WAVELET ANALYSIS

History, Theory and Applicatons with a Case Study in Finance

Asst. Prof. Dr. Özcan CEYLAN

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E_ISBN 978-625-6104-36-5

Eylül 2024 – Afyonkarahisar

Dizgi/Mizanpaj: YAZ Yayınları

Kapak Tasarım: YAZ Yayınları

YAZ Yayınları. Yayıncı Sertifika No: 73086

M.İhtisas OSB Mah. 4A Cad. No:3/3
İscehisar/AFYONKARAHİSAR

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Preface

The Fourier transform and its extensions, such as the wavelet transform, have proven to be invaluable tools for analyzing signals and data in a wide range of applications. Their ability to decompose signals into their frequency components and provide information about their time-varying characteristics has made them indispensable in fields ranging from engineering and physics to medicine and finance.

This book aims to introduce this fast-growing area especially to researchers in finance and economics by providing an overview of history, theory, and implementations of wavelets in a simple and intuitive manner.

The first chapter starts by presenting the Fourier series and related Fourier transformation methods, and therewith discusses their strengths and shortcomings.

Multi-resolution analysis that addresses the shortcomings of the Fourier transformations is presented in chapter 2. A variety of wavelet analysis techniques are also summarized in this chapter.

The third chapter outlines the main application areas of wavelets including popular industrial implications, and their use in finance literature.

The book ends with a case study where recent wavelet analysis methods are applied to a set of selected stock market data.

CHAPTER 1

HISTORICAL BACKGROUND OF WAVELET ANALYSIS: FOURIER TRANSFORMATIONS

The Fourier transform, a powerful mathematical tool, has its roots in the study of periodic functions and their representation as sums of simpler trigonometric functions. Its development can be traced back to the early 19th century, with significant contributions from mathematicians like Joseph Fourier, Augustin-Louis Cauchy, and Bernhard Riemann.

The concept of the Fourier transform is principally based on the Fourier series, which Joseph Fourier introduced in his 1807 work "On the Propagation of Heat in Solid Bodies." Fourier proposed that any periodic function could be represented as an infinite sum of sine and cosine functions. In its simplest form, an *L*-periodic representation of a Fourier series that is defined over the interval [*0, L*) may be written as follows:

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty}\left[\, a_k \cos\left(\frac{2\pi k x}{L}\right) + \, b_k \sin\left(\frac{2\pi k x}{L}\right)\right] \quad (1.1a)$$

where

$$a_k = \frac{2}{L}\int_0^L f(x)\, cos\left(\frac{2\pi kx}{L}\right) dx \; (1.1b)$$

$$b_k = \frac{2}{L}\int_0^L f(x)\, sin\left(\frac{2\pi kx}{L}\right) dx \; (1.1c)$$

A Fourier series may also be written in complex form by employing the Euler's formula (i.e., $e^{ikx} = \cos(kx) + i \sin(kx)$):

$$f(x) = \sum_{k=-\infty}^{\infty} c_k\, e^{ik\pi x/L} \; (1.2a)$$

where

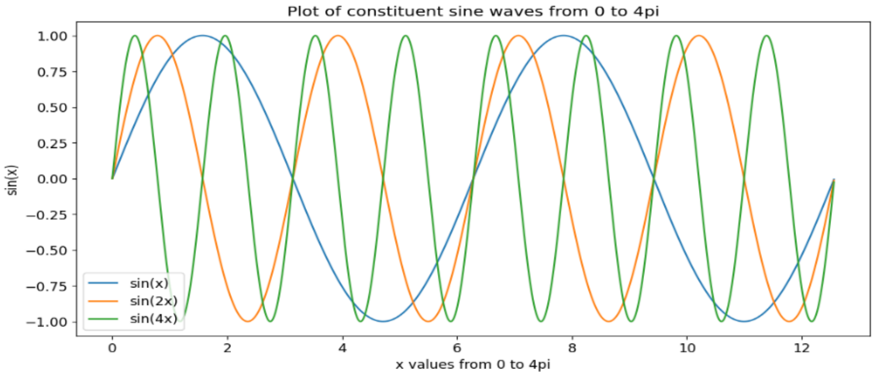
$$c_k = \frac{1}{2L}\int_{-L}^{L} f(x)\; e^{-ik\pi x/L}\, dx \; (1.2b)$$

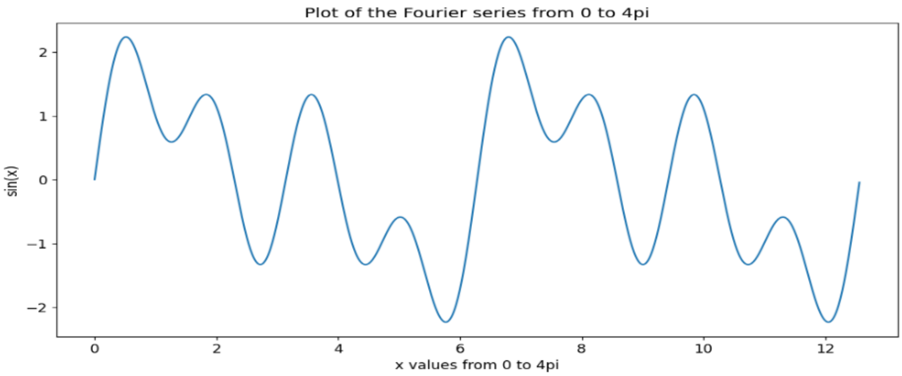
A Fourier series may thus be expressed as a superposition of the complex exponential functions with (discrete) frequencies $k\pi/L$ and amplitudes c_k. Put this way, the series may be defined only on the frequency domain.

To provide an intuition, a simple Fourier series is illustrated in Figure 1.1. The series is created using only three sine waves of different frequencies. More complex series could also be formed by employing more sine and cosine waves with varying frequencies and amplitudes. The figure also reveals the main shortcoming of the Fourier series: note that the series repeats itself after the point $x = 2\pi$, as it is defined over the interval [*0, 2π*). For all x, $f(x) = f(x + 2\pi)$. Fourier series may thus fall short analyzing non-periodic signals, where the frequency content changes over time.

Despite its flaw, this groundbreaking idea laid the foundation for the development of Fourier analysis and the subsequent formulation of the Fourier transform which can also be applied to non-periodic signals. Indeed, the Fourier transform integral is obtained at the limit of a Fourier series. When the length of the interval over which the Fourier series is defined goes to infinity (i.e., while $L \rightarrow \infty$), the series becomes non-periodic. The Fourier transform can thus be seen as a generalization of Fourier series. While Fourier series are used to represent periodic functions, the Fourier transform extends this concept to non-periodic functions.

Figure 1.1. A Fourier series and its constituent sine waves





This generalization leads to a qualitative transformation in the frequencies that define the series: while Fourier series represent a function in terms of its discrete frequency components, the Fourier transform uses a function of continuous integral of complex exponentials that forms a frequency spectrum. To see this, take the Fourier series defined by the equation (1.2), and obtain its limit as $L \to \infty$. Let ω_k denote the angular frequency defined as $k\pi/L$ to obtain the expression of frequency steps, $\Delta\omega = \pi/L$. It follows that $\Delta\omega \to 0$ while $L \to \infty$. Assuming that f is an integrable function defined on $\mathbb{R}$, the Fourier transform may be formulated as follows:

$$\mathcal{F}(f) = \int_{-\infty}^{\infty} f(x)e^{-i\omega x}\, dx \ (1.3a)$$

The inverse Fourier transform allows one to recover the original function f from its Fourier transform $\mathcal{F}$.

$$\mathcal{F}^{-1}(f) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \mathcal{F}(f)e^{i\omega x}\, dx \ (1.3b)$$

At its core, the Fourier transform is a mathematical operation that decomposes a function or signal into its constituent frequency components. It provides a way to represent a signal as a combination of sine and cosine waves of different frequencies, amplitudes, and phases. This decomposition is invaluable for understanding the underlying structure and characteristics of the signal.

One of the key advantages of Fourier transforms is their ability to perform time-frequency analysis. This means that they can provide information about both the frequency content of a signal and the time at which those frequencies occur. A first step to achieve this is to formulate a Discrete Fourier Transform (DFT), a finite-length version of the Fourier transform, that may be employed to decompose consecutive partitions of the signal into their frequency components.

$$\mathcal{F}_k = \sum_{j=0}^{n-1} f_j \, e^{-i2\pi jk/n} \quad (1.4)$$

where $\mathcal{F}_k$ is the kth frequency component and f_j is the jth sample of the signal, and n is the total number of samples.

