



Asymmetric causality between the U.S. housing market and its stock market: Evidence from state level data

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ABSTRACT

Previous research that investigated the link between the U.S. housing market and its stock market concentrated on the wealth effect by assuming the stock prices to be another determinant of house prices. However, the meltdown of housing market and its subsequent impact on the stock market and the U.S. economy in 2008 pointed to causal relation that could run from housing market to stock market. When we tested this hypothesis using state level data, we found short-run symmetric causality from stock prices to house prices in 10 states and from house prices to stock prices in 20 states. However, when we engaged in asymmetric causality, these numbers increased to 25 and 41 respectively. Surprisingly, in 39 out of 41 states in which house prices caused stock prices, it was decline in house prices that caused stock prices, supporting the events of 2008 as well as asymmetric impacts. We also found cointegration of the two markets in more than half of the states.

1. Introduction

The main cause of the Great Recession of 2008 here in the U.S. was identified to be the burst of the bubble in the U.S. housing market. As house prices began to fall and the U.S. economy entered into a recessionary cycle, the U.S. stock market began to suffer and shares of most firms began to lose.¹ Based on such an observation, we would expect to see house prices to be a determinant of stock prices. Yet, the few studies assessing the impacts of changes in stock prices on house prices, known as the “wealth effect”, tend to include stock prices in a model of house price determination. Once they include some other determinants of house prices such as household income and mortgage rates, the main concern has been to determine if the two markets are integrated or segmented. The findings are mixed at best. While early studies such as Liu, Hartzell, Greig, and Grissom (1990), Okunev and Wilson (1997) did not find any link between the two markets, more recent studies that applied advances in error-correction modeling and cointegration approaches, did find support for cointegration between the two markets. Example includes Liow and Yang (2005), Liow (2006), Liu and Su (2010), Tsai, Lee, and Chiang (2012), Ding, Chong, and Park (2014), Lin and Fuerst (2014), and Bahmani-Oskooee and Wu (2017).²

The above studies were recently criticized by Bahmani-Oskooee and Ghodsi (2018) for using aggregate data from a specific country. Almost all mentioned studies have used an overall index of house prices and share prices from an individual country. In hope of finding more support for the wealth effect, Bahmani-Oskooee and Ghodsi (2018) used an index of house prices from each state of the U.S. and tried to identify the states that have benefitted from recent gains in the U.S. stock market. Like previous studies, they relied upon a model

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¹ For more see Bahmani-Oskooee and Ghodsi (2016).

² For a detailed review of these studies see Bahmani-Oskooee and Ghodsi (2018).

of house price determination that includes the index of S & P 500 as another determinant of house prices. They did not consider the possibility of causal effect from house prices to S & P 500. To fill this gap, in this paper we consider the short-run and the long-run causality that may exist between S & P 500 index and house prices in each state of the United States. The evidence in support of causal relation between the two variables extends to more states when we engage in asymmetric causality between the two variables. To show how, in Section II we introduce the symmetry and asymmetry causality detection approaches. We then present the results in Section III with our summary that appears in Section IV. Data definition and sources are cited in an [Appendix](#).³

2. The model and the methods

Based on our observation of declines in house prices in the U.S. as the main cause of the Great Recession of 2008 and the eventual decline in the stock market, we begin with postulating house prices (HP) as a determinant of stock prices (SP) as outlined by specification (1) below:

$$\text{LnSP}_t = a + b\text{LnHP}_t + \varepsilon_t \quad (1)$$

Equation (1) outlines house prices as a determinant of stock prices and once it is estimated by any method, estimate of b is said to be a long-run elasticity. However, (1) cannot be used to detect short-run causality that may run from house prices to stock prices. To detect causality between the two variables, a common practice is to rely upon the concept of Granger causality. According to [Granger \(1969\)](#) in detecting causality that may run from house prices to stock prices, we must account for the past history of stock prices by concentrating on a specification such as (2):⁴

$$\Delta \text{LnSP}_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta \text{LnSP}_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta \text{LnHP}_{t-i} + \mu_t \quad (2)$$

[Granger \(1969\)](#) demonstrated that if after accounting for past performance of stock prices, lagged value of house prices (HP) in (2) are jointly significant, the HP causes SP. This is tested by estimating (2) using a lag-selection criterion and establishing the fact that $\sum \delta_i / = 0$ using the F or Wald test. As time-series approaches advance, later [Granger \(1988, p. 203\)](#) identified another source of causality from HP to SP which is detected through an error-correction specification as outlined by (3):

$$\Delta \text{LnSP}_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta \text{LnSP}_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta \text{LnHP}_{t-i} + \lambda \varepsilon_{t-1} + \mu_t \quad (3)$$

The second source of causality from HP to SP is through lagged error term by establishing the fact that an estimate of λ is negative and significant. [Banerjee, Dolado, and Mestre \(1998\)](#) demonstrate that the t -test that is used to test the significance of λ has a new distribution for which they tabulate new critical values. They also demonstrate that if λ is negative and significant, that will be an indication of cointegration between the two variables. Indeed, the first channel is referred to as short-run causality and the second one as long-run causality ([Jones & Joulfaian, 1991, p. 151](#)). Note that an alternative way of establishing cointegration or long-run causality is to show that both variables in (1) are integrated of order one, $I(1)$, but the residuals are integrated of order zero, $I(0)$.⁵

