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Application of Wavelet Decomposition to Detect Housing Boom-Bust Cycles

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Abstract: Generally, busts in housing prices lead to their booms. Short-term deviations of a house price cycle from its long-term upward trend can be a common phenomenon relevant to such changes. A periodically cyclical fluctuation has occurred to the Iranian housing market in the long run, e.g., nearly every 6 years. Moreover, business cycles, financial stability and household welfare are significantly influenced by the movements occurred in house prices. Central banks, financial supervision authorities and other economic agents highly need to be able to predict house prices. To determine house prices based on their cyclical components in this research, a wavelet decomposition method was utilized. Then, the boom-bust cycles of low frequency housing prices were analyzed.

Key words: Wavelet, decomposition, wavelet power spectrum, housing cycles, central banks, frequency

INTRODUCTION

Boom and bust episodes historically affect housing markets. It is generally believed that the house price cycles of housing markets in many countries are triggered by short-term deviations from long-term upward trends. Short-term fluctuations around the growth path lead to long-term growths in house prices. Harmful impacts are exerted on the households, financial intermediaries and the whole economy through the gradual housing booms that may suddenly lead to a burst. In many countries, the largest class of assets is represented by the residential housing sector. A major source of crisis widely occurring to the financial system can be a housing boom-bust cycle. To detect a deviation from "intrinsic" values and control the potential large swings of these housing cycles in the markets, a more precise analysis is recquired for policymakers.

Association of an enhanced demand for housing services with the declining land supply has generally led to this increasing trend in house prices in the long run. The increasing housing value and overtime has been caused by for instance, the raising income and consequent rising demand for housing. Therefore, the rising trend of house prices has been driven by economic forces. It has been argued that a cyclical fluctuation of every 6 years has periodically occurred in the Iranian housing market. Since late 1990's, a sharp upward movement in the Iranian house prices has happened every 6 years due to booming of the housing market. However, the boom in the housing market during the 6 years period has been believed to be caused by the economic condition, not simply by the psychological expectation on the cyclical upturn in house prices. Therefore, a close relationship of the housing market structure besides macroeconomic variables with the cyclical patterns of housing prices has been evidenced. Compared to equity price busts, housing price busts have been seen to exert stronger and faster adverse effects on the banking system as described below.

Due to the larger amounts of non-performed loans, banks have encountered a quicker rise in cost provisions affected by housing price busts. A more constrained lending capacity has been implied by a faster and further reduction of bank's capital-to-asset coverage.

Following the housing price busts, solvency problems have influenced on the banks in some cases. According to Bordo and Eichengreen (2002), all the major banking crises have chronologically coincided with housing price busts in the industrial countries during the postwar period.

Two-third ($18 billion) of a typical real estate portfolio is represented by households (Tracy *et al*., 1999). However, the recent run-up in prices has not been much understoond when regarding the enormous size of this sector.

Private consumption may be resulted from the housing market developments through several possible channels. The relative price and wealth changes have first affected house price changes via. spending. Nevertheless, negative wealth impacts for new buyers may have offset positive wealth influences for landlords. Additionally, the consumption expenditures of tenants have been affected by the rental house price changes to the same extent. Moreover, negative income impacts on owner-occupiers could have originated from increases in the imputed

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rents. Also, asymmetric information and credit market imperfections would have provided a second channel through this issue.

