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Asymmetric Causality between Unemployment Rate and House Prices in each State of the U.S.

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The Great Recession of 2008 in the U.S. was mostly attributed to the U.S. housing market bubble that came to an end in 2007. In this paper, we provide empirical evidence on the above conjecture by detecting the asymmetric causality between house prices and unemployment rate in each state of the U.S. We find that indeed, decreases in house prices cause unemployment in 39 states. There is evidence in only 19 states that an increase in house prices causes unemployment. Since an asymmetric analysis requires the use of nonlinear models, we use nonlinear models and find evidence of asymmetric cointegration between the two variables in all states.

Keywords

House Prices, Unemployment Rate, Asymmetry, United States

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1. Introduction

The neo-classical framework indicates that house prices are determined by the law of demand and supply for 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, the cost of land and construction 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 that affects the housing market and other sectors of the economy. For example, the Great Recession of 2008 in the U.S. has been said to be the result of the housing market bubble burst. Abnormal increases 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 extended to other sectors of the U.S. economy via multiplier effects, causing the unemployment rate to rise in every state. In turn, unemployed individuals who were unable to pay their mortgage 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 mutually cause each other.

Almost all studies related to the housing market have focused on household income and interest rates as the two main determinants of house prices and tried to establish a short-run causality and long-run relationship among these two 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), who have investigated short-run causalities or long-run relationships 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 formulate the supply and demand link for housing in the U.S., identify the unemployment rate as one of many determinants of house prices. Their model estimates reveal that the recovery of house prices in the late 1980s could be attributed to less unemployment and lower interest rates. Similar results are later obtained by Apergis (2003) and Apergis and Rezitis (2003) who use data from Greece. They conclude that interest rates, inflation, and employment are the main determinants of house prices in Greece. Finally, Abelson et al. (2005) find a long-run elasticity of -0.2 between real house prices and unemployment rate in Australia. Unlike studies which use an aggregate measure of house prices and unemployment rate from each country, Kim and Bhattacharya (2009) use 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 use data from 1969 to 2004, their findings can 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 focusing on four regions, we use data from each of the 51 states of the U.S. and try to find causality between house prices and the unemployment rate in each state. Our approach will be different from those in previous studies and based on asymmetric cointegration and error-correction modeling which require the use of nonlinear rather than linear models. To this end, an introduction on the models and methods is provided in Section II. We then report the empirical results in Section III. Finally, Section IV concludes, while data sources and variable definitions are reported in the Appendix.

2. Models and Methods

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

$$LnHP_t = a + bLnUN_t + \varepsilon_t \tag{1}$$

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

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

In the error-correction model (ECM; Equation 2), Granger (1988, p. 203) points to two possible sources of causality. One is through the first-differenced variable where the *UN* Granger causes *HP* if $\sum \hat{\delta}_i \neq 0$ and the other is through ε_{t-1} if an estimate of λ is negative and significant. In the literature, the first causality is referred to as the short-run causality and the second as the long-run causality (Jones and Joulfaian, 1991, p. 151). Furthermore, Banerjee et al. (1998) demonstrate that if the estimate of λ is negative and significant, then the

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

two variables are said to converge toward their long-run equilibrium values or are cointegrated.[2]

The main assumption behind Equation (2) is that both the *HP* and *UN* variables are integrated of the order one, I(1), and that is why we use their first differences as a stationary variable. In case one is already a stationary variable at level, I(0), and the other is I(1), Pesaran et al. (2001) modify Equation (2) and rely on Specification (3):

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

They then recommend applying the *F* test to establish the joint significance of lagged level variables as a sign of cointegration. Since the distribution of the *F* test is non-standard, they tabulate new critical values that account for integrating properties of variables which could be a combination of I(0) and I(1).[3] Bahmani-Oskooee and Oyolola (2007) have extended the same concept of causality testing from Equations (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 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 Specification (3) by ECM_{t-1}, we estimate the new specification one more time and if ECM_{t-1} carries a negative and significant coefficient, then long-run causality and cointegration are established.[4]