What happens if one variable is $I(1)$ and the other $I(0)$? In a multivariate models, the question will change to what to do when we have combination of $I(1)$ and $I(0)$ variables which are the properties of almost all time-series macro variables. [Pesaran, Shin, and Smith \(2001\)](#) propose an alternative approach within which variables could be combination of $I(1)$ and $I(0)$. They solve (1) for ε_t first, lag the solution by one period, and substitute the result for ε_{t-1} in (3) to arrive at:

$$\Delta \text{LnSP}_t = \alpha + \sum_{i=1}^{n1} \beta_i \Delta \text{LnSP}_{t-i} + \sum_{i=0}^{n2} \delta_i \Delta \text{LnHP}_{t-i} + \lambda \text{LnSP}_{t-1} + \lambda b \text{LnHP}_{t-1} + \mu_t \quad (4)$$

Once (4) is estimated using a lag selection criterion, [Pesaran et al. \(2001\)](#) propose two tests to establish cointegration. One is the F test to establish joint significance of lagged level variables and the other is the t -test to show that an estimate of λ is negative and significant. However, since variables in a given model could be combination of $I(1)$ and $I(0)$, both tests do have new critical values that they tabulate. Note that the long-run effects of HP on SP that is reflected in an estimate of b in long-run model (1) is derived here by normalizing the estimate obtained for LnHP_{t-1} by estimate obtained for LnSP_{t-1} . Short-run effects are still inferred by estimates of δ_i 's and short-run causality is established by showing that $\sum \delta_i \neq 0$.

In all of the above specifications, there is a common assumption of asymmetric effects of changes in house prices or stock prices, i.e., estimate of b is the same for house price increase as well as house price decrease. However, this need not be the case and indeed it was not the case. The rate at which stock prices dropped during 2008 Financial Crisis because of the collapse of the housing market has not been the same the rate at which both markets have recovered. This implies that the effects of house price changes on stock prices could

³ Other time-series studies that have emphasized fundamentals but not stock prices are: [Chen and Patel \(1998\)](#), [Meen \(2002\)](#), [Apergis \(2003\)](#), [Abbott and De Vita \(2012, 2013\)](#), [Chen, Tsai, and Chang \(2007\)](#), [McQuinn and O'Reilly \(2008\)](#), [Kim and Bhattacharya \(2009\)](#) and [Zhou \(2010\)](#). There are also several panel studies. The list includes [Malpezzi \(1999\)](#), [Gallin \(2006\)](#), [Mikhed and Zemcik \(2009\)](#), [Holly, Pesaran, and Yamagata \(2010\)](#), [Madsen \(2012\)](#), and [Bahmani-Oskooee and Ghodsi \(2017\)](#).

⁴ Note that (2) is based on the assumption that both variables are first-differenced stationary or integrated of order one, $I(1)$.

⁵ This is the original theorem proposed by [Engle and Granger \(1987\)](#).

be asymmetric. In order to show this possibility, we will follow [Shin, Yu, and Greenwood-Nimmo \(2014\)](#) who modified models like (4) and introduced the concept of asymmetric cointegration and asymmetric causality. The modification basically involves replacing $LnHP$ variable in (1) and (4) by two new time-series variables, one representing only house price increases and one representing house price declines. To that end we form $\Delta Ln HP$ first. This new time-series variable includes positive and negative changes. We then use the concept of partial sum to construct the POS as partial sum of positive changes and NEG as partial sum of negative changes representing our two new variables. These two new variables are constructed as:

$$POS_t = \sum_{j=1}^t \max(\Delta LnHP_j, 0), \quad NEG_t = \sum_{j=1}^t \min(\Delta LnHP_j, 0) \quad (5)$$

The next step is to shift back to (1) and (4) and replace $LnHP$ variable with POS and NEG variables to arrive at:

$$\begin{aligned} \Delta LnSP_t = & \alpha + \sum_{i=1}^{n1} \beta_i \Delta LnSP_{t-i} + \sum_{i=0}^{n2} \delta_i^+ \Delta POS_{t-i} + \sum_{i=0}^{n3} \delta_i^- \Delta NEG_{t-i} \\ & + \rho_0 LnSP_{t-1} + \rho_1^+ POS_{t-1} + \rho_1^- NEG_{t-1} + \xi_t \end{aligned} \quad (6)$$

Specifications like (6) are usually referred to as Nonlinear Autoregressive Distributed Lag (NL-ARDL) models due to method of constructing the two partial sum variables. However, the original model (4) is labeled as the Linear ARDL (L-ARDL) model.