While the DFT is a powerful tool, its direct computation can be computationally expensive, especially for large datasets. The naive implementation of the Fourier transform involves a nested loop, which results in a computational complexity of

$O(n^2)$, where N is the number of data points. This makes it impractical for large-scale applications. The Fast Fourier Transform (FFT) algorithm, developed by James Cooley and John Tukey in 1965, dramatically reduces the computational complexity of Fourier transforms. By exploiting the properties of discrete Fourier transforms of even and odd length sequences, the FFT algorithm scales as $O(n*log(n))$ This significant improvement in computational efficiency made Fourier analysis practical for a wide range of applications.

The FFT transforms a time-domain signal into a frequency-domain representation. As it calculates the frequency content of a signal over its entire duration, it may only be sufficient for analyzing stationary signals with a fixed frequency content. Nevertheless, the FFT constitutes the basis for a more advanced tool, Short-Time Fourier Transformation (STFT) that can be employed to analyze non-stationary signals with time-varying frequency content.

The STFT involves dividing the signal into overlapping windows and applying FFTs to each window. This provides information about the frequency content of the signal within each window, allowing for the analysis of how the frequency components change over time. The STFT, also known as the

Gabor Transform, computes windowed Fourier transforms over sliding windows as follows (Gabor, 1946):

$$\mathcal{G}(f)(t,\omega) = \int_{-\infty}^{\infty} f(\tau)e^{-i\omega\tau}\, g(\tau - t)d\tau \quad (1.5)$$

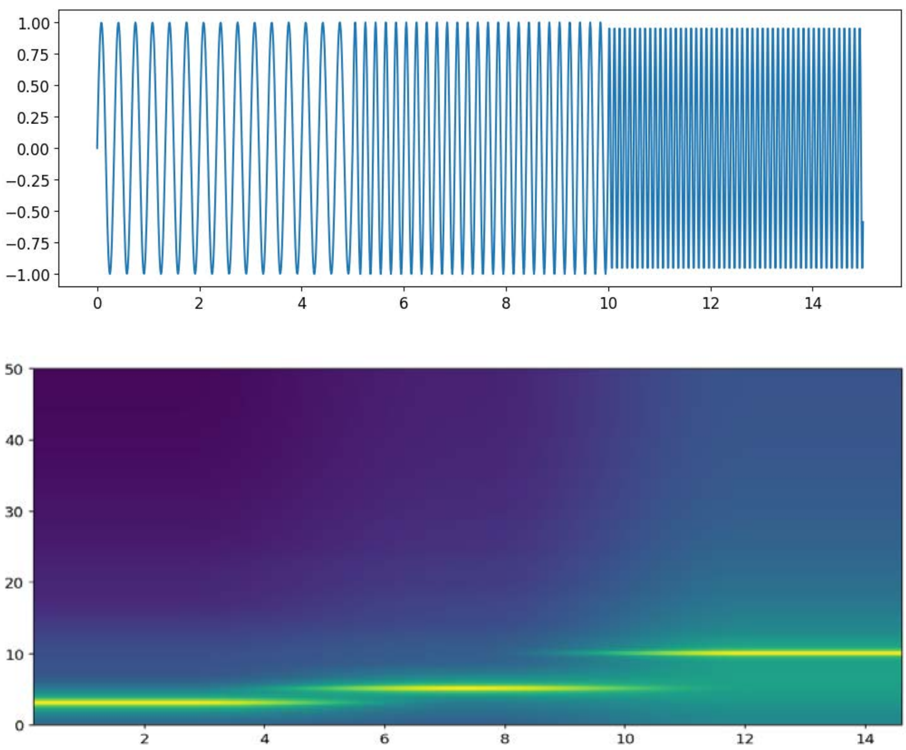
where $g(\tau)$ is the window function that determines the center and the width of the sliding window.

The results of the STFT are usually presented through a spectrogram. A spectrogram is a two-dimensional plot that shows the frequency content of a signal as it changes over time. The vertical axis of a spectrogram represents the frequency while time is represented by the horizontal axis. The color or intensity of each point in the spectrogram represents the magnitude of the corresponding frequency component at that time.

To illustrate, a sinusoidal signal is created as plotted at the top of Figure 1.2 below. The signal is non-periodic with increasing frequencies in time: 3 Hertz (vibrations per second) from t=0 to t=5, 5 Hertz between t=5 and t=10, and 10 Hertz from t=10 till t=15. STFT is applied to the series using a block size of 512 with 30 overlapping samples between blocks. The resulting spectrogram is plotted at the bottom of Figure 1.2.

The choice of window function, $g(\tau)$, affects the time-frequency resolution of the STFT. A wider window provides better frequency resolution but poorer time resolution, while a narrower window provides better time resolution but poorer frequency resolution. This inevitable tradeoff that is known as the Gabor limit is mathematically connected to and can be derived from the well-known Heisenberg uncertainty principle by considering the signal as a quantum wave function (Gabor, 1946). In essence, both principles highlight the inherent uncertainty in the ability to precisely measure and localize physical quantities.

Figure 1.2. A sinusoidal wave and its spectrogram



The Gabor limit is defined as a product of the variance of the function $f(x)$, as related to the time domain, and the variance of its Fourier transform $\mathcal{F}(\omega)$, as related to the frequency domain:

$$\int_{-\infty}^{\infty} x^2\, |f(x)|^2\, dx \int_{-\infty}^{\infty} \omega^2\, |\mathcal{F}(f)|^2\, d\omega \;\geq \frac{1}{16\pi^2} \quad (1.6)$$

This means that one cannot simultaneously localize a signal in both time and frequency domains with arbitrary precision. There is a fundamental limit ($\frac{1}{16\pi^2}$) to the accuracy with which one can simultaneously measure the time and frequency of a wave. This limit is largely overcome by the multiresolution analysis conducted using wavelets that will be summarized in the next chapter.

CHAPTER 2

A TURNING POINT: FROM WAVES TO WAVELETS

As outlined in the previous chapter, while the Fourier transform is a valuable tool, it has limitations when dealing with signals with rapidly changing frequency content. In such cases, the wavelet transform offers a more flexible and powerful approach. Wavelet transforms use a set of basis functions called wavelets, which are localized both in time and frequency. This allows for better resolution of transient signals and non-stationary phenomena.

At the heart of wavelet analysis lies the mother wavelet, symbolized as ψ. This foundational function serves as the blueprint for creating an array of related wavelets through two key transformations: dilation (expanding or contracting the wavelet), and shift (moving the wavelet across the temporal axis). Any wavelet function may thus be defined as follows:

$$\psi^{\sim}{}_{\tau,s}(t) = |s|^{-0.5}\psi\left(\frac{t-\tau}{s}\right) \quad (2.1)$$

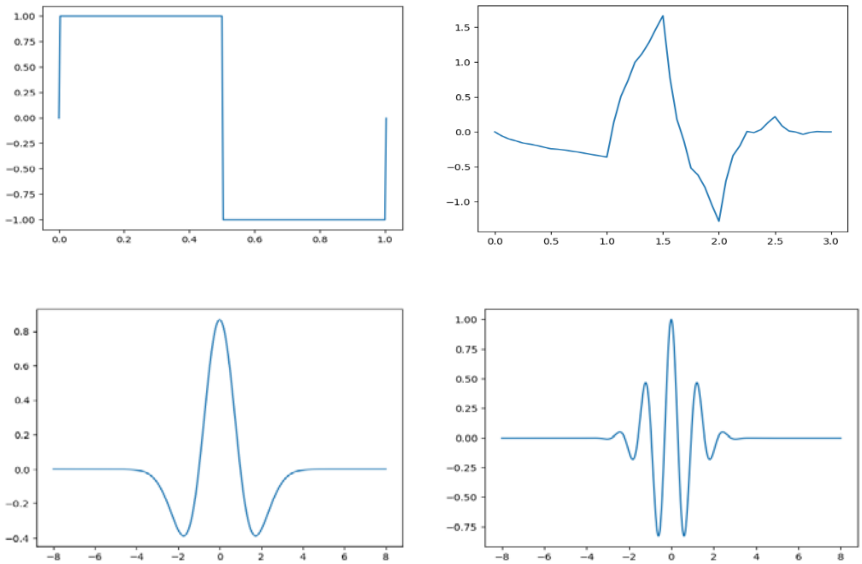
where τ is the translation parameter that determines the shift in the mother wavelet and s is known as the scaling parameter that determines the dilation. A wavelet with a higher scale captures a signal with lower frequency.

