Causal relationship between asset prices and output in the US: Evidence from state-level panel Granger causality test[*]

Furkan Emirmahmutoglu
Department of Econometrics
Gazi University, Turkey

Nicholas Apergis
Department of Banking and Financial Management
University of Piraeus, Greece

Beatrice D. Simo-Kengne
Department of Economics
University of Pretoria, South Africa

Tsangyao Chang
Department of Finance
Feng Chia University, Taichung, Taiwan

Rangan Gupta*
Department of Economics
University of Pretoria, South Africa
rangan.gupta@up.ac.za

Abstract. This paper investigates the causal relationship between asset prices and per capita output across 50 US states and the District of Columbia over 1975 to 2012. A bootstrap panel Granger causality approach is applied on a trivariate VAR comprising of real house prices, real stock prices and real per capita personal income (proxying output), which allows us to account not only for heterogeneity and cross-sectional dependence, but also for interdependency between the two asset markets. Empirical results reveal the existence of a unidirectional causality running from both asset prices to output. This confirms the leading indicator property of asset prices for the real economy, while also substantiating the wealth and/or collateral transmission mechanism. Moreover, the absence of reverse causation from the personal income per capita to both housing and stock prices tend to suggest that non-economic fundamentals may have played an important role in the formation of bubbles in these markets.

***Keywords*:** house prices, stock prices, output, Granger causality
***JEL Classification*:** C32, G10, O18

1. Introduction

With the "Great recession", it has become increasingly clear that asset prices constitute a class of leading indicators of the real economy. Forward-looking, asset prices may provide useful information about the pace of future economic activity, specifically the future changes in

[*] We would like to thank two anonymous referees for many helpful comments that markedly improved the quality of the paper. However, any remaining errors are solely ours.

output and/or inflation (Stock and Watson, 2003; Forni et al., 2003; Gupta and Hartley, 2013). Despite the evidence of this leading indicator property, the causal relationships between output and asset prices appear to be complicated and empirically difficult to identify (IMF, 2000). One strand of the literature emphasizes that asset prices influence current expenditure solely to the extent that they are" leading indicators" of the future variations in economic activity. Considering that current prices represent the discounted value of the expected dividend growth, to the extent that asset prices are traded in fully and well-informed auction markets, expectation about the future dividend growth tend to be rational. From this valuation model hypothesis, there is no causal relationship running from asset prices to the real economy; asset markets being essentially a "side show" of the causal link between current and future output growth (IMF, 2000).

Differently from the "side show" perspective, the permanent income hypothesis supports a behavioural causal relationship running from asset prices to economic activity through the traditional wealth and/or collateral effects. Rather than restricted to the single leading indicators role, increasing asset prices have a direct effect on agents' lifetime wealth which in turn may affect the consumption behaviour and henceforth the output. Indirectly, changes in asset prices may also influence the borrowing capacity of households and firms with significant implications on the consumption and investment plans which in turn stimulate the production process. Consequently, the causality, if any, is expected to run from asset prices to output; with consumption effect serving as a key link between the two variables. However, some researchers including Bajari et al. (2005), Li and Yao (2007) and Buiter (2008) indicate that asset price changes do not necessary have a significant net effect on aggregate consumption; hence advocating the absence of any causal relationship between asset prices and output.

Besides the wealth and/or collateral mechanisms, Demary (2010) documents a direct mechanism through which economic activity may impact house prices. When there is a positive shock on output, firms increase the labour demand which raises households' labour revenue. The subsequent increase in income can be either invested in assets or consumed (in housing and non housing goods). When the economy is in upswing, having a job qualifies for cheap mortgage loan and firms need more office space. This will trigger the demand for housing which will translate into an increase in house prices. Similarly, economic expansion may signal appropriate time for investing in stocks, resulting in an increase in stock prices. Consequently, the causality may also run from economic activity to asset prices; making the relationship between the financial and real sectors a bidirectional one. Given the difficulty to practically disentangle between the above transmission mechanisms, the nature of the causal linkages between asset prices and output should be investigated empirically.

Housing and stock are the two widely held assets in the US. Based on Iacoviello (2011), non-housing wealth (housing wealth) was calculated to be 41.04 percent (37.78 percent) of a US household's total assets, and 52.07 percent (47.93 percent) of a US household's total net worth. Given the relative importance of equities and housing in the US households' total wealth, the dynamics of asset prices are likely to be correlated with the business cycle fluctuations. In fact, the average growth rate of real per capita personal income of 1.12 percent in 1980s is associated with an average annual growth rate of -0.71 percent in real house prices and 5.70 percent in real stock prices. In 1990s, these growth rates increase and reach 1.32 percent, 0.07 percent and 11.08 percent, respectively. In the last decade, while real house prices grow faster at an average growth rate of 1.50 percent, there is a slowdown in the evolution of both real per capita personal income and real stock prices which record an annual growth of 0.86 percent and -3.89 percent, respectively. However, this apparent co-movement of asset prices with income (as depicted by Figure A1 in the Appendix of the paper) does not prove that fluctuations in asset prices cause changes in income or vice versa. The present study tests the existence of the causal relationship between housing/stock market prices and output across 50 US states and the District of Columbia (DC) over the period 1975-2012. Understanding the causal direction between asset prices and income is important, since this determines possible policy interventions in case of shocks to each of these variables.

Empirically, there is strong evidence that changes in asset prices affect the US economic activity, particularly consumption (see Simo-Kengne et al (2013) and Simo-Kengne et al., (forthcoming), for a detailed literature reviews). However, there are few exceptions that focus on the output-effect of asset prices. These include Mauro (2000), Carlstrom et al. (2002), Demary (2010), Miller et al. (2011), Apergis et al., (forthcoming) and Nyakabawo et al., (forthcoming). While, Mauro (2000) finds a positive impact of stock returns on output growth, Miller et al. (2012) depicts a positive impact of house price appreciation on economic growth; with both these studies suggesting a unidirectional causality running from asset prices to output. Unlike these authors, Demary (2010) identifies important feedbacks from macroeconomic variables (including output) to house prices, hence suggesting a bi-directional relationship between house prices and macroeconomy. This finding was in line with, Carlstrom et al. (2002), where the authors documents a two-way causality between stock market and output. More recently, Apergis et al. (forthcoming) explicitly investigates the causality between house prices and output across US metropolitan areas, and finds bi-directional causality, as in the national level analysis of Nyakabawo et al., (forthcoming), based on time-varying causality. However, the study byet al., (forthcoming), as well as Nyakabawo et al., (forthcoming), fails to account for interdependency between asset markets (house and stock) with possible implications on the causal linkages with the real sector. More importantly, Apergis et al., (forthcoming), relies on a panel Vector Error Correction Methodology (VECM) which requires pretesting for stationarity and cointegration and is therefore subject to pre-test bias. To mitigate the issue of pre-test bias, Emirmahmutoglu and Kose (2011) recently proposed a bootstrap panel causality algorithm which does not entail pretesting of the time series properties but requires the size of the time series (T) to be greater than the number of cross sections (N). Therefore, the present application makes use of the bootstrap methodology to analyse the causal relationship between asset markets and output across individual US states, categorized as agricultural and industrial[1], and the for the entire panels of agricultural and industrial states. This, in turn, helps us understand which states are specifically driving the causal relationships for the agricultural and industrial states taken together. To the best of our knowledge, this is the first attempt to analyze causal relationships between asset prices and output for the US states, at individual and aggregate levels, by accounting for cross-sectional dependence and heterogeneity.[2]

A modified version of the panel causality developed by Emirmahmutoglu and Kose (2011), originally to analyze causality in a bivariate-setting, is employed which allows us to control not only for heterogeneity and cross sectional dependence across states, but also for

[1] Based on data from the US Department of Agriculture (USDA)-Economic Research Service, if the total agricultural production in a particular state as a percentage of the total agricultural production of the US is less than (greater than) 1 percent, the state is categorised as industrial (agricultural). Based on this categorization, agricultural states are: Alabama (AL), Arkansas (AR), Arizona (AZ), California (CA), Colorado (CO), Florida (FL), Georgia (GA), Iowa (IA), Idaho (ID), Illinois (IL), Indiana (IN), Kansas (KS), Kentucky (KY), Michigan (MI), Minnesota (MN), Missouri (MO), Mississippi (MS), North Carolina (NC), North Dakota (ND), Nebraska (NE), New Mexico (NM), New York (NY), Ohio (OH), Oklahoma (OK), Oregon (OR), Pennsylvania (PA), South Dakota (SD), Tennessee (TN), Texas (TX), Virginia (VA), Washington (WA), Wisconsin (WI). While industrial states are: Alaska (AK), Connecticut (CT), Delaware (DE), Hawaii (HI), Louisiana (LA), Massachusetts (MA), Maryland (MD), Maine (ME), Montana (MT), New Hampshire (NH), New Jersey (NJ), Nevada (NV), Rhode Island (RI), South Carolina (SC), Utah (UT), Vermont (VT), West Virginia (WV), Wyoming (WY) and the district of Columbia (DC).

[2] The only study that can be considered related to our work, is the paper by Chang et al. (forthcoming). This study, based on an approach proposed by Konya (2006) - a different panel causality test which is based on Seemingly Unrelated Regressions (SUR) estimator yielding a Wald test with country-specific bootstrap critical values, analyzed bi-variate causality between house prices and output for the nine provinces of South Africa. This test too does not require pretesting for unit roots and cointegration apart from the lag structure. However, this approach does not provide a meta-analysis to help us conclude whether and which cross-sectional units drive the results for the entire panel.

interactions between housing and stock markets. Since US states are subject to significant spatial effects given their high level of integration, Peasaran (2006) points out that ignoring cross sectional dependency may lead to substantial bias and size distortions. Furthermore, unlike traditional causality approaches which rely on cointegration techniques, the bootstrap methodology does not require testing for integration and cointegration, hence preventing the issue of pre-test bias (Emirmahmutoglu and Kose, 2011). The next section sets out the empirical procedure and discusses the estimation results. Then, the last section concludes.