The main assumption so far behind any of the above specifications is that if an increase in the *UN* causes the *HP* to decline, a decrease in the *UN* causes the *HP* to rise, by the same proportion. However, changes in the *UN* could have asymmetric effects on *HP*. When the *UN* declines, more people are working with expected increases in their current and future incomes which could translate into an increase in demand for housing and eventually an increase in *HP*. However, when the *UN* increases, the adverse effect may not be as strong as anticipated since some unemployed individuals may continue financing their mortgage out of their savings until they find another job. In order to incorporate

[2] Note that Banerjee et al. (1998) list new critical values for the t test to be used in judging the significance of λ. Furthermore, the Wald test is applied to test if $\sum \hat{\delta}_i \neq 0$

[3] Since almost all of the 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 is listed by Pesaran et al. (2001, p. 303).

the asymmetric effects of the *UN* on house prices, we follow Shin et al. (2014) and first form changes in the *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 Equation (4) below:

$$\begin{aligned} POS_t &= \sum_{j=1}^{t} \Delta LnUN_j^+ = \sum_{j=1}^{t} \max(\Delta LnUN_j, 0) \\ NEG_t &= \sum_{j=1}^{t} \Delta LnUN_j^- = \sum_{j=1}^{t} \min(\Delta LnUN_j, 0) \end{aligned} \tag{4}$$

In Equation (4), the positive (*POS*) variable which is the partial sum of the positive changes only reflects an increase in the *UN* and the negative (*NEG*) variable which is the partial sum of the negative changes only reflects a decrease in the *UN*. Shin et al. (2014) then propose moving back to Specification (3) and replacing *LnUN* with *POS* and *NEG* variables. The new specification is as follows:

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

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

Bahmani-Oskooee and Ghodsi (2017b) have extended the concept of symmetric causality from Specifications (3) to (5). Following their approach, if an increase in the *UN* is to cause *HP*, we must establish $\sum \hat{\delta}_i^+ \neq 0$ by applying the Wald test. Similarly, if a decline in the *UN* is to cause *HP*, $\sum \hat{\delta}_i^- \neq 0$ should be established. As for the long run causality, again, we use normalized long-run estimates and a long-run specification to generate the error term, ECM, in this context. We then replace the linear combination of lagged level variables by using ECM_{t-1} and test for the significance of this term.[6] By switching the

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

[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* $\hat{c} = \hat{\rho}_1^- / -\hat{\rho}_0$.

dependent and independent variables in Equation (1) and following Specifications (2)-(5), we will be able to also test for causality that could run from changes in *HP* to *UN*.[7]

3. Results

In this section, we estimate both the linear and nonlinear models by using quarterly data over the period of1976Q1-2016Q1from each state of the U.S.[8] A maximum of eight lags are imposed onto each first differenced variable, and Akaike's criterion (AIC) is used to select the optimum model. Any estimate (coefficient or diagnostic statistic) that is significant at the 10% level, is identified by * and that which is significant at the 5% level is indicated with **. Furthermore, a dummy variable is included to account for the exact timing of the global financial crisis of 2008. We assign a value of 1 for the period prior to 2008Q3 and zero thereafter.[9] States in which the dummy is significant are identified by #.

Due to the volume of the results, clearly, we cannot report all of 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.

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

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[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 the bankruptcy of the Lehman Brothers on 15 September 2008 (Grammatikos and Vermeulen, 2012, p. 518).
[10] Note that in this case, the lack of a short-run causality is supported by an insignificant short-run coefficient attached to $\Delta LnUN$ in Panel A or by an insignificant Wald test of 2.64 to test if $\sum \hat{\delta}_i = 0$.

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**
$\boldsymbol{\Delta LnUN_t}$	-.02(1.57)		$\boldsymbol{\Delta LnHP_t}$	-.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)**	
$\boldsymbol{\Delta POS_t}$		-.05 (2.50)**	$\boldsymbol{\Delta POS_t}$		-.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)**
$\boldsymbol{\Delta NEG_t}$		.01 (.25)	$\boldsymbol{\Delta NEG_t}$		.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)**

(Continued…)

(Table 1 Continued)

Section I: *Ln HP = F (Ln UN)*			**Section II: *Ln UN = F (Ln HP)***		
Panel B: Long-Run	**Linear ARDL**	**Nonlinear ARDL**	**Panel B: Long-Run**	**Linear ARDL**	**Nonlinear ARDL**
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 the coefficient estimates are the 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 the financial crisis of 2008 is significant.

