"Asymmetric Causality between Unemployment Rate and House Prices in Each State of the U.S.A."

Mohsen Bahmani-Oskooee*
The Center for Research on International Economics and
Department of Economics
The University of Wisconsin-Milwaukee
bahmani@uwm.edu

Seyed Hesam Ghodsi
Department of Economics, Business and Finance
Lake Forest College
Lake Forest, Illinois 60045
ghodsi@lakeforest.edu

ABSTRACT

The Great Recession of 2008 here in the U.S. was mostly attributed to bubble in the U.S. housing market that came to an end in 2007. In this paper we try to provide empirical evidence to the above conjecture by engaging in asymmetric causality detection between house prices and unemployment rate in each state of the U.S. We find that indeed, in 39 states decrease in house prices caused unemployment rate. Only in 19 states there was evidence of increase in house prices causing the rate of unemployment. Since asymmetry analysis requires using nonlinear models, there was also evidence of asymmetry cointegration between the two variables in all states.

JEL Classification: R13

Key words: House Prices, Unemployment Rate, Asymmetry, United States

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I. Introduction

A reference to the neo-classical framework reveals that house prices are determined by the law of demand for and supply of housing. Therefore, any factor that affects the demand and supply will affect house prices. While on the demand side of the market one could list factors like mortgage rates, household income, and demographic factors, on the supply side of the market, cost of land, construction costs and availability of credit to finance such costs are important determinants (Chen and Patel 1998). However, abnormal movement in house prices themselves could be a major factor in affecting the housing market and other sectors of the economy. For example, the main source of the Great Recession of 2008 in the U.S. was said to be the burst of housing market bubble. Abnormal increase in house prices, mostly due to excessive lending to unqualified buyers and subprime mortgages had to come to an end. Decline in construction business that contributed to an increase in unemployment was extended to other sectors of the U.S. economy via multiplier effects, causing unemployment rate to rise in every state. In turn, unemployed individuals who were unable to pay their mortgages had to sell or adhere to foreclosures, which in turn, exacerbated the decline in house prices. Clearly, it appears that these two macro variables can cause each other.

Almost all studies related to housing market have concentrated on household income and interest rates as two main determinants of house prices and have tried to establish short-run causality and long-run relationship among these variables. A few examples include Chen and Patel (1998), Case and Shiller (2003), Gallin (2006), Chen *et al*. (2007), McQuinn and O'Reilly (2008), Holmes and Grimes (2008), Kim and Bhattacharya (2009), Holly *et al*. (2011), Abbott and De Vita (2012 and 2013), and Katrakilidis and Tranchanas (2012) have investigated short-run causality or long-run relationship between house prices and income or some variables other than unemployment rate in different countries. For a detailed review of these and other studies see Bahmani-Oskooee and Ghodsi (2016).

There are only a limited number of studies that have investigated the potential link between house prices and employment or unemployment. Peek and Wilcox (1991) who formulated the supply of and the demand for housing in the U.S., identified the unemployment rate as one of many determinants of house prices. Their estimates of the model revealed that the recovery of house prices in the late 1980 could be attributed to lower unemployment and lower interest rates. Similar results were later confirmed by Apergis (2003) and Apergis and Rezitis (2003) using data from Greece. As they conclude, interest rates, inflation, and employment are main determinants of house prices in Greece. Finally, when Australian data were analyzed by Abelson *et al*. (2005), a long-run elasticity of -0.2 between real house prices and unemployment rate was discovered. Unlike these studies which have used an aggregate measure of house prices and unemployment rate from each country, Kim and Bhattacharya (2009) used data from the U.S. and four of its regions, i.e., West, Northeast, South, and Midwest to find strong evidence of Granger causality from house prices to employment. Although they used data from 1969-2004 period, their findings could easily explain the main cause of the Great Recession of 2008 in the U.S.

In this paper we take an additional step and rather than concentrating on four regions, we use data from each of the 51 states of the U.S. and try to detect causality between house prices and unemployment rate in each state. Our approach will be different than previous studies and will be based on asymmetric cointegration and error-correction modeling which requires using nonlinear rather than linear models. To this end, the models and methods are introduced in Section II. We then report the empirical results in Section III. Finally, while Section IV concludes, sources of the data and definition of the variables are reported in an Appendix.

II. The Models and Methods

Since our goal is to engage in causality detection between house prices which we denote by HP and unemployment rate, denoted by UN, we begin with a simple log linear relation between the two variables as outlined by equation (1) where house prices depend on unemployment rate:[1]

$$LnHP_t = a + bLnUN_t + \varepsilon_t \qquad (1)$$

Equation (1) is a long-run relationship between HP and UN. Since Granger causality is a short-run concept, in order to detect causality that runs from unemployment rate to house prices we must rewrite (1) in an error-correction format as in (2):

$$\Delta LnHP_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta LnHP_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta LnUN_{t-i} + \lambda \varepsilon_{t-1} + \mu_t \qquad (2)$$

Within error-correction model (2), Granger (1988, p. 203) points out to two possible sources of causality. One is through the first-differenced variable where UN granger causes HP if $\sum \hat{\delta}_i \neq 0$ and the other one is through ε_{t-1} if an estimate of λ is negative and significant. In the literature, the first causality is referred to as short-run causality and the second as the long-run causality (Jones and Joulfaian, 1991, p. 151). Furthermore, Banerjee *et al.* (1998) demonstrated that if an estimate of λ is negative and significant, then the two variables are said to converge toward their long-run equilibrium values or they are cointegrated.[2]

The main assumption behind specification (2) is that both HP and UN variables are integrated of order one, I(1), and that is why we use their first differences as a stationary variable.