2. Empirical analysis

The analysis in this paper is based on annual data for 50 US states, as well as the District of Columbia (DC), over the period 1975-2012. All transaction-based (estimated using sales prices and appraisal data) house price data are obtained from the Federal Housing Finance Agency (FHFA), while stock price, measured by the S&P500 is acquired from the FRED database of the Federal Reserve bank of St. Louis. Following the extant literature on regional (state and MSA-levels) analyses, output is proxied by the per capita personal income drawn from the Bureau of Economic Analysis (BEA).[3,4] All the three variables are deflated by the consumer price index (CPI), obtained also from the FRED database, to obtain their corresponding real values. At this stage, it is important to point out that: (i) Personal income

[3] As defined in the BEA regional accounts at http://www.bea.gov/regional/definitions/, which we quote: "Personal income is the income received by persons from participation in production, plus transfer receipts from government and business, plus government interest (which is treated like a transfer receipt). It is defined as the sum of wages and salaries, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance. Because the personal income of an area represents the income that is received by, or on behalf of, all the persons who live in that area, and because the estimates of some components of personal income (wages and salaries, supplements to wages and salaries, and contributions for government social insurance) are made on a place-of-work basis, state personal income includes an adjustment for residence. The residence adjustment represents the net flow of compensation (less contributions for government social insurance) of interstate commuters."

[4] Note that, data on state-level GDP is available from the regional database of the BEA. But, there is a break in 1997 in the way the GDP data is measured. In light of this, the BEA has a cautionary note at: http://www.bea.gov/regional/docs/product/, which we quote: "There is a discontinuity in the GDP-by-state time series at 1997, where the data change from SIC industry definitions to NAICS industry definitions. This discontinuity results from many sources. The NAICS-based statistics of GDP by state are consistent with U.S. gross domestic product (GDP) while the SIC-based statistics of GDP by state are consistent with U.S. gross domestic income (GDI). With the comprehensive revision of June 2014, the NAICS-based statistics of GDP by state incorporated significant improvements to more accurately portray the state economies. Two such improvements were recognizing research and development expenditures as capital and the capitalization of entertainment, literary, and other artistic originals. These improvements have not been incorporated in the SIC-based statistics. In addition, there are differences in source data and different estimation methodologies. This data discontinuity may affect both the levels and the growth rates of GDP by state. Users of GDP by state are strongly cautioned against appending the two data series in an attempt to construct a single time series for 1963 to 2013." In light of this, we, as in the existing literature, prefer the usage of personal income as a proxy for output at the state-level.

for the states are available at quarterly frequency, but only annual data is available for per capita personal income - which is believed to be the appropriate measure of output when analyzing causality with asset prices, and (ii) Even though, data are available for the (annual) personal income per capita, (monthly) stock prices, and (monthly) CPI for periods before the starting point of our analysis, house prices are only available from 1975 onwards, while nominal personal per capita income ends in 2012. Hence, the starting point and the end point of the sample of analysis, besides the data frequency, is purely driven by availability of information on the variables. Tables A1 to A4 in the Appendix of the paper provides the descriptive statistics of real house prices and real per capita personal income across agricultural and industrial states. The mean values of the real per capita personal income range between 121.51 and 224.26 for agricultural states and between 120.65 and 209.42 for industrial states. This variable records a standard deviation ranging between 16.22 and 61.33 for agricultural states and between 14.13 and 41.27 for industrial states. With respect to real house prices, the mean values range from 0.97 to 2.09 for agricultural states and from 1.01 to 2.28 for the industrial states; corresponding to a standard deviation ranging from 0.09 to 0.65 and 0.12 to 0.73, respectively. Since real stock prices are similar across states, this variable displays a mean of 3.94, and a standard deviation of 2.19. With a chi-squared probability of 0.18, the Jarque-Bera test indicates normality of the real stock prices data, just like output and house price across the majority of states (see column 8 of Tables 1 to 4).

As indicated above, cross-sectional dependency may play an important role in detecting causal linkages between economic variables. Because of high degree of economic and financial integration across US states, shocks originating in one state are likely to spillover onto other states and these spillover effects, if ignored, may result in misleading inference due to misspecification. Similar consequences may occur when the homogeneity restriction is imposed to parameters in the presence of cross section specific characteristics (Granger, 2003; Breitung, 2005). To determine the appropriate specification, we, therefore, test for cross sectional dependence and slope homogeneity which in turn, outline the efficiency of the panel causality method used in this study.

2.1. Testing for cross-sectional dependence

To test for cross-sectional dependency, the Lagrange Multiplier (*LM* hereafter) test of Breusch and Pagan (1980) has been extensively used in empirical studies. The procedure to compute the LM test requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \text{ for } i = 1, 2, ..., N;\ t = 1, 2, ..., T \tag{1}$$

where i is the cross section dimension, t is the time dimension, x_{it} is $k \times 1$ vector of explanatory variables, α_i and β_i are respectively the individual intercepts and slope coefficients that are allowed to vary across states. In the *LM* test, the null hypothesis of no-cross section dependence- $H_0 : Cov(u_{it}, u_{jt}) = 0$ for all t *and* $i \neq j$- is tested against the alternative hypothesis of cross-section dependence $H_1 : Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan (1980) developed the *LM* test as:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{2}$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of equation (1) for each *i*. Under the null hypothesis, the *LM* statistic has asymptotic chi-square with $(N(N-1)/2)$ degrees of freedom. It is important to note that the *LM* test is valid for for relatively small N and sufficiently large T.

However, the cross-sectional dependence (*CD*) test is subject to decreasing power in certain situations that the population average pair-wise correlations are zero, although the underlying individual population pair-wise correlations are non-zero (Pesaran et al., 2008). Furthermore, in stationary dynamic panel data models the *CD* test fails to reject the null hypothesis when the factor loadings have zero mean in the cross-sectional dimension. In order to deal with these problems, Pesaran et al. (2008) proposes a bias-adjusted test which is a modified version of the *LM* test by using the exact mean and variance of the *LM* statistic. The bias-adjusted *LM* test is:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \tag{3}$$

where μ_{Tij} and v_{Tij}^2 are respectively the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, that are provided in Pesaran et al. (2008). Under the null hypothesis with first $T \rightarrow \infty$ and then $N \rightarrow \infty$, LM_{adj} test is asymptotically distributed as standard normal.

2.2. Testing for slope homogeneity

Second issue in a panel data analysis is to decide whether or not the slope coefficients are homogenous. The causality from one variable to another variable by imposing the joint restriction for whole panel is the strong null hypothesis (Granger, 2003). Moreover, the homogeneity assumption for the parameters is not able to capture heterogeneity due to region specific characteristics (Breitung, 2005).

The most familiar way to test the null hypothesis of slope homogeneity- $H_0 : \beta_i = \beta$ for all *i*- against the hypothesis of heterogeneity- $H_1 : \beta_i \neq \beta_j$ for a non-zero fraction of pair-wise slopes for $i \neq j$ - is to apply the standard *F* test. The *F* test is valid for relatively small cross-sectional dimension (*N*) and sufficiently large time dimension (*T*) of a panel; the explanatory variables are strictly exogenous; and the errors are homoscedastic. By relaxing homoscedasticity assumption in the *F* test, Swamy (1970) developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. However, both the *F* and Swamy's test require panel data models where *N* is small relative to *T*. Pesaran and Yamagata (2008) proposed a standardized version of Swamy's test (the so-called $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ test is valid as $(N,T) \rightarrow \infty$ without any restrictions on the relative expansion rates of *N* and *T* when the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, first step is to compute the following modified version of the Swamy's test:

$$\tilde{S} = \sum_{i=1}^{N} \left(\hat{\beta}_i - \tilde{\beta}_{WFE} \right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left(\hat{\beta}_i - \tilde{\beta}_{WFE} \right) \tag{4}$$

where $\hat{\beta}_i$ is the pooled OLS estimator, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, M_τ is an identity matrix, the $\tilde{\sigma}_i^2$ is the estimator of σ_i^2.[5] Then the standardized dispersion statistic is developed as:

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}} \right) \tag{5}$$

[5] In order to save space, we refer to Pesaran and Yamagata (2008) for the details of estimators and for Swamy's test.

Under the null hypothesis with the condition of $(N,T)\to\infty$ so long as $\sqrt{N}/T\to\infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has asymptotic standard normal distribution. The small sample properties of $\tilde{\Delta}$ test can be improved under the assumption of normally distributed errors, as with the anadjusted version of the statistic, by using the following bias adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{\operatorname{var}(\tilde{z}_{it})}}\right) \tag{6}$$

where the mean $E(\tilde{z}_{it}) = k$ and the variance $\operatorname{var}(\tilde{z}_{it}) = 2k(T-k-1)/T+1$.

The results of these selected tests are summarized in Table 1. The null hypothesis of slope homogeneity and cross sectional independence are rejected, hence confirming the evidence of heterogeneity as well as spatial effects across US states. These results motivate the decision to rely on the methodology for causal analysis in heterogeneous panels. We use two alternative approaches. The first approach is based on the homogenous non-causality test of Dumitrescu and Hurlin (2012) that takes into account both heterogeneity of the slope coefficients and that of the causality hypothesis. As the second approach, we use the also use the approach proposed by Emirmahmutoglu and Kose (2011), based on Meta analysis in heterogeneous mixed panels which accounts for cross-sectional dependence.