Error-correction model (6) could be estimated by using a lag selection criterion and we can then test asymmetric causality by applying the Wald test to determine if either $\sum \delta_i^+ \neq 0$ or $\sum \delta_i^- \neq 0$. If the first condition is established, that will support short-run causality from increase in house prices to stock prices. The second condition is to show short-run causality of decrease in house prices. Furthermore, cointegration between $LnSP$, POS and NEG variables will be established by applying the F test to establish joint significance of lagged level variables or the t -test to determine if ρ_0 is significantly negative. It must be indicated that in the case of the F test, [Shin et al. \(2014, p. 291\)](#) recommend treating POS and NEG as one variable and using the critical values for the case of $k = 1$. This is mostly due to dependency between POS and NEG and the fact that critical values are higher for the case of one exogenous variable ($k = 1$) compared to two variables, i.e., $k = 2$.⁶ By switching the two variables in equation (1) and going through the same analysis, we will also assess the asymmetric causality from the stock market to the housing market.⁷

3. The results

In this section, we estimate both linear ARDL model (4) and the nonlinear ARDL model (6) using house price index from each of the 50 states and DC in the United States. Quarterly data covering the period 1975I-2016III are used to carry out the empirical exercise.⁸ As a preliminary exercise, we first thought to verify an important requirement of the ARDL approach that all variables have to be either I(0) or I(1). To this end, we applied the well-known ADF test to the level as well as first-differenced variables and reported the results in [Table 1](#). As can be seen, only in two states of Maryland and New Jersey the house price is neither I(0) nor I(1). Thus, the results for these two states should be viewed with some caution.

Next we estimate both the linear ARDL model (4) and the nonlinear ARDL model (6). A maximum of eight lags is imposed on each first-differenced variable and Akaike's Information Criterion (AIC) is used to select an optimum model. Using the critical values that are reported in the notes to each table, we identify an estimate by * (**) if that estimate is significant at the 10% (5%) level. While [Table 2](#) reports the outcome of the estimates from the linear model, [Table 3](#) does the same from the nonlinear ARDL model.

From Panel A which includes short-run causality detection and long-run cointegration test results for the case of stock prices causing house prices, we gather that in the linear ARDL model, stock prices Granger cause house prices in the short run in a total of 10 states. In these states (i.e., California, Colorado, Florida, Louisiana, Montana, North Carolina, Nebraska, New Mexico, Oregon, and Wyoming) the Wald statistic is significant supporting $\sum \delta_i \neq 0$. However, long-run causality or cointegration is supported by either the t -test or the F test in 29 states. This supports the wealth effects in most states. However, when we consider causality from house prices to stock prices in Panel B, while we find short-run causality in 20 states, it does not last into the long run since neither the F test nor the t -test is significant in any state. This is also reflected in poor sizes of adjusted R^2 s in Panel B compared to those in Panel A. In sum, whereas in the short-run there is more evidence of house prices causing stock prices, supporting the melt down in the housing market as the source of 2008 Financial Crisis, we do not observe this in the long run.⁹

The results become somewhat stronger when we separate increase in both variables from declines and shift to estimates of the nonlinear models that are reported in [Table 3](#). From Panel A in [Table 3](#), there is evidence of short-run causality from stock prices to house prices in a total of 25 states. While in 12 states (i.e., Alabama, Indiana, Mississippi, Montana, New Mexico, Oklahoma, Utah, and Wyoming) increased stock prices cause house prices, in another 13 states (i.e., Colorado, Florida, Georgia, Kansas, Kentucky, Louisiana, Minnesota, Missouri, North Carolina, Nebraska, New Jersey, Nevada, and South Carolina) decline in stock prices causes house prices. In

⁶ For some other application of these methods see [Bahmani-Oskooee and Saha \(2015, 2016\)](#).

⁷ For some other application of these methods see [Arize, Malindretos, and Igwe \(2017\)](#), [Al-Shayeb and Hatemi \(2016\)](#).

⁸ Note that no data were available for Puerto Rico.

⁹ Note also that to establish stability of short-run and long-run coefficient estimates, we have applied the well-known CUSUM and CUSUMSQ tests to the residuals of every model. While the first test is reported as QS, the second is reported as QS² in all tables. Stable estimates are identified by "S" and unstable ones by "US". Clearly, all estimates are stable.

Table 1

Results of the ADF Unit Root Test Applied to the Level and First-Differenced variables.