Literature review: Significant responses to house price movements by the South African Reserve Bank (SARB) were suggested by Inglesi-Lotz *et al*. (2012) and Simo-Kengne *et al*. (2012, 2013a, b, 2014, 2015) and who studied the interest rate behaviors in response to house movements in South Africa. No random walk is associated with the housing price behavior as evidenced by Karl and Shiller (1986). In their study, a positive auto-correlation was found with housing returns in a way that future housing returns could be predicted by various information variables. As shown by Muellbauer and Murphy (1997), the disparities in the economic structures and performances of regional housing markets besides locational characteristics of various house prices have emerged across the UK regions. During 1975-2005, the increased average annual land rate of almost 3.5% adjusted to inflation was found by Davis and Heathcote (2004) after computing this type of differential land price index. Using a non-observed model of components which allowed the analysis of both long-term trends in regional house prices and cycles, Clarke and Coggin dealt with the US regional housing cycles for which they decomposed the US into 2 major regional groups of distinct housing cycles. However, in their research, a linear trend model was employed in a context of non-linear data. It should be noted that a regime-switching model can be also utilized for house price cycles with non-linear data. To examine house price volatility in varied housing market segments in the UK, Tsai employed Markov-switching ARCH Models. Moreover, for the analysis of South African housing market and its reaction to the relevant monetary policy during boom and bust periods, Simo-Kenge *et al*. (2013a) applied Markov-switching VAR in addition to regime-dependent impulse response functions. As mentioned by Meen (1999), regional house price behaviors can be decomposed into the 3 components of common movements for all regions, regressor-induced changes reflecting economic growth differences between the regions and structural differences of regional housing markets based on a spatial coefficient heterogeneity. The long and short-term movements and variations in regional house prices can be mainly and primarily explained by the first two and last components, respectively. Based on simulations, Meen (1999) showed that regional variables can produce ‘ripple effects’ even when they grow at the same rate of national shocks. These are national changes such as changes in unemployment on regional house prices. This can be only explained by regional differences of the structures of regional housing markets. Thus, structural differences of regional housing markets are greatly important as they can explain price ripple effects based on the spatial spill-over processes. Moreover, different housing cycles across the regions are implied by the mentioned ripple effect. Furthermore, based on the exogenous shock type and regional market features, there may be varied durations of the regimes in a cycle. Demographics, government policy and income trends act as the fundamental drivers emphasized in different studies on aggregate housing prices. In their well-known research, Mankiw and Weil (1989) explained population demographics to be the prime determinants. They predicted falling prices during two subsequent decades due to the reduced growth rate of the prime home-owning group triggered by the maturation of the baby boom generation. Martin (2005) re-emphasized the importance for demographics though noticing their inaccurate predictions. As Glaeser *et al*. (2005) argued, limitations in the artificial supply have been largely reflected by price enhancements, since, 1970. Also, a key driver of the phenomenon of “superstar cities” cited by Gyourko can be an inelastically supplied land. The mediating urban dynamics and house prices can be determined by house supply as emphasized by Glaeser and Gyourko (2005a, b). In addition, an asymmetric growth was noted by them to be created through the lasting housing nature. There is a probability that prior to the demolishment of houses, house prices reduce in the declining areas. A swift growth can occur to the housing stock and population when a quick expanding supply is followed in response to the demand pressures with little pressure on house prices. New housing supply elasticity has been shown through recent evidence to be significantly influenced by a regulation (Glaeser and Gyourko, 2002; Green *et al*., 2005). However, Nieuwerburgh and Weill (2006) argued about the modest aggregate impact of restrictions in some local markets as long as no limitations exist in the regional markets. In other words, the cross-sectional housing price distributions opposed to the aggregate are primarily affected. For exploring long-term variations in the income distribution, Neiuwerburgh and Weill (2006) presented a model. Generally, a user cost approach introduced by Hendershott and Slemrod has been employed in most studies on housing prices, however, a different approach was taken into account in this research. The detailed description of the mentioned branch of literature can be too voluminous. A user cost framework has been applied by the first 3 articles referenced in footnote 2 in hope of examining the recent housing boom.

MATERIALS AND METHODS

Data multiplication by the windows possessing limited lengths and smooth ends is performed to avoid a spectral leakage. A higher temporal resolution of the evolutionary power spectrum would lead to a lower accuracy of the result. Furthermore, numerous high and under-represented low-frequency cycles are incorporated into short-term windows, respectively.

Base functions or wavelets with smooth ends per se are applied through a wavelet transform compared to the Fourier transform (Lau and Weng, 1995). Having small wave packets of a specific frequency, wavelets approach zero at both ends. Changes in the time/frequency domain can be readily mapped by them due to their being stretched and translated through a flexible frequency/time resolution. Mathematically, a signal y(t) can be decomposed into $\Psi_{a,b}(t)$ as some elementary functions derived from a mother wavelet $\Psi(t)$ by dilation and translation via. a wavelet transformation.

