

Rethinking the CAPM beta on emerging markets: A wavelet coherence approach to the Moroccan financial sector

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Abstract: This study examines whether the systematic risk of Moroccan financial stocks is constant over time and across investment horizons, as the Capital Asset Pricing Model (CAPM) assumes. Using daily data from January 2013 to June 2026, we estimate a time- and frequency-varying beta for two banks (Attijariwafa Bank and Banque Centrale Populaire) and two insurers (Wafa Assurance and AtlantaSanad) against the MASI. The beta is derived from continuous wavelet coherence, signed through the wavelet phase, and compared with static OLS and 60-day rolling betas. A reliability index measures the share of the time-frequency plane over which co-movement is significant against a Monte Carlo red-noise null. A sharp sectoral divide emerges: banks are strongly and positively integrated with the market, especially at longer horizons, whereas insurers display weak, intermittent, and occasionally negative exposure. The reliability index falls from 61.9% for Attijariwafa Bank to 15.4% for AtlantaSanad, and insurer betas become aggressive during low-frequency stress episodes such as COVID-19. A single OLS beta therefore misrepresents systematic risk at most horizons. Investors and regulators in concentrated emerging markets should rely on horizon-specific hedge ratios and treat the diversification benefits of insurers as conditional on calm market conditions.

Keywords: CAPM, Emerging markets, Signed systematic risk, Time-frequency beta, Wavelet coherence.

1. Introduction

The Capital Asset Pricing Model (CAPM), developed by Treynor [1], Sharpe [2], and Lintner [3], remains the workhorse of risk measurement. Its key parameter, the beta, measures the sensitivity of an asset's excess return to that of the market portfolio and is commonly estimated by ordinary least squares (OLS) on the market model. This estimate rests on two assumptions: that beta is stable over time, and that a single coefficient adequately captures risk regardless of the investor's horizon. Both assumptions are weakly supported empirically. A large literature, from Blume [4] and Fabozzi and Francis [5] to Bos and Newbold [6], documents the time instability of beta and has motivated time-varying estimators such as rolling regressions and conditional GARCH-type models [7, 8]. Less well known, but equally important, is the horizon dimension: the CAPM assumes homogeneous agents, so that investors with different holding periods share the same measure of systematic risk. This assumption is questionable, since the risk borne by a high-frequency trader differs from that borne by a long-term institutional investor [9, 10].

Wavelet analysis makes it possible to relax both assumptions simultaneously. By jointly decomposing the asset-market relationship in the time and frequency domains, continuous wavelet methods show how systematic risk evolves over time and across investment horizons, overcoming the limitations of purely frequency-based (Fourier) techniques that discard time information. Building on the wavelet coherence and phase tools of Torrence and Compo [11], Torrence and Webster [12] and

Mestre and Terraza [13] proposed a time-frequency beta derived from the wavelet coherence between an asset and the market, with its sign recovered from the wavelet phase. Their application to French blue chips shows that both the intensity and the sign of systematic risk vary across the time-frequency plane, with direct consequences for portfolio managers.

This paper applies and extends that framework to the Moroccan stock market, which has not yet been studied in this way. The choice of the financial sector is deliberate. The Casablanca Stock Exchange is highly concentrated: the banking sector alone accounts for close to one third of total market capitalisation and is the main driver of the MASI index [14]. Analysing the coherence between this sector and the market therefore amounts to analysing the core of domestic systematic risk. Moreover, the sample period 2013–2026 contains several major macro-financial events, namely the COVID-19 shock and Bank Al-Maghrib's exceptional monetary easing, the 2022–2023 inflation surge followed by monetary tightening and normalisation, recurrent droughts, and the September 2023 earthquake. Together, these events provide a demanding test of the stability of systematic risk profiles [15, 16].

