[3] Lastly, the Dow Jones Industrial Average (DJ), which is used to measure stock prices, is collected from Yahoo*!* Finance™.[4] With the exception of the interest rate, all of the variables are converted into natural logarithms.

[2] The standard VAR approach, followed later by vector error correction modeling (VECM), is chosen over a Bayesian VAR model, given the variable selection problem associated with the latter (Louzis, 2014). Moreover, the empirical strategy employed here offers computational convenience and continues to represent the standard practice of modelling in macroeconomics.

[3]The 10-year U.S. Treasury yield is an appropriate measure for R in this contextgiven that investment demand is largely determined by the long-term interest rate.

[4]The Dow Jones Industrial Average (DJIA) is used to measure stock prices because it is a widely-known and frequently-used stock index.

Summary statistics, including mean, median and standard deviation, for the overall sample (i.e., 1993-2014) are provided in Table 1.[5] A test for structural breaks based on Chow (1960) is also conducted. This test indicates the existence of a breakpoint at the end of 2000, based on an *F*-statistic of 2.32, a log-likelihood ratio of 7.02 and a Wald statistic of 6.96, each of which is significant at the 10% level.[6] This test also indicates the existence of a breakpoint at the end of 2008, based on an *F*-statistic of 6.21, a log-likelihood ratio of 18.43 and a Wald statistic of 18.65, each of which is significant at the 5% level.[7] These results support our prior comment about the instructiveness of the period under study (i.e., 1993-2014), which includes a housing boom that started in early 2000 and that busted in 2008. In the section that follows, we turn to statistical estimation and discussion of the empirical findings.

III. Estimation and Empirical Findings

Given that time series data may be non-stationary, giving rise to spurious associations, it is important to test for stationarity, and the possibility of long-term relationships among the variables in the system, of each series. Therefore, before estimating the model, we conduct tests to check the stationarity of each variable data series and the existence of long-term relationship among them. In order to establish the stationarity of the data series, as well as the existence of long-term relationships among them, unit root tests are conducted using both the Augmented Dickey-Fuller (1979) and Phillips-Perron (1988) approaches. These test results are reported in Table 2, and show that the variables in the system are nonstationary in logarithm form. They are, however, stationary in first-difference form, indicating that they are integrated of order one. After establishing the stationarity of the data series, a cointegration test is conducted to check for any long-run

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[5] For example, as indicated there the mean values for *DJ* and *R* are approximately 9,840 and 4.6 percent, respectively, with standard deviations of 3,368 and 1.5 percent, respectively.
[6] These statistics point toward rejection of the null hypothesis of "no breakpoint."
[7] Again, these statistics point toward rejection of the null hypothesis of "no breakpoint."

relationship among the variables in the model. The cointegration test result is reported in Table 3, and indicates that the null hypothesis of "no cointegration" is rejected. Therefore, following Engle and Granger (1987) a vector error correction model (VECM) is developed and estimated.

To implement the VECM, a Wald test is conducted in order to explore any causality among the different pairs of variables. The causality test results are reported in Table 4. In the case of housing prices and output, these tests detect only one-way causality running from housing prices (HP) to output (Y). In the case of stock prices (DJ) and output (Y), we detect causality running from both directions (i.e., stock prices (DJ) Granger cause output (Y), and output (Y) Granger causes stock prices (DJ)). As far as the interest rate (R) and output (Y) relationship is concerned, no causality of any kind is detected. Next, Table 4 also reveals that stock prices (DJ) and housing prices (HP) Granger cause each other. This finding is not surprising given that an increase in stock prices (DJ) creates a wealth effect which can lead to a higher level of housing consumption, while an increase in housing prices generates additional home equity, which households can use to expand their stock portfolios. Likewise, the Table 4 results also point towards bidirectional causality between the stock prices (DJ) and the interest rate (R), which is also consistent with the theoretical expectation that when stock prices rise households are more likely to adjust their financial portfolios in favor of stock holdings (and vice versa).

As far as the interest rate (R) and housing prices (HP) are concerned, tests detect only one-way causality running from the interest rate (R) to housing prices (HP), indicating that R Granger causes HP, while HP does not Granger cause R. This result suggests that when the interest rate is low households consume more housing (and vice versa), while a change in the demand for housing does not affect the interest rate. Lastly, and as also reported in Table 4, a significant two-way causal relationship (in the Granger sense) exists between Y (output) and DJ (stock prices), R (the interest rate) and DJ (stock prices) and R (the interest rate) and HP (housing prices). However, only one-way causality is observed between Y (output) and HP (housing prices) and between Y (output) and R (the interest rate). These run from Y (output) to HP (housing prices) and from Y (output) to R (the interest rate).