Daughter wavelets in the form of a set of basis functions are created through the dilation and translation of mother wavelet $\Psi(t)$ induced by a as varied scale parameters and b as shift parameters, respectively. Here, there is an inverse relationship between the scale and wavelet frequency. To compute the wavelet coefficients $\Psi_{a,b}(t)$, the mentioned basis functions are convoluted with y(t). Sampling of the time/history measurement y(t) is performed at discrete points with a constant interval of Δt_s in the time domain. The mentioned points serve for specifying b as the shift parameter. The $\Psi(.)$ stands for a wavelet as a 'small wave' function. Contrary to a 'large wave' (like a sine wave) repeatedly growing and decaying over an infinite period of time, a small wave grows and decays within a finite period.

A wavelet is a form of wave that has an effective limited duration with an average value of zero. We need to know a wavelet application method after its definition. To this aim, a Fourier analysis should be addressed. A given function can be composed of sinusoidal waves with varied frequencies and amplitudes which are perfectly ample when dealing with a stationary function. Breakdown of a Fourier analysis can occur when there are singularities or changing frequencies over time as frequently exist. The average changing frequencies over the whole function is given by the mentioned analysis which is not so much important. Changing of a given function from one time period to another can be determined through a wavelet analysis which matches a wavelet function of different scales and positions with that function. The more flexible wavelet analysis allows us to match the type of function we are analyzing by selecting a specific wavelet while the classical Fourier analysis is based on the fixed sine or cosine waves. The mother wavelet is generally specified by function $\Psi(t)$. This mother wavelet can be translated and dilated to create a double-indexed family of wavelets:

$$\Psi_{a,b} = \frac{1}{a^{\frac{1}{2}}}\Psi\left(\frac{t-b}{a}\right) \tag{1}$$

where, a>0 and t is finite 1. The normalisation on the right-hand side of Eq. 1 was chosen, so that, $\Psi_{a,b}(t) = ||\Psi||$ for all a, t.

The Continuous Wavelet Transform (CWT) of a function y(t), represents the function or the time history y(t) as a sum of dilated (by a scale parameter a) and time-shifted (by a shift parameter b) wavelets. Because wavelets are localized waves that span a finite time duration, CWT can represent time-varying characteristics of y(t). It is mathematically defined as:

$$W(a,b) = \frac{1}{a^{\frac{1}{2}}}\int \Psi^*\left(\frac{t-b}{a}\right)y(t)dt \tag{2}$$

where, b denotes the position (translation) and a (>0) the scale (dilation) of the wavelet (Lau and Weng, 1995). The wavelet transform of the signal y(t) about the mother wavelet $\Psi(t)$ is defined as the convolution integral:

$$W(a,b) = \frac{1}{a^{\frac{1}{2}}}\int \Psi^*\left(\frac{t-b}{a}\right)y(t)dt \tag{3}$$

where, Ψ^* is the complex conjugate of Ψ defined on the open time and scale real (b, a) half plane. The top three panels of Fig. 1 shows the first three levels of detail in the wavelet decomposition. Levels 0 through 2 contain the housing price-cycle components of housing price, corresponding to 16-32, 8-16 and 4-8 quarter cycles. Level 3 detail which corresponds to high frequency noise with cycles <4 quarters is not reported. The wavelet analysis reveals interesting changes in the volatility of the housing price-cycle component at various scales. At the scale corresponding to 16-32 quarter cycles, the largest housing price-cycle fluctuations occurred in the 2007 through 2008. At higher scales corresponding to 8-16 and 4-8 quarter cycles, the largest volatility occurred before the 2007-2008. Now, we extract them from the original signal using the wavelet filtering method. The sum of the three housing price-cycle components is shown in the bottom panel of Fig. 1 and 2.