LnHP					
	Level	First Difference		Level	First Difference
Alaska	−1.92 [0] ^a	−7.64 [4]* ^{a,b,c}	North Carolina	−1.87 [4]	−3.65 [3]*
Alabama	−2.06 [4]	−3.89 [4]**	North Dakota	−0.22 [3]	−11.04 [2]**
Arkansas	−1.98 [0]	−16.04 [0]**	Nebraska	−1.52 [4]	−3.81 [4]**
Arizona	−3.01 [3]**	−3.82 [2]**	New Hampshire	−2.35 [3]	−3.30 [4]**
California	−2.58 [3]*	−2.60 [2]*	New Jersey	−2.13 [3]	−2.39 [4]
Colorado	−1.38 [4]	−3.14 [3]**	New Mexico	−2.70 [1]*	−3.86 [3]**
Connecticut	−2.76 [4]*	−3.60 [2]**	Nevada	−3.58 [3]**	−3.15 [2]**
Delaware	−1.33 [3]	−3.87 [4]**	New York	−1.26 [3]	−3.64 [4]**
Florida	−3.48 [4]*	−2.61 [4]*	Ohio	−1.98 [3]	−3.11 [4]**
Georgia	−1.98 [4]	−3.11 [4]**	Oklahoma	−1.34 [3]	−4.87 [2]**
Hawaii	−1.09 [4]	−5.10 [4]**	Oregon	−1.26 [4]	−3.25 [2]**
Iowa	−1.68 [4]	−3.16 [4]**	Pennsylvania	−1.60 [4]	−3.58 [3]**
Idaho	−1.38 [3]	−3.02 [4]**	Rhode Island	−2.67 [4]	−2.55 [3]*
Illinois	−2.14 [4]	−3.60 [0]**	South Carolina	−1.07 [4]	−3.66 [4]**
Indiana	−1.64 [2]	−3.17 [4]**	South Dakota	−0.71 [3]	−12.60 [2]**
Kansas	−2.16 [4]	−2.80 [4]*	Tennessee	−1.60 [4]	−3.83 [4]**
Kentucky	−1.61 [4]	−4.23 [3]**	Texas	−1.53 [4]	−3.81 [4]**
Louisiana	−1.77 [4]	−3.44 [3]**	Utah	−1.56 [4]	−3.32 [3]**
Massachusetts	−2.61 [4]*	−2.35 [3]	Virginia	−1.79 [4]	−3.10 [3]**
Maryland	−1.99 [4]	−2.26 [4]	Vermont	−1.20 [2]	−9.15 [4]**
Maine	−1.24 [3]	−3.69 [4]**	Washington	−1.37 [2]	−2.98 [3]**
Michigan	−2.32 [4]	−3.09 [3]**	Wisconsin	−1.27 [3]	−5.78 [2]**
Minnesota	−1.36 [4]	−2.90 [4]**	West Virginia	−1.58 [3]	−8.47 [3]**
Missouri	−3.03 [4]**	−2.91 [3]**	Wyoming	−1.32 [4]	−3.87 [3]**
Mississippi	−1.99 [2]	−4.55 [4]**	District of Columbia	−0.84 [4]	−2.91 [3]**
Montana	−0.77 [3]	−5.97 [2]**	LnSP	−0.52[1]	−10.7[0]**

^a Maximum number of lags imposed is 4 and numbers inside the parentheses are the optimum lag order in the ADF test selected by AIC.^b The critical values for the ADF test statistic (for $n < 50$) at 5% and 10% levels are -2.93 and -2.60 respectively.^c ** and * indicate that the relevant test statistic is significant at 5% and 10% levels respectively.

the first group, the Wald test is significant and supports $\sum \hat{\delta}_i^+ \neq 0$ and in the second group it supports $\sum \hat{\delta}_i^- \neq 0$. These are clear signs of asymmetric impacts of stock prices on house prices. Of course, both hypotheses are supported in four states of Ohio, Pennsylvania, Virginia, and the District of Columbia. Do short-run effects last into the long-run causal effects or cointegration? The answer is in the affirmative in 24 states. The results in Panel B of Table 3 which reflect house prices causing stock prices are quite interesting. Decline in house prices causing stock prices in the short-run, is now overwhelmingly supported in 39 states in which the significant Wald-test supports $\sum \hat{\delta}_i^- \neq 0$ or rejects the null of $\sum \hat{\delta}_i^- = 0$. Clearly, this must be attributed to nonlinear adjustments of house prices. Of course, increase in house prices also causes stock prices in only five states of Alaska, Florida, Michigan, Rhode Island, and South Dakota. In these states the significant Wald-statistic supports $\sum \hat{\delta}_i^+ \neq 0$. Unlike the linear model, the short-run effects translate in to the long run in 16 states since asymmetric cointegration is supported either by the F or t -test in these states.¹⁰

4. Summary and conclusion

The wealth effect refers to the fact that an increase in an individual's wealth leads to an increase in his/her spending. This notion has been applied to the relation between the stock market and the housing market with mixed outcomes. Researchers have been concerned whether the two markets are integrated or segmented. They have mostly supported the segmentation hypothesis by including a measure of stock prices in a model of house price determination to test the wealth effect by using aggregate indexes from an individual country. Bahmani-Oskooee and Ghodsi (2018) recently deviated from this tradition and disaggregated the U.S. house prices by states and employed a standard model of house price determination by including S & P 500 index as another determinant of house prices in each state of the United States. By using both the linear and nonlinear ARDL methods, they were able to discover more support for the wealth effect hypothesis at the state level in the short-run relative to the long-run.

The melt down in the U.S. housing market which was said to be the main source of the Great Recession of 2008 was also the main source of 2008 Financial Crisis and decline in stock prices. In this paper, we investigate the symmetric and asymmetric short-run and long-run causality between S & P 500 index and a house price index from each of the 50 states of the U.S. as well as the District of Columbia. Our findings could be best summarized by saying that when the linear ARDL method which assumes the effects to be symmetric was used, we found evidence of short-run causality from stock prices to house prices in 10 states. However, when we switched the variables in the procedure, we found house prices causing stock prices in 20 states. These numbers increased to 25 and 41

¹⁰ Note that in both tables and both panels we have also reported the outcome of stability tests by applying the CUSUM and CUSUMSQ tests. The first is headed by Q and the second by Q². Stable estimates are indicated by "S" and unstable ones by "U". Clearly, all estimates are stable.

Table 2

Results from the linear model (4).