The first mother wavelet, called the Haar wavelet, is developed in 1910 (Haar, 1910). Despite its simplicity, the Haar wavelet exhibits all the basic properties of wavelets. Haar wavelets are orthogonal, meaning that the inner product of two Haar wavelets at different scales or locations is zero. This property ensures that the wavelet coefficients obtained from the decomposition of a signal are independent and can be used to reconstruct the original signal without any redundancy. Haar wavelets also satisfy the compact support property: The wavelet function is non-zero only within a finite interval, and its integral over its entire domain is zero. This is because the positive and negative areas under the curve tend to cancel each other out.

Since the development of the Haar wavelet, especially starting from 1980s, many other more complex wavelet functions are introduced. Gabor’s work in 1946 paved the way for new wavelet functions. In his study, Gabor introduced the concept of “Gabor atoms”, which were essentially localized sine waves. In 1982, Morlet et al. (1982) applied Gabor's work to seismic data analysis. They introduced the Morlet wavelet, which is a commonly used wavelet function that combines a Gaussian window with a complex exponential. This wavelet has better localization in the time domain compared to the Mexican Hat wavelet, another popular wavelet, used particularly in geophysics. In 1988, Ingrid Daubechies introduced a family of orthogonal wavelets with compact support, now known as Daubechies wavelets (Daubechies, 1988). Daubechies wavelets can be constructed with varying degrees of regularity, allowing for a trade-off between time-frequency localization and smoothness. Higher-order Daubechies wavelets have smoother shapes and better frequency resolution, while lower-order wavelets have better time resolution. Daubechies wavelets, along with the Morlet wavelet, are the ones that are the most frequently used to analyze financial time series that often exhibit sudden changes or spikes.

While skipping the mathematical formulations, to provide an idea on the wavelet functions, a selection of important wavelet functions is illustrated in Figure 2.1. The Haar wavelet is plotted at the top left, and the Mexican Hat wavelet is plotted at the bottom left of the figure. Among its many types, the second order Daubechies wavelet is plotted at the top right of the figure, while the Morlet wavelet is found at the bottom right. For simplicity, the imaginary components of the wavelets are omitted, only the real components are plotted in the figure.

Figure 2.1. Plots of several important wavelet functions



Through their capacity to be localized in both time and frequency domains, wavelets provide the foundation for multi-resolution analysis, a mathematical framework that decomposes signals into a series of wavelet coefficients at different scales or resolutions. This allows for the analysis of signals at diverse levels of detail, which is particularly useful for non-stationary signals.

Figure 2.2. Spectrogram vs. multi-resolution analysis

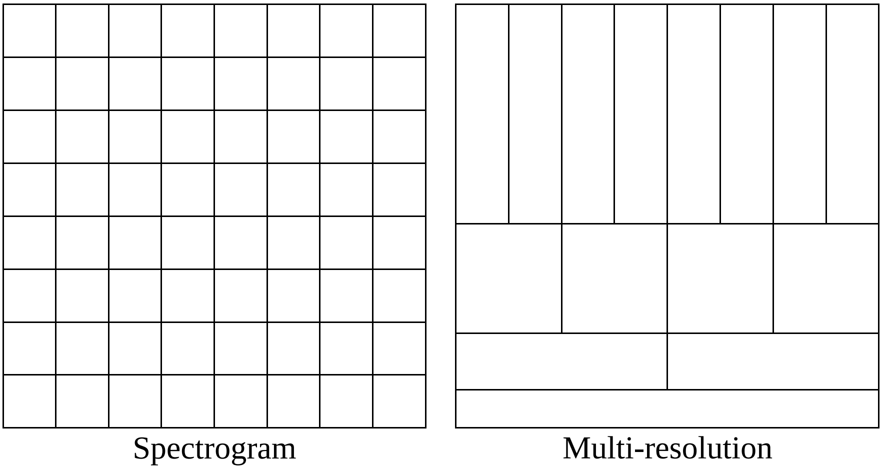
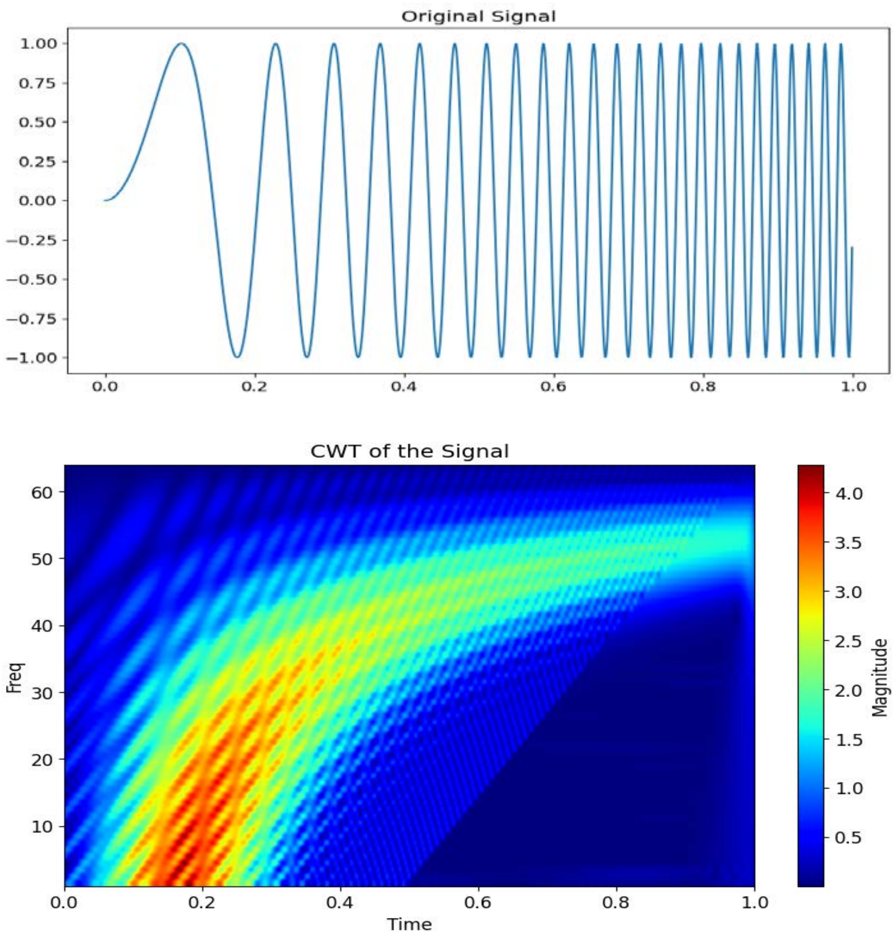


Figure 2.2 illustrates the main difference between the spectrogram and the multi-resolution analysis. Like the spectrogram, multi-resolution analysis also provides frequency information on the vertical axis, and time information on the horizontal axis. While fixed sliding windows are used in spectrograms, multi-resolution analysis employs windows of varying dimensions. One needs coarser scales to capture the information on the overall shape or trend of the signal, while the details like sharp edges, transients and high-frequency components are well captured through finer scales. By decomposing a signal into its wavelet coefficients, we can analyze the signal at different scales and identify features that may be obscured at other scales. As such, wavelets provide an optimal tradeoff between time and frequency resolution.

Figure 2.3. Multi-resolution analysis plot



The wavelet coefficients used in the multi-resolution analysis are obtained through applying wavelet transformations that are applied in a similar way to the Fourier transformations presented in the previous chapter. The continuous wavelet transformation is formulated as follows:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x\,(t)\psi^{\sim *}{}_{\tau,s}(t)dt, \tau, s \in \mathrm{R}, s \neq 0 \;(2.2)$$

where $x(t)$ is the input signal and $\psi^{\sim *}{}_{t,s}(t)$ is the complex conjugate of the wavelet function $\psi^{\sim}{}_{t,s}$ given in equation (2.1).

Figure 2.3. illustrates the continuous wavelet transform of a sinusoidal signal with continuously increasing frequencies. The corresponding multi-resolution analysis plot captures the concave increasing function of frequencies.

A discrete version of wavelet transformation is usually employed for decomposing a signal into its main and detail (noise) components. For discrete wavelet transformation the following family of discrete wavelet functions are used instead.

$$\psi^{\sim}{}_{j,k}(t) = \frac{1}{s^j}\psi\left(\frac{t - k\tau}{s^j}\right) \;(2.3)$$

Wavelet analysis does not only apply to univariate data. Wavelet coherence measures are also developed to analyze comparative characteristics of two or more signals. This can be conceived as a multi-resolution counterpart of the standard correlation measure in statistics:

$$\gamma_{x,y}(\tau\,, s) = \frac{S\left(\left|W_{xy}(\tau\,, s)\right|\right)}{\left[S(|W_{xx}(\tau\,, s)|)S\left(\left|W_{yy}(\tau\,, s)\right|\right)\right]^{0.5}} \;(2.4)$$

Wavelet coherence measure is simply based on cross-wavelet transformation of the two signals in question x and y, cross-wavelet transformation of the signal pair is obtained through what follows:

$$W_{xy}(\tau , s) = W_x(\tau , s)W_y^*(\tau , s) \quad (2.5)$$

where W_y^* is the complex conjugate of W_y.