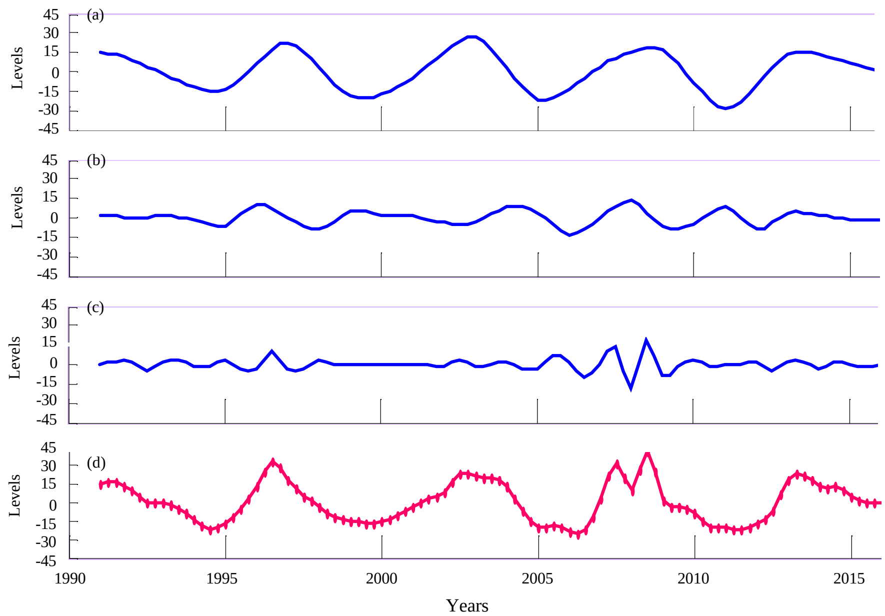

Fig. 1: The first three levels of detail in the wavelet decomposition; Housing price cycles decomposed by wavelet filter: a) Level 0 detail: 16-32 quarter cycles; b) Level 1 detail = 8-16 quarter cycles; c) Level 2 detail: 4-8 quarter cycles and d) Levels 0-3 detail 4-32 quarter cycles

Fig. 2: Housing price decomposed by wavelet: 4-32 quarter cycles

In Fig. 2, high scale →stretched wavelet →slowly changing, coarse features →low frequency. Low scale →compressed wavelet →rapidly changing details →high frequency.

RESULTS AND DISCUSSION

According to Castagna and Sun (2006), a continuous expression of a seismic trace based on time and frequency can be produced by the method of spectral decomposition for seismic exploration. Wavelet transforms were widely utilized (Daubechies, 1992), since, the firstly used short-time Fourier transform (Cohen, 1995) had a weak temporal resolution in a fixed window. However, a scale-to-frequency transform must be conducted since the signal is projected onto a scale time plane through a wavelet transform.

A MATLAB structure or a wavelet object containing the wavelet transform information is created by function mkwobj. The wavelet object features are dependent on the signal length and sampling rate analyses. A set of daughter wavelet spectra, each of which represents a scaled mother wavelet is generated by the function. N different types of wavelets, namely, Paul, Morlet,

Morlet 10, Complex Morlet, Mexican Hat and Derivative of Gaussian (DOG) can be constructed using this function. Furthermore, mkwobj () computes a pre-determined set of wavelet scales which specify the construction of the daughter wavelet spectra, based on an array of center frequencies. Each daughter wavelet corresponds with a Fourier frequency period via. a "center frequency" possessing the highest energy.

The reason for the higher frequencies of the sweep with less energy in spite of owning the same number of cycles in the time domain can be explained by these characteristics of the wavelets. We have already recognized the same number of cycles for each daughter wavelet which is a scaled version of a mother wavelet. Furthermore, it can be understood that a smaller area of time is occupied by one cycle of a higher frequency wavelet compared to that of a lower frequency wavelet considering the inverse proportion of the period to a signal frequency. On the contrary, a smaller area of frequency is occupied by one cycle of a higher frequency wavelet compared to that of a lower frequency wavelet. The equivalent energies between the signal components allow the representation of time and frequency information via. the energy constant of the areas occupied in the time or frequency domain following an extension from this feature of the Complex Wavelet Transform (CWT). In other words, the signal representations can be normalized through the energy constant in several ways. In an example, normalization has been possible by using the estimated Fourier period while it was done via. the total estimated energies for each wavelet in the current study. The area under the wavelet spectrum curve which represents the total energy for each wavelet can be calculated as the sum of the values obtained from each daughter wavelet. Each normalized scale is divided by its own energy. A set of wavelet coefficients is normalized by function qnrg based on the wavelet energies. There exist similar energies at each scale. As predicted, the coefficients were normalized to equate each scale to the maximum point in the original matrix of coefficients known as maximum relative energy. For this purpose, a normalizing function would be the mentioned features of the wavelet energies. Considering the energy constant for scaling the data between the time and frequency domains of the wavelets, between which the bandwidths appear and regarding the tradeoff between the magnitudes, the energy constant inverse can normalize the coefficients towards the time domain. Then, the hyper-scaled original signal within the time domain can be demonstrated by the sum of the normalized coefficients. Likewise, the smoothed frequency spectrum of the original signal can be shown by the sum of the normalized coefficients of the