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[1] Studies like Chen *at al.* (2007), Hatzius (2008), Campbell *et al.* (2011), and Bahmani-Oskooee and Ghodsi (2017) have included other variables and have not engaged in causality detection.

[2] Note that Banerjee *et al.* (1989) tabulate new critical values for the t test to be used in judging significance of λ. Furthermore, the Wald test is applied to test if $\sum \hat{\delta}_i \neq 0$.

In case one is already stationary variable at level, I(0), and the other is I(1), Pesaran *et al*. (2001) modify (2) and rely upon specification (3):

$$\Delta LnHP_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta LnHP_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta LnUN_{t-i} + \lambda_0 LnHP_{t-1} + \lambda_1 LnUN_{t-1} + \mu_t \qquad (3)$$

They then recommend applying the F test to establish joint significance of lagged level variables as a sign of cointegration. Since distribution of the F test is non-standard, they tabulate new critical values that account for integrating properties of variables which could be combination of I(0) and I(1).[3] Bahmani-Oskooee and Oyolola (2007) have extended the same concept of causality testing from (2) to (3). Short-run causality is established again by applying the Wald test to establish $\sum \hat{\delta}_i \neq 0$. To test for long-run causality and to establish cointegration in line with the approach of Banerjee *et al.* (1998), we use the normalized long-run estimate of λ_1 and equation (1) and generate the error term which we denote it by ECM. After replacing the linear combination of lagged level variables in (3) by ECM_{t-1}, we estimate the new specification one more time and if ECM_{t-1} carries a negative and significant coefficient, long-run causality and cointegration is established.[4]

The main assumption so far behind any of the above specifications is that if an increase in unemployment rate causes house prices to decline, a decrease in unemployment rate should cause them to rise, by the same proportion. However, changes in unemployment rate could have asymmetric effects on house prices. When unemployment rate declines, more people are working with expected increase in their current and future income which could translate to an increase in demand for housing and eventually to increase in house prices. However, when unemployment rate rises, the adverse effect may not be as strong as we expect since some unemployed individuals

[3] Since almost all macro variables are either I(0) or I(1), there is no need for pre-unit root testing under this approach.

[4] Note that within this approach the t-ratio that is used to judge the significance of ECM_{t-1} has upper and lower bound critical values that Pesaran *et al.* (2001, p. 303) tabulate.

may continue financing their mortgage out of saving till they locate another job. In order to incorporate the asymmetric effects of unemployment rate on house prices, we follow Shin *et al.* (2014) and first form changes in UN variable as ΔLnUN which includes positive changes as well as negative changes. We then use the concept of partial sum and generate two new time series variables as outlined by (4) below:

$$POS_t = \sum_{j=1}^{t} \Delta LnUN_j^{+} = \sum_{j=1}^{t} \max(\Delta LnUN_j, 0),$$
$$NEG_t = \sum_{j=1}^{t} \Delta LnUN_j^{-} = \sum_{j=1}^{t} \min(\Delta LnUN_j, 0) \qquad (4)$$

In (4), the POS variable which is the partial sum of positive changes reflects only increase in unemployment rate and the NEG variable which is the partial sum of negative changes reflects only a decrease in unemployment rate. Shin *et al.* (2014) then propose moving back to error-correction model (3) and replacing *LnUN* by *POS* and *NEG* variables. The new specification is as follows:

$$\Delta LnHP_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta LnHP_{t-i} + \sum_{i=0}^{n2} \delta_i^{+} \Delta POS_{t-i} + \sum_{i=0}^{n3} \delta_i^{-} \Delta NEG_{t-i}$$
$$+ \rho_0 LnHP_{t-1} + \rho_1^{+} POS_{t-1} + \rho_1^{-} NEG_{t-1} + \xi_t \qquad (5)$$

Due to method of construction of partial sum variables, models like (5) are referred to as nonlinear ARDL models, whereas (3) is referred to as a linear ARDL model. Shin *et al*. (2014) demonstrate that Pesaran *et al.*'s (2001) bounds testing approach applied to the linear model is equally applicable to the nonlinear model (5). They even argue that the critical value of the F test should stay the same when we move from the linear model (3) to nonlinear model (5) even though (5) has one more exogenous variable.[5] This is due to dependency between the partial sum variables.

[5] See Shin *et al*. (2014, p. 291).

Bahmani-Oskooee and Ghodsi (2017b) have extended symmetric causality concepts from (3) to (5). Following their approach, if increase in unemployment rate is to cause house prices, we must establish $\sum \hat{\delta}_i^+ \neq 0$ by applying the Wald test. Similarly, if a decline in unemployment rate is to cause house prices, $\sum \hat{\delta}_i^- \neq 0$ should be established. As for the long run causality, again, we use normalized long-run estimates and the long-run specification to generate the error term, ECM, in this context. We then replace the linear combination of lagged level variables by ECM_{t-1} and test for the significance of this term.[6] By switching the dependent and independent variables in equation (1) and following through specifications (2)-(5), we will also be able to test causality that could run from changes in house prices to unemployment rate.[7]

III. The Results

In this section, we estimate both the linear and nonlinear models using quarterly data over the period 1976Q1-2016Q1from each state of the United States of America.[8] A maximum of eight lags are imposed on each first differenced variable and Akaike's criterion (AIC) is used to select an optimum model. Any estimate (coefficient or diagnostic statistic) that is significant at the 10% level, is identified by * and those that are significant at the 5% level, are indicated by **. Furthermore, a dummy variable is included to account for exact timing of the Global Financial Crisis of 2008. We assigned a value of 1 for the period prior to 2008Q3 and zero thereafter.[9] States in which the dummy was significant are identified by # in each state.

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[6] Note that the long-run asymmetric model in this case will take the following form: $LnHP_t = a + bPOS_t + cNEG_t$ where $\hat{b} = \hat{\rho}_1^+ / -\hat{\rho}_0$ and $\hat{c} = \hat{\rho}_1^- / -\hat{\rho}_0$.