There are numerous extensions of the wavelet coherence measure, including the partial wavelet coherence (obviously, a multi-resolution counterpart of the standard partial correlation measure). In Chapter 4 of this book, these wavelet coherence measures will be applied to real data.

CHAPTER 3

WAVELETS IN PRACTICE

Although wavelet analysis is a relatively method in economics and finance, this technique has a long history in more technical areas such as signal processing, geophysics and engineering. Wavelet analysis has thus already found numerous applications across various industries, providing valuable insights and solutions to a wide range of problems. This chapter starts with a brief presentation of the key industrial implications of wavelet analysis and proceeds with an overview of its recent applications in finance.

3.1. Industrial implications of wavelet analysis

Wavelet analysis has led to the most fundamental developments in audio and image processing and gave birth to numerous applications that marked the digital era. For instance, in music processing, wavelet analysis is used for audio compression, noise reduction, and feature extraction. Popular applications include Auto-tune, MP3 and Shazam.

Auto-tune is an audio processing tool that can be used to correct pitch in singing or other audio recordings. Wavelets play a crucial role in autotune by providing a powerful tool for analyzing and manipulating the frequency content of audio signals. Wavelet analysis is first used to decompose the signal into its frequency components to identify the fundamental frequency of the singer's voice at each point in time. Then, this information is used to identify pitch deviations from the desired target pitch. These identified deviations are corrected by shifting the frequency of the vocal components to match the desired pitch or by modifying the waveform to create a more consistent pitch.

MP3s are used to reduce file size while preserving audio quality. They are also used to remove background noise from a recorded conversation. In essence MP3 uses the Modified discrete cosine transform (MCDT), a method that is similar to the Short-time Fourier transform, to translate the signal into the frequency domain. Obtained frequency coefficients are then quantized and coded in the compression process. Wavelets are also used to remove noise from the audio signal before applying the MDCT and thereby improve the quality of the compressed audio and reduce the amount of data needed to represent the signal.

Shazam, the popular music identification application leverages wavelet analysis to efficiently identify songs. Shazam first decomposes the incoming audio signal into its constituent frequency components using a wavelet transform. Using the wavelet coefficients, Shazam extracts characteristic features of the song, like dominant frequencies or rhythmic patterns. A "fingerprint" is created based on these extracted features. This unique fingerprint of the song is then compared to a database of known songs.

Wavelets are used for image denoising, removing noise from images captured under low-light conditions or with sensor artifacts. They are also used for image compression, reducing the file size of images without significantly degrading their quality. Among numerous applications in image processing, it is worth explaining the use of wavelets in JPEG 2000 and in film restauration.

JPEG 2000 is a newer image compression standard that offers several advantages over the original JPEG format, including better compression efficiency, lossless compression, and the ability to provide progressive transmission. Wavelets play a crucial role in JPEG 2000, providing a more efficient and effective way compared to Discrete Cosine Transform (DCT) used in the original JPEG format. JPEG 2000 first decomposes the image into a series of wavelet coefficients using the Discrete wavelet transform. These wavelet coefficients are then quantized to reduce the number of bits required to represent them. The quantized coefficients are coded to further reduce the file size by assigning shorter codes to more frequent coefficients.

Wavelet analysis has become an invaluable tool in the restoration of old movies, which are often plagued by various forms of degradation, such as noise and scratches. By decomposing the film into different frequency bands using wavelets, noise is identified and removed while preserving the essential features of the image, and by analyzing the spatial and temporal characteristics of scratches, wavelet-based algorithms distinguish them from the underlying image content and effectively remove them. Wavelets can even be used to interpolate missing frames in damaged or incomplete films. By analyzing the motion and content of the surrounding frames, wavelets can generate plausible estimates of the missing frames, improving the overall smoothness and continuity of the restored film.

Geophysicists have long contributed to wavelet theory, and as a result there have been important applications of wavelet analysis in this area. Wavelets are used to analyze seismic data collected from earthquakes or controlled sources to identify subsurface structures, such as oil and gas reservoirs. By decomposing the seismic signal into different scales, geophysicists can identify different types of geological formations. Wavelets are used to detect faults in the Earth's crust by analyzing the discontinuities in seismic signals. This information is crucial for understanding the geological structure of a region and assessing potential risks.

The use of wavelets in mining emerged as an industrial side-product of geophysical studies. By analyzing the seismic response of the subsurface wavelets can help characterize reservoir properties. Potential mineral targets are identified by analyzing the spectral characteristics of geophysical data. Wavelets are used to detect anomalies in geophysical data, such as magnetic or gravity anomalies, which may indicate the presence of mineral deposits, and they can be further used to estimate the grade of these mineral deposits by analyzing the spatial distribution of mineral content within the ore body.

These are just a few examples of the industrial implications of wavelet analysis. They are also used for various purposes, for instance, in manufacturing for quality control by analyzing product characteristics and identifying defects, or in biomedical engineering for image reconstruction, denoising, and feature extraction in medical imaging modalities like MRI and CT scans.

3.2. Wavelet applications in finance

Although wavelet analysis started to be applied relatively recently in finance, there is an already well-established and growing body of literature. As any time-series data can be treated as a signal, wavelet analysis methods developed for signal processing could directly be adopted to analyze financial/economic data at multiple scales and identify patterns that may be hidden using traditional methods.

Wavelets have been very useful in analyzing financial volatility. It is now a stylized fact that financial volatility follows a heteroscedastic pattern, with high volatility periods tending to be followed by low volatility and vice versa. Wavelets can effectively capture the non-stationary and heteroscedastic nature of financial volatility. It is empirically shown that the efficiency of traditional volatility estimation and prediction methods such as GARCH models are improved when combined with wavelet analysis (Capobianco, 1999; Mederessi and Hallara, 2018). Indeed, wavelet-based denoising of financial time-series provides significant reductions in prediction error for various forecasting models (Tamilselvi et al., 2024).

Through wavelet analysis, one can identify the economic and financial cycles and predict their turning points by splitting a financial time series into multiple time scales and frequencies (Yamada and Honda, 2005; Bai et al. 2015). In a similar manner, wavelets may help to detect signs of market anomalies, and to identify market regimes and crashes which can have a crucial impact on risk management. Wavelet analysis can also be used to measure the short and long-run exposures of a portfolio to different risk factors (Mestre, 2021). By decomposing the portfolio returns into different scales, it is possible to identify the sources of risk and assess the portfolio's sensitivity to these factors.

Wavelet coherence measures are used to examine the relationships between different financial variables, such as stock prices, interest rates, and exchange rates (Andries et al. 2014; Ferer et al, 2016). This analysis technique may also be effective for investigating contagion and connectedness among different markets (Ranta, 2013; Dewandaru et al., 2015).

These are just a few examples of the many applications of wavelet analysis in finance. As the complexity of financial markets continues to increase, wavelet analysis is likely to play an even more important role in future research and applications.

CHAPTER 4

CASE STUDY:

LOCAL OR GLOBAL? WAVELET COHERENCE ANALYSIS OF THE RELATION BETWEEN ECONOMIC POLICY UNCERTAINTY AND SELECTED STOCK MARKET INDICES

4.1. Introduction and related literature

For capital budgeting and portfolio management purposes, understanding the factors that drive stock returns and volatilities is of utmost importance for practitioners in financial markets. Concordantly, a plethora of academic research has been conducted aiming to identify macroeconomic and financial variables with considerable predictive power regarding stock market movements (see Rapach and Zhou (2013) for a survey). Behavioral finance literature contributed to this endeavor by introducing several sentiment-based proxies and indices that are propitious for improving the market return prediction (Baker and Wurgler, 2007; Roger, 2014; Huang, Jiang, Tu, Zhou, 2015).

Since the Lehman Brothers bankruptcy in 2008, the global economy has been going through an unprecedented, growing uncertainty. Considering the central importance of uncertainties in financial markets, Baker, Bloom and Davis (2016) introduced the Economic Policy Uncertainty (EPU) index to explain the instabilities in the Unites States during the subprime mortgage crisis. Upon its empirical success, the EPU index has received considerable attention from academics and has been applied to various markets within different settings. The use of EPU in academic research got even wider following the replication of the index for various countries using a similar textual analysis-based methodology. Currently, there are twenty-eight country-specific EPUs developed in addition to global, regional and the U.S. state-level EPUs.