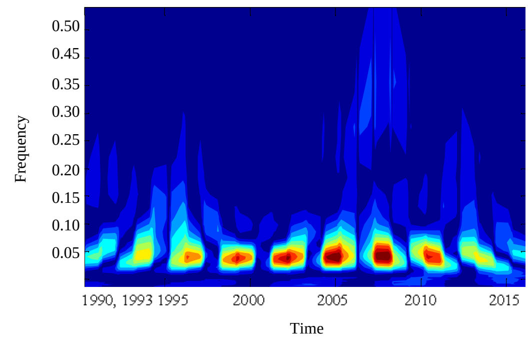

Fig. 3: Wavelet power spectrum of housing price; Wavelet power spectrum

scales. Notably, the wavelet object resolution determines the representation quality. Nevertheless, some power of the time domain seems to be missing around the waveform edges. Also, a well-represented frequency domain can be seen. The blue and red lines in the bottom of the right panel are representatives of the sum of the raw coefficients reflecting the same features of the original spectrum and that of the normalized coefficients exhibiting energy equation for active frequencies, respectively. Thus, the wavelet transforms of 120 scales were computed by using a Morlet mother wavelet through function CWT. The scales were then converted into pseudo frequencies by using the Morlet mother wavelet, scal2freq and a sampling period of 3. Finally, significant periodicities at the corresponding frequencies of 0.05-0.1 to 28-32 cycles were clearly achieved by this plot.

A wavelet power spectrum is portrayed in Fig. 3 with a significant period at 4 cycles persisting through the full length of the time vector. A frequency of $f = 16^{-1} = 0.062$ displayed in a vertical axis is corresponding to the period of $\tau = 16$ quarters. Significant periodicities at a frequency of 0.06 are clearly shown by the plot to be corresponding to the 16 quarter cycles.

Figure 3 indicates occurrence of the most powerful booms during 2007-2008. A much higher resolution was obviously obtained on the time and frequency axes through the wavelet power spectrum as compared to the windowed Fourier method. A better mapping of the temporal changes occurring to the cyclicities was seen through the wavelet transform that applies short packets of waves rather than calculating the power spectrum for each segment after dividing the time series into overlapping segments. In the CWT, MATLAB internal function 'scal2frq' converts the scale into a pseudo frequency based on $Fa = Fc/(a \cdot \Delta)$ in which a, Fa, Fc and Δ denote a scale, the pseudo frequency corresponding to scale a (Hz), the center frequency of a wavelet (Hz) and sampling period, respectively. As an excellent tool, CWT provides time/frequency information on any scales. For example, too much information can be available on the high-power surge between 0.05 and 0.1 levels during 2005-2010, since, an over-computation of such situations is possible via. CWT when power detection at one scale is targeted at. Thus, an immense freedom of choice will be provided by CWT which can detect the function size while the slope and its discontinuities can be detected by the first and second derivatives, respectively as well. Meanwhile, the high and low variabilities are indicated in red and blue colors. Higher energies, mostly diurnal and semidiurnal waves of energetic frequencies are shown in a red color. Housing price cycles demonstrate variability as a time/frequency function.

There is some missing power of the time domain around the waveform edges. Yet, there is a good representation of the frequency domain. At the bottom of the right panel, the sum of the raw coefficients is shown with a blue line which is exactly corresponding to that of the original spectrum. On the other hand, the sum of the normalized coefficients is represented with a red line which is indicative of the energy equation for active frequencies.

CONCLUSION

In this study, the behavior of housing price cycles was investigated during the occurrence of housing boom-bust cycles in Iran by presenting a 2-state nonlinear econometric model based on a Markov-Switching Model via. wavelet decomposition. To analyze the boom/bust of housing prices, the low-frequency cyclical components of housing prices extracted through wavelet decomposition were entered into the Markov-Switching Model.

Consequently, the housing price booms and busts were found to be asymmetric, thus, revealing longer housing busts than housing booms. Accordingly, the expected durations of the boom and bust regimes were discovered to nearly last for 5 and 23 quarters, respectively. Furthermore, the least energistic boom was shown to have occurred in 2011Q1-2012Q1. The major reason for such a behavior during the sample period could be the increased alternative assets including gold price and exchange rate, besides a hyperinflation in Iran.

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