[7] For some other application of these methods see Apergis (2003), Apergis and Miller (2006), De Vita and Kyaw (2008), Verheyen (2013), Durmaz (2015), Bahmani-Oskooee and Fariditavana (2016), and Aftab *et al.* (2017).

[8] For details see the Appendix.

[9] The break point is based on bankruptcy of Lehman Brothers on 15 September 2008 (Grammatikos and Vermeulen, 2012, p. 518).

Due to volume of the results, clearly, we cannot report all the estimates for all 51 states. Therefore, we review the results for one state, Montana, in Table 1 and then summarize them for all states.

Table 1 goes about here

In section I of Table 1, we report the full-information results for both the linear and nonlinear model in which UN is independent variable, just like equation (1). In Section II we switch the variables and UN becomes the dependent variable so that we can assess possibility of causality running from house prices to unemployment rate. Let us now consider the linear model, HP = F (UN) in Section I. From panel A and short-run estimates, apparently we observe no significant short-run effects of change in unemployment rate to house prices. However, when long-run is realized, from Panel B and long-run estimates, increase in unemployment rate has negative and significant effects on house prices, in line with our expectation. The two variables are cointegrated at least by ECM_{t-1} criterion since it carries a significantly negative coefficient which also supports long-run causality.[10]

Three other diagnostic statistics for this model are also reported. Although we have included a dummy (denoted by DUM) to account for 2008 Financial Crisis which is significant in this case, we do test for stability of short-run and long-run coefficient estimates by applying the well-known CUSUM and CUSUMSQ tests. We indicate stable estimates by "S" and unstable estimates by "U". Clearly, estimates are stable as we have indicated. Finally size of adjusted R^2 is reported to judge goodness of the fit.

[10] Note that in this case lack of short-run causality is supported by insignificant short-run coefficient attached to ΔLnUN in Panel A or by insignificant Wald test of 2.64 to test if $\sum \hat{\delta}_i = 0$.

In the second column of Section I, we consider the estimates of the nonlinear model (5). As can be seen, both ΔPOS and ΔNEG carry at least one lagged significant coefficient, implying that both increase and decrease in unemployment rate in Montana have short-run effects. These short-run effects are asymmetric because at current lag t, coefficients estimates differ from each other. Furthermore, the fact that number of optimum lags attached to ΔPOS is different than the ones attached to ΔNEG, support short-run adjustment asymmetry. Additionally, since the Wald test to establish $\sum \hat{\delta}_i^{+} = 0$ is insignificant but the one to establish $\sum \hat{\delta}_i^{-} = 0$ is highly significant, there is evidence of short-run asymmetric causality in this state. In the short-run while increase in unemployment rate does not cause house prices, decrease in unemployment rate does. However, due to nature of the VAR system, short-run estimates usually oscillate in signs in every model and the only way to judge the ultimate effect is to allow for the adjustment to complete and rely upon the long-run estimates. From Panel B and long-run coefficient estimates, we gather that both the POS and NEG carry significant and negative coefficients, supporting the notion that in the long-run increased unemployment rate will cause house prices to decline and decreased unemployment rate will cause it to rise. This long-run causality that is in line with our expectations is supported by a significant ECM_{t-1}. These estimates are also valid since cointegration is established by a significant F test. Clearly, nonlinear adjustment of the unemployment rate has attributed to significant results and increased adjusted R^2**.**

Next we switch the two variables in both models and assess causality that may run from house prices to unemployment rate. The results for both models are reported in Section II of Table 1. From the linear model and short-run estimates, it is clear that changes in house prices do have short-run effects on unemployment rate in Montana since two of the three lags are significant. Since sum of the lagged coefficients are highly significant, there is evidence of short-run causality from house prices to unemployment rate in Montana. These short-run effects last into the long-run since in Panel B, *LnHP* carries a negative and significant coefficient. Thus, house prices cause unemployment rate in the long run as well. Again, this is supported by significant ECM_{t-1} for long-run causality and by the F test for cointegration. Other statistics are the same as before except the size of adjusted R^2 which is substantially higher when house prices is treated as independent variable. The nonlinear model supports the same idea in that both ΔPOS and ΔNEG which reflect increase and decrease in house prices do have short-run effects on unemployment rate in Montana. Again, since the Wald test is insignificant for $\sum \hat{\delta}_i^+ = 0$ but not for $\sum \hat{\delta}_i^- = 0$, increased prices does not cause unemployment rate in the short run but decreased prices do. Once again, the ultimate effects are reflected in the long-run effects. From Panel B, it is again clear that both POS and NEG carry negative and significant coefficient estimate, implying that in the long run increase in house prices cause unemployment rate to decline and decrease in house prices cause it to rise. This long-run causality is further confirmed by significantly negative coefficient estimate of ECM_{t-1} and by significant F test for asymmetric cointegration.[11]

Based upon the above review of the results for Montana, we now discuss the results for all 51 states. We summarize the short-run results by saying that in the linear model *HP = F (UN),* the *ΔLnUN* variable carried at least one lagged significant coefficient in 24 states. However, in the associated nonlinear model, *HP = F (POS, NEG*) at least either the POS or NEG carried significant coefficients in 38 states, supporting relatively more short-run effects in the nonlinear model. However, when the two variables were switch, in the linear model where *LnUN = F (LnHP),* the *ΔLnHP* variable carried at least one lagged significant coefficient in 44 states. However, in the associated nonlinear model at least the ΔPOS or ΔNEG carried significant coefficients in 50 states,

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[11] The remaining diagnostics are similar to the linear model except there is some evidence of serial correlation.

again supporting more short-run effects in the nonlinear model, similar to the case of Montana in Table 1. Clearly, although the nonlinear models yield relatively more significant short-run effects, the model in which the house price is the independent variable yields short-run effects in almost all states.[12]

Based on the above review, we now summarize the results for all states and report them in Tables 2 (linear models) and 3 (nonlinear models).

