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Abstract

This paper analyses the convergence of US house prices. Our results confirm the existence of some degree of segmentation in the US housing market. We also provide robust evidence that the bursting of the housing price bubble has altered this market, observing different results when the sample includes information posterior to 2010. However, we appreciate different effects depending on the geographical level of disaggregation that is employed.

1. Introduction

The evolution of the housing market has recently attracted the attention of a number of economists. This market has always been relevant in the economies of developed countries because of the influence of the activity of the construction sector on the other sectors. Interest has increased in recent years due to the recognised impact of the evolution of house prices on the crisis that is currently plaguing most economies. In this regard, we should recall that one of the sources of the current economic situation is related to the boom and bust of house prices in some countries, with Spain and the USA being very clear examples of this question.

Some economists have tried to explain the movements in house prices by emphasizing the possible existence of common factors which act as market references. For instance, we can recall the papers of McDonald and Taylor (1993) and Cook (2003) for the UK and Meen (2003) for the USA. These papers show a certain degree of segmentation in the housing markets under analysis. Canarella et al. (2012) has recently analyzed the presence of a convergence process between US house prices by applying unit root tests to the S&P Case-Shiller home price indexes, the method commonly employed in the abovementioned studies. These authors obtain partial evidence of the segmentation of the US housing market, which reinforces the results of the previous papers. Canarella et al (2012) also show the influence of the east and west coast metropolitan areas, again confirming the results of MacDonald and Taylor (1993).

In spite of the importance of these results for understanding the behavior of the US housing market, we should note the recent contributions of Phillips and Sul (2007, 2009). These authors question the use of unit root tests for analyzing convergence, given that failing to reject the unit root null hypothesis does not necessarily imply the absence of convergence. Consequently, it seems to be appropriate to apply their new techniques to the US housing data in order to verify the possible segmentation of the market or, by contrast, to prove the existence of convergence towards a unique common factor.

Against this background, the aim of our paper is to apply the convergence methodology described in Phillips and Sul (2007, 2009) to the S&P Case-Shiller house prices database with the idea of challenging the robustness of the results previously found in the literature. To that end, the rest of this paper is organised as follows. Section 2 describes the database and presents the results, whilst the final section contains a review of the obtained results.

2. Testing for stochastic convergence in US housing markets: Data and Results

2.1 Data Base

As we have already mentioned, the data used in this paper have been obtained from the S&P/Case-Shiller Home Price Indices (HPI) database. Contrary to Canarella et al (2012), we prefer to use the non-seasonally-adjusted monthly house price indices given that the use of seasonal filters may change the time properties of the variables, as is discussed in Ghysels and Perron (1993). We have considered the following 19 MSAs: Phoenix (AZ), Los Angeles (CA), San Diego (CA), San Francisco (CA), Denver (CO), Washington (DC), Miami (FL), Tampa (FL), Atlanta (GA), Chicago (IL), Boston (MA), Detroit (MI), Minneapolis (MN), Charlotte (NC), Las Vegas (NV), New York (NY), Cleveland (OH), Portland (OR) and Seattle (WA) and the common sample covers the period 1991:01-2013:03. This implies the exclusion of the information of Dallas (TX), whose data are only available from 2000 on.

2.2. Convergence analysis

The convergence analysis is based on the application of the techniques described in Phillips and Sul (2007, 2009). Following these authors, we have eliminated the cyclical components by way of the HP filter, see Hodrick and Prescott (1997). We have also moved the base year to the beginning of the period and have discarded some initial observations with the aim of removing the effects created by the base year initialization. Consequently, the effective sample size covers the period 2000:M1-2013:M3. The estimation of the log-t coefficient is -1.17, whilst its corresponding t-ratio is -183.63, which allows us to easily reject the null hypothesis of convergence at the 1% significance level. The absence of evidence of house price convergence for the total sample leads us to consider the possible existence of some convergence clubs by using the clustering method also described in Phillips and Sul (2007, 2009). Table 1 reports the club classification obtained.

We can observe the presence of 4 differentiated clubs. The first includes the MSAs of Denver and Portland. The second includes three big metropolitan areas in the North East (Boston, New York and Washington) as well as Charlotte and Seattle. The third club is the most numerous and is made up of Phoenix, Los Angeles, San Diego, San Francisco, Miami, Tampa, Atlanta, Chicago, Minneapolis and Cleveland. Finally, the fourth club only contains Detroit and Las Vegas.