	Panel A: S&P500 Causing House Prices (SP → HP)					Panel B: House Prices Causing S&P500 (HP → SP)				
	$\sum \hat{\delta}_i \neq 0^d$	t-test ^c	F-Test	Adj R ²	Q (Q ²)	$\sum \hat{\delta}_i \neq 0$	t-test	F-Test	Adj R ²	Q (Q ²)
Alaska	0.81	−0.04 (1.67) ^a	1.82 ^b	0.16	S (S)	1.50	−0.01 (1.12)	0.70	0.08	S (S)
Alabama	0.65	−0.04 (2.42)	3.49	0.18	S (S)	4.97 **	−0.01 (1.17)	1.95	0.09	S (S)
Arkansas	0.90	−0.02 (1.18)	1.06	0.013	S (S)	8.66 **	−0.01 (2.01)	2.27	0.13	S (S)
Arizona	0.27	−0.03 (3.19)*	5.05*	0.42	S (S)	4.83 **	−0.01 (1.12)	2.06	0.09	S (S)
California	6.78**	−0.02 (4.13)**	8.66**	0.73	S (S)	1.15	−0.009 (0.70)	0.97	0.13	S (S)
Colorado	3.29*	−0.02 (3.05)*	4.95*	0.28	S (S)	2.23	−0.01 (1.13)	1.48	0.08	S (S)
Connecticut	1.82	−0.02 (2.96)*	4.33	0.36	S (S)	0.0005	−0.008 (0.79)	0.96	0.05	S (S)
Delaware	0.14	−0.03 (2.47)	3.02	0.38	S (S)	0.004	0.05 (0.70)	0.74	0.05	S (S)
Florida	4.60**	−0.04 (4.59)**	10.61**	0.52	S (S)	3.44 *	−0.01 (1.007)	1.89	0.09	S (S)
Georgia	0.48	−0.06 (4.14)**	9.01**	0.28	S (S)	1.02	−0.006 (0.61)	2.21	0.09	S (S)
Hawaii	0.13	−0.06 (2.22)	2.62	0.22	S (S)	0.80	−0.01 (1.11)	1.01	0.05	S (S)
Iowa	2.27	−0.04 (3.15)*	6.13**	0.34	S (S)	5.83 **	−0.01 (1.46)	1.41	0.08	S (S)
Idaho	0.03	−0.05 (3.39)**	6.28**	0.36	S (S)	5.00 **	−0.01 (1.38)	1.76	0.09	S (S)
Illinois	.0008	−0.04 (3.38)**	6.02**	0.24	S (S)	0.12	−0.002 (0.20)	1.10	0.05	S (S)
Indiana	0.92	−0.04 (3.05)*	4.88*	0.20	U (S)	4.05 **	−0.01 (1.26)	1.66	0.08	S (S)
Kansas	2.07	−0.02 (2.48)	4.18	0.23	S (S)	9.81 **	−0.02 (2.53)	3.79	0.12	S (S)
Kentucky	0.39	−0.03 (2.71)	4.27	0.20	S (S)	7.16 **	−0.02 (1.50)	2.25	0.10	S (S)
Louisiana	2.72*	−0.01 (1.50)	1.64	0.23	S (S)	1.21	−0.01 (1.67)	1.71	0.11	S (S)
Massachusetts	0.02	−0.02 (3.58)**	6.61**	0.51	S (S)	0.02	−0.01 (0.73)	0.72	0.05	S (S)
Maryland	0.01	−0.02 (3.30)**	5.62*	0.46	S (S)	0.001	−0.007 (0.58)	0.82	0.05	S (S)
Maine	1.12	−0.04 (2.58)	3.35	0.46	S (S)	0.03	−0.006 (0.50)	0.86	0.05	S (S)
Michigan	1.88	−0.03 (3.45)**	5.98**	0.32	S (S)	0.85	−0.007 (0.61)	1.42	0.10	S (S)
Minnesota	1.28	−0.03 (3.54)**	6.58**	0.41	S (S)	2.55	−0.01 (0.76)	1.64	0.09	S (S)
Missouri	1.01	−0.04 (3.22)**	5.44**	0.65	U (S)	3.73 **	−0.01 (0.98)	2.37	0.12	S (S)
Mississippi	1.41	−0.05 (1.96)	2.91	0.23	S (S)	7.83 **	−0.02 (2.15)	2.97	0.11	S (S)
Montana	3.47*	−0.04 (2.73)	4.35	0.37	S (S)	0.38	−0.01 (1.04)	0.72	0.05	S (S)
North Carolina	2.91*	−0.06 (4.23)**	9.06**	0.26	S (S)	0.40	−0.004 (0.27)	0.89	0.05	S (S)
North Dakota	0.02	−0.004 (0.16)	4.02	0.18	S (S)	0.80	−0.01 (1.090)	0.76	0.05	S (S)
Nebraska	3.99**	−0.03 (2.79)	4.57	0.17	S (S)	11.99 **	−0.03 (2.50)	3.84	0.17	S (S)
New Hampshire	0.20	−0.04 (4.41)**	9.62**	0.52	S (S)	0.02	−0.007 (0.64)	0.97	0.05	S (S)
New Jersey	0.58	−0.02 (3.48)**	6.08**	0.48	S (S)	0.40	−0.007 (0.61)	0.78	0.05	S (S)
New Mexico	4.76**	−0.04 (3.09)*	4.79*	0.20	S (S)	0.68	−0.01 (1.008)	0.75	0.05	S (S)
Nevada	0.39	−0.04 (4.48)**	10.11**	0.53	S (S)	4.88 **	−0.01 (1.44)	2.56	0.12	S (S)
New York	2.07	−0.04 (3.93)**	7.90**	0.28	S (S)	0.05	−0.01 (0.84)	0.72	0.05	S (S)
Ohio	0.46	−0.02 (2.67)	3.83	0.38	S (S)	3.19 *	−0.01 (1.15)	1.59	0.09	S (S)
Oklahoma	0.65	−0.01 (1.25)	1.02	0.12	U (S)	3.22 *	−0.02 (2.10)	2.21	0.08	S (S)
Oregon	2.80*	−0.03 (3.34)**	5.98**	0.38	S (S)	5.30 **	−0.03 (1.70)	2.08	0.09	S (S)
Pennsylvania	0.002	−0.04 (3.80)**	7.42**	0.29	S (S)	0.05	−0.009 (0.72)	0.73	0.05	S (S)
Rhode Island	0.32	−0.02 (3.33)**	5.58*	0.55	S (S)	0.01	−0.01 (1.09)	0.69	0.12	S (S)
South Carolina	1.40	−0.05 (3.33)**	6.24**	0.26	S (S)	1.93	−0.005 (0.43)	1.83	0.10	S (S)
South Dakota	2.00	−0.07 (1.90)	2.89	0.28	S (S)	10.85**	−0.02 (1.78)	2.13	0.15	S (S)
Tennessee	0.83	−0.05 (2.64)	4.17	0.13	S (S)	3.89 **	−0.01 (0.84)	1.76	0.09	S (S)
Texas	0.06	−0.01 (1.03)	1.63	0.35	S (S)	1.02	−0.01 (1.48)	1.31	0.05	S (S)
Utah	2.69*	−0.03 (3.03)*	4.90*	0.27	S (S)	5.79 **	−0.02 (1.56)	1.735	0.09	S (S)
Virginia	1.50	−0.02 (2.99)*	4.17	0.31	S (S)	1.20	−0.008 (0.65)	0.83	0.05	S (S)
Vermont	0.06	−0.08 (2.28)	2.62	0.31	S (S)	0.73	−0.01 (0.780)	0.76	0.05	S (S)
Washington	0.10	−0.03 (3.73)**	7.34**	0.47	S (S)	0.75	−0.009 (0.51)	0.75	0.05	S (S)
Wisconsin	1.23	−0.03 (3.03)*	3.95	0.15	S (S)	2.64	−0.01 (1.003)	1.25	0.14	S (S)
West Virginia	1.03	−0.02 (0.78)	2.93	0.36	S (S)	1.02	−0.01 (1.17)	1.37	0.05	S (S)
Wyoming	3.72**	−0.01 (1.96)	3.26	0.21	S (S)	0.32	−0.01 (1.16)	0.75	0.05	S (S)
District of Columbia	0.14	−0.02 (2.50)	3.63	0.41	S (S)	2.24	−0.01 (1.12)	1.166	0.06	S (S)