Tables 2 and 3 go about here

From the estimates of the linear models in Table 2, we gather that unemployment causes house prices only in five states of Alaska, California, Hawaii, Iowa, and Illinois in the short run, since only in these five states $\sum \hat{\delta}_i \neq 0$. However, since ECM_{t-1} carry significantly negative coefficient in 21 states, unemployment rate causes house prices more in the long run than short run. Furthermore, cointegration between house prices and unemployment rate is confirmed by either F test or ECM_{t-1} test in 25 states, supporting the long-run link between the two variables. The outcome changes substantially when we switch the two variables in the linear model and shift to the case of house prices causing unemployment. There is now evidence of house prices causing unemployment in 43 states in the short run. This supports the melt down of the U.S. economy in the Great Recession of 2007-8 which was said to be due to the burst of the housing market bubble. Such strong findings are further supplemented by evidence of long-run causality in 32 states, reflected by the negative and significant coefficient attached to $ECM_{t-1.}$ Additional support is provided by cointegration, at least by one of the tests (again, F or ECM_{t-1}), in 39 states. Although we have included a dummy to account for 2008 Financial Crisis, again, we do test for stability of short-run and long-run coefficient estimates by applying the CUSUM and CUSUMSQ tests in

[12] These results are available from the authors upon request.

each model. These are denoted by Q and Q^2 in the table and do support stability of our estimates. Like the case of Montana, size of the adjusted R^2 is higher when house price is the independent variable.

How do the results change when we shift to the results from nonlinear models? From Table 3, when we consider the first part and causality from unemployment rate to house prices, we gather that increase in unemployment rate causes house prices in the short run in 15 states such as Alaska, Iowa, etc. In these states $\sum \hat{\delta}_i^+ \neq 0$ is supported by significant Wald test. In 10 other states decrease in unemployment rate causes house prices, again in the short run since in these states $\sum \hat{\delta}_i^- \neq 0$ is supported by significant Wald test. Clearly, introducing nonlinear adjustment of unemployment rate has resulted in more cases of unemployment causing house prices asymmetrically in the short run. The evidence becomes even stronger when we consider long-run causality in this case. ECM_{t-1} carries significantly negative coefficient in 35 states.

Once again, outcome is much stronger in the results for house prices causing unemployment in the nonlinear model. As can be seen, in 37 states it is the decline in house prices that causes unemployment rate in the short run, again, consistent with 2007-8 situation in the U.S. Increase in house prices cause unemployment only in 20 states. These results are supplemented by significant ECM_{t-1} for long-run causality in 41 states and by either the F or ECM_{t-1} test for cointegration in almost all states. If we chose the size of adjusted R^2 as a model selection criterion, there is overwhelming support for the nonlinear adjustment of house prices that cause unemployment rate in almost all states and this supports current housing market recovery and low rate of unemployment in most states of the U.S.

IV. Summary and Conclusion

In any market, prices are determined by the law of demand and supply and the housing market is no exception. In addressing fluctuation in house prices, researchers try to identify factors that affect the demand or supply. In the U.S., government policies are aimed at stabilizing the housing market by controlling the mortgage rates. However, other factors are equally important to be identified. In 2008 when the house prices in the U.S. began to decline abnormally, new constructions stopped. Recession in the housing market spread to the rest of the U.S. economy resulting in the Great Recession. Although the federal government quickly acted by lowing the interest rates, we conjecture growth in the U.S. economy and gradual decline in unemployment rate have also contributed to housing market recovery, hence in an increase in house prices.

In this paper, we investigate the link between real house prices and unemployment rate using state level data from the United State. Assuming the relation between the two variables to be linear or the effects of one variable on the other to be symmetric, we find that while in five states unemployment rate causes house prices, in 43 states house prices cause unemployment rate supporting the Great Recession of 2008 which was said to be mostly due to decline in house prices. However, in order to justify this fact, we took an additional step and separated declines in house prices from increases in house prices and engaged in asymmetric causality detection and asymmetric cointegration analysis. This practice amounted to using nonlinear models. We found that indeed, in 37 states it was the decrease in house prices that causes unemployment rate. The evidence of increase in house prices causing unemployment rate was limited to 20 states. Furthermore, the evidence of unemployment rate causing house prices in the nonlinear model was limited to several states. A major policy implication of our findings is that stabilizing the housing market and house prices do contribute to economic stability led by stable unemployment rate.

Appendix
Data Sources and Definitions

Quarterly data over the period 1976Q1-2016Q1 are used to carry out the empirical exercise. They come from the following sources:

a. U.S. Federal Housing Finance Agency
b. U.S. Bureau of Labor Statistics

Variables:

HP: House price index. This is a broad measure of the movement of single-family house prices constructed and published by source (a). We have deflated house prices HP the prices by CPI data (source b) to get the real house prices.

UN: Unemployment rate.

Each month the Current Employment Statistics program surveys about 146,000 businesses and government agencies, representing approximately 623,000 individual worksites, in order to provide detailed industry data on employment, hours, and earnings of workers on nonfarm payrolls for all 50 States, the District of Columbia, Puerto Rico, the Virgin Islands, and about 450 metropolitan areas and divisions. They then measure the unemployment rate in each state that are published by source (b).