Given that this cluster procedure is too conservative and tends to find more groups than actually exist, we have tested whether adjacent clusters can be merged into larger groups. Table 2 shows that Clubs 2 and 3 can be merged into a very large club of 15 MSAs.

In order to better understand the results, we have constructed a new index for the 3 clubs finally obtained by using the arithmetic average of the prices included in each club. Figure 1 reflects these indexes. We can now see that the values at the beginning of the sample are similar for Clubs 2+3 and 4, whilst those of the Club 1 are lower. By contrast, the rank of the indexes is quite different at the end of the sample, with Clubs 1 and 2+3 exhibiting a similar pattern, whilst the index of Club 4 collapses and returns to its initial position. Furthermore, we can also observe differences in the manner in which the clubs have suffered the bursting of the housing bubble given that the distance between the maximum value and that of the end of the sample is not similar in all the cases: the reductions are 14% for Club 1, 30% for Club 2+3 and 47% for Club 4.

As we have seen, the bursting of the housing bubble seems to play an important role in the explanation of the results. In order to explore this fact in depth, we have repeated the cluster analysis but now allowing the end of the sample size to change from 2006:M1 to 2013:M3. Table 3 reports some of these results. We can observe that most of the MSAs are included in a single group when the sample size ends in 2006:M1. However, we can appreciate that this initial group disaggregates when the sample size increases. Thus, we can see a clear alteration of the clustering results over time, which leads us to study whether we can find statistical evidence of a change in the cluster results as a consequence of the bursting of the housing bubble.

Let us assume the existence of n clubs. Then, we assign the value n to the MSAs included in the n-th club (n+1 if the MSA does not converge). If we allow the sample end points to vary between 2006:M1 and 2013:M3, then we have a group of 75 series which contains the information related to the cluster analysis. We have applied the Kruskal-Wallis and the van der Waarden statistics[1] to these series in order to test whether they have been generated by the same general distribution. Figure 2 reflects the evolution of the p-values of these two statistics. It is straightforward to see that these p-values cannot initially reject the null hypothesis, but they plummet to below 5% after 2009:M11, which allows us to conclude that the number and the composition of the

[1] See Conover (1980) in this regard.

clubs have altered and, consequently, that the US housing market has significantly varied after this date.

This result is quite important for understanding the behavior of the US housing prices of the 19 MSAs, but we do not know whether it can be extended to the total US housing market. To test this, and following Kim and Rous (2012), we have decided to carry out a similar analysis but now employing the data published by the US Federal Housing Finance Agency which cover the 1975:Q1-2013:Q1 period and include information about the 50 States and the District of Columbia. We again allow the sample end points to vary between 2006:Q1 and 2013.Q1. Table 4 reports the results of the cluster analysis, whilst Figure 3 plots the p-values of the Kruskal-Wallis and the van der Vaarden statistics. As we can appreciate, the number of clubs again changes over time: there are 7 clubs when the sample closes at 2006:Q1, whilst there are only 4 clubs when the end point is after 2010:Q1. We can also observe that the p-values of the nonparametric tests fall below 5% whenever the end point belongs to the interval 2010:Q1-2013:Q1, which strengthens the evidence for a change in the US housing market after 2010.

3. Conclusions

The results obtained in this paper provide evidence of the existence of some degree of segmentation in the US housing market, reinforcing those of Canarella et al (2012) and Kim and Rous (2012).

We have also analyzed the effect of the bursting of the housing bubble. Our results lead us to conclude that this event has clearly altered the US housing market because the cluster analysis offers very different results depending on when the sample ends. The use of nonparametric tests allows us to date the occurrence of this change in 2010. We can also observe that the effect seems to be different for the two databases employed.

When the database only refers to the 19 MSAs, we appreciate an increase in the segmentation of the market because the number of clubs rises when the post-2010 information is used. By contrast, we can see that the number of clubs falls when the State-level data are employed).