Next, a vector error correction model (VECM) is employed. The estimated cointegration equation from the VECM provides the long run relationship between Y (output) and the other variables in the model. The estimated cointegration equation for the full sample period is as follows (with t-values in parentheses):

$$\underset{}{Y} = \underset{(7.14)}{0.16\,HP} + \underset{(17.68)}{0.23\,DJ} + \underset{(3.01)}{0.01\,R} \qquad (2)$$

The estimated parameters in (2) indicate that housing prices (HP) and stock prices (DJ) exert a positive and significant effect on long-run economic growth, both results that are consistent with economic theory and conventional wisdom. The coefficient attached to the interest rate (R) is also positive and statistically significant, suggesting that interest rates have a positive effect on long-run economic growth. Although this particular result seems counterintuitive, it is likely capturing the U.S. Federal Reserve's efforts to increase interest rates in response to a growing economy.

The VECM also provides estimates of the short-run effects of a change in each of the variables in the model on all of the other variables in the model. The variance decompositions (VDC) show the proportion of forecast error variance for each variable that is attributable to its own innovations and shocks to the other variables in the system. The transmission of innovations among variables may occur via many channels. Thus, this approach is useful in explaining the strength of the exogeneity of the variables. The VDC (over four months, seven months and 10 Months, respectively) for the different sample periods are presented in Tables 5 through 8. First, Table 5 reports the full sample (1993-2014) results of the variance decompositions (VDC) of Y, HP, DJ and R because of shocks in each of these variables separately one at a time. The estimates indicate that in the four months period almost 87 percent of the variation in Y (output) is explained by its own innovation. This result declines to 72 percent in the seven months period, and again to 64 percent in the 10 months period. Similarly, over the long run (i.e. by the 10 months period) DJ (stock prices) accounts for about 34 percent of the variation in Y (output), HP (housing prices) accounts for about three percent of variation in Y (output), and R (the interest rate) explains less than one-fourth of one percent of the variation in Y (output).

In terms of housing prices (HP), shocks to the housing market account for over 95 percent of the variation in HP (housing prices) in the four months period. This figure falls to 87 percent in the 10 months period. Similarly, over the long run (i.e., by the 10 months period) about 13 percent of variation in HP (housing prices) is explained by Y (output), while DJ (stock prices) and R (the interest rate) each accounts for less than one percent of variation in HP (housing prices). Next, with regard to DJ (stock prices), shocks to the stock market account for about 88 percent of the variation in DJ (stock prices) in the four months period. This figure falls to 78 percent over the 10 months period, whereas Y (output) accounts for about 20 percent of variation in DJ (stock prices), while HP and R each accounts for less than two percent variation in DJ (stock prices). Lastly, the test results indicate that shocks to R (the interest rate) explain about 85 percent of the variation in R (the interest rate) over both the short run and the long run. At the same time, DJ explains about 12 percent of variation in R (the interest rate), while Y (output) and HP (house prices) each explains little more than one percent variation in R (the interest rate).

Table 6 presents VDC for the 1993 to 2001 sample period. As indicated there, by the 10 months period about 65 percent of variation in Y (output) is explained by itself, while about 13 percent of the variation in Y (output) is explained by each of DJ (stock prices) and R (the interest rate). The remaining variable, HP (housing prices), explains about 9 percent of variation in Y (output). During this sample period, about 95 percent of variation in HP (housing prices) is explained by itself, while about four percent of the variation in HP is by each of Y (output) and DJ (stock prices). The remaining variable, R (the interest rate), explains about one percent of variation in HP (housing prices) during this period. Similarly, about 84 percent of variation in DJ (stock prices) is explained by shocks to the stock market, while HP (housing prices) explains about 12 percent of the variation in DJ (stock prices). The remaining portion of the variation in DJ (stock prices), or about five percent, is explained by Y (output) and R (the interest rate) collectively. As far as R (the interest rate) is concerned, only about 50 percent of its variation is explained by its own innovations, while about 40 percent of is variation is explained by innovations in Y (output). The remaining four percent and five percent of the variation in R (the interest rate) is explained by HP (housing prices) and DJ (stock prices), respectively.