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Table 1: Full-Information Estimates for State of Montana					
	Section I: Ln HP = F (Ln UN)			*Section II: Ln UN = F (Ln HP)*	
Panel A: Short-Run	**Linear ARDL**	**Nonlinear ARDL**	**Panel A: Short-Run**	**Linear ARDL**	**Nonlinear ARDL**
$\Delta LnUN_t$	**-.02(1.57)**		**$\Delta LnHP_t$**	**-.14 (1.28)**	
$\Delta LnUN_{t-1}$			$\Delta LnHP_{t-1}$	-.28 (2.45)**	
$\Delta LnUN_{t-2}$			$\Delta LnHP_{t-2}$	-.40 (3.73)**	
$\Delta LnUN_{t-3}$			$\Delta LnHP_{t-3}$		
$\Delta LnUN_{t-4}$			$\Delta LnHP_{t-4}$		
$\Delta LnUN_{t-5}$			$\Delta LnHP_{t-5}$		
$\Delta LnUN_{t-6}$			$\Delta LnHP_{t-6}$		
$\Delta LnUN_{t-7}$			$\Delta LnHP_{t-7}$		
ΔPOS_t		**-.05 (2.50)****	**ΔPOS_t**		**-.57 (1.90)***
ΔPOS_{t-1}			ΔPOS_{t-1}		-.03(.11)
ΔPOS_{t-2}			ΔPOS_{t-2}		-.45(1.34)
ΔPOS_{t-3}			ΔPOS_{t-3}		-.70(2.44)**
ΔPOS_{t-4}			ΔPOS_{t-4}		.53(1.86)*
ΔPOS_{t-5}			ΔPOS_{t-5}		.03(.12)
ΔPOS_{t-6}			ΔPOS_{t-6}		-.11(.39)
ΔPOS_{t-7}			ΔPOS_{t-7}		.73(2.83)**
ΔNEG_t		**.01 (.25)**	**ΔNEG_t**		**.02(.08)**
ΔNEG_{t-1}		.01(.18)	ΔNEG_{t-1}		-.30(1.15)
ΔNEG_{t-2}		.14(1.82)*	ΔNEG_{t-2}		-.40(1.57)
ΔNEG_{t-3}		-.15(2.16)**	ΔNEG_{t-3}		.28(1.10)
ΔNEG_{t-4}		.11(1.38)	ΔNEG_{t-4}		-.56(2.31)**
ΔNEG_{t-5}		.12(1.52)	ΔNEG_{t-5}		.03(.14)
ΔNEG_{t-6}		-.01(.17)	ΔNEG_{t-6}		-.03(.14)
ΔNEG_{t-7}		.28(3.80)**	ΔNEG_{t-7}		-.64(2.95)**
Panel B: Long-Run			**Panel B: Long-Run**		
Constant	2.72 (8.69)**	2.63 (11.56)**	Constant	4.49 (3.88)**	1.68(15.59)**
$LnUN_t$	-.81 (3.20)**		$LnHP_t$	-1.09 (1.70)*	
POS_t		-.67 (2.48)**	POS_t		-.59 (3.82)**
NEG_t		-.71 (2.71)**	NEG_t		-.51 (2.78)**
Dum	-.31(3.07)**	.02(.12)	Dum	.008(.04)	-.19(2.31)**
Panel C:Diagnostic			**Panel C: Diagnostic**		
F	4.46	7.45**	F	6.56**	6.52**
ECM_{t-1}	-.06 (3.03)**	-.08(4.18)**	ECM_{t-1}	-.08(3.56)**	-.17 (4.67)**
QSUM (QSUMSQ)	S(S)	S(S)	QSUM (QSUMSQ)	S(S)	S(S)
Adjusted R^2	.29	.37	Adjusted R^2	.93	.93
Wald Tests:			**Wald Tests:**		
$\sum \hat{\delta}_i = 0$	2.64		$\sum \hat{\delta}_i = 0$	9.93**	
$\sum \hat{\delta}_i^+ = 0$		.43	$\sum \hat{\delta}_i^+ = 0$		1.07
$\sum \hat{\delta}_i^- = 0$		4.67**	$\sum \hat{\delta}_i^- = 0$		9.47**

Notes:

a)- Numbers inside the parentheses next to coefficient estimates are absolute values of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b).-The upper bound critical value of the F-test for cointegration when there is one exogenous variable (k=1) is 4.78 (5.73) at the 10% (5%) level of significance. These come from Pesaran *et al*. (2001, Table CI, Case III, p. 300). C).- The upper bound critical value of the t-test for significance of ECM_{t-1} is 2.91 (3.22) at the 10% (5%) level when k =1.

d). All Wald tests are distributed as χ^2 with one degree of freedom. The critical value is 2.71 (3.84) at the 10% (5%) level.

Table 2: Results from the Linear Model (3)