The first empirical studies generally concentrated on the U.S. market and reported a negative relationship between the local EPU and the U.S. stock market performance (Antonakakis, Chatziantoniou and Filis, 2013; Kang and Ratti, 2013; Brogaard and Detzel, 2015; Liu and Zhang, 2015). Considering the central role of the U.S. regarding the global markets, the following strand of research extended the analysis to examine the effects of policy uncertainty spillovers from the U.S. to other markets (Li and Peng, 2017; Ahmad and Sharma, 2018; Hu, Kutan and Sun, 2018) and from the other markets to the U.S. (Huang, Ma, Bouri and Huang, 2022). Some other studies adopted this framework to scrutinize cross-country interdependencies between various stock markets and showed that the impact of EPU varies depending on the market and market conditions (Liow, Liao and Huang, 2018; Phan, Sharma and Tran, 2018; Youssef, Mokni and Ajmi, 2021; Yuan, Li, Li, and Zhang, 2022).

The explanatory power of the global EPU (GEPU) index is also investigated in several empirical studies. Phan et. al (2018) revealed that, in addition to country-specific EPUs, the GEPU can also be an effective predictor for excess stock returns in Canada, India, South Korea, Japan, and the U.S. Taking in account the documented spillover effects, Chiang (2019) employed both country-specific EPUs and the GEPU to compare the predictive powers of local and global uncertainty innovations regarding stock returns and volatilities in G7 countries and found that the GEPU is generally a more important factor in predicting stock market movements.

The magnitude of the impact of EPUs on stock markets may also vary depending on the sample period, the data frequency and the method employed in the analysis. Chiang (2022) showed that the impact of the GEPU on U.S. stocks decreases during the Covid-19 pandemic. This unexpected result is explained by an indirect decoupling effect that COVID-19 pandemic had on U.S. stock returns through the resulting change in the U.S. EPU. Shi and Wang (2023) revealed that the U.S. EPU has a considerable impact on major stock markets at both daily and monthly frequencies especially during the Global Financial Crisis and while the cross-market impact of Chinese EPU is observed only at a monthly frequency in the post-crisis period. Applying quantile regressions, Huang and Liu (2022) investigated the asymmetric effects of EPU on G7 stock returns and found that, compared to decreases, the increases in EPU have greater effects on G7 stock returns except for Germany. Balcilar, Gupta, Kim and Kyei (2019) showed that while linear Granger causality tests refute the predictive power of domestic and foreign EPUs for Malaysian and South Korean stock markets, these causalities could be proven to exist using a nonparametric causality-in quantiles test. Accounting for non-linearities regarding the relations among financial variables, Yao, Liu and Ju (2020) employed multifractal methods to analyze the cross-correlation features among the U.S. EPU, the NASDAQ index and oil prices, and revealed that there is a significant long-range cross-correlation between each pair within any time interval, and that the U.S. EPU has the least contribution to the coupling correlations.

This study reevaluates the relationship between EPU and stock market returns addressing the above cited issues through the wavelet coherence analysis method developed by Grinsted, Moore and Jevrejeva (2004). In different scientific areas such as geophysics, engineering and medicine, wavelets have long been employed as multiresolution analysis tools for signal processing. The wavelet transformation decomposes a signal into many finite waves of different scales. While lower-scale wavelets capture high-frequency transient features of a signal with a fine time resolution, higher-scale wavelets extract low frequency information with a fine frequency resolution. Wavelet analysis offers a more detailed perspective than Fourier analysis by examining both frequency and time components of data. This advantage has made it valuable in econometrics for uncovering complex patterns in economic variables. Wavelet coherence analysis specifically helps identify how these relationships evolve over time (Kirik, Oygur and Erzurumlu, 2023). The relevant literature cited above pointed out that the characteristics of relationship between EPUs and stock market performance varies depending on different market conditions. Wavelet coherence analysis can locate these varying co-movements in time. In addition, the choice of frequencies does not induce much bias for wavelet analysis results as wavelets assure fine frequency resolution especially for higher scales. Moreover, wavelets are highly adaptive. Through the translation and scale parameters, wavelets can approximate any type of signal or time-series variable, including the non-stationary ones.

The chapter examines how changes in country-specific and global economic policy uncertainty (EPU) impact various stock markets. Given the potential for high correlation among EPU indices, especially during turbulent periods, we employ partial wavelet coherence analysis Hu and Si (2021) to isolate the unique relationship between each country's EPU and its respective stock market, controlling for global EPU effects. In this study, partial wavelet coherences are computed for each selected market by alternately using country-specific EPU and GEPU as excluding variable.

For the empirical study, stock market index return data for three developed (France, Germany and Japan) and three developing countries (Brazil, China and Mexico) are collected to investigate whether the effects of country-specific EPU and GEPU show distinct features depending on the country characteristics. The monthly data period spans from January 1997 through June 2023 and covers major turbulent periods such as the 9/11 terrorist attacks, the Dot-Com bubble, the Global Financial Crisis, the European sovereign debt crisis, the Brexit, the trade war between the U.S and China, the Covid-19 pandemic and the war between Russia and Ukraine.

The empirical results show that the GEPU is generally a more important factor in predicting stock market movements when compared to the country-specific EPUs. Nevertheless, the explanatory power of EPUs varies depending on the considered stock market and period. The overriding role of the GEPU is observed especially for the developed countries in the sample. The highest coherency is observed in the Japanese market throughout the sample period. According to the partial wavelet coherence results, the GEPU is revealed to be the predominant uncertainty factor for the NIKKEI 225 index till 2018. By then, domestic policy uncertainties start to be a prior concern for the Japanese financial market. Chinese stock market is found to be the least affected by economic policy uncertainties at the domestic and global levels. The standalone effect of the GEPU on the Chinese stock market is only remarkable during the Global Financial Crisis, while the domestic EPU offers no additional explanatory power. For the French financial market, the GEPU has remarkable influence on stock return performance even after controlling for the domestic EPU, while the domestic EPU exhibits almost no marginal effect on stock return performance. The relation between EPUs and the German stock market shows some similarities to the French case. However, compared with what is observed in France, the effect of GEPU is more limited in Germany. Similar features are observed for the Brazilian and

Mexican stock markets. The observed negative relationship between these stock markets' performances and the EPUs is concentrated in the first part of the sample period, but as the effects of EPU and GEPU mostly overlap, neither the GEPU nor the domestic EPU exhibits remarkable marginal influence on the stock market index returns except for some short periods. The results would provide some valuable insights for modeling the relation between the stock markets and EPUs.

The remainder of the chapter is organized as follows: Subsection 2 presents the dataset, and the empirical methodology employed in the paper. Subsection 3 reports and discusses the empirical results. Subsection 4 concludes the study.

4.2. Data and empirical methodology

4.2.1. Data

The empirical study investigates the effect of both country-specific EPUs and the GEPU on the stock market returns of developed and developing countries. Data on France, Germany and Japan are included in the analysis to represent the developed countries, and those on Brazil, China and Mexico are collected regarding the developing countries in the sample. For each country, major stock market indices (CAC 40 for France, DAX 40 for Germany, NIKKEI 225 for Japan, BOVESPA for

Brazil, SSE Composite for China and S&P IPC (MXX, in short) for Mexico) are considered as representative indices. The stock market index data are obtained from www.investing.com. Logarithmic differences of the index levels are then computed to generate the stock market index return series.

The original Economic Policy Uncertainty (EPU) index was developed by Baker, Bloom, and Davis (2016) for the U.S. market, incorporating news coverage, tax code uncertainty, and economic forecasts. This methodology has been adapted to construct EPU indices for various countries and regions. The GEPU index is a GDP-weighted average of 21 country-specific EPUs. This study employs both the GEPU and country-specific EPU indices, along with their logarithmic differences, as primary datasets. The data is freely available at www.policyuncertainty.com. The monthly data period used in the empirical study spans from January 1997 through June 2023.

4.2.2. Empirical Methodology: Wavelet Transformations and Wavelet Coherence Measures

Wavelet analysis employs wavelet transformations, utilizing a mother wavelet function to decompose data into different frequency components while preserving time localization information. The Morlet wavelet, a combination of a complex exponential and a Gaussian window, is commonly chosen as the mother wavelet due to its effectiveness in representing various data series, particularly financial time series.

