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Bull or bear markets: A wavelet dynamic correlation perspective

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ABSTRACT

In this paper, we contribute to the literature on the international stock market co-movements and contagion, especially during the recent subprime crisis, by researching the interconnections between international stock markets in time-frequency domain.

Our innovative approach consists on carrying out a wavelet decomposition of return time series before investigating the correlation dynamics across stock markets during the recent financial crisis. It thus enables us to show how the contagion dynamics between international stock market returns are changing across time scales corresponding to investors with heterogeneous time horizons. Moreover, our results reveal that the contagion dynamics depends on the bull or bear periods of stock markets, on stock markets maturity, and on regional aspects. Therefore, all these finding should be considered from an international portfolio diversification perspective.

1. Introduction

In the last three decades, the flows of capital, goods and services have dramatically increased affecting the global economy. This process of globalization allows portfolio managers to benefit from international diversification and to be less exposed to market risk. However, the markets globalization constitutes a source of risks due to transmission of shocks from one country to other countries during financial crisis as was demonstrated by 1987 US stock market crash, the dot-com bubble burst in 2000, and the ongoing global financial crisis.

Forbes and Rigobon (2002) defined contagion as a significant increase in the degree of the co-movement among financial markets during episodes of high turbulence. Many researchers studied the contagion effect across world stock markets during various financial crises. Masih and Masih (1997, 2001), Choudhry et al. (2007) used cointegration to investigate international integration of financial markets. Agarwal (2000) found a correlation coefficient of 0.01 between India and world developed markets. Longin and Solnik (1995) showed that correlations between USA equity returns and seven OECD stock markets rose by about 0.36 over the period from 1960 to 1990. King and Wadhwani (1990) showed a strong evidence of contagion from US to Japan and UK stocks after the 1987 US stock crash. Bertero and Mayer (1990) extended the analysis to a sample of 23 industrialized countries and emerging market countries, and find that correlation coefficients increase appreciably following the US stock market crash. Hamao et al. (1990) used GARCH model during 1987 U.S. stock markets and showed a strong volatility spillover from US stock markets to UK and Japan ones.

In this paper, we extend the contagion literature by adding the time scales to the picture. To attain this goal, we first carry out a wavelet decomposition of major stock market returns into different time-scales. Then, we focus on the correlation between the decomposed return time series in order to explore how they are correlated in a scale by scale basis.

The wavelet analysis enables to represent the local behavior of heterogeneous markets participants. Indeed, some participants have an investment horizon of several minutes or hours to several days such as large investment banks who are more interested in short-term movements of the stock markets. Some other participants such as commercial banks, insurance companies with the investment horizon of several weeks or months may be more concerned with medium term performance. In contrast, pension funds can have an investment horizon of several years. Therefore, the multiscale dynamic correlation analysis will permit to shed more lights on the shocks transmission across international stock markets especially for different categories of investors, from those who trade on the short-term horizon to those who trade on medium or long term.

We apply the wavelet analysis to stock market indices in order to reveal the potential presence of contagion after the bankruptcy of Lehman Brothers bank. We consider it the most important event,

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because it was followed by an enormous increase of financial markets volatility. The detection of contagion will be achieved by rolling wavelet correlations.

Empirical results revealed that the wavelet correlation of stock markets with S&P 500 differ significantly when talking about the short-term, the medium or the long-term horizon. The wavelet correlation indicate that stock market indices tends to grow with every additional scale between S&P500 and all other stock market indices, the highest correlation was observed at the high scale corresponding to low frequencies.

From a risk management perspective, the analysis of the wavelet correlation can be very useful. Indeed, the identification of time-scales where correlation is lower could ensure the benefits of portfolio diversification for investors who are looking for alternative investment opportunities. On the one hand, a short term investor can quite well diversify his portfolio, because the wavelet correlation is low, on the other hand, a long term investor is in a more complicated situation, because the wavelet correlation is much higher.

Wavelet correlation is achieving increasing popularity in financial time series analysis. Many authors showed that correlations of stock markets differ when we take into account different time horizon. Among them Gallegati (2005) revealed that the correlation between five MENA equity markets (Egypt, Israel, Jordan, Morocco and Turkey) increases from high frequency scale to low frequency scale and also that the weakest co-movement was found at high frequencies. Ranta (2010) studied correlations among major world indices (S&P500, FTSE100, DAX, NIKKEI) and reached the same conclusion. Fernandez-Macho (2011) analyzed correlations among 11 Eurozone stock market returns and indicated that they are highly correlated, the lowest correlation coefficient was observed at a daily scale.

The remainder of this paper is organized as follows. Section 2 describes the wavelet decomposition. Section 3 provides the data and the empirical results. In Section 4, we carry out a robustness check. Section 5 concludes.