	Unemployment Rate Causing House Prices (UN →HP)					House Prices Causing Unemployment Rate (HP →UN)				
	$\sum \hat{\delta}_i \neq 0$	*ECM_{t-1}*	*F-Test*	*Adj R^2*	*Q (Q^2)*	$\sum \hat{\delta}_i^{'} \neq 0$	*ECM_{t-1}*	*F-Test*	*Adj R^2*	*Q (Q^2)*
Alaska	5.65**	-.03(1.17)	3.02	.16	S (S)	.55	-.04(2.26)	2.782	.94	S (S)
Alabama	.0945	-.06(3.18)*	4.92*	.13	S (S)	12.55**	-.05(2.56)	6.41**	.61	S (S)
Arkansas#	.002	-.03(2.01)	3.56	.04	S (S)	15.72**	-.05 (2.74)	5.57*	.85	S (S)
Arizona	.18	-.02(2.68)	4.14	.40	S (S)	15.92**	-.06(2.60)	4.44	.64	S (S)
California	3.10*	-.01(1.38)	1.38	.70	S (S)	18.47**	-.08(4.66)**	12.49**	.74	S (S)
Colorado#	1.07	-.01(2.43)	3.27	.40	S (S)	7.50**	-.08(3.30)**	5.67**	.68	S (S)
Connecticut	.001	-.02(2.78)	5.98**	.39	S (S)	6.06**	-.07(3.19)*	6.63**	.67	S (S)
Delaware	.54	-.02(2.26)	3.30	.27	S (S)	2.61	-.02(2.26)	3.82	.66	S (S)
Florida#	.32	-.04 (5.14)**	8.93**	.59	S (S)	22.66**	-.09(4.48)**	14.09**	.56	S (S)
Georgia	.002	-.04(3.53)**	6.47**	.20	S (S)	6.22**	-.07(2.36)	5.43*	.32	S (S)
Hawaii#	2.90*	-.05(2.44)	8.11**	.21	S (S)	2.05	-.08(2.85)**	6.64**	.22	S (S)
Iowa#	6.89**	-.06 (4.18)**	6.11**	.35	S (S)	9.33**	-.05(2.43)	7.46**	.85	S (S)
Idaho#	.13	-.08 (4.55)**	8.22**	.37	S (S)	14.38**	-.12(3.14)*	7.08**	.83	S (S)
Illinois	6.61**	-.02(1.95)	1.83	.20	S (S)	18.14**	-.08(3.25)*	6.26**	.59	S (S)
Indiana	.04	-.05(3.85)**	7.54**	.19	S (S)	5.94**	-.03(1.01)	6.17**	.46	S (S)
Kansas	.37	-.03(3.21)*	3.82	.17	S (S)	8.53**	-.09(3.50)**	7.59**	.74	S (S)
Kentucky#	.05	-.04 (3.41)**	3.95	.26	S (S)	16.11**	-.08(2.99)*	7.04**	.73	S (S)
Louisiana	.03	-.01(1.44)	2.83	.26	S (S)	3.41*	-.08(2.76)	4.25	.18	S (S)
Massachusetts	.001	-.009(2.39)	4.59	.53	S (S)	13.78**	-.07(3.83)**	7.80**	.85	S (S)
Maryland#	.16	-.02 (4.03)**	6.08**	.51	S (S)	14.17**	-.09(4.26)**	9.41**	.60	S (S)
Maine	.001	-.02(1.96)	2.26	.26	S (S)	17.67**	-.08(3.71)**	8.94**	.89	S (S)
Michigan	1.65	-.04(3.95)**	9.12**	.31	S (S)	3.57*	-.04(1.26)	3.35	.61	S (S)
Minnesota	.05	-.01(1.87)	2.74	.35	S (S)	7.75**	-.08(2.98)*	6.51**	.83	S (S)
Missouri	.005	-.04(3.30)**	4.77	.55	S (S)	21.41**	-.10(3.55)**	10.82**	.71	S (S)
Mississippi	.37	-.06(2.51)	3.59	.25	S (S)	6.15**	-.06(2.57)	3.66	.42	S (S)
Montana#	2.64	-.06 (3.03)**	4.46	.29	S (S)	9.93**	-.08(3.56)**	6.56**	.93	S (S)

Table 1 continued.										
North Carolina	.64	-.02(1.98)	2.19	.25	S (S)	13.44**	-.09(3.66)**	7.50**	.44	S (S)
North Dakota#	.002	-.05 (1.93)	3.07	.21	S (S)	.40	-.02(.77)	.74	.90	S (S)
Nebraska	.57	-.02(2.03)	2.31	.08	S (S)	17.01**	-.11(4.37)**	11.57**	.82	S (S)
New Hampshire	.26	-.01(2.08)	2.70	.46	S (S)	14.65**	-.12(4.62)**	11.95**	.81	S (S)
New Jersey	1.19	-.008(1.86)	2.24	.53	S (S)	10.51**	-.09(3.81)**	8.37**	.66	S (S)
New Mexico	1.47	-.05(3.02)*	5.04*	.19	S (S)	.10	-.03(1.65)	2.44	.62	S (S)
Nevada	.008	-.04(4.10)**	9.06**	.49	S (S)	15.12**	-.04(2.38)	6.08**	.64	S (S)
New York#	.99	-.02 (2.92)*	6.35**	.31	S (S)	10.66**	-.10(4.00)**	8.72**	.68	S (S)
Ohio#	.76	-.03(3.30)**	4.85*	.36	S (S)	20.92**	-.11 (3.41)**	7.02**	.63	S (S)
Oklahoma	.48	-.01(1.86)	6.24**	.22	S (S)	.48	-.06(2.14)	3.75	.29	S (S)
Oregon#	.10	-.01 (1.76)	1.33	.40	S (S)	10.57**	-.10(3.35)**	6.11**	.77	S (S)
Pennsylvania#	.001	-.03 (3.12)*	3.63	.31	S (S)	16.41**	-.07(3.65)**	7.72**	.80	S (S)
Rhode Island	.45	-.01(1.79)	2.60	.47	S (S)	23.76**	-.09(4.88)**	14.72**	.88	S (S)
South Carolina	1.22	-.02(1.78)	2.11	.16	S (S)	8.24**	-.08(3.79)**	7.84**	.43	S (S)
South Dakota#	2.55	-.07 (1.63)	1.98	.28	S (S)	.24	-.05(1.95)	1.96	.83	S (S)
Tennessee#	1.19	-.07 (3.91)**	4.59	.17	S (S)	4.92**	-.05(2.31)	3.08	.46	S (S)
Texas	.68	-.01(1.74)	5.58*	.29	S (S)	7.03**	-.11(3.65)**	8.13**	.57	S (S)
Utah#	1.04	-.02 (2.45)	3.00	.28	S (S)	10.98**	-.09(3.92)**	9.90**	.78	S (S)
Virginia#	.001	-.02 (3.19)*	3.70	.32	S (S)	13.53**	-.10(3.91)**	8.76**	.56	S (S)
Vermont	.05	-.04(1.68)	2.53	.25	S (S)	12.31**	-.08(3.99)**	9.26**	.90	S (S)
Washington	.65	-.01 (2.07)	1.84	.41	S (S)	7.33**	-.09(3.77)**	7.85**	.83	S (S)
Wisconsin	.04	-.01(1.48)	1.96	.14	S (S)	23.45**	-.09(3.66)**	8.81**	.82	S (S)
West Virginia	.20	-.08(3.09)*	9.78**	.45	S (S)	13.07**	-.06(2.87)	6.44**	.71	S (S)
Wyoming#	.48	-.04 (3.88)**	8.47**	.22	S (S)	.08	-.03(1.16)	2.50	.84	S (S)
District of Columbia#	1.94	-.01 (1.98)	2.93	.51	S (S)	15.22**	-.10(3.88)**	8.05**	.70	S (S)