The continuous wavelet transform is formulated as the following:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\psi^{\sim *}{}_{\tau,s}(t)dt, \tau, s \in \mathrm{R}, s \neq 0, (4.1)$$

where τ and s determines the location (time) and length (scale) of the wavelet, respectively. $\psi^{\sim *}{}_{t,s}(t)$ is the complex conjugate of $\psi^{\sim}{}_{t,s}(t)$ that is expressed as

$$\psi^{\sim}{}_{t,s}(t) = |s|^{-0.5}\psi\left(\frac{t-\tau}{s}\right) \ (4.2)$$

where ψ is the mother wavelet function. Mother wavelet can also be shifted in time in function of the translation parameter (τ), while scale parameter (s) is used to shrink or expand the wavelet.

To examine the time-frequency relationship between two series, x and y, cross-wavelet transformation should be obtained through what follows:

$$W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s) \ (4.3)$$

where W_y^* is the complex conjugate of W_y.

Using this cross-wavelet transform, the complex wavelet coherence, can be defined as follows:

$$\gamma_{x,y}(\tau\,,s) = \frac{S(|W_{xy}(\tau\,,s)|)}{[S(|W_{xx}(\tau\,,s)|)S(|W_{yy}(\tau\,,s)|)]^{0.5}} \quad (4.4)$$

where S is a smoothing operator for time and frequency. As it can be seen from the Equation (4.4), wavelet coherence is a time-frequency domain counterpart of the correlation measure. Wavelet coherence localizes correlation coefficients in the time-frequency plane.

The squared partial correlation coherence measure is then obtained based the complex coherence excluding the effect of a third variable *z* as follows:

$$\rho^2_{x,y\bullet z} = \frac{|\gamma_{x,y}(\tau\,,s) - \gamma_{y,z}(\tau\,,s)\gamma^*_{x,z}(\tau\,,s)|^2}{(1 - R^2_{x,z}(\tau\,,s))(1 - R^2_{y,z}(\tau\,,s))} \quad (4.5)$$

where $R^2_{x,z}$ and $R^2_{y,z}$ are the squared bivariate coherences of the conditioning variable *z* with *x* and *y*, respectively.

Monte Carlo simulation methods replace traditional significance tests to assess the significance of these complex coherence measures. Unlike the correlation measures, $\gamma_{x,y}$ and $\rho^2_{x,y\bullet z}$ can only take values between 0 and 1, and the sign of the wavelet coherence is measured by phase differences represented by arrows of different orientations shown in high coherence regions in a wavelet coherence plot. Arrows pointing to the right denote that the two series are in phase (positively related), the arrows pointing to the left indicate that the series are in anti-phase (negatively related). The angles of the arrows provide information on lead-lag relationships. Arrows pointing to the left and up and to the right and down denote that the first variable leads the second. Otherwise, the second variable leads the first.

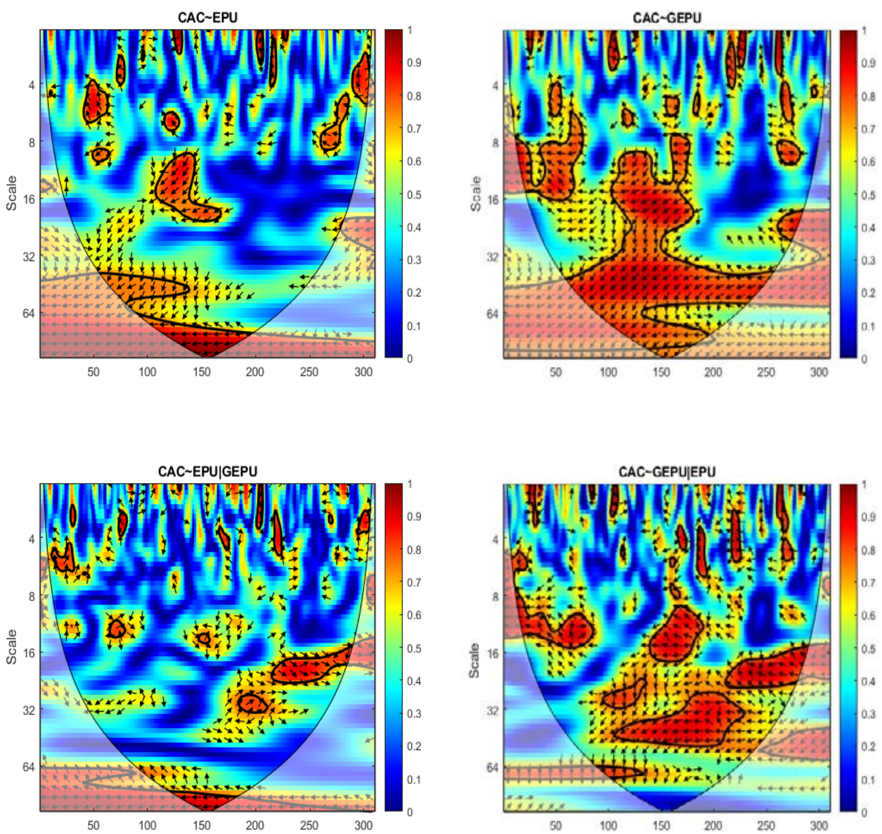
4.3. Empirical results

Empirical results for each market are visually presented in Figures 1 through 6 using wavelet coherence and partial wavelet coherence plots. The vertical axis of these plots represents the scale, inversely proportional to frequency, with higher scales corresponding to lower frequencies. The time dimension is given in the horizontal axis. The time points 50, 100, 150, 200, 250, 300 correspond to February 2001, April 2005, June 2009, August 2013, October 2017, and December 2021, respectively. The thick black contours indicate areas of significant coherence at the 5% level, determined through Monte Carlo simulations. Color intensity, ranging from dark blue (low coherence) to dark red (high coherence), reflects the strength of the relationship. The cone of influence, a region influenced by data boundaries, is shaded lighter.

The two plots at the top of each figure provide the wavelet coherence results for the stock market of the country studied regarding the country-specific EPU at the left, and the GEPU at the right plots. The bottom-left plot in each figure presents partial wavelet coherencies between the stock market returns and the country-specific EPU that are obtained by controlling for the effect of the GEPU, while the coherencies between the stock index returns and the GEPU that are obtained through partialling out the effect of the country-specific EPU are given at the bottom-right plot.

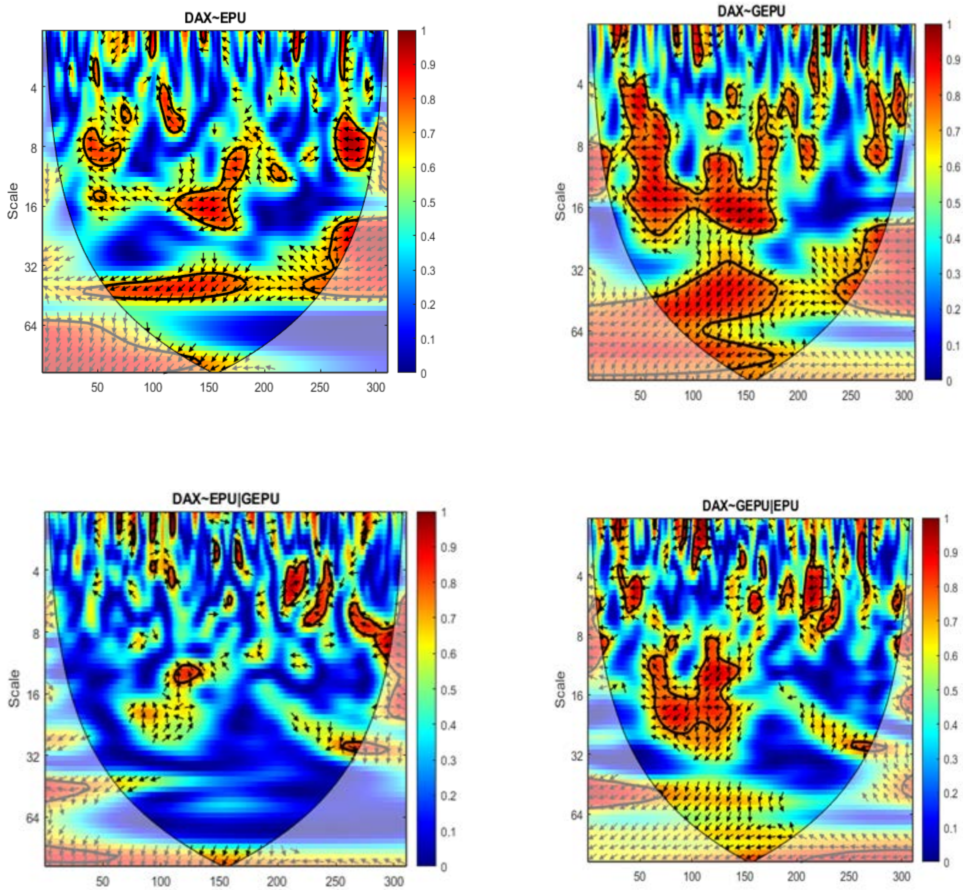
The Figure 1 presents the empirical results regarding the French market. The wavelet coherency results reveal that global uncertainties affect the CAC 40 index returns much more heavily than domestic instabilities. For almost all significant associations, index returns are in anti-phase with the innovations in EPU and GEPU. Phase differences seem to change with the scale: CAC 40 index returns tend to lead EPU and GEPU for higher frequencies, while GEPU and EPU become leading variables at medium and large scales (>12 months). When controlled for the GEPU, the effect of EPU almost disappears for the French stock market. An interesting, seemingly unexpected result can be observed in the partial wavelet coherence plots. There are two significant islands in the bottom-left plot at the medium scales, one spanning from the mid-2012 through the end of 2014, and another from 2016 onwards, where the CAC 40 index returns and the EPU in France are in-phase. In these periods, a strong negative relationship between the stock returns and the GEPU is obviously dominating the market. Starting from 2012, the CAC 40 index followed an increasing trend despite very high levels of domestic EPU, thanks to the decreasing GEPU levels throughout this period. After 2016, the EPU in France started to co-move closely with the GEPU, creating a very strong decoupling effect.