^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 is 2.91 (3.22) at the 10% (5%) level when $k = 1$. These come from Pesaran et al. (2001, Table CII, Case III, p. 303).^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.

respectively when increase in prices was separated from declines and an asymmetry assumption was implemented by using the nonlinear ARDL approach. The most striking outcome was related to the latter group in which house prices caused stock prices. In 39 out of 41 states, it was the decline in house prices that caused stock prices to change, supporting the event of 2008. The list was dominated by large states in terms of size of the population such as Californian and Florida. All in all, we find more short-run causality that runs from house prices to stock prices. We also found support for cointegrated markets (not segmented markets) in little more than half of the states. One implication of our findings is that models of stock price determination should consider house prices as another determinant of stock prices. Future research can move in two different directions. The first is to replicate our findings by using time-series data from

Table 3

Results from nonlinear model (6).

	Panel A: S&P500 Causing House Prices (SP → HP)						Panel B: House Prices Causing S&P500 (HP → SP)					
	$\sum \hat{\delta}_i^+ \neq 0^d$	$\sum \hat{\delta}_i^- \neq 0$	t-test ^c	F-Test	Adj R ²	Q (Q ²)	$\sum \hat{\delta}_i^+ \neq 0$	$\sum \hat{\delta}_i^- \neq 0$	t-test	F-Test	Adj R ²	Q (Q ²)
Alaska	0.37	0.76	−0.05 (1.80) ^a	1.32 ^b	0.18	S (S)	2.86*	0.22	−0.05 (2.43)	2.270	0.11	S (S)
Alabama	6.37**	1.36	−0.04 (2.25)	2.84	0.21	S (S)	0.98	5.33**	−0.05 (2.68)	3.00	0.11	S (S)
Arkansas	1.61	0.02	−0.02 (1.20)	1.70	0.03	S (S)	1.30	18.17**	−0.06 (3.29)*	4.23	0.18	S (S)
Arizona	1.13	2.13	−0.03 (3.26)*	3.63	0.45	S (S)	1.31	0.92	−0.05 (3.31)*	4.27	0.17	S (S)
California	0.54	9.13	−0.02 (4.71)**	7.44**	0.74	S (S)	0.16	11.06**	−0.03 (2.16)	2.96	0.20	S (S)
Colorado	1.32	2.97*	−0.03 (3.07)	3.950	0.31	S (S)	1.45	14.98**	−0.07 (3.31)*	4.72	0.17	S (S)
Connecticut	0.68	0.07	−0.03 (3.15)	3.67	0.50	S (S)	0.01	3.80*	−0.07 (3.04)	3.66	0.13	S (S)
Delaware	0.067	1.12	−0.04 (2.68)	2.51	0.41	S (S)	0.03	3.37*	−0.04 (2.41)	2.54	0.19	S (S)
Florida	0.03	7.22**	−0.04 (4.64)**	7.38**	0.58	S (S)	4.84**	7.40**	−0.02 (1.41)	1.28	0.28	S (S)
Georgia	0.47	3.80**	−0.06 (4.55)**	7.04**	0.30	S (S)	0.03	4.82**	−0.04 (2.13)	3.09	0.12	S (S)
Hawaii	0.07	0.22	−0.12 (3.05)	3.07	0.24	S (S)	2.15	0.060	−0.04 (2.40)	2.22	0.09	S (S)
Iowa	0.43	0.36	−0.04 (2.97)	3.65	0.32	S (S)	0.17	13.06**	−0.06 (2.86)	3.55	0.14	S (S)
Idaho	0.45	0.28	−0.06 (3.67)**	4.96*	0.40	S (S)	0.24	6.48**	−0.05 (2.81)	3.26	0.17	S (S)
Illinois	1.92	1.14	−0.04 (3.37)*	4.73	0.25	S (S)	0.06	5.09**	−0.04 (2.07)	2.60	0.11	S (S)
Indiana	5.08**	2.17	−0.05 (3.51)*	4.41	0.27	S (S)	1.06	9.08**	−0.10 (3.34)*	4.19	0.13	S (S)
Kansas	1.13	4.20**	−0.02 (2.48)	2.95	0.23	S (S)	1.45	22.69**	−0.08 (3.97)**	6.19**	0.20	S (S)
Kentucky	0.88	2.90*	−0.04 (3.46)*	5.57*	0.30	S (S)	0.15	14.77**	−0.09 (3.50)*	5.03*	0.16	S (S)
Louisiana	0.0006	3.22*	−0.01 (1.38)	1.16	0.24	S (S)	0.23	2.45	−0.06 (2.83)	2.94	0.13	S (S)