Table 7 reports the VDC results for the period 2002 to 2008. During this time frame, about 64 percent of the variation in Y (output) is, over 10 months, explained by itself, while 23 percent is explained by DJ (stock prices), eight percent is explained by R (the interest rate) and five percent is explained by HP (housing prices). During the same time period, 82 percent of variation in HP (housing prices) is explained by Y (output) and four percent by R (the interest rate). For DJ (stock prices), 81 percent of the variation is explained by itself. The remaining 19 percent of the variation in DJ (stock prices) is explained by three other variables, out of which 10 percent is explained by Y (output), five percent by R (the interest rate) and about four percent by HP (housing prices). During the same period, about 30 percent of variation in the variable R (the interest rate) is explained by itself, while 39 percent is explained by DJ (stock prices), 24 percent is explained by HP (housing prices) and seven percent is explained by Y (output).

During the final sample period – 2009to 2014 (see Table 8) – we observe that by the 10 months period Y (output) explains about 50 percent of its own variation and DJ (stock prices) explains about

45 percent of variation in Y (output). The remaining variables, HP (housing prices) and R (the interest rate), explain about three and two percent of the variation in Y (output), respectively. During this period, approximately 92 percent of the variation in HP (housing prices) is explained by its own innovations, whereas only about eight percent of the variation in HP (housing prices) is collectively explained by the other variables. With respect to DJ (stock prices), its own innovation explains only 63 percent of its variation. Among the other variables, R (the interest rate) explains about 16 percent of the variation in DJ (stock prices), Y (output) explain about 14 percent of the variation in DJ (stock prices) and HP (housing prices) explains the remaining seven percent of variation in $D\ J$(stock prices). Finally, with regard to the variable R (the interest rate), about 68 percent of its variation is explained by itself, at least after the 10 months period. Of the remaining 32 percent of the variation in R (the interest rate) that is explained by other variables, DJ (stock prices) explains about 14 percent of the variation while Y (output) explains about 12 percent of the variation. Over the same time period, HP (housing prices) explains only six percent of the variation in R (the interest rate).

IV. Summary and Conclusions

This paper examines the relationships between housing prices, stock prices, the interest rate and the aggregate output level in the U.S. economy, with a particular focus on the effects of housing prices and stock prices on aggregate output. Monthly data from 1993 to 2014 indicate bi-directional causality between (1) aggregate output and stock prices, (2) stock prices and housing prices and (3) the interest rate and stock prices. The data also suggest that there is one-way causality between housing prices and aggregate output, and between the interest rate and housing prices, while empirical testing failed to detect any causality between the interest rate and aggregate output of the U.S. economy. Moreover, evidence from variance decompositions shows that about 65 percent of the variation in aggregate output is explained by its own innovations (by the end of third quarter) in all of our estimations, while stock prices appear to have largest effect on aggregate output, explaining about 34 percent of its variation during the 1993-2014 period. In contrast, housing prices and the U.S. Treasury yield contribute only modest impacts on aggregate output in the U.S. Separate estimation and variance decompositions for sample periods 1993-2001, 2002-2008 and 2009-2014 show that the impact of housing prices relative to stock prices has been waning over time. In summary, the overall findings suggest that the effect of housing prices on the U.S economy is not as large as expected. Instead, the wealth effect created by changes in stock prices has a relatively large impact on U.S. aggregate output.

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Table 1. Summary Statistics

	Mean	Std Dev	Median	Max	Min	Skewness	Kurtosis
Y	88.56	10.42	90.62	106.3	64.44	−0.793	2.787
HP	167.8	40.18	180.3	228.6	104.1	−0.167	1.573
DJ	9,839.5	3,368.3	10,351	17,828	3,310	−0.129	2.773
R	4.568	1.525	4.570	7.960	1.530	−0.068	2.214

Table 2. Unit Root Tests

	Augmented Dickey-Fuller Tests		*Phillips-Perron Tests*	
Y	−2.79	−4.02*	−2.08	−15.4*
HP	−1.07	−5.26*	−0.77	−6.77*
DJ	−2.13	−15.8*	−2.18	−15.8*
R	−4.10*	−1.60	−3.70†	−12.5*

Notes: ADF = augmented Dickey-Fuller test, PP = Phillips-Perron test. *[†] indicates 5%[10%] level of significance.