2.3. The causality analysis

Following Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2011), we consider heterogeneous panel Vector Autoregressive model with three variables *y*, *x* and *z* where:

y = Real per capita personal income

x = Real house prices

z = Real stock prices

$$y_{it} = \alpha_{1i} + \sum_{j=1}^{k_i + d\max_i} \beta_{1ij} y_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \gamma_{1ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \delta_{1ij} z_{i,t-j} + \varepsilon_{1it} \tag{7}$$

$$x_{it} = \alpha_{2i} + \sum_{j=1}^{k_i + d\max_i} \beta_{2ij} y_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \gamma_{2ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \delta_{2ij} z_{i,t-j} + \varepsilon_{2it} \tag{8}$$

$$z_{it} = \alpha_{3i} + \sum_{j=1}^{k_i + d\max_i} \beta_{3ij} y_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \gamma_{3ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \delta_{3ij} z_{i,t-j} + \varepsilon_{3it} \tag{9}$$

where, in our case, z_i, being the real stock price, is the same for all i and the null hypothesis are as follows:

$$H_0 : \gamma_{1i1} = \gamma_{1i2} = \cdots = \gamma_{1i,k_i} = 0 \quad \textit{for all } i = 1, 2, ..., N \tag{10}$$

$$H_0 : \delta_{1i1} = \delta_{1i2} = \cdots = \delta_{1i,k_i} = 0 \quad \textit{for all } i = 1, 2, ..., N \tag{11}$$

$$H_0 : \beta_{2i1} = \beta_{2i2} = \cdots = \beta_{2i,k_i} = 0 \quad \textit{for all } i = 1, 2, ..., N \tag{12}$$

$$H_0 : \delta_{2i1} = \delta_{2i2} = \cdots = \delta_{2i,k_i} = 0 \quad \textit{for all } i = 1, 2, ..., N \tag{13}$$

$$H_0 : \beta_{3i1} = \beta_{3i2} = \cdots = \beta_{3i,k_i} = 0 \quad \textit{for all } i = 1, 2, ..., N \tag{14}$$

$$H_0 : \gamma_{3i1} = \gamma_{3i2} = \cdots = \gamma_{3i,k_i} = 0 \quad \textit{for all } i = 1, 2, ..., N \tag{15}$$

Under the null (10), x does not Granger cause y for all i. Under the null (11), z does not Granger cause y for all i. Under the null (12), y does not Granger cause x for all i. Under the null (13), z does not Granger cause x for all i. Put simply, we test causality from x to y and from z to y in equation (7). A similar procedure is applied for causality from y to x and from z to x in equation (8) or from y to z and from x to z in equation (9).

Under the alternative we allow slope coefficients to differ across the groups in order to account for model heterogeneity. Additionally, based on the general non-causality testing approach in Dumitrescu and Hurlin (2012), we allow some, but not all, coefficients specified under the null hypotheses in equations (10)-(15) to be equal to zero. For instance, we allow $N_1 < N$ individual processes with no causality form x to y under alternative H_1 specified for equation (10). This can be specified as:

$$\begin{aligned} H_1 : & \gamma_{1i1} = \gamma_{1i2} = \cdots = \gamma_{1i,k_i} = 0 \quad \text{for } i = 1, 2, ..., N_1 \\ & \gamma_{1i1} \neq 0, \gamma_{1i2} \neq 0, \cdots, \gamma_{1i,k_i} \neq 0, \ \text{for } i = N_1 + 1, N_1 + 2, ..., N \end{aligned} \tag{16}$$

An analogous alternative can be specified for each of the null statements in equations (11)-(15).

Dumitrescu and Hurlin (2012) proposed a test an average Wald test based on the average of the individual Wald statistics associated with testing the Granger non-causality in equations (10)-(15) for each of the units $i = 1, 2, ..., N$. The average Wald statistic is calculates as

$$W_{N,T}^{Hnc} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \tag{17}$$

where $W_{i,T}$ denotes the individual Wald statistics calculated by imposing the non-causality null restriction in equations (10)-(15) only for the *i*th cross-section.

This structure of the average Wald statistics is similar to the unit root testing approach of Im, Peseran, and Shin (2003). In order illustrate this test, consider the non-causality null in equation (10) with the corresponding alternative in equation (16). If the null is not rejected using the average Wald statistic in equation (17), then variable x does not Granger cause variable y for all cross-sectional units of the panel. If the null is rejected and $N_1 = 0$, then we have homogenous causality result for all cross-sectional units, but regression model may not be homogenous, allowing slopes to differ across individual units. If, on the other hand, $N_1 > 0$, then the causality relationship is heterogeneous. In this last case, the causality relationship vary from one unit to another and from one sample to another.

Dumitrescu and Hurlin (2012) show that the average Wald test sequentially converges to a standard Gaussian distribution. We additionally base our analysis on the critical values of the mean Wald statistic obtained from the bootstrap procedure since the mean Wald test does not converge for fixed N and fixed T and empirical distribution must be used. The bootstrap procedure is also used for the Meta analysis. As an example for testing the non-causality hypothesis that x dos not Granger cause y in equation (10), the steps of our bootstrap procedure proceed as follows:

Step 1. In order to determine the maximal order of integration of three variables ($d\max_i$) in the VAR system for each cross-sectional unit, we use multiple unit root test proposed by Dickey and Pantula (1987). We then estimate the regression (1) by OLS for each individual and select the lag order k_i's via Schwarz information criterion (SIC) by starting with $k_{\max} = 4$.

Step 2. By using k_i and $d\max_i$ from Step 1, we re-estimate equation (7) by OLS under the null in equation (10). Thus, we obtain the residuals for each individual unit:

$$\hat{\varepsilon}_{1it} = y_{it} - \hat{\alpha}_{1i} - \sum_{j=1}^{k_i + d\max_i} \hat{\beta}_{1ij} y_{i,t-j} - \sum_{j=1}^{k_i + d\max_i} \hat{\delta}_{1ij} z_{i,t-j} \tag{18}$$

$$\hat{\varepsilon}_{2it} = x_{it} - \hat{\alpha}_{2i} - \sum_{j=1}^{k_i + d\max_i} \hat{\beta}_{2ij} y_{i,t-j} - \sum_{j=1}^{k_i + d\max_i} \hat{\gamma}_{2ij} x_{i,t-j} - \sum_{j=k_i+1}^{k_i + d\max_i} \hat{\delta}_{2ij} z_{i,t-j} \tag{19}$$

$$\hat{\varepsilon}_{3it} = z_{it} - \hat{\alpha}_{3i} - \sum_{j=1}^{k_i + d\max_i} \hat{\beta}_{3ij} y_{i,t-j} - \sum_{j=1}^{k_i + d\max_i} \hat{\gamma}_{3ij} x_{i,t-j} - \sum_{j=k_i+1}^{k_i + d\max_i} \hat{\delta}_{3ij} z_{i,t-j} \tag{20}$$

Step 3. Stine (1987) suggests that residuals have to be centered with

$$\tilde{\varepsilon}_{jt} = \hat{\varepsilon}_{jt} - (T-k-l-2)^{-1} \sum_{k+l+2}^{T} \hat{\varepsilon}_{jt}, \qquad j = 1,2,3 \tag{21}$$

where $\hat{\varepsilon}_{jt} = \left(\hat{\varepsilon}_{j1t}, \hat{\varepsilon}_{j2t}, \ldots, \hat{\varepsilon}_{jNt}\right)'$, $k = \max(k_i)$ and $l = \max(d\max_i)$. Furthermore, we develop the $\left[\tilde{\varepsilon}_{jit}\right]_{N \times T}$ from these residuals. We select randomly a full column with replacement from the matrix at a time to preserve the cross covariance structure of the errors. We denote the bootstrap residuals as $\tilde{\varepsilon}^{*}_{jit}$ where $t = 1,2,\ldots,T$.

Step 4. We generate as recursively the bootstrap sample of y^{*}_{it}, x^{*}_{it}, and z^{*}_{it} under the null in equation (10):

$$y^{*}_{it} = \hat{\alpha}_{1i} + \sum_{j=1}^{k_i + d\max_i} \hat{\beta}_{1ij} y^{*}_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \hat{\delta}_{1ij} z^{*}_{i,t-j} + \tilde{\varepsilon}^{*}_{1it} \tag{22}$$

$$x^{*}_{it} = \hat{\alpha}_{2i} + \sum_{j=1}^{k_i + d\max_i} \hat{\beta}_{2ij} y^{*}_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \hat{\gamma}_{2ij} x^{*}_{i,t-j} + \sum_{j=k_i+1}^{k_i + d\max_i} \hat{\delta}_{2ij} z^{*}_{i,t-j} + \tilde{\varepsilon}^{*}_{2it} \tag{23}$$

$$z^{*}_{it} = \hat{\alpha}_{3i} + \sum_{j=1}^{k_i + d\max_i} \hat{\beta}_{3ij} y^{*}_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} \hat{\gamma}_{3ij} x^{*}_{i,t-j} + \sum_{j=k_i+1}^{k_i + d\max_i} \hat{\delta}_{3ij} z^{*}_{i,t-j} + \tilde{\varepsilon}^{*}_{3it} \tag{24}$$

where $\hat{\alpha}_{1i}$, $\hat{\beta}_{1ij}$, $\hat{\gamma}_{1ij}$ and $\hat{\delta}_{1ij}$ are obtained from Step 2 for all i and j.

Step 5. Substitute y^{*}_{it}, x^{*}_{it}, and z^{*}_{it}, respectively for y_{it}, x_{it}, and z_{it} and estimate (7) without imposing any parameter restrictions on it and then the individual Wald statistics are calculated to test non-causality null hypothesis separately for each individual. Using these individual Wald statistics, which have an asymptotic chi-square distribution with k_i degrees of freedom, we compute individual *p*-value's. Then, the mean Wald test statistic is obtained.

Based on the above steps, we generate the bootstrap empirical distribution of the mean Wald test statistic by repeating steps 3–5 with 2000 times and specify the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions.