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

In the second column of Section I, we consider the estimates of the nonlinear model (Specification (5)). As can be seen, both *ΔPOS* and *ΔNEG* carry at least one lagged significant coefficient, thus implying that both increases and decreases in *UN* 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 the 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 that to establish $\sum \hat{\delta}_i^- = 0$ is highly significant, there is evidence of an asymmetric causality in the short-run in this state. In the short-run, while increases in the *UN* do not cause *HP*, decreases in the *UN* do cause *HP*. However, due to nature of the vector autoregressive (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 on the long-run estimates. From Panel B and the long-run coefficient estimates, we gather that both *POS* and *NEG* carry significant and negative coefficients, thus supporting the idea that in the long-run, high *UN* will cause *HP* to decline and low *UN* will cause *HP* to rise. This long-run causality which 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 *UN* has attributed to significant results and increased the adjusted R^2**.**

Next, we switch the two variables around in both models and assess causality that may run from *HP* to *UN*. 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 HP have short-run effects on the *UN* in Montana since two of the three lags are significant. Since the sum of the lagged coefficients is highly significant, there is evidence of short-run causality from *HP* to the *UN* in Montana. These short-run effects last into the long-run since in Panel B, *LnHP* carries a negative and significant coefficient. Thus, *HP* cause *UN* in the long run as well. Again, this is supported by a significant ECM_{t-1} for long-run causality and the *F* test for cointegration. Other statistics are the same as before except the size of the adjusted R^2 which is substantially higher when *HP* are treated as an independent variable. The nonlinear model supports the same idea in that both *ΔPOS* and *ΔNEG* which reflect increases and decreases in *HP* have short-run effects on the *UN* 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 do not cause the *UN* 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 estimates, thus implying that in the long run, increases in *HP* cause the *UN* to decline and decreases in the *HP* cause the *UN* to increase. This long-run causality is further confirmed by the significantly negative coefficient estimate of ECM_{t-1} and the significant *F* test for asymmetric cointegration.[11]

Based on 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 carries at least one lagged significant coefficient in 24 states. However, in the associated nonlinear model, *HP = F (POS, NEG*) at least either the *ΔPOS* or *ΔNEG* carries significant coefficients in 38 states, thus supporting relatively more short-run effects in the nonlinear model. However, when the two variables are switched around, in the linear model where *LnUN = F (LnHP)*, the *ΔLnHP* variable carries at least one lagged significant coefficient in 44 states. However, in the associated nonlinear model, at least the *ΔPOS* or *ΔNEG* carries significant coefficients in 50 states, 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 *HP* 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).

From the estimates of the linear models in Table 2, we gather that the *UN* causes *HP* in only five states in the short run: Alaska, California, Hawaii, Iowa, and Illinois, since $\sum \hat{\delta}_i \neq 0$ only in these five states. However, since ECM_{t-1} carries a significantly negative coefficient in 21 states, the *UN* causes *HP* more in the long run than short run. Furthermore, cointegration between *HP* and *UN* is confirmed by either the *F* test or ECM_{t-1} test in 25 states, thus 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 HP causing unemployment. There is now evidence of *HP* causing unemployment in 43 states in the short run. This supports the melt down of the U.S. economy in the Great Recession of 2008 which was said to be due to the housing market bubble burst. Such strong findings are further supplemented by evidence of long-run causality in 32 states, reflected by the negative and significant coefficients attached to the ECM_{t-1}. Additional support is provided

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

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

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 the 2008 financial crisis, again, we test for the stability of the short-run and long-run coefficient estimates by applying the CUSUM and CUSUMSQ tests in each model. These are denoted by Q and Q^2 in the table and support the stability of our estimates. Like the case of Montana, the size of the adjusted R^2 is higher when *HP* are the independent variable.