Massachusetts	2.09	2.13	−0.02 (3.89)**	5.15*	0.52	S (S)	0.14	5.23**	−0.05 (2.53)	2.69	0.13	S (S)
Maryland	0.17	1.46	−0.05 (4.59)**	6.79**	0.49	S (S)	0.20	3.99**	−0.04 (2.46)	2.90	0.13	S (S)
Maine	1.27	0.03	−0.06 (2.73)	2.79	0.46	S (S)	0.94	0.745	−0.04 (2.38)	3.35	0.10	S (S)
Michigan	0.002	1.42	−0.04 (4.05)**	5.77*	0.33	S (S)	9.99**	1.28	−0.10 (2.78)	3.12	0.19	S (S)
Minnesota	0.04	3.11**	−0.03 (3.41)*	4.27	0.42	S (S)	0.12	9.69**	−0.05 (2.63)	3.24	0.14	S (S)
Missouri	0.73	3.34**	−0.04 (3.50)*	4.23	0.66	S (S)	1.16	8.01**	−0.04 (2.48)	3.19	0.15	S (S)
Mississippi	4.22**	0.47	−0.05 (2.17)	3.81	0.32	S (S)	1.96	11.538**	−0.05 (2.62)	3.07	0.18	S (S)
Montana	3.85**	0.56	−0.05 (2.79)	3.64	0.38	S (S)	0.30	0.04	−0.05 (2.44)	2.28	0.08	S (S)
North Carolina	0.40	3.54*	−0.06 (4.14)**	5.95**	0.26	S (S)	0.746	5.59**	−0.05 (2.46)	3.36	0.12	S (S)
North Dakota	0.95	0.55	−0.005 (0.18)	2.66	0.18	S (S)	0.37	0.05	−0.04 (2.38)	1.98	0.08	S (S)
Nebraska	0.22	6.14**	−0.03 (2.82)	3.10	0.18	S (S)	0.57	25.44**	−0.09 (4.21)**	6.86**	0.29	S (S)
New Hampshire	0.03	0.01	−0.05 (4.75)**	7.58**	0.53	S (S)	0.04	8.40**	−0.08 (3.46)*	5.37*	0.25	S (S)
New Jersey	0.11	2.56*	−0.03 (4.11)**	5.71*	0.50	S (S)	0.40	5.48**	−0.06 (2.86)	3.60	0.14	S (S)
New Mexico	4.570**	0.03	−0.04 (2.39)	2.28	0.24	S (S)	0.28	5.46**	−0.06 (3.05)	3.30	0.13	S (S)
Nevada	0.98	2.65*	−0.04 (4.45)**	6.73**	0.53	S (S)	0.02	3.49*	−0.02 (1.82)	1.13	0.23	S (S)
New York	0.23	2.16	−0.05 (4.20)**	6.31**	0.31	S (S)	1.92	9.39**	−0.07 (3.37)*	5.04*	0.18	S (S)
Ohio	3.68**	4.62**	−0.03 (3.58)**	4.55	0.43	S (S)	0.006	11.09**	−0.10 (3.29)*	4.42	0.15	S (S)
Oklahoma	4.68**	0.461	−0.01 (1.10)	1.97	0.29	S (S)	0.03	4.163**	−0.06 (2.90)	3.09	0.11	S (S)
Oregon	2.15	0.78	−0.03 (3.58)**	4.62	0.40	S (S)	0.68	13.14**	−0.09 (3.83)**	5.31*	0.17	S (S)
Pennsylvania	3.41*	5.22**	−0.06 (4.35)**	6.48**	0.34	S (S)	0.63	0.81	−0.03 (1.94)	2.07	0.08	S (S)
Rhode Island	0.01	1.02	−0.03 (3.46)*	4.29	0.56	S (S)	9.32**	20.73**	−0.07 (3.63)**	4.97*	0.25	S (S)
South Carolina	1.11	2.96*	−0.05 (3.11)	4.31	0.25	S (S)	2.68	0.30	−0.05 (2.54)	3.48	0.16	S (S)
South Dakota	1.92	0.49	−0.07 (1.75)	2.53	0.33	S (S)	3.43*	8.84**	−0.07 (3.52)*	3.69	0.12	S (S)
Tennessee	1.21	0.593	−0.05 (2.62)	2.59	.16	S (S)	0.08	8.439**	−0.06 (2.99)	4.09	0.15	S (S)
Texas	1.47	2.33	−0.01 (0.93)	0.81	0.36	S (S)	0.88	9.93**	−0.07 (3.34)*	4.26	0.13	S (S)
Utah	8.83**	2.47	−0.03 (2.99)	3.60	0.40	S (S)	0.57	8.846**	−0.07 (3.54)**	4.47	0.16	S (S)
Virginia	13.26**	5.79**	−0.03 (3.01)	3.39	0.38	S (S)	0.32	8.99**	−0.05 (3.27)*	4.34	0.18	S (S)
Vermont	2.02	1.65	−0.11 (2.26)	1.98	0.31	S (S)	0.10	0.15	−0.03 (2.19)	2.71	0.10	S (S)
Washington	0.27	0.42	−0.04 (3.95)**	5.41*	0.52	S (S)	0.0001	5.57**	−0.05 (2.40)	3.05	0.16	S (S)
Wisconsin	0.42	2.45	−0.03 (2.70)	3.288	0.17	S (S)	0.01	3.299*	−0.04 (2.01)	1.84	0.19	S (S)
West Virginia	0.83	0.003	−0.02 (0.96)	3.67	0.40	S (S)	0.34	0.31	−0.03 (1.85)	1.93	0.07	S (S)
Wyoming	22.98**	1.75	−0.009 (0.92)	5.54*	0.24	S (S)	0.37	5.42**	−0.06 (2.63)	2.94	0.10	S (S)
District of Columbia	5.89**	4.51**	−0.04 (2.87)	3.04	0.49	S (S)	0.20	4.601**	−0.05 (2.67)	3.12	0.12	S (S)