Figure 4.1. (Partial) wavelet coherence analysis results for France



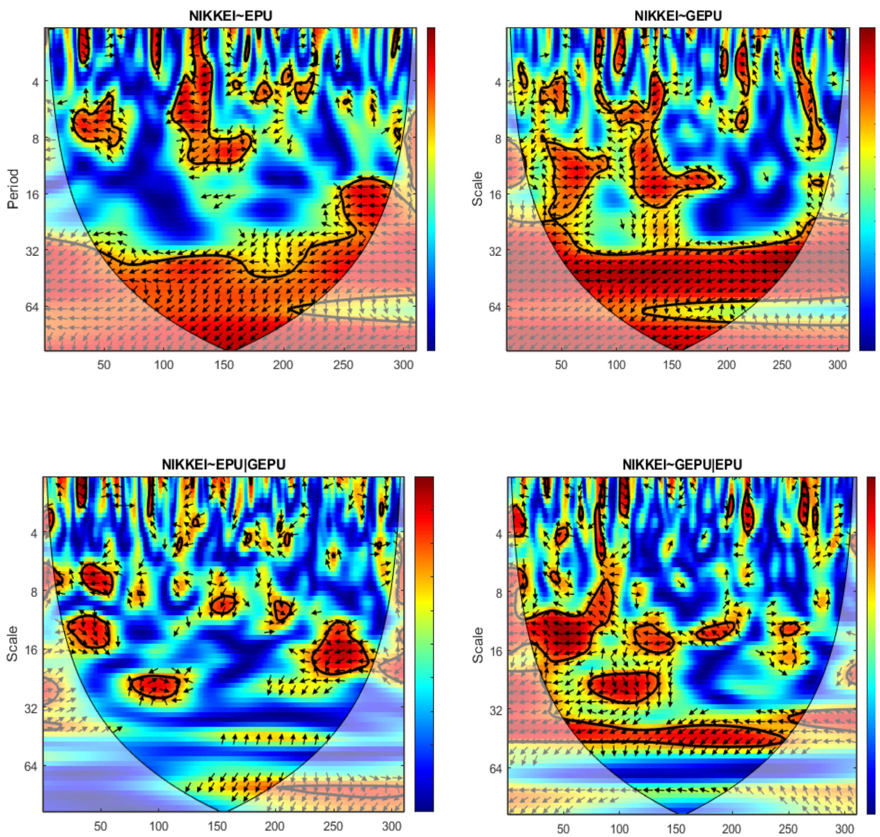
Wavelet coherence analysis results for the German market are given in the Figure 2. Similarly to the French case, the significant negative relationships between stock returns and the domestic EPU tend to disappear when this relationship is controlled for the effects of the GEPU. The marginal effect of the EPU in Germany can only be observed within short time-periods at medium and lower scales. Some intriguing decoupling effects between EPU and GEPU are reflected in opposite phase differences depicted in the partial wavelet coherence plots. For instance, from mid-2014 through the end of 2015, at the lower scales (4 to 8 months), the DAX 40 index returns are in phase with the domestic EPU and in anti-phase with the GEPU. These coherencies of opposite characteristics could not be observed in the initial wavelet coherence plots, as they cancel each other out. Regarding the stock return performance, the dominating source of uncertainties alters through the sample period. The standalone effect of the GEPU on the DAX 40 index returns is considerable at the medium scales for a long period between 2003 and 2009, while the negative relationship between the stock index returns and the domestic EPU tend to overweigh starting from 2019.

Figure 4.2.(Partial) wavelet coherence analysis results for Germany



The Figure 3 depicts the wavelet coherence analysis results regarding the Japanese market. The NIKKEI 225 index returns are highly coherent with both the EPU in Japan and the GEPU at higher scales throughout the sample period. Except for some ephemeral positive coherencies observed at the high-frequency region, the index

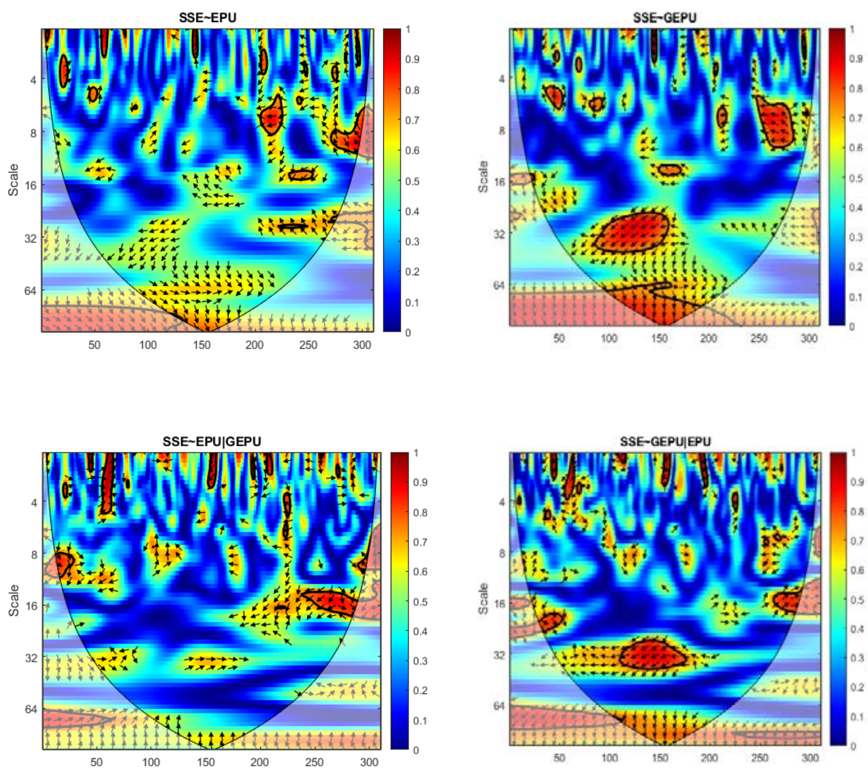
Figure 4.3. (Partial) wavelet coherence analysis results for Japan



returns are clearly in anti-phase with the domestic and global policy uncertainties. Nevertheless, the partial wavelet coherence the observed negative relationship between the index returns and the domestic EPU ceases to hold in many instances when controlled for the GEPU. The GEPU seems to be the predominant uncertainty factor for the NIKKEI 225 index till 2018. By that year, domestic policy uncertainties start to be a prior concern for the Japanese financial market.