Causality test results are reported in Tables 2 and 3 for agricultural and industrial states (including DC), respectively. The first panel (panel A) of these Tables tests the causality from asset prices to output. The bootstrapped values of the mean Wald test appear to be considerably higher than the bootstrap critical values at the 1 percent level of significance. This suggests that house prices and stock prices Granger cause output which corroborates the individual state results with small *p*-values in the majority of states. It is worth noting that, individual results are more consistent for the stock price-output causality than the house price-output causality and this is true across both categories of states. For the agricultural states, only 3 states out of 32 display insignificant Wald statistics (high *p*-values) for stock price-output causality, namely AR, IA and TN, with the non-rejection of the null of no-causality holding barely for IA. For the house price-output causality, there are 14 states, namely CA, CO, FL, ID, IL, KY, MI, MN, NE, NY, OR, PA, SD and TN, for which the null of no-causality is rejected On the other hand, 15 (AK, CT, DC, DE, MA, MD, MT, NH, NJ, NV, SC, UT, VT, WV and WY) out of 19 industrial states have low *p*-values for the null of no causality running from stock price to output, compared to 9 states (AK, CT, DC, HI, MA, MT, NH, NJ and UT) for the case of causality running from house price to output (See Table 6).

Panel B of these tables test the causality running from output to housing and stock prices. The null hypothesis of no Granger causality is rejected, as the bootstrap critical values at the 10%, 5% and 1% levels of significance are substantially higher than the bootstrapped values of the mean Wald test. A similar story holds for state-level results, with the exception of few states which indeed have significant Wald statistics, but mostly at the 10 percent level of significance across both agricultural and industrial states. This is the case for OK and TX (WV and WY) for agricultural (industrial) states for which the causality runs from output to house prices, compared to AL, AZ, CO, ID, MS and NM (AK, DC, HI, MT, NV and UT) for agricultural (industrial) states, in which cases the outputs of these causes the stock price. These findings suggest that output does not Granger cause housing and stock prices. Further, based on Panel C of Tables 2 and 3, irrespective of the categorization of the states, there is no evidence of the causality between housing prices and stock prices[6]; suggesting that house prices cannot predict stock prices and vice versa.[7,8]

[6] Though few agricultural states, namely, AZ, FL and OR display relatively low *p*-values, indicating causality running from housing prices in these states to stock price, while stock price is found to cause house price only in

In contrast to Apergis et al. (forthcoming), who report a bidirectional causality between house prices and output at the metropolitan level, our findings (summarized in Table 8) support a unidirectional causality running from asset prices (housing and stock prices) to output at the state-level. The observed difference could be attributed to the pre-test bias as the panel VECM methodology used by Apergis et al. (forthcoming) requires pre-testing for cointegration and stationarity. Such a line of thinking was corroborated when we discovered bi-directional causality between asset prices and output for industrial and agricultural states, as well as all the states taken together, based on a panel VECM approach similar to that of Apergis et al. (forthcoming) – results of which are available upon request from the authors. In summary, our results substantiate the important role of asset prices in driving business cycle fluctuations, but no feedback from the real economy on to both housing and stock prices.[9] Our results confirm the leading indicator abilities of asset prices at the regional level, something that has

---

NE. For the industrial states, stock price only causes house price in WY, with no evidence of reverse causality from house price to stock price.

[7] All the results of the meta-analysis based on the average Wald test statistic, also continues to hold based on the Fisher statistic, as developed and used by Emirmahmutoglu and Kose (2011). Complete details of these results are available upon request from the authors.

[8] Following the suggestion of an anonymous referee, we also conducted our analysis using real GDP per capita as a measure of state-level output. Based on the meta-analysis, we found that there is one way causality from house price to real GDP per capita for the agricultural states only, and from real GDP per capita to stock prices for both the agricultural and industrial states. As far as state-level results are concerned, we observe the following: For the agricultural states, real house price causes real GDP per capita in AR, FL, IL, IN, KY, MI, MO, MS, OH, OK, PA and WI, while AZ, CA, IN, MI and WI are where we observe real GDP per capita causing real house price. Real stock price causes output in AR, CO, IN, KS, MN, OH and TX, with the feedback observed from the states of GA, ID, IN, KY, MI, MS, NE, NM, NY, OH and WA. Real stock price causes real house price in CA and MO, while the reverse holds in FL, IN, MO, NE, PA and VA. For the industrial states, real house price causes output in HI, NH, NV, VT and WV, while the causality running from output to house price holds for DE and WY. Stock price causes output in HI, MT and WY, while output in AK, DC, LA, MT, NJ, RI, SC, WV and WY is found to cause stock price. Finally, stock price causes house price in only DC, while house prices in DE and LA causes stock price. However, given the problems associated with the measure of state-level GDP, as discussed in Footnote 4, we are reluctant to put our confidence on these results. Complete details of these results are, however, available upon request from the authors.

[9] Any anonmous referee suggested that we conduct sub-sample analysis accounting for the stock market crash of the 1990 and the recent financial crisis. In this regard, it is important to note that our analysis requires us to have T>N – this was also the specific reason as to why we categorized the states into agricultural and industrial. So, even though we realize that structural breaks are likely to exist in the full-sample, we cannot use our panel-data based methodology to carry out sub-sample analysis. Instead, we extracted the first principal component for each of real personal per capita income of the agricultural states, real personal per capita income of the industrial states, real house price of the agricultural states and real house price of the industrial states. Then, we set up two trivariate time series models comprising of the principal components for the measure of output and house prices, and the stock price for both the agricultural and industrial states. Note that, to ensure that we work with the variables in levels, we used the methodology proposed by Bai (2004), to extract these factors from non-stationary (I(1)) rather than I(0) variables. We carried out the analysis for two sub-samples: 1975-1989, and 1990-2006. Our results showed that, both for the industrial and agricultural states, causality runs from the asset prices to output in the sub-sample 1990-2006. In addition, for this sub-sample, there is weak evidence of real stock price causing output of the industrial states at the 10% level of significance. So, in general, it is evident that asset prices leads output, but this is especially for the latter half of the sample. Complete details of these results are available upon request from the authors.

been widely shown to exist at the aggregate level by (see for example, Forni et al., 2003; Stock and Watson, 2003; Rapach and Weber, 2004).[10]

3. Conclusion

This study implements a newly developed bootstrap panel causality approach to investigate the causal linkages between asset prices and output per capita across the 50 US states and the District of Columbia over the period 1975-2012. Empirical results indicate that, when cross-state dependency, heterogeneity and asset market interconnections are controlled for, the causality runs from asset prices (both housing and stock prices) to output, not only at the level of individual states, but also taking together all the agricultural and industrial states.

Whilst the unidirectional causality running from asset prices to output substantiates the wealth and /or collateral transmission mechanism, the reverse causation found by Apergis et al. (forthcoming) at the metropolitan level disappears at the state-level, using our methodology. The fact that, we also observed bi-directional causality between asset prices and output, using a panel VECM as in Apergis et al., (forthcoming) applied to our data on agricultural and industrial states, possibly highlights, though cannot be confirmed for sure due to differences in observational units (MSA versus states), the ability of the bootstrap methodology in alleviating the issue of pretest bias in causality testing, and, in the process, the possible influence asset markets interdependency may exert on causal linkages with the real sector.

Our findings provide important policy implications. First, they show that asset market development might be an efficient tool to stimulate economic growth. Conversely, business cycle dynamics are less likely to determine asset price fluctuations, at least at the state-level. Second, policymakers have to identify any asset bubble in early stage to avoid much larger bubble burst in the future. Third, it is necessary to prevent the over-heating of the economy in response to any positive asset price shock that may raise the volatility of future GDP growth. Fourth, the real estate market should receive priority from policy makers since the housing price effect plays a significant role. As part of future research, if state-level data on consumption (proxied by retail sales) can be obtained, it would be interesting to conduct not

[10] Based on the suggestion of an anonymous referee, we also conducted the analysis for the aggregate US economy, using real personal per capita income as a measure of output, for the sake of comparability. Our analysis shows that only real stock price causes output at the aggregate level. The lack of causality from real house price to output, as observed in the state-level is in line with the results of Nyakabawo et al., (forthcoming). Our results highlight the importance of not generalizing results for the aggregate level for the state-level, since this could possibly lead to incorrect policy decisions. Complete details of these results are available upon request from the authors.

only panel causality tests between consumption and asset prices, but also use panel cointegration techniques to obtain state-level consumption functions, to determine the importance of the wealth effect at a regional level for the US economy. This is important, since, as we show, one cannot generalize national-level policies for the states.

However, it is also important to acknowledge a limitation of our study: The rejection of the null of homogenous non-causality for the entire panel (based on the meta analysis) does not tend to provide exact guidance with respect to the number or the identity of the particular panel units for which the null of non-causality is rejected, since the individual Granger causality tests are actually purely-time series based, which in turn disregards cross-sectional dependence (even though the meta-analysis does account for cross-sectional dependence based on a bootstrapped procedure). Hence, the suggestions of specific cross-sections driving the aggregate panel based on the meta-analysis, cannot be considered as conclusive evidence. Note that, this limitation is not only specific to our modeling approach, but is in fact also applicable to the works of Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2013) – the two studies we follow. In light of this, future analysis should be aimed at developing meta-analysis for panel Granger causality tests, which also controls for cross-sectional dependence when obtaining cross-sectional-level causality results. This in turn, will allow us to obtain accurate information on the cross-sections that might be driving the result for the entire panel.

References

Apergis, N., Simo-Kengne, B.D., Gupta, R. and Chang, T. (forthcoming). The dynamic relationship between house prices and output: Evidence from US metropolitan areas. *International Journal of Strategic Property Management*.

Bai, J. (2004). Estimating cross-section common stochastic trends in nonstationary panel data, *Journal of Econometrics*, 122, 137-183.

Bajari, P., Benkard, C.L., and Krainer, J. (2005). House prices and consumer welfare. *Journal of Urban Economics* 58:474-487.

Baltagi, B.H. (2008). Econometrics.*4th Edition*, Springer-Verlag Berlin Heidelberg.

Breitung, J. 2005. A parametic approach to the estimation of cointegration vectors in panel data. *Econometric Reviews*, 24:151-173.