The contribution of the paper is threefold. First, to the best of our knowledge, it is one of the first applications of time-frequency beta estimation to the Moroccan market during such a recent and eventful period. Second, by contrasting aggressive, neutral, and defensive stocks across the banking and insurance sub-sectors, the analysis allows a comparative reading that single-asset studies cannot provide. Third, we interpret the results economically, linking the time-frequency patterns of coherence and beta to the Moroccan macro-financial context and drawing concrete implications for horizon-based allocation and dynamic hedging. The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the wavelet methodology, and Section 4 describes the data. Section 5 reports and discusses the results, and Section 6 concludes.

2. Literature Review

2.1. Time-Varying Systematic Risk

The stability of beta, a maintained hypothesis of the standard CAPM, has been challenged since the earliest empirical tests. Blume [4] documents the tendency of betas to regress towards unity over time, while Fama and MacBeth [17], Fabozzi and Francis [5] and Bos and Newbold [6] provide evidence that systematic risk is better described as a stochastic, time-varying process than as a fixed parameter. These findings prompted the development of dynamic estimators. Rolling and recursive regressions capture low-frequency drift in beta, whereas conditional models, multivariate GARCH specifications in particular, model the covariance between asset and market returns as an explicit function of the information set Bollerslev, et al. [7]. Groenewold and Fraser [18] and Brooks, et al. [8] compare competing modelling techniques and confirm that allowing beta to vary materially improves the description of systematic risk. Although these approaches accommodate temporal instability, they share a common limitation: they operate in the time domain alone and therefore cannot distinguish short-run from long-run sensitivities, implicitly treating shocks at all frequencies as equivalent.

2.2. Wavelets and Multiscale Finance

The frequency, or horizon, dimension of systematic risk was introduced by the multiresolution literature. Wavelet analysis, first developed in signal processing by Grossmann and Morlet [19] and formalised by Mallat [20], decomposes a time series into components associated with different frequency bands while preserving their localisation in time. Gençay, et al. [9] and Gençay, et al. [10] apply this decomposition to the CAPM and show that systematic risk is not scale-independent: betas estimated at different horizons differ systematically, which is inconsistent with the assumption of homogeneous agents. Subsequent work relied on the continuous wavelet transform and its associated coherence and phase tools to study co-movement and lead-lag relationships between financial variables [21–23]. Within this stream, Mestre and Terraza [24] and Mestre and Terraza [13] define a time-frequency beta obtained from wavelet coherence and signed through the wavelet phase, and show for

French equities that the intensity, stability and even the sign of systematic risk vary simultaneously in time and frequency. Mestre [25] extends the approach to a time-frequency multi-beta model including oil, gold and Fama-French factors, and finds that long-horizon investors are exposed to risk sources that short-horizon traders hardly perceive. We adopt the coherence-based, phase-signed beta as the methodological core of this paper.

2.3. Emerging Markets, Crises and the Moroccan Case

Evidence on time-varying and scale-dependent systematic risk in emerging markets remains comparatively scarce, even though the characteristics of these markets (high concentration, low liquidity and strong sensitivity to macroeconomic and climatic shocks) make the stability of beta particularly doubtful. Rua and Nunes [26] show, using wavelet-based measures, that the market risk of emerging economies varies markedly across time and frequency. In the Gulf region, Masih, et al. [27] find a clear multiscale tendency of beta in all GCC markets, and Ben Mabrouk [28] confirms that the risk-return relationship on the Saudi market is a multiscale phenomenon. The COVID-19 pandemic renewed interest in time-frequency methods: Jeris and Nath [29] document strong, horizon-dependent effects of pandemic-related uncertainty on US bank indices, and Costa, et al. [30] show that the reaction of the Brazilian stock market and its sectors to COVID-19 varied across both time and frequency. More recently, Tetteh and Owusu Junior [31] analyse twelve African stock markets, including Morocco, and find that their co-movement with advanced markets is frequency-dependent and changed between the pre-COVID, COVID, and post-COVID periods.