The wavelet coherence analysis results depicted in Figure 4 reveal that the SSE Composite index return performance is much less

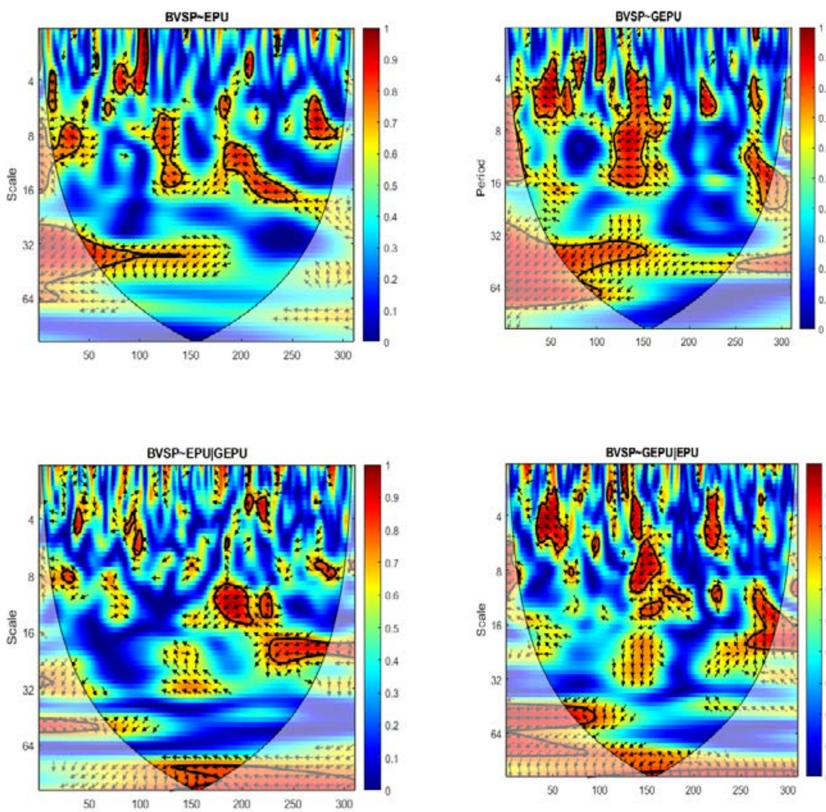
Figure 4.4. (Partial) wavelet coherence analysis results for China



related to economic policy uncertainties at the domestic and global levels. Significant relationships between the domestic EPU and stock market index returns can only be observed within short periods after 2013. Standalone negative effect of the domestic EPU occurs at medium scales (~18 months), only by 2018. Compared to the domestic EPU, the GEPU exhibits a higher coherence with the stock market index returns. The significant phase difference at higher scales (2 to 4 years) that is observed between the mid-2007 and 2012 persists even after controlling for the domestic EPU: increasing GEPU levels led to negative returns in Chinese stock market during the Global Financial Crisis.

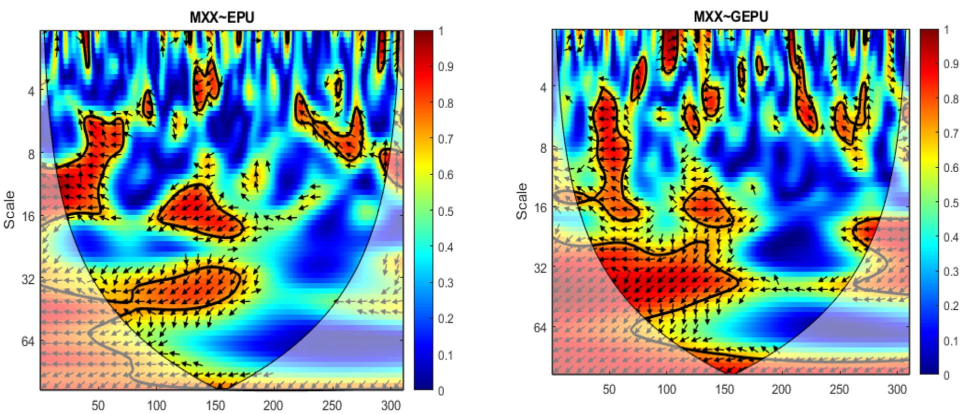
The Figure 5 provides the wavelet coherence analysis plots for the Brazilian market. At first sight, it can be remarked that the BOVESPA index returns are negatively related to both domestic and global EPUs at higher scales during the first part of the sample until the beginning of 2010. Interestingly, these areas of significant coherences almost disappear in the partial wavelet coherence plots, meaning that neither the GEPU nor the domestic EPU had a standalone, marginal influence on the stock market index returns in this time period and frequency. For this part of the sample, using the domestic EPU would provide no considerable additional explanatory power regarding the Brazilian stock market returns. The marginal influence of the domestic EPU starts to be effective in the second half of the sample period, by mid-2011. The effect of the GEPU remains mostly intact at the medium and lower scales during several time intervals throughout the sample period even after controlling for the effect of the domestic EPU.

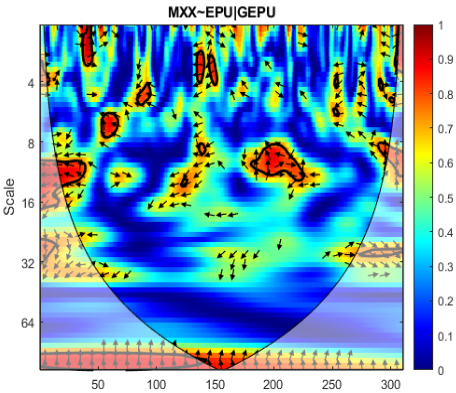
Figure 4.5. (Partial) wavelet coherence analysis results for Brazil

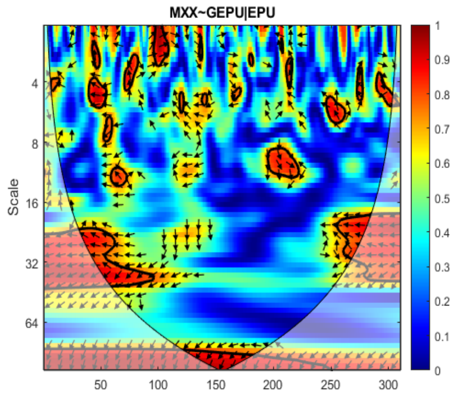


Wavelet coherence analysis results regarding the Mexican market are depicted in the Figure 6. Similarly to the Brazilian market, the negative effects of both domestic and global EPUs are more frequently observed during the first part of the sample till mid-2010. During this period, the effects of domestic and global EPUs mostly overlap. After controlling for the GEPU, the marginal negative effect of the domestic EPU remains only for some short periods at the medium and lower scales. The standalone effect of the GEPU can be partly observed at the higher scales at the beginning and the end of the sample period. In addition, some ephemeral coherencies between the MXX index returns and the GEPU remain at the higher frequencies.

Figure 4.6. (Partial) wavelet coherence analysis results for Mexico







4.4. Summary and concluding remarks

This case study reassessed the relationship between EPU and stock market performance through wavelet coherence analysis. The effects of both global and country-specific EPUs are analyzed for a sample of stock markets including three developed (France, Germany and Japan) and three developing countries (Brazil, China and Mexico) to investigate whether the effect of EPUs at the domestic and global levels show distinct features depending on the country characteristics. Considering the observed fact that the EPU indices tend to co-move especially in highly turbulent periods, partial wavelet coherence analysis is also conducted by alternately using country-specific EPU and GEPU as excluding variable in order to assess the marginal explanatory power of EPUs regarding stock market index returns.

The empirical results show that the GEPU is generally a more important factor in predicting stock market movements when compared to the country-specific EPUs. Nevertheless, the explanatory power of EPUs varies depending on the considered stock market and period. The overriding role of the GEPU is observed especially for the developed countries in the sample. The highest coherency is observed in the Japanese market throughout the sample period. According to the partial wavelet coherence results, the GEPU is revealed to be the predominant uncertainty factor for the NIKKEI 225 index till 2018. By then, domestic policy uncertainties start to be a prior concern for the Japanese financial market. Chinese stock market is found to be the least affected by economic policy uncertainties at the domestic and global levels. The standalone effect of the GEPU on the Chinese stock market is only remarkable during the Global Financial Crisis, while the domestic EPU offers no additional explanatory power. For the French financial market, the GEPU has remarkable influence on stock return performance even after controlling for the domestic EPU, while the domestic EPU exhibits almost no marginal effect on stock return performance. The relation between EPUs and the German stock market shows some similarities to the French case. However, compared with what is observed in France, the effect of GEPU is more limited in Germany. Similar features are observed for the Brazilian and

Mexican stock markets. The observed negative relationship between these stock markets' performances and the EPUs is concentrated in the first part of the sample period, but as the effects of EPU and GEPU mostly overlap, neither the GEPU nor the domestic EPU exhibits remarkable marginal influence on the stock market index returns except for some short periods. These results would provide some important insights for modeling the relation between the stock markets and EPUs.

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WAVELET ANALYSIS

History, Theory and Applicatons with a Case Study in Finance

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ISBN: 978-625-6104-36-5

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