Notes:

a. Numbers inside the parentheses next to coefficient estimates are absolute values of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there is one exogenous variable (k=1) is 4.78 (5.73) at the 10% (5%) level of significance. These come from Pesaran *et al*. (2001, Table CI, Case III, p. 300).

c. The upper bound critical value of the t-test for significance of ECM_{t-1} is 2.91 (3.22) at the 10% (5%) level when k =1.

d. All Wald tests are distributed as χ^2 with one degree of freedom. The critical value is 2.71 (3.84) at the 10% (5%) level.

e. # indicates the dummy to account for Financial Crisis of 2008 was significant.

Table 3: Results from Nonlinear Model (5)												
	Unemployment Rate Causing House Prices (UN →HP)						House Prices Causing Unemployment Rate (HP →UN)					
	$\sum \hat{\delta}_i^+ \neq 0$	$\sum \hat{\delta}_i^- \neq 0$	***ECM_{t-1}***	***F-Test***	***Adj R^2***	***Q (Q^2)***	$\sum \hat{\delta}_i^+ \neq 0$	$\sum \hat{\delta}_i^- \neq 0$	***ECM_{t-1}***	***F-Test***	***Adj R^2***	***Q (Q^2)***
Alaska	3.16*	.46	-.04(1.20)	1.91	.16	S (S)	3.20*	.42	-.10(3.29)**	3.62	.94	S (S)
Alabama#	.10	5.65**	-.08 (3.55)**	4.71	.25	S (S)	1.99	10.34**	-.07(3.22)*	4.71	.61	S (S)
Arkansas	2.23	4.34**	-.02(1.56)	2.05	.07	S (S)	1.15	11.23**	-.05(3.21)*	4.21	.85	S (S)
Arizona#	.0006	1.85	-.03(2.92)	2.81	.45	S (S)	.09	14.58**	-.14(4.22)**	4.33*	.65	S (S)
California#	.07	.41	-.02(3.32)**	4.46	.71	S (S)	5.29**	4.83**	-.09(4.05)**	6.39**	.77	S (S)
Colorado	.007	.22	-.02(2.68)	2.87	.34	S (S)	.33	7.62**	-.09(3.48)**	5.15*	.68	S (S)
Connecticut	.02	.25	-.02(2.73)	2.98	.42	S (S)	.50	12.82**	-.08(3.47)**	5.11*	.67	S (S)
Delaware#	.006	.25	-.05(3.07)	3.29	.26	S (S)	.84	9.00**	-.14 (3.75)**	4.86*	.68	S (S)
Florida	1.17	.66	-.04(3.80)**	4.84*	.49	S (S)	.94	18.25**	-.10(4.34)**	8.17**	.56	S (S)
Georgia#	.88	.01	-.06(4.63)**	7.29**	.31	S (S)	.02	9.42**	-.14 (2.98)	4.09	.37	S (S)
Hawaii	.07	2.54	-.16(3.66)**	7.27**	.24	S (S)	21.42**	23.70**	-.13(4.64)**	10.77**	.31	S (S)
Iowa	6.92**	1.74	-.08(4.83)**	8.24**	.40	S (S)	18.42**	.61	-.03(1.67)	3.39	.85	S (S)
Idaho	3.05*	.15	-.06(2.96)	3.43	.45	S (S)	5.69**	16.61**	-.13(3.28)**	5.26*	.83	S (S)
Illinois#	3.80**	4.55*	-.08 (6.12)**	11.42**	.43	S (S)	.006	22.45**	-.11(3.72)**	5.77**	.62	S (S)
Indiana#	3.95**	1.19	-.07(4.95)**	9.20**	.27	S (S)	.36	6.80**	-.09 (2.62)	3.96	.48	S (S)
Kansas	.35	1.19	-.03(3.60)**	4.27	.25	S (S)	.08	8.54**	-.11(3.51)**	5.41*	.75	S (S)
Kentucky#	4.62**	3.70**	-.09 (5.47)**	8.89**	.46	S (S)	4.24**	29.21**	-.10(3.27)**	7.01**	.74	S (S)
Louisiana#	1.37	1.73	-.12(3.54)**	2.29	.24	S (S)	9.21**	.02	-.17 (4.29)**	5.45*	.25	S (S)
Massachusetts	.64	2.19	-.02(3.86)**	5.47*	.61	S (S)	1.05	9.13**	-.06(3.11)	4.61	.84	S (S)
Maryland#	.58	1.88	-.05(4.75)**	7.54**	.50	S (S)	1.49	11.51**	-.12 (4.20)**	5.72*	.66	S (S)
Maine	.16	.04	-.06(3.08)	3.47	.25	S (S)	8.32**	21.60**	-.08(3.75)**	9.37**	.90	S (S)
Michigan#	.14	.76	-.06 (4.07)**	5.29*	.35	S (S)	3.55*	8.66**	-.08 (2.60)	6.02**	.67	S (S)
Minnesota	.79	.23	-.03(3.71)**	5.26*	.41	S (S)	.26	19.34**	-.12(4.11)**	10.48**	.85	S (S)
Missouri#	.10	.001	-.08 (5.44)**	9.11**	.53	S (S)	5.13**	15.01**	-.08(2.85)	6.88**	.71	S (S)
Mississippi	.91	.07	-.07(2.78)	3.27	.25	S (S)	5.42**	20.10**	-.09(3.76)**	5.74**	.47	S (S)
Montana#	.43	4.67**	-.08(4.18)**	7.45**	.37	S (S)	1.07	9.47**	-.17 (4.67)**	6.52**	.93	S (S)