For Morocco specifically, existing studies stress the concentration of the Casablanca Stock Exchange, the dominant weight of the banking sector in the MASI, and the market's exposure to agricultural cycles and to the monetary policy of Bank Al-Maghrib [14, 15]. Recent empirical work has examined the explanatory power of the CAPM against the Fama-French three-factor model [32] and the ability of classical volatility models to capture the dynamics of the MASI and MASI ESG indices [33]. Both studies conclude that standard time-domain models leave a substantial part of Moroccan return dynamics unexplained. However, to our knowledge, the joint time-frequency dynamics of coherence and beta between the Moroccan financial sector and the market have not been systematically investigated. This gap is the point of departure of the present study: by applying the continuous wavelet time-frequency beta to contrasting banking and insurance stocks over 2013–2026, we provide multiscale, crisis-inclusive evidence for this concentrated emerging market and interpret it in light of its macro-financial context.

3. Methodology

This section describes the continuous wavelet framework used to estimate a time- and frequency-varying systematic risk. We proceed in four steps: the static market model used as a benchmark; the continuous wavelet transform (CWT) and the cross-wavelet spectrum; wavelet coherence and phase; and, finally, the time-frequency beta derived from them. The framework builds on Torrence and Compo [11], Rua [21], Rua and Nunes [26], and Mestre and Terraza [13].

3.1. The Market Model and the Static Beta

The CAPM [2, 3] relates the risk premium of an asset to that of the market through the security market line, which is estimated empirically by the market model:

$$r_{i,t} = \alpha + \beta r_{m,t} + \varepsilon_t, \quad (1)$$

where $r_{i,t}$ is the return (or risk premium) of asset i , $r_{m,t}$ is the market return, ε_t is an i.i.d. $(0, \sigma_\varepsilon^2)$ disturbance, and β measures systematic risk. When estimated by OLS, β is, by construction, constant over time and identical across investment horizons. Both properties are empirically questionable [5, 6]: the intensity of the asset-market relationship varies over time, and an asset weakly linked to the market

in the long run may be more tightly linked in the short run, or vice versa. The instability of β is closely tied to the hypothesis of heterogeneous agents [10], which motivates a joint time-frequency treatment.

3.2. The Continuous Wavelet Transform

Wavelet analysis decomposes a time series jointly in time and frequency. It thereby overcomes the absence of time information in Fourier analysis while mitigating the time-frequency trade-off inherent in the windowed (short-time) Fourier transform [21]. A wavelet is a “small wave” $\psi(t)$ with zero mean and unit energy that is localised in both time and frequency. From a mother wavelet $\psi(t)$, a family of daughter wavelets is generated by translation (parameter τ , denoting the time position) and dilation (parameter s , denoting the scale, which is inversely related to frequency):

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

where $1/\sqrt{s}$ is a normalisation factor ensuring comparability across scales. The CWT of a series $x(t)$ is its projection onto this family:

$$W_x(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi^*\left(\frac{t-\tau}{s}\right) dt, \quad (3)$$

where ψ^* denotes the complex conjugate. The coefficients $W_x(s, \tau)$ describe the variations of the series in the neighbourhood of $t = \tau$ at scale s ; varying τ and s therefore trace the evolution of the series over time within each frequency band. The original series can be recovered from its transform,

$$x(t) = \frac{1}{C_\psi} \int_0^{+\infty} \int_{-\infty}^{+\infty} W_x(s, \tau) \psi_{s,\tau}(t) \frac{d\tau ds}{s^2}, \quad (4)$$

provided that the admissibility condition holds:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(f)|^2}{|f|} df < \infty, \quad (5)$$

where $\hat{\psi}(f)$ is the Fourier transform of $\psi(t)$. This condition, together with

$$\int_{-\infty}^{+\infty} \psi(t) dt = 0 \quad \text{and} \quad \int_{-\infty}^{+\infty} |\psi(t)|^2 dt = 1, \quad (6)$$

guarantees that the wavelet has zero mean and that energy is preserved by the decomposition.