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Table 1. Initial convergence club classification. 19 MSAs

	MSAs	Log t	t-stat
Club 1	Denver, Portland.	1.11	1.69
Club 2	Washington, Boston, Charlotte, New York, Seattle.	0.12	3.58
Club 3	Phoenix, Los Angeles, San Diego, San Francisco, Miami, Tampa, Atlanta, Chicago. Minneapolis, Cleveland.	0.53	11.12
Club 4	Detroit, Las Vegas.	1.41	0.76

The clubs reported have been obtained by applying the algorithm proposed by Phillips and Sul (2007), which aims to find groups of countries with similar convergence speeds to the average. The term log t stands for a parameter which is twice the speed of convergence of this club towards the average. t-stat is the convergence test statistic, which is distributed as a simple one-sided t-test with a critical value of −1.65 (see Phillips and Sul, 2007 for further details).

Table 2. Testing for club merging club classification. 19 MSAs

Clubs	Log t	t-stat
Club 1 + Club 2	-0.18	-20.74*
Club 2 + Club 3	-0.00	-0.02
Club 2 + Club 3 + Club 4	-0.77	-38.62*

See note of Table 1.

* Denotes the rejection of the convergence null hypothesis when the 1% significance level is employed.

Table 3. Effect of changing the end of the sample on the cluster analysis. 19 MSAs

	2006:M1	2009:M1	2010:M1
Club 1	Boston, Chicago, Denver, Detroit, Los Angeles, Las Vegas, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, Seattle, San Francisco, Tampa, Washington	Boston, Denver, Los Angeles, Las Vegas, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, Seattle, San Francisco, Tampa, Washington	Boston, Denver, New York, Portland, Seattle, Washington
Club2		Atlanta, Charlotte, Detroit	Charlotte, Chicago, Cleveland, Los Angeles, Las Vegas, Miami, Minneapolis, Phoenix, San Diego, San Francisco, Tampa
Club3		Chicago, Cleveland	Atlanta, Detroit
No Convergence	Atlanta, Charlotte, Cleveland		

This Table reflects the results of the cluster analysis when the end of the sample is 2006:M1, 2009:M1 and 2010:M1, respectively, for columns 2, 3 and 4. The technical details are described in the footnote to Table 1.

Table 4. Effect of changing the end of the sample on the cluster analysis. State Database.

	2006:Q1	2009:Q1	2010:Q1	2013:Q1
Club 1	CA, DC	CA, DC	CA, DC	CA, DC
Club 2	MA, ME, NH, RI, WA	AZ, FL, HI, MD, ME, NH, NJ, NY, RI, VA, WA	FL, HI, MA, MD, ME, NH, NJ, NY, OR, RI, VA, WA	CT, DE, HI, MA ,MD, ME, MT, NH, NJ, NY, OR, RI, VA, VT, WA, WY
Club 3	CO, CT, FL, HI, MD, MN,NJ, NV, NY,OR, VA	CT, DE, NV, OR, VT	AK,AZ, CO, CT, DE, ID, IL,MN, MT, NM, NV, PA, UT, VT, WY	AK, AZ, CO, FL,,ID, IL,KY, LA, MN,NC, ND, NM, PA, SC,SD, TX, UT, WI,WV
Club 4	AZ, DE, IL, MI, MT, NM, PA, UT, VT, WI,WY	AK, CO, ID, IL,MI, MN, MT, NM, PA, UT,WI, WY	AL, AR, GA, IA, IN, KS, KY, LA, MI, MO, MS, NC, ND, NE, OH, OK, SC, SD, TN, TX, WI, WV	AL, AR, GA, IA, IN, KS, MI, MO, MS, NE, NV, OH, OK ,TN
Club 5	AK, GA, IA, KY, LA, MO ,NC, OH ,SC	GA, KY ,LA ,MO, NC, SC, TN,WV		
Club 6	ID, IN, KS, SD, TN, TX, WV	AL, AR, IA, IN, KS,ND, NE, OH, OK, SD, TX		
Club 7	AL, AR, OK			
No Convergence	MS,ND	MA,MS		

This table reflects the results of the cluster analysis for the 50 US States plus the District of Columbia. The sample sizes cover the periods from 1975:Q1 to 2006:Q1, 2009:Q1, 2010:Q1 and 2013:Q1, respectively, for columns 2-5. The technical details are similar to those used in Kim and Rous (2012) to obtain the results included in Table 4.
The names of the States are represented by their official abbreviations.