Table 2 continued.												
North Carolina#	.15	2.97*	-.09 (4.76)**	9.04**	.49	S (S)	.57	17.68**	-.13(4.08)**	7.83**	.54	S (S)
North Dakota	.47	.81	-.04(1.72)	3.21	.24	S (S)	.16	.63	-.06(1.93)	1.86	.90	S (S)
Nebraska	12.80**	3.55*	-.03(2.55)	8.07**	.29	S (S)	2.72*	13.53**	-.08(3.45)**	5.19*	.84	S (S)
New Hampshire	.40	4.32**	-.03(3.36)*	4.98*	.50	S (S)	.12	11.38**	-.11(3.92)**	7.34**	.81	S (S)
New Jersey	.07	1.40	-.03(3.53)**	4.76	.59	S (S)	.04	7.42**	-.08(3.17)*	4.70	.67	S (S)
New Mexico#	3.38*	.53	-.05(3.26)*	4.42	.24	S (S)	.82	.01	-.10 (3.61)**	3.99	.74	S (S)
Nevada#	1.79	.81	-.05(4.38)**	6.88**	.49	S (S)	.21	17.35**	-.11 (5.04)**	6.20**	.67	S (S)
New York#	1.96	.16	-.05(4.22)**	9.63**	.34	S (S)	2.15	.50	-.11 (3.27)**	3.39	.69	S (S)
Ohio#	3.94**	1.82	-.05 (4.09)**	4.45	.52	S (S)	10.24**	42.10**	-.14(4.41)**	10.15**	.65	S (S)
Oklahoma	9.18**	.85	-.01(2.12)	6.72**	.27	S (S)	1.81	1.13	-.06(2.02)	1.80	.42	S (S)
Oregon	.003	.12	-.03(3.35)**	4.07	.44	S (S)	.34	17.07**	-.14(4.55)**	8.24**	.77	S (S)
Pennsylvania	2.49	.50	-.05(4.07)**	6.58**	.33	S (S)	.04	22.30**	-.08(4.08)**	6.94**	.81	S (S)
Rhode Island#	4.29**	2.78*	-.03(3.01)	4.04	.50	S (S)	6.97**	18.36**	-.11 (4.35)**	9.93**	.89	S (S)
South Carolina	.21	1.22	-.06(3.42)**	3.78	.16	S (S)	.10	12.84**	-.12(4.30)**	7.26**	.44	S (S)
South Dakota	.34	.15	-.11(2.46)	3.52	.30	S (S)	.06	1.40	-.06(2.08)	3.87	.84	S (S)
Tennessee	.92	.99	-.09(4.32)**	6.08**	.16	S (S)	1.50	14.09**	-.11(3.99)**	5.72*	.49	S (S)
Texas#	.03	.23	-.01 (2.00)	3.82	.32	S (S)	2.58	1.11	-.09(3.38)**	4.88*	.58	S (S)
Utah#	2.26	.06	-.03(2.43)	2.40	.33	S (S)	4.22**	.03	-.07 (3.39)**	6.09**	.83	S (S)
Virginia#	3.15*	.60	-.05(4.46)**	6.78**	.34	S (S)	.09	10.48**	-.12 (3.84)**	4.30**	.59	S (S)
Vermont	5.03**	2.48	-.19(3.55)**	4.50	.37	S (S)	2.71*	10.83**	-.09(4.14)**	7.89**	.91	S (S)
Washington#	2.78*	1.63	-.04(3.49)**	4.54	.45	S (S)	4.52**	.07	-.11 (4.27)**	7.82**	.85	S (S)
Wisconsin#	.02	2.95*	-.07 (4.70)**	4.46	.22	S (S)	.05	20.39**	-.11(4.27)**	7.83**	.82	S (S)
West Virginia#	.03	2.01	-.11(3.98)**	9.00**	.43	S (S)	4.17**	2.19	-.14 (4.56)**	7.03**	.81	S (S)
Wyoming#	.41	.29	-.04(3.24)*	6.80**	.34	S (S)	3.07*	2.16	-.20 (4.74)**	10.63**	.90	S (S)
District of Columbia#	3.75*	.18	-.07 (4.04)**	3.96	.53	S (S)	10.84**	.18	-.10(2.99)	2.76	.69	S (S)

Notes:

a. Numbers inside the parentheses next to coefficient estimates are absolute values of t-ratios. *, ** indicate significance at the 10% and 5% levels respectively.

b. The upper bound critical value of the F-test for cointegration when there is one exogenous variable (k=1) is 4.78 (5.73) at the 10% (5%) level of significance. These come from Pesaran *et al*. (2001, Table CI, Case III, p. 300).

c. The upper bound critical value of the t-test for significance of ECM_{t-1} is 3.21 (3.53) at the 10% (5%) level when k =2.

d. All Wald tests are distributed as χ^2 with one degree of freedom. The critical value is 2.71 (3.84) at the 10% (5%) level.

e. # indicates the dummy to account for Financial Crisis of 2008 was significant.