Breusch, T.S., and Pagan, A. R. 1980. The Lagrange Multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 47(1):239-253.

Bricker, J., Kennickel, A.B., Moore, K.B. and Sabelhaus, J. (2012). Changes in US family finances from 2007 to 2010: evidence from survey of consumer finances. *Federal Reserve Bank Bulletin* 98 (2): 1-79.

Buiter, W.H. (2008). Housing wealth isn't wealth. Working Paper 14204, National Bureau of Economic Research, Cambridge.

Carlstrom, C.T., Fuerst, T.S. and Loannidou, V.P. (2002). Stock prices and output growth: An examination of the credit channel. Federal Reserve Bank of Cleveland.

Chang, T., Simo-Kengne, B.D. and Gupta, R. (forthcoming). The causal relationship between house prices and growth in the nine provinces of South Africa: evidence from panel- Granger causality tests. *International Journal of Sustainable Economy*.

Demary, M. 2010. The interplay between output, inflation, interest rates and house prices: International evidence. *Journal of Property Research* 27(1):1-17.

Dickey, D.A. and Pantula, S.G. 1987. Determining the order of differencing in autoregressive processes. *Journal of Business and Economic Statistics* 5 (4):455-461.

Dumitrescu, E.I., and C. Hurlin. 2012. Testing for Granger Non-causality in Heterogeneous Panels. *Economic Modelling* 29: 1450–1460.

Emirmahmutoglu, F. and N. Kose. 2011. Testing for Granger causality in heterogeneous mixed panels. *Economic Modelling* 28: 870-876.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. 2003. Do financial variables help forecasting inflation and real activity in the euro area? Journal of Monetary Economics, 50(6):1243-1255.

Frees, E.W. (1995). Assessing cross-sectional correlation in panel data. *Journal of Econometrics* 69: 393-414.

Granger, C.W.J. 2003. Some aspects of causal relationships. *Journal of Econometrics,* 112:69-71.

Gupta, R. and Hartley, F. (2013). The role of asset prices in forecasting inflation and output in South Africa. *Journal of Emerging Market Finance*, 12(3): 239-291.

IMF (2000). World economic outlook. Asset prices and the business cycle. *World Economic and Financial Surveys*.

Im, K.S., M.H. Pesaran, and Y. Shin. 2003. Testing for Unit Roots in Heterogenous Panels. *Journal of Econometrics* 54: 91-115.

Kónya, L. (2006), Exports and growth: granger causality analysis on OECD countries with a panel data approach. *Economic Modelling* 23:978–992.

Li, W. and Yao, R. 2007. The life cycle effects of house price changes. *Journal of Money, Credit and Banking* 39(6):1376-1409.

Mauro, P. (2000). Stock returns and output growth in emerging and advanced economies. IMF Working Paper, WP/00/89.

Miller, N., L. Peng and M. Sklarz. 2011. House prices and economic growth. *The Journal of Real Estate Finance and Economics* 42(4): 522-541.

Nyakabawo, W., Miller, S.M., Balcilar, M., Das, S. and Gupta, R., (forthcoming), "Temporal Causality between House Prices and Output in the U.S.: A Bootstrap Rolling-Window Approach", *North American Journal of Economics and Finance.*

Pesaran, M.H. (2004). General diagnostic tests for cross section dependence in panels. CESifo Working Papers No.1233, 255–60.

Pesaran, M.H. 2006. Estimation and Inference in Large Heterogeneous Panels with Multifactor Error Structure. *Econometrica* 74 (4): 967-1012.

Pesaran, M.H., Ullah, A. and Yamagata, T. 2008. A bias-adjusted LM test of error cross-section independence. *Econometrics Journal* 11:105–127.

Pesaran, M.H., Yamagata, T. 2008. Testing slope homogeneity in large panels. Journal of *Econometrics* 142:50–93.

Poterba, J. M., 2000. Stock market wealth and consumption. *Journal of Economic Perspectives* 14: 99-118.

Rapach, D. E. and Weber, C. E., 2004. Financial variables and the simulated out-of-sample forecastability of U.S. output growth since 1985: an encompassing approach, *Economic Inquiry*, 42 (4): 717–738.

Simo-Kengne, B.D., Bittencourt, M. and Gupta, R. (2013), The impact of house prices on consumption in South Africa: Evidence from provincial-level panel VARs. *Housing Studies* 28(8):1133-1154.

Simo-Kengne, B.D., Miller, S.M. and Gupta, R. (forthcoming), Time varying effects of housing and stock prices on US consumption. *Journal of Real Estate Finance and Economics*.

Stine, R.A. 1987. Estimating properties of autoregressive forecasts. *Journal of the American Statistical Association* 82, 1072-1078.

Stock, J.H. and Watson, M.W. (2003). Forecasting output and inflation: The role of asset prices. Journal of Economic Literature 41, 788-829..

Swamy, P.A.V.B. 1970. Efficient inference in a random coefficient regression model. *Econometrica* 38:311–323.

Table 1: Cross-sectional Dependence and Homogeneity Tests

	Agricultural States	**Industrial States and the District of Columbia**
CD_{BP}	2455.925***	9491.887***
CD_{LM}	123.555***	285.620***
CD	46.318***	95.921***
LM_{adj}	155.179***	251.201***
$\tilde{\Delta}$	61.733***	36.907***
$\tilde{\Delta}_{adj}$	1.759**	1.046

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 2: The Granger Causality Results of Agricultural States

Panel A	House prices do not Granger cause output $x \overset{?}{\rightarrow} y$			Stock prices do not Granger cause outpute $z \overset{?}{\rightarrow} y$		
			Individual Statistics			
State	k_i	W_i	p_i	k_i	W_i	p_i
AL	2	3.748	0.153	2	7.357	0.025**
AR	2	1.938	0.379	2	2.144	0.342
AZ	2	4.094	0.129	2	10.204	0.006***
CA	2	4.801	0.091*	2	12.809	0.002***
CO	2	5.185	0.075*	2	34.029	0.000***
FL	2	15.040	0.001***	2	6.126	0.047**
GA	2	3.423	0.181	2	16.940	0.000***
IA	2	3.192	0.203	2	4.516	0.105
ID	2	5.004	0.082*	2	10.216	0.006***
IL	2	9.370	0.009***	2	15.521	0.000***
IN	2	2.332	0.312	2	16.950	0.000***
KS	2	2.623	0.269	2	24.572	0.000***
KY	2	5.135	0.077*	2	10.563	0.005***
MI	2	9.090	0.011**	2	17.116	0.000***
MN	2	4.687	0.096*	2	20.578	0.000***
MO	2	4.583	0.101	2	8.601	0.014**
MS	2	0.987	0.610	2	6.001	0.050***
NC	2	2.151	0.341	2	11.242	0.004***
ND	1	0.552	0.457	1	2.729	0.099*
NE	4	28.775	0.000***	4	41.580	0.000***
NM	2	2.264	0.322	2	8.361	0.015**
NY	2	13.703	0.001***	2	16.968	0.000***
OH	2	0.670	0.715	2	11.657	0.003***
OK	2	2.700	0.259	2	27.572	0.000***
OR	3	15.287	0.002***	3	13.181	0.004***
PA	2	5.591	0.061*	2	16.427	0.000***
SD	3	12.695	0.005***	3	32.539	0.000***
TN	2	4.988	0.083*	2	4.086	0.130
TX	2	1.143	0.565	2	46.575	0.000***
VA	2	4.339	0.114	2	5.791	0.055*
WA	2	4.3754	0.1122	2	11.1837	0.0037***
WI	2	4.127	0.127	2	6.541	0.038**

Panel Test Statistics

Mean Wald Test Statistic: 5.958***	**Mean Wald Test Statistic:** 15.142***
Bootstrap Critical Values:	**Bootstrap Critical Values:**
*** 1%: 5.553	*** 1%: 6.807
** 5% : 4.466	** 5% : 5.059
* 10% : 3.903	* 10% : 4.313

Panel B		Output does not Granger cause house prices $y \overset{?}{\rightarrow} x$			Stock prices do not Granger cause house prices $z \overset{?}{\rightarrow} x$	
Individual Statistics						
State	k_i	W_i	p_i	k_i	W_i	p_i
AL	2	0.2349	0.8892	2	0.2217	0.8951
AR	2	2.8215	0.2440	2	0.3551	0.8373
AZ	2	1.5114	0.4697	2	0.7403	0.6906
CA	2	0.7084	0.7017	2	2.5452	0.2801
CO	2	4.3725	0.1123	2	4.2581	0.1189
FL	2	1.6044	0.4484	2	2.3267	0.3124
GA	2	2.6460	0.2663	2	2.7581	0.2518
IA	2	1.4586	0.4822	2	1.0473	0.5923
ID	2	0.4116	0.8140	2	0.2806	0.8691
IL	2	3.1294	0.2091	2	1.0862	0.5809
IN	2	0.2622	0.8771	2	0.3404	0.8435
KS	2	2.9709	0.2264	2	0.9979	0.6072
KY	2	0.4129	0.8135	2	0.8022	0.6696
MI	2	0.5092	0.7752	2	0.5644	0.7541
MN	2	0.3010	0.8603	2	4.3455	0.1139
MO	2	1.3140	0.5184	2	0.1264	0.9388
MS	2	1.8910	0.3885	2	0.6690	0.7157
NC	2	0.6479	0.7233	2	3.8353	0.1469
ND	1	0.5059	0.4769	1	0.0405	0.8405
NE	4	5.7872	0.2156	4	8.7860	0.0667*
NM	2	0.4986	0.7794	2	1.1037	0.5759
NY	2	1.7205	0.4231	2	0.0498	0.9754
OH	2	0.4115	0.8140	2	1.9459	0.3780
OK	2	5.6833	0.0583*	2	2.3691	0.3059
OR	3	0.7615	0.8586	3	5.2300	0.1557
PA	2	0.9569	0.6197	2	0.6430	0.7251
SD	3	4.7128	0.1941	3	1.8799	0.5977
TN	2	0.1655	0.9206	2	1.0832	0.5818
TX	2	6.8918	0.0319**	2	0.9949	0.6081
VA	2	0.3209	0.8518	2	1.5347	0.4642
WA	2	0.4214	0.8100	2	0.0054	0.9973
WI	2	0.1280	0.9380	2	0.1953	0.9070
Panel Test Statistics						
Mean Wald Test Statistic: 1.780				**Mean Wald Test Statistic:** 1.775		
Bootstrap Critical Values:				**Bootstrap Critical Values:**		
*** 1%: 5.948				*** 1%: 6.516		
** 5% : 4.673				** 5% : 4.981		
* 10% : 4.099				* 10% : 4.108		