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

Once again, the outcome is much stronger in the results for *HP* causing unemployment in the nonlinear model. As can be seen, it is the decline in *HP* in 37 states that causes the unemployment in the short run, again, consistent with the 2008 crisis in the U.S. Increases in *HP* cause the *UN* in only 20 states. These results are supplemented by a significant ECM_{t-1} for long-run causality in 41 states and either the *F* or ECM_{t-1} test for cointegration in almost all states. If we choose the size of the adjusted R^2 as a model selection criterion, there is overwhelming support for the nonlinear adjustment of *HP* that cause the *UN* in almost all states and this supports the current housing market recovery and low rate of unemployment in most states of the U.S.

4. 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 fluctuations in *HP*, 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 equally important factors need to be identified. In 2008, when the *HP* in the U.S. began to decline abnormally, new constructions stopped. The recession in the housing market spread to the rest of the U.S. economy which resulted in the Great Recession. Although the federal government quickly acted by lowing the interest rates, we conjecture that growth in the U.S. economy and gradual decline in the *UN* have also contributed to the housing market recovery, hence an increase in *HP*.

Table 2 Results from the Linear Models (3)

	Unemployment Rate Causing House Prices ($UN \rightarrow HP$)					House Prices Causing Unemployment Rate ($HP \rightarrow UN$)				
	$\sum \hat{\delta}_i \neq 0$	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)

(Continued…)

(Table 2 Continued)

	Unemployment Rate Causing House Prices ($UN \rightarrow HP$)					House Prices Causing Unemployment Rate ($HP \rightarrow UN$)				
	$\sum \hat{\delta}_i \neq 0$	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)
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)
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)

(Continued…)

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(Table 2 Continued)

	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	$Q\ (Q^2)$
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 the coefficient estimates are the 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 the financial crisis of 2008 is significant.

Table 3 Results from the Nonlinear Models (5)

	Unemployment Rate Causing House Prices ($UN \rightarrow HP$)						House Prices Causing Unemployment Rate ($HP \rightarrow UN$)					
	$\sum\hat{\delta}_i^+ \neq 0$	$\sum\hat{\delta}_i^- \neq 0$	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)

(Continued…)

(Table 3 Continued)

	Unemployment Rate Causing House Prices ($UN \rightarrow HP$)						House Prices Causing Unemployment Rate ($HP \rightarrow UN$)					
	$\sum \hat{\delta}_i^+ \neq 0$	$\sum \hat{\delta}_i^- \neq 0$	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)
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)
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)

(Continued…)

(Table 3 Continued)

	Unemployment Rate Causing House Prices ($UN \rightarrow HP$)						House Prices Causing Unemployment Rate ($HP \rightarrow UN$)					
	$\sum \hat{\delta}_i^+ \neq 0$	$\sum \hat{\delta}_i^- \neq 0$	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)
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 the coefficient estimates are the 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 the financial crisis of 2008 is significant.

In this paper, we investigate the link between real *HP* and the *UN* by using state level data from the U.S. Assuming the relation between these two variables to be linear or the effects of one variable on the other to be symmetric, we find that while the *UN* causes *HP* in five states, the *HP* in 43 states cause the *UN* thus supporting the Great Recession of 2008 which was said to be mostly due to declines in *HP*. However, in order to justify this fact, we take an additional step and separate the declines from increases in *HP*s and engaged in finding asymmetric causality and carrying out an asymmetric cointegration analysis. This practice amounts to the use of nonlinear models. We find that indeed, it is the decrease in *HP* that causes the *UN* in 37 states. Evidence of an increase in *HP* causing the *UN* is limited to 20 states. Furthermore, evidence of the *UN* causing *HP* in the nonlinear model is limited to several states. A major policy implication of our findings is that stabilizing the housing market and *HP* contributes to economic stability led by a stable *UN*.

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Appendices

Appendix I Data Sources and Definitions

Quarterly data over the period of 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

Appendix II Variables

HP: House price index. This is a broad measure of the movement of single-family house prices constructed and published by the U.S. Federal Housing Finance Agency. We have deflated house prices HP by using consumer price index (CPI) data (U.S. Bureau of Labor Statistics) to obtain the real house prices.

UN: Unemployment rate. Each month, the Current Employment Statistics Program surveys about 146,000 businesses and government agencies, which represent 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 the U.S. Bureau of Labor Statistics.