We use the complex Morlet wavelet, which offers an optimal balance between time and frequency localization [26]:

$$\psi^M(t) = \pi^{-1/4} e^{if_0 t} e^{-t^2/2}, \quad (7)$$

where f_0 is the non-dimensional central frequency, set to $f_0 = 6$ to satisfy the admissibility condition. With this value, the wavelet scale s is almost equal to the Fourier period, which allows the scale axis to be read directly as an investment horizon. In practice, the scale grid is discretised with a step δ_j ; following Torrence and Compo [11], the maximum decomposition order is

$$J = \delta_j^{-1} \log_2 \left(\frac{N \delta t}{s_0} \right), \quad (8)$$

where N is the sample size, δt is the time step, and $s_0 = 2 \delta t$ is the smallest resolvable scale. A value of $\delta_j = 1/12$ provides fine frequency resolution at a reasonable computational cost. The set of scales is $s_j = s_0 2^{j\delta_j}$, $j = 0, 1, \dots, J$, and each scale maps to an investment horizon expressed in trading days.

3.3. Cross-Wavelet Spectrum, Coherence and Phase

Given two series $x(t)$ and $y(t)$ with transforms $W_x(s, \tau)$ and $W_y(s, \tau)$, the cross-wavelet spectrum captures their local covariance in the time-frequency plane:

$$SW_{xy}(s, \tau) = W_x(s, \tau) W_y^*(s, \tau). \quad (9)$$

It is complex-valued because the Morlet wavelet is complex. Its modulus $|SW_{xy}(s, \tau)|$ measures the common power of the two series at each date and scale, that is, the regions in which they jointly exhibit high variance.

Wavelet coherence measures the local, scale-by-scale squared correlation between the two series. By analogy with Fourier coherence, it is defined from the cross-spectrum and the two auto-spectra, $|SW_x|^2$ and $|SW_y|^2$, as

$$WQ_{\tau,s} = \frac{|G(s^{-1}SW_{xy})|^2}{G(s^{-1}|SW_x|^2) G(s^{-1}|SW_y|^2)}, \quad (10)$$

which yields, at each scale s and time τ , a coefficient between 0 and 1 that plays the role of a local coefficient of determination, that is, the explanatory power of $x(t)$ over $y(t)$. Because the unsmoothed coherence of a complex wavelet equals unity everywhere, a time-frequency smoothing operator G is required. It combines smoothing in time at a given scale, G_{time} , and smoothing across scales at a given time, G_{scale} :

$$G(W) = G_{scale}(G_{time}(W)), \quad (11)$$

with the expressions of Torrence and Webster [12]:

$$G_{time}(W) = W * c_1 e^{-t^2/(2s^2)}, \quad G_{scale}(W) = W * c_2 \Pi(0.6s), \quad (12)$$

where c_1 and c_2 are normalisation constants and Π is the rectangle function.

The complex cross-spectrum also delivers the wavelet phase, which indicates the sign of the local co-movement and any lead-lag relationship. The phase is the angle defined by the imaginary ($\Im$) and real ($\Re$) parts of the cross-spectrum:

$$\theta_{\tau,s} = \arctan\left(\frac{\Im(SW_{xy}(\tau, s))}{\Re(SW_{xy}(\tau, s))}\right), \quad \theta_{\tau,s} \in (-\pi, \pi]. \quad (13)$$

On the coherence maps, the phase is displayed as arrows: a rightward arrow denotes series that are in phase (positively correlated) and a leftward arrow denotes series that are in antiphase (negatively correlated); an upward (downward) arrow indicates that the first (second) variable leads. We summarise the sign through the indicator

$$\vartheta_{\tau,s} = \begin{cases} +1, & |\theta_{\tau,s}| \in [0, \pi/2] \quad (\text{in phase, positive}), \\ -1, & |\theta_{\tau,s}| \in (\pi/2, \pi] \quad (\text{anti-phase, negative}). \end{cases} \quad (14)$$

3.4. The Time-Frequency Beta

The link between coherence and beta parallels that between the coefficient of determination and the slope in a simple regression [13]. Taking the square root of the coherence in Eq. (10) and multiplying it by the ratio of the auto-spectra isolates the absolute value of the time-frequency beta:

$$|\beta_{\tau,s}| = (WQ_{\tau,s})^{1/2} \frac{G(s^{-1}|SW_y|^2)^{1/2}}{G(s^{-1}|SW_x|^2)^{1/2}}. \quad (15)$$

Here x denotes the market and y the asset, so that $|\beta_{\tau,s}|$ is the local sensitivity of the asset to the market, indexed by both time τ and scale s . This expression generalises the OLS beta: the coherence, weighted by the ratio of the smoothed standard deviations of the two series, delivers a systematic risk coefficient that is specific to each date and each investment horizon.