Panel C	Output does not Granger cause stock prices $y \overset{?}{\rightarrow} z$			House prices do not Granger cause stock prices $x \overset{?}{\rightarrow} z$		
Individual Statistics						
State	k_i	W_i	p_i	k_i	W_i	p_i
AL	2	4.9701	0.0833*	2	0.8594	0.6507
AR	2	2.2573	0.3235	2	0.5246	0.7693
AZ	2	6.3086	0.0427**	2	6.2042	0.0450**
CA	2	1.0775	0.5835	2	2.6281	0.2687
CO	2	4.8611	0.0880*	2	1.3332	0.5135
FL	2	4.2752	0.1179	2	6.5256	0.0383**
GA	2	3.4949	0.1742	2	2.0734	0.3546
IA	2	3.4872	0.1749	2	0.1012	0.9506
ID	2	4.7139	0.0947*	2	4.4685	0.1071
IL	2	1.7871	0.4092	2	0.0981	0.9522
IN	2	0.9014	0.6372	2	0.1602	0.9230
KS	2	0.9449	0.6235	2	0.2545	0.8805
KY	2	0.7141	0.6997	2	0.3152	0.8542
MI	2	1.1115	0.5736	2	1.9705	0.3733
MN	2	2.0445	0.3598	2	0.0428	0.9788
MO	2	3.1872	0.2032	2	0.0984	0.9520
MS	2	6.6251	0.0364**	2	2.4630	0.2919
NC	2	4.2830	0.1175	2	1.2801	0.5273
ND	1	0.6056	0.4364	1	0.2833	0.5945
NE	4	2.5536	0.6351	4	2.2616	0.6878
NM	2	7.2903	0.0261**	2	3.4492	0.1782
NY	2	2.1833	0.3357	2	0.5499	0.7596
OH	2	0.6424	0.7253	2	0.2734	0.8722
OK	2	1.5950	0.4505	2	0.1351	0.9347
OR	3	5.3434	0.1483	3	7.7971	0.0504*
PA	2	3.4716	0.1763	2	0.1010	0.9508
SD	3	2.3828	0.4968	3	0.4497	0.9298
TN	2	1.8368	0.3992	2	0.9343	0.6268
TX	2	3.5560	0.1690	2	1.6174	0.4454
VA	2	3.3318	0.1890	2	1.3373	0.5124
WA	2	1.6357	0.4414	2	2.1714	0.3377
WI	2	0.5751	0.7501	2	0.0165	0.9918

Panel Test Statistics

Mean Wald Test Statistic: 3.122	**Mean Wald Test Statistic:** 1.588
Bootstrap Critical Values:	**Bootstrap Critical Values:**
*** 1% : 6.717	*** 1%: 6.253
** 5% : 5.303	** 5% : 4.910
* 10% : 4.389	* 10% : 4.201

Note: *x*=real house prices; *y*=real percapita personal income and *z*= real stock prices.

Table 3: The Granger Causality Results of Industrial States and the District of Columbia

Panel A	House prices do not Granger cause output $x \overset{?}{\rightarrow} y$			Stock prices do not Granger cause output $z \overset{?}{\rightarrow} y$		
Individual Statistics						
State	k_i	W_i	p_i	k_i	W_i	p_i
AK	1	4.3269	0.0375**	1	3.8365	0.0501*
CT	2	18.2740	0.0001***	2	16.2394	0.0003***
DC	2	6.450	0.040**	2	15.066	0.001***
DE	2	2.3358	0.3110	2	4.6296	0.0988*
HI	2	5.9618	0.0507*	2	2.4669	0.2913
LA	2	1.7724	0.4122	2	3.4033	0.1824
MA	2	16.0911	0.0003***	2	20.9696	0.0000***
MD	2	1.6228	0.4442	2	8.8869	0.0118**
ME	2	2.1036	0.3493	2	4.1260	0.1271
MT	2	5.5805	0.0614*	2	13.1308	0.0014***
NH	2	10.7936	0.0045***	2	9.2972	0.0096***
NJ	2	7.9579	0.0187**	2	14.0451	0.0009***
NV	2	1.3388	0.5120	2	11.8773	0.0026***
RI	2	4.0776	0.1302	2	0.1599	0.9232
SC	1	0.4263	0.5138	1	7.6069	0.0058***
UT	2	9.7624	0.0076***	2	23.4064	0.0000***
VT	1	2.4841	0.1150	1	4.2052	0.0403**
WV	1	1.5899	0.2073	1	3.7851	0.0517*
WY	2	0.9598	0.6188	2	16.7487	0.0002***
Panel Test Statistics						
Mean Wald Test Statistic: 5.360***				**Mean Wald Test Statistic:** 9.474***		
Bootstrap Critical Values:				**Bootstrap Critical Values:**		
*** 1%: 4.863				*** 1%: 5.733		
** 5% : 3.945				** 5% : 4.324		
* 10% : 3.429				* 10% : 3.634		

Panel B	Output does not Granger cause house prices $y \overset{?}{\rightarrow} x$			Stock prices do not Granger cause house prices $z \overset{?}{\rightarrow} x$		
Individual Statistics						
State	k_i	W_i	p_i	k_i	W_i	p_i
AK	1	1.3763	0.2407	1	0.2568	0.6123
CT	2	0.6797	0.7119	2	0.1050	0.9489
DC	2	1.2031	0.5480	2	3.6282	0.1630
DE	2	0.6131	0.7360	2	3.0736	0.2151
HI	2	3.6552	0.1608	2	2.1372	0.3435
LA	2	0.3063	0.8580	2	0.4134	0.8133
MA	2	0.3128	0.8552	2	0.1827	0.9127
MD	2	0.2011	0.9044	2	2.8447	0.2412
ME	2	0.6593	0.7192	2	0.4654	0.7924
MT	2	3.3035	0.1917	2	0.7988	0.6707
NH	2	0.8965	0.6387	2	1.4585	0.4823
NJ	2	1.5297	0.4654	2	0.2834	0.8679
NV	2	1.0422	0.5939	2	3.0184	0.2211
RI	2	1.4020	0.4961	2	2.4263	0.2973
SC	1	0.0864	0.7688	1	0.1480	0.7004
UT	2	0.1407	0.9321	2	0.1959	0.9067
VT	1	0.6125	0.4338	1	0.8239	0.3641
WV	1	3.8704	0.0491**	1	0.0845	0.7712
WY	2	12.7908	0.0017***	2	4.6254	0.0990*

Panel Test Statistics

Mean Wald Test Statistic: 1.784	**Mean Wald Test Statistic:** 1.229
Bootstrap Critical Values:	**Bootstrap Critical Values:**
*** 1%: 5.203	*** 1%: 5.344
** 5%: 4.037	** 5% : 4.089
* 10%: 3.474	* 10% : 3.549

Panel C	Output does not Granger cause stock prices $y \overset{?}{\rightarrow} z$			House prices do not Granger cause stock prices $x \overset{?}{\rightarrow} z$		
Individual Statistics						
State	k_i	W_i	p_i	k_i	W_i	p_i
AK	1	3.8683	0.0492**	1	0.9833	0.3214
CT	2	4.3513	0.1135	2	1.7807	0.4105
DC	2	7.5063	0.0234**	2	0.2080	0.9012
DE	2	3.3580	0.1866	2	0.8060	0.6683
HI	2	5.1344	0.0768*	2	2.9497	0.2288
LA	2	2.0449	0.3597	2	1.5295	0.4654
MA	2	1.7643	0.4139	2	2.7706	0.2502
MD	2	3.8063	0.1491	2	2.3601	0.3073
ME	2	0.3506	0.8392	2	1.8397	0.3986
MT	2	4.8730	0.0875*	2	1.8081	0.4049
NH	2	1.6996	0.4275	2	1.0731	0.5848
NJ	2	2.7720	0.2501	2	0.0202	0.9899
NV	2	4.7662	0.0923*	2	3.2830	0.1937
RI	2	3.4992	0.1738	2	2.1780	0.3366
SC	1	1.1627	0.2809	1	0.9533	0.3289
UT	2	6.8760	0.0321**	2	2.8453	0.2411
VT	1	0.8293	0.3625	1	0.1417	0.7066
WV	1	0.0486	0.8256	1	0.5206	0.4706
WY	2	0.9260	0.6294	2	0.6657	0.7169
Panel Test Statistics						
Mean Wald Test Statistic: 2.830 **Bootstrap Critical Values:** *** 1%: 6.014 ** 5% : 4.315 * 10% : 3.615				**Mean Wald Test Statistic:** 1.615 **Bootstrap Critical Values:** *** 1%: 4.923 ** 5% : 3.837 * 10% : 3.387		

Note: See note to Table 2.