2. Wavelet methodology

2.1. Spectral analysis

While economic time series analysis is generally yielded in the time domain, the spectral analysis is a complementary approach based on the frequency domain. Spectral analysis decomposes a time series into a spectrum of cycles of varying length by means of a Fourier transform, and is a useful tool to extract and quantify the main oscillatory components of a series. Thus, it is possible to formally identify trends, low frequency components, business cycles, seasonalities, etc. (Granger and Hatanaka, 1964; Priestly, 1965). However, the spectral methods are crippled by the underlying assumption of stationarity. Given the fact that most of the economic and financial time series are non-stationary, spectral approach fails to take account of this. Fourier analysis is thus not useful for analyzing periodic and stationary signals whose moments change over time. To overcome the limitations of the standard Fourier transform, Gabor (1946) introduced the initial concept of Short Time Fourier Transform (STFT). The advantage of STFT is that it uses an arbitrary but fixed-length window for analysis, over which the actual non-stationary signal is assumed to be approximately stationary. Therefore, the length of the window is the main issue involved in STFT. Indeed, a short window can enhance time information whereas a long one will enhance the frequency resolution. Hence, a longer window implies the loss of time information (nonstationarities), and a shorter window implies the loss of frequency information.

To overcome these drawbacks, wavelet transform was introduced. It has a major advantage over the Fourier approaches in that it has a nice property: its window size adjusts itself optimally to longer basis functions at low frequencies and to shorter basis functions at high frequencies. Consequently, it has good frequency resolution for low frequency movements and good time resolution for high frequency movements. Thus, wavelet transform due to its ability to perform local analysis of a time series is capable of capturing sudden regime changes, abrupt jumps, ARCH effects, outliers, shocks, and long memory in an economic time series. Therefore, wavelets overcome the limitations of Fourier analysis as they combine information from both time-domain and frequency-domain, do not require stationary, and allow us to extract the different frequencies driving any macroeconomic variable in the time domain by decomposing into its time scale components, each reflecting the evolution of the signal trough time at a particular frequency. Moreover, wavelet analysis is capable of unveiling relationships between economic variables in the time-frequency domain, allowing a simultaneous assessment of variables relationships at different frequencies and the dynamics of these links over time.

2.2. Basics of wavelets

The wavelet transform is based on two wavelet filters which are respectively called *mother wavelet* and the *father wavelet*. The mother wavelet can be denoted by $\psi(t)$. This function is defined on the real axis and must satisfy two conditions:

$$\int_{-\infty}^{+}\psi(t)dt = 0, \int_{-\infty}^{+}|\psi|^2(t)dt = 1. \tag{1}$$

In order to quantify the change in a function at a particular frequency and at a particular point in time, the mother wavelet $\psi(t)$ is dilated and translated:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{2}$$

where u and s are respectively the time location and scale parameters or frequency ranges. The term $\frac{1}{\sqrt{s}}$ ensures that the norm of $\psi_{u,s}(t)$ is equal to unity. The continuous wavelet transform (CWT), $W(u,s)$ which is a function of the two parameters u and s, is then obtained by projecting the original function $x(t)$ onto mother wavelet $\psi_{u,s}(t)$,

$$W(u,s) = \int_{-\infty}^{+\infty}x(t)\psi_{u,s}(t)dt. \tag{3}$$

In order to assess the variations of the function on a large scale (i.e. at a low-frequency), a large value for s must be chosen, and vice-versa. CWT is computationally complex and contains a high amount of redundant information, its discrete variant (DWT) is more parsimonious as it uses a limited number of translated and dilated versions of the mother wavelet to decompose a given signal (Gençay et al., 2002). u and s are chosen in such a way to summarize the information contained in the signal in a minimum of wavelet coefficients by setting $s = 2^{-j}$ and $u = k2^{-j}$, where j and k are integers representing the set of discrete translations and discrete dilatations(Gençay et al., 2002). Thus, the DWT of a time series with T observations is calculated only at dyadic scales, i.e.at scales 2^j and the largest number of scales equals to the integer J such that $J = [\log_2(T)]$.

The DWT is based on two discrete wavelet filters which are called mother wavelet $h_l = (h_0,....,h_{L-1})$ and the father wavelet $g_l = (g_0,....., g_{L-1})$. The mother wavelet integrates (sums) to zero, $\sum_{l=0}^{L-1} h_l = 0$, and has unit energy, $\sum_{l=0}^{L-1} h_l^2 = 1$.

In addition, the wavelet filter h is orthogonal to its event shifts; $\sum_{l=0}^{L-1} h_l h_{l+2n} = 0$ for all integers $n \neq 0$. The mother wavelet, associated with a difference operator, is a high-pass filter. On the other hand, the