^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 is 3.21 (3.53) at the 10% (5%) level when $k = 2$ in the nonlinear model. These come from Pesaran et al. (2001, Table CII, Case III, p. 303).

^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.

other countries, even at the aggregate level. The second is to use panel data across many countries.

Appendix

Data sources and definitions

Quarterly data over the period 1976Q1–2016Q3 are used to carry out the empirical exercise. They come from the following sources:

- a. U.S. Federal Housing Finance Agency
- b. Yahoo Finance

Variables

HP: House price index. This is a broad measure of the movement of single-family house prices constructed and published by source (a). This index is a weighted, repeat sales index; measuring average price changes, repeat sales, or refinancings on the same single-family house. This information is gained by studying repeat mortgage transactions on single-family properties whose mortgages have been securitized or purchased by Fannie Mae or Freddie Mac since 1975. The HPI provides an accurate indicator of house prices trends at different geographic levels. The breadth of its sample provides more information than other house prices indexes. This data is available for the nine Census Bureau divisions, the 50 states and District of Columbia, and for Metropolitan Statistical Areas and Divisions. Federal Housing Finance Agency publishes monthly and quarterly HPI data. In this study, seasonally adjusted real HPI is used by adjusting the HPI by Consumer Price Index from U.S. Bureau of Labor Statistics.

SP: Stock Prices measured by the index of S&P 500. The S&P 500 closing data are used from Yahoo Finance. S&P500 is one of the most commonly followed equity indices of American stock market and regarded as the best single measure of large-cap U.S. equities. There is over USD 7.8 trillion benchmarked to the index. Total index assets comprising approximately USD 2.2 trillion. The index includes 500 leading companies and captures about 80% coverage of market capitalization, source (b).

Appendix A. Supplementary data

Supplementary data related to this article can be found at <https://doi.org/10.1016/j.jeca.2018.e00095>.

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