Table 4: Summary of Bootstrap Panel Mean Wald Granger Causality Test

Agricultural States

	Mean Wald Statistic	Bootstrap Critical Values		
		1%	5%	10%
x does not Granger cause *y*	5.958***,	5.553	4.466	3.903
z does not Granger cause *y*	15.142***	6.807	5.059	4.313
y does not Granger cause *x*	1.78	5.948	4.673	4.099
z does not Granger cause *x*	1.775	6.516	4.981	4.108
y does not Granger cause *z*	3.122	6.717	5.303	4.389
x does not Granger cause *z*	1.588	6.253	4.91	4.201

Industrial States and the District of Columbia

	Mean Wald Statistic	Bootstrap Critical Values		
		1%	5%	10%
x does not Granger cause *y*	5.36***	4.863	3.945	3.429
z does not Granger cause *y*	9.474***	5.733	4.324	3.634
y does not Granger cause *x*	1.784	5.203	4.037	3.474
z does not Granger cause *x*	1.229	5.344	4.089	3.549
y does not Granger cause *z*	2.83	6.014	4.315	3.615
x does not Granger cause *z*	1.615	4.923	3.837	3.387

Note: Critical values are computed using 2000 bootstrap draws. *** denotes rejection at the 1% level based on the bootstrap critical value.

Table 5: Summary of p-values of Individual Granger Causality Test (Agricultural states)

States	*x* does not Granger cause *y*	*z* does not Granger cause *y*	*y* does not Granger cause *x*	*z* does not Granger cause *x*	*y* does not Granger cause *z*	*x* does not Granger cause *z*
AL	0.153	0.025**	0.8892	0.8951	0.0833*	0.6507
AR	0.379	0.342	0.244	0.8373	0.3235	0.7693
AZ	0.129	0.006***	0.4697	0.6906	0.0427**	0.0450**
CA	0.091*	0.002***	0.7017	0.2801	0.5835	0.2687
CO	0.075*	0.000***	0.1123	0.1189	0.0880*	0.5135
FL	0.001***	0.047**	0.4484	0.3124	0.1179	0.0383**
GA	0.181	0.000***	0.2663	0.2518	0.1742	0.3546
IA	0.203	0.105	0.4822	0.5923	0.1749	0.9506
ID	0.082*	0.006***	0.814	0.8691	0.0947*	0.1071
IL	0.009***	0.000***	0.2091	0.5809	0.4092	0.9522
IN	0.312	0.000***	0.8771	0.8435	0.6372	0.923
KS	0.269	0.000***	0.2264	0.6072	0.6235	0.8805
KY	0.077*	0.005***	0.8135	0.6696	0.6997	0.8542
MI	0.011**	0.000***	0.7752	0.7541	0.5736	0.3733
MN	0.096*	0.000***	0.8603	0.1139	0.3598	0.9788
MO	0.101	0.014**	0.5184	0.9388	0.2032	0.952
MS	0.61	0.050***	0.3885	0.7157	0.0364**	0.2919
NC	0.341	0.004***	0.7233	0.1469	0.1175	0.5273
ND	0.457	0.099*	0.4769	0.8405	0.4364	0.5945
NE	0.000***	0.000***	0.2156	0.0667*	0.6351	0.6878
NM	0.322	0.015**	0.7794	0.5759	0.0261**	0.1782
NY	0.001***	0.000***	0.4231	0.9754	0.3357	0.7596
OH	0.715	0.003***	0.814	0.378	0.7253	0.8722
OK	0.259	0.000***	0.0583*	0.3059	0.4505	0.9347
OR	0.002***	0.004***	0.8586	0.1557	0.1483	0.0504*
PA	0.061*	0.000***	0.6197	0.7251	0.1763	0.9508
SD	0.005***	0.000***	0.1941	0.5977	0.4968	0.9298
TN	0.083*	0.13	0.9206	0.5818	0.3992	0.6268
TX	0.565	0.000***	0.0319**	0.6081	0.169	0.4454
VA	0.114	0.055*	0.8518	0.4642	0.189	0.5124
WA	0.1122	0.0037***	0.81	0.9973	0.4414	0.3377
WI	0.127	0.038**	0.938	0.907	0.7501	0.9918

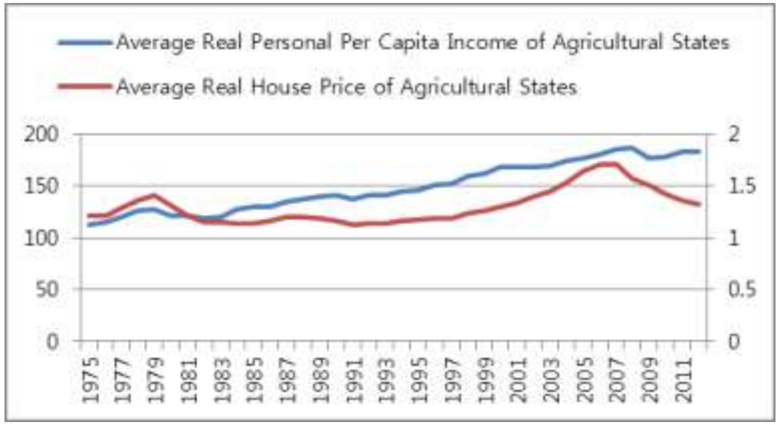
Note: See note to Table 2.

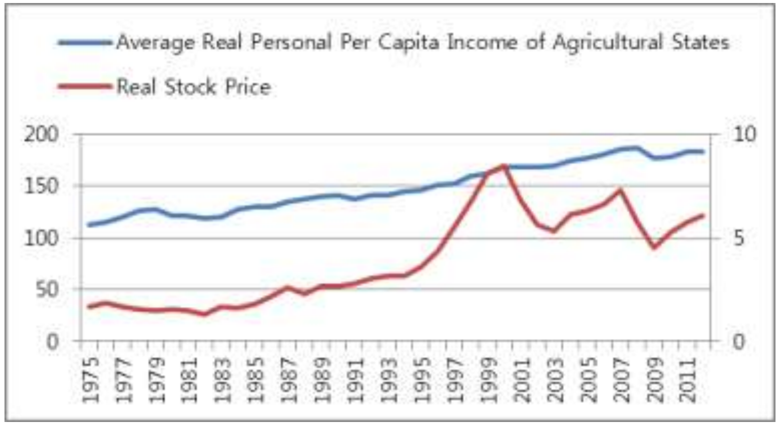
Table 6: Summary of p-values of Individual Granger Causality Test (Industrial states and the District of Columbia)

States	*x* does not Granger cause *y*	*z* does not Granger cause *y*	*y* does not Granger cause *x*	*z* does not Granger cause *x*	*y* does not Granger cause *z*	*x* does not Granger cause *z*
AK	0.0375^{**}	0.0501^{*}	0.2407	0.6123	0.0492^{**}	0.3214
CT	0.0001^{***}	0.0003^{***}	0.7119	0.9489	0.1135	0.4105
DC	0.040^{**}	0.001^{***}	0.548	0.163	0.0234^{**}	0.9012
DE	0.311	0.0988^{*}	0.736	0.2151	0.1866	0.6683
HI	0.0507^{*}	0.2913	0.1608	0.3435	0.0768^{*}	0.2288
LA	0.4122	0.1824	0.858	0.8133	0.3597	0.4654
MA	0.0003^{***}	0.0000^{***}	0.8552	0.9127	0.4139	0.2502
MD	0.4442	0.0118^{**}	0.9044	0.2412	0.1491	0.3073
ME	0.3493	0.1271	0.7192	0.7924	0.8392	0.3986
MT	0.0614^{*}	0.0014^{***}	0.1917	0.6707	0.0875^{*}	0.4049
NH	0.0045^{***}	0.0096^{***}	0.6387	0.4823	0.4275	0.5848
NJ	0.0187^{**}	0.0009^{***}	0.4654	0.8679	0.2501	0.9899
NV	0.512	0.0026^{***}	0.5939	0.2211	0.0923^{*}	0.1937
RI	0.1302	0.9232	0.4961	0.2973	0.1738	0.3366
SC	0.5138	0.0058^{***}	0.7688	0.7004	0.2809	0.3289
UT	0.0076^{***}	0.0000^{***}	0.9321	0.9067	0.0321^{**}	0.2411
VT	0.115	0.0403^{**}	0.4338	0.3641	0.3625	0.7066
WV	0.2073	0.0517^{*}	0.0491^{**}	0.7712	0.8256	0.4706
WY	0.6188	0.0002^{***}	0.0017^{***}	0.099^{*}	0.6294	0.7169

Note: See note to Table 2.

APPENDIX:


Average Real Personal Per Capita Income of Agricultural States
Average Real House Price of Agricultural States
200
150
100
50
0
2
1.5
1
0.5
0
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011


Average Real Personal Per Capita Income of Agricultural States
Real Stock Price
200
150
100
50
0
10
5
0
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011

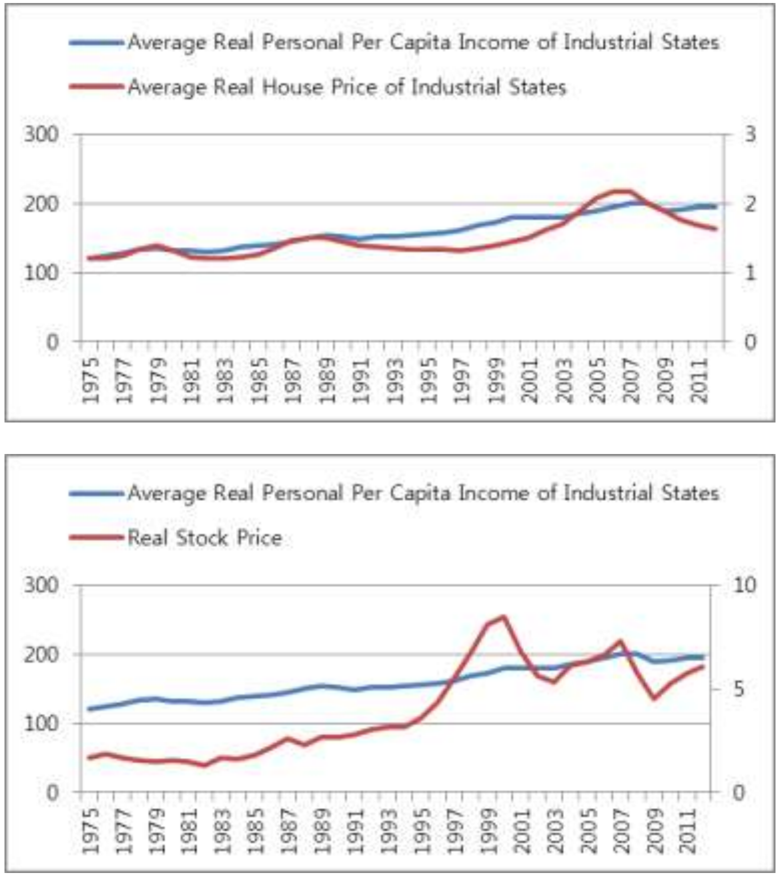


Figure A1: Relationship between Real Per Capita Personal Income and Asset prices: (1975-2012)