Table 3. Cointegration Test Results

H_0	Trace Statistics	5% Critical Value
$r = 0$	171.03*	47.86
$r \leq 1$	99.48*	29.80
$r \leq 2$	42.05*	15.49
$r \leq 3$	13.27*	3.84

Notes: * denotes rejection of H_0 at the 5% level of significance.

Table 4. Granger Causality/Block Exogeneity Wald Test

	Wald Test		
H_0	χ^2	df	*p*-value
HP ==>*Y*	9.26†	4	0.0549
DJ ==>*Y*	11.7*	4	0.0200
R =/=>*Y*	4.74	4	0.3145
Y =/=>*HP*	4.57	4	0.3342
DJ ==>*HP*	12.7*	4	0.0128
R ==>*HP*	6.47‡	4	0.1662
Y ==>*DJ*	26.7#	4	0.0000
HP ==>*DJ*	6.65‡	4	0.1558
R ==>*DJ*	8.15†	4	0.0862
Y =/=>*R*	6.20‡	4	0.1845
HP =/=>*R*	4.37	4	0.3587
DJ ==>*R*	21.1*	4	0.0169

Notes: ==> indicates "Granger causes" and =/=> indicates "does not Granger cause. All variables are in log form. #[*](†){‡} denotes the 1%[5%](10%){20%} level of significance.

Table 5. Variance Decomposition Results, Full Sample

	Variance Decomposition of Y *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	87.42	0.72	11.29	0.57
7	72.24	2.42	25.00	0.34
10	62.54	3.42	33.81	0.23

	Variance Decomposition of HP *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	2.98	96.50	0.39	0.12
7	7.63	92.01	0.22	0.14
10	13.04	86.59	0.23	0.13

	Variance Decomposition of DJ *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	11.14	0.64	88.11	0.11
7	15.96	0.77	82.54	0.73
10	19.76	0.59	78.39	1.26

	Variance Decomposition of R *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	0.77	1.33	11.17	86.73
7	1.19	1.23	12.41	85.17
10	1.65	1.17	11.74	85.40

Table 6. Variance Decomposition Results, 1993-2001

	Variance Decomposition of Y *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	85.50	4.72	1.68	8.10
7	73.39	6.91	8.26	11.44
10	65.44	8.56	12.75	13.25

	Variance Decomposition of HP *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	0.37	9.11	0.06	0.47
7	2.24	97.22	0.03	0.51
10	4.19	94.70	0.32	0.79

	Variance Decomposition of DJ *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	1.88	1.60	94.77	1.75
7	2.01	10.19	84.13	3.67
10	1.59	11.60	83.78	3.27

	Variance Decomposition of R *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	29.31	3.82	6.32	60.55
7	36.28	2.48	6.41	54.83
10	40.17	3.87	4.73	51.23

Table 7. Variance Decomposition Results, 2002-2008

	Variance Decomposition of Y *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	84.74	2.43	10.04	2.79
7	73.36	3.93	16.87	5.84
10	63.86	5.41	22.76	7.97

	Variance Decomposition of HP *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	0.58	98.42	0.02	0.98
7	0.73	95.15	0.03	4.09
10	13.96	81.60	0.14	4.30

	Variance Decomposition of DJ *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	6.47	2.13	88.74	2.66
7	10.08	3.68	82.19	4.05
10	9.65	4.26	80.83	5.26

	Variance Decomposition of R *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	0.59	15.69	26.24	57.48
7	5.29	23.07	31.78	39.86
10	7.34	23.35	38.40	29.91

Table 8. Variance Decomposition Results, 2009-2014

	Variance Decomposition of Y *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	84.07	2.45	13.35	0.13
7	61.56	2.79	34.61	1.04
10	49.98	3.37	44.57	2.07

	Variance Decomposition of HP *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	1.90	94.03	3.71	0.36
7	2.11	92.57	5.17	0.15
10	2.19	92.22	5.48	0.11

	Variance Decomposition of DJ *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	9.67	3.55	72.76	14.02
7	12.29	6.16	66.26	15.29
10	13.84	7.37	62.97	15.81

	Variance Decomposition of R *Explained By:*			
Period	*Y*	*HP*	*DJ*	*R*
4	11.53	3.01	23.15	62.31
7	11.48	5.05	17.57	65.90
10	12.28	5.99	14.01	67.72