Figure 1. Arithmetic mean of house price indices for each convergence club.

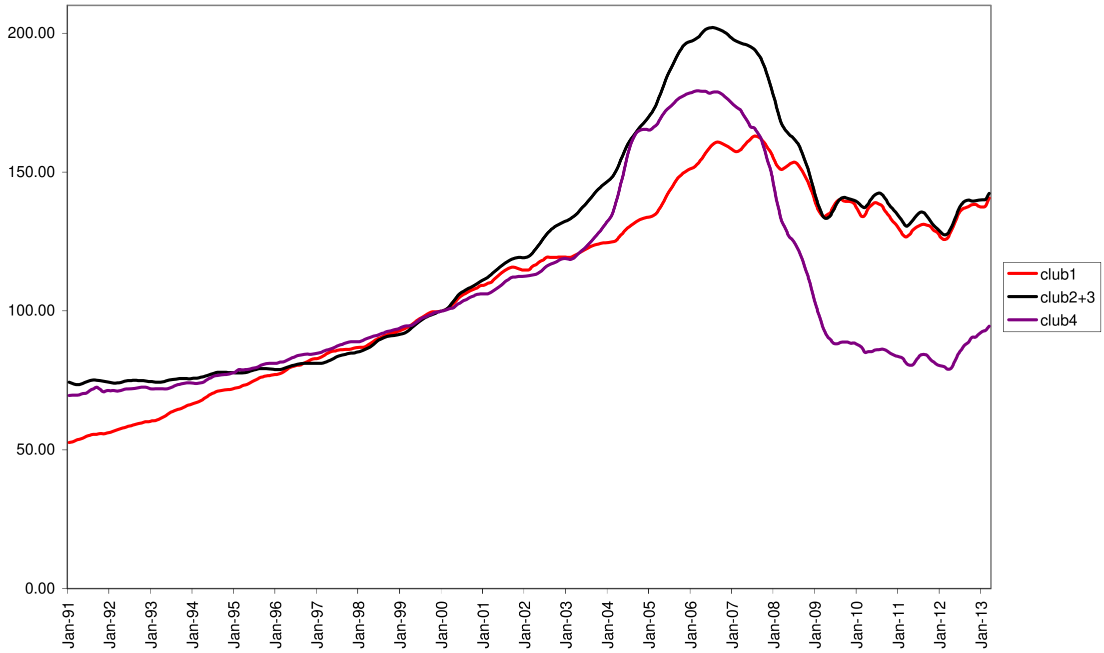
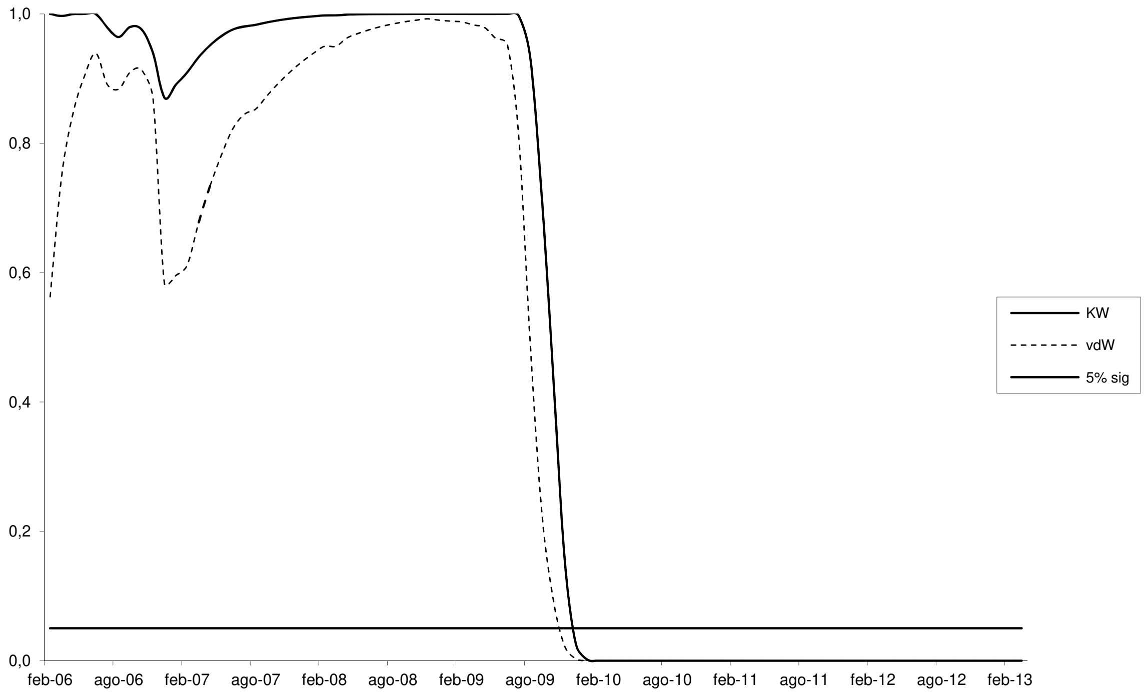
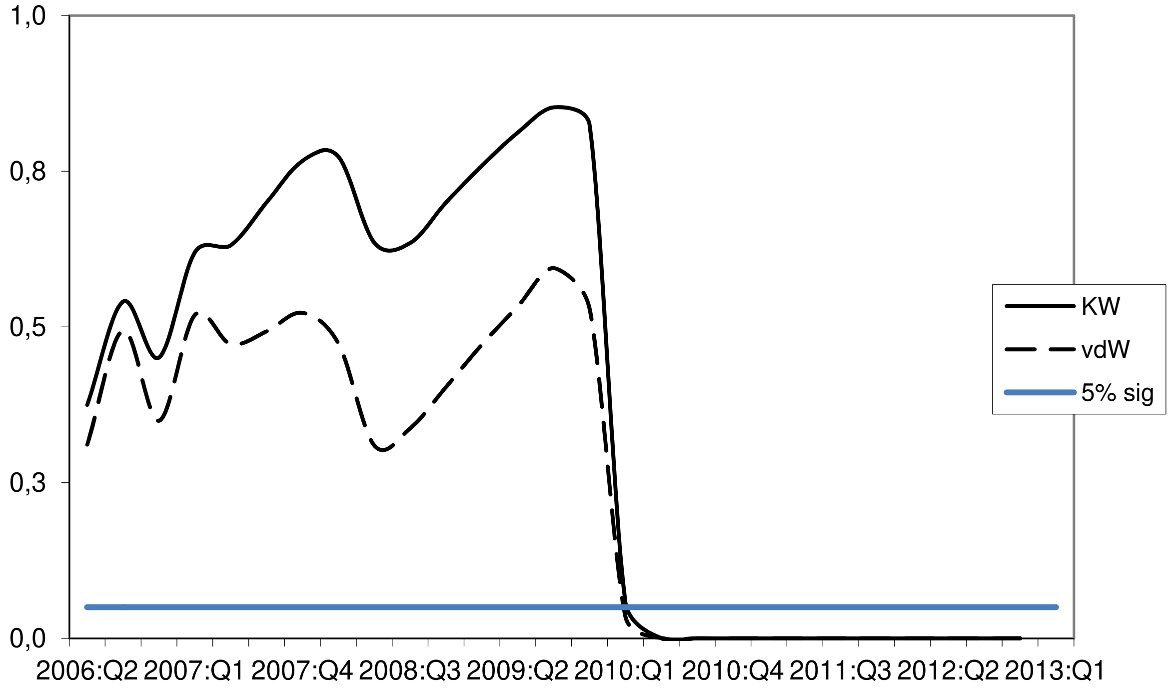


Figure 2. P-values of the Kruskal-Wallis and van der Waarden statistic. 19 MSAs



This figure reflects the p-values of the Kruskal-Wallis (KW) and var der Waarden (vdW) statistics when they are applied to the results of the cluster analysis for the sample sizes that cover the period 1991:M1-x, with x = 2006:M1,…, 2013:M3.

Figure 3. P-values of the Kruskal-Wallis and van der Waarden statistic.
State-level database



This figure reflects the p-values of the Kruskal-Wallis (KW) and var der Waarden (vdW) statistics when they are applied to the results of the cluster analysis for the sample sizes that cover the period 1975:Q1-x, with x = 2006:Q1,…, 2013:Q1.