Table A1. Summary Statistics of Real Per Capita Personal Income (Agricultural States)

State	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
AL	127.69	169.75	91.47	22.17	0.01	1.65	2.85
AR	121.85	155.60	89.59	20.70	0.20	1.72	2.84
AZ	139.51	175.08	106.23	18.90	0.23	1.99	1.92
CA	173.28	213.47	136.96	21.67	0.26	1.79	2.75
CO	166.67	211.07	121.34	28.61	0.16	1.51	3.67
FL	153.98	193.93	113.26	22.99	-0.03	1.94	1.78
GA	141.47	174.73	98.98	24.23	-0.28	1.68	3.27
IA	146.05	186.88	117.88	21.47	0.42	1.82	3.33
ID	129.29	161.08	102.03	18.33	0.16	1.59	3.30
IL	169.45	207.24	134.51	23.45	0.04	1.55	0.04
IN	142.03	166.21	112.03	18.20	-0.12	1.55	3.40
KS	151.48	191.61	119.11	21.57	0.31	1.74	3.09
KY	127.06	154.59	94.81	19.63	0.01	1.54	3.34
MI	151.41	174.17	121.05	16.22	-0.25	1.84	2.52
MN	164.48	205.82	119.59	28.67	0.07	1.53	3.43
MO	145.86	178.70	110.53	20.69	-0.01	1.64	2.92
MS	113.49	146.53	80.74	21.47	0.19	1.58	3.42
NC	138.62	171.73	96.89	24.38	-0.28	1.63	3.47
ND	141.55	228.94	101.46	31.05	1.14	3.53	8.80**
NE	150.42	192.75	115.91	25.11	0.25	1.63	3.36
NM	125.94	158.58	96.92	18.73	0.37	1.77	3.26
NY	182.86	236.40	133.78	31.80	0.04	1.87	2.01

OH	149.76	173.81	117.10	18.20	-0.14	1.61	3.15
OK	136.08	178.49	105.43	19.86	0.66	2.22	3.71
OR	148.20	177.60	117.87	19.54	0.03	1.49	3.60
PA	157.03	192.60	118.65	23.80	0.05	1.63	2.98
SD	139.83	200.78	100.71	29.94	0.50	1.90	3.50
TN	136.46	169.06	96.46	23.89	-0.16	1.56	3.43
TX	147.23	187.58	110.13	22.41	0.34	1.75	3.17
VA	165.94	213.72	114.39	30.45	0.04	1.77	2.40
WA	164.54	208.85	125.43	26.33	0.22	1.56	3.57
WI	150.94	181.95	116.89	21.68	0.09	1.46	3.80

Note: The sample period is from 1975 to 2012. ***, ** and * indicate significance at the 1% , 5% and 10% level, respectively. J.-B.(Jarque-Bera) test is a normal test, which follows a chi-squared distribution.

Table A2: Summary Statistics of Real Per Capita Personal Income (Industrial States and the District of Columbia)

State	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
AK	188.38	217.78	169.55	14.13	0.26	1.89	2.38
CT	209.42	275.96	139.19	41.27	-0.12	1.74	2.59
DC	224.26	335.03	153.80	61.33	0.59	2.00	3.80
DE	164.99	196.66	129.36	21.11	-0.18	1.73	2.73
HI	165.44	197.34	135.52	18.13	0.15	1.97	1.81
LA	132.07	179.28	95.16	24.36	0.62	2.17	3.57
MA	187.70	247.75	123.85	40.26	-0.04	1.67	2.79
MD	182.82	231.39	132.24	32.24	0.09	1.73	2.58
ME	138.57	174.18	96.46	25.35	-0.03	1.63	2.97
MT	131.72	167.26	111.48	19.16	0.66	1.90	4.72^{*}
NH	167.57	212.35	107.52	32.42	-0.22	1.77	2.67
NJ	194.19	248.28	135.37	34.95	-0.11	1.69	2.75
NV	163.54	198.00	134.91	17.48	0.31	2.19	1.64
RI	157.95	199.33	112.30	27.73	0.01	1.75	2.47
SC	127.01	158.04	90.78	21.47	-0.15	1.61	3.18
UT	127.93	161.84	99.28	19.00	0.32	1.61	3.70
VT	144.83	189.68	99.86	28.69	0.11	1.68	2.81
WV	120.65	152.10	95.45	17.95	0.32	1.71	3.28
WY	161.94	232.52	128.09	32.74	0.81	2.22	5.14^{*}

Note: The sample period is from 1975 to 2012. ***, ** and * indicate significance at the 1% , 5% and 10% level, respectively. J.-B.(Jarque-Bera) test is a normal test, which follows a chi-squared distribution.

Table A3: Summary Statistics of Real House Prices (Agricultural States)

State	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
AL	1.29	1.51	1.13	0.11	0.51	2.02	3.19
AR	1.14	1.42	0.97	0.10	0.50	2.78	1.68
AZ	1.25	2.11	1.00	0.26	1.96	6.35	42.28***
CA	1.64	3.21	0.83	0.55	1.31	4.29	13.61***
CO	1.37	1.81	0.99	0.26	0.32	1.79	2.97
FL	1.37	2.38	1.12	0.31	2.08	6.54	47.44***
GA	1.33	1.61	1.13	0.12	0.63	2.42	3.10
IA	1.10	1.46	0.91	0.14	0.61	2.81	2.43
ID	1.20	1.68	0.95	0.18	0.87	3.31	4.97*
IL	1.39	1.84	1.07	0.20	0.53	2.78	1.87
IN	1.18	1.41	1.04	0.09	0.48	2.48	1.89
KS	1.09	1.39	0.89	0.12	0.54	2.94	1.92
KY	1.25	1.44	1.09	0.11	0.10	1.66	2.87
MI	1.26	1.66	0.95	0.20	0.51	2.14	2.81
MN	1.31	1.87	1.06	0.24	1.00	2.74	6.46**
MO	1.25	1.47	1.08	0.12	0.41	1.99	2.68
MS	1.13	1.44	0.94	0.13	0.67	2.83	2.93
NC	1.34	1.64	1.15	0.12	0.66	2.67	2.99
ND	1.07	1.46	0.85	0.16	0.54	2.26	2.71
NE	1.17	1.42	0.97	0.11	0.12	2.33	0.80
NM	1.25	1.62	1.02	0.13	0.86	3.54	5.25*

NY	2.09	3.19	1.29	0.56	0.31	2.12	1.85
OH	1.21	1.43	1.04	0.11	0.18	1.86	2.26
OK	0.97	1.34	0.77	0.16	0.78	2.45	4.38
OR	1.36	2.25	0.89	0.37	0.67	2.67	3.05
PA	1.47	1.95	1.12	0.21	0.49	2.65	1.76
SD	1.18	1.40	0.96	0.13	0.01	1.63	2.94
TN	1.26	1.48	1.10	0.10	0.26	2.22	1.39
TX	1.06	1.36	0.87	0.14	0.54	2.13	3.05
VA	1.50	2.29	1.14	0.31	1.23	3.35	9.84**
WA	1.48	2.45	0.91	0.40	0.74	2.77	3.57
WI	1.27	1.63	1.01	0.18	0.30	1.94	2.32

Note: The sample period is from 1975 to 2012. ***, ** and indicate significance at the 1% , 5% and 10% level, respectively. J.-B.(Jarque-Bera) test is a normal test, which follows a chi-squared distribution.

Table A4: Summary Statistics of Real House Prices (Industrial States and the District of Columbia)

State	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
AK	1.19	1.49	0.88	0.18	-0.01	1.56	3.27
CT	1.69	2.35	1.18	0.36	0.31	1.93	2.40
DC	1.63	3.06	0.93	0.65	1.01	2.53	6.89**
DE	1.68	2.46	1.19	0.33	0.83	2.98	4.46
HI	1.59	2.64	0.96	0.48	0.56	2.34	2.71
LA	1.03	1.36	0.78	0.15	0.09	2.13	1.25
MA	2.28	3.72	1.24	0.73	0.20	2.00	1.80
MD	1.58	2.61	1.18	0.39	1.33	3.83	12.43***
ME	1.76	2.51	1.23	0.38	0.51	2.15	2.82
MT	1.27	1.83	0.92	0.25	0.62	2.39	3.08
NH	1.65	2.44	1.15	0.38	0.53	2.05	3.20
NJ	1.78	2.87	1.13	0.49	0.58	2.43	2.63
NV	1.23	2.05	0.82	0.26	1.74	5.85	32.11***
RI	1.83	3.02	1.11	0.53	0.68	2.60	3.19
SC	1.36	1.66	1.22	0.12	0.89	2.82	5.08*
UT	1.29	1.86	0.92	0.23	0.30	2.61	0.82
VT	1.59	2.23	1.09	0.31	0.64	2.34	3.31
WV	1.01	1.37	0.83	0.15	1.14	3.23	8.43
WY	1.03	1.39	0.69	0.21	0.08	1.74	2.52

Note: The sample period is from 1975 to 2012. ***, ** and * indicate significance at the 1% , 5% and 10% level, respectively. J.-B.(Jarque-Bera) test is a normal test, which follows a chi-squared distribution.