Because it rests on the square root of the coherence, Eq. (15) does not convey the sign of beta. The sign is restored through the phase indicator $\vartheta_{\tau,s}$ defined in Eq. (14), which gives the signed time-frequency beta:

$$\beta_{\tau,s} = \vartheta_{\tau,s}(WQ_{\tau,s})^{1/2} \frac{G(s^{-1}|SW_y|^2)^{1/2}}{G(s^{-1}|SW_x|^2)^{1/2}}. \quad (16)$$

The quantity $\beta_{\tau,s}$ is central to this paper. Read across time at a fixed scale, it describes the dynamics of systematic risk at a given horizon; read across scales at a fixed date, it reveals the horizon structure of risk; and, suitably averaged, it yields both a scale-averaged beta (a dynamic, horizon-aggregated series comparable to the rolling beta) and a time-averaged multiscale beta (the frequency signature of the asset's risk). Estimates falling within the cone of influence, where edge effects distort the finite-sample spectra, are discarded, and the significance of the coherence at the 5% level is assessed by Monte Carlo simulation against a red-noise null.

3.4.1. Two Dynamic Estimators of Systematic Risk

Our empirical design departs from that of Mestre and Terraza [13] in that it compares two ways of letting the market beta vary over time. For the empirical implementation, we adopt the notation commonly used in applied work, in which τ denotes the scale (horizon) and t the date. The first estimator is the standard rolling-window beta, obtained by re-estimating the market model on a moving sample of fixed length w :

$$\hat{\beta}_t^{roll} = \frac{\sum_{k=t-w+1}^t (r_{m,k} - \bar{r}_{m,t})(r_{i,k} - \bar{r}_{i,t})}{\sum_{k=t-w+1}^t (r_{m,k} - \bar{r}_{m,t})^2} = \frac{\widehat{Cov}_{t,w}(r_i, r_m)}{\widehat{Var}_{t,w}(r_m)}, \quad (17)$$

where $\bar{r}_{m,t}$ and $\bar{r}_{i,t}$ are the within-window means and $w = 60$ trading days throughout.

The second estimator is obtained from the wavelet decomposition. Let $W_i(\tau, t)$ and $W_m(\tau, t)$ be the continuous wavelet transforms of the asset and market returns at scale τ and date t , and let $S(\cdot)$ be the time-scale smoothing operator. Writing $S_{im} = S(\tau^{-1}W_i W_m^*)$ for the smoothed cross-spectrum and S_{ii} , S_{mm} for the smoothed auto-spectra, the squared wavelet coherence and the wavelet phase are

$$R^2(\tau, t) = \frac{|S_{im}(\tau, t)|^2}{S_{ii}(\tau, t) S_{mm}(\tau, t)}, \quad \phi(\tau, t) = \arctan \frac{\Im\{S_{im}(\tau, t)\}}{\Re\{S_{im}(\tau, t)\}}. \quad (18)$$

The signed time-frequency beta is then defined as

$$\beta(\tau, t) = \text{sgn}[\phi(\tau, t)] \sqrt{R^2(\tau, t)} \sqrt{\frac{S_{ii}(\tau, t)}{S_{mm}(\tau, t)}}, \quad \text{sgn}[\phi] = \begin{cases} +1, & |\phi| \leq \pi/2 \quad (\text{in phase}), \\ -1, & |\phi| > \pi/2 \quad (\text{anti-phase}), \end{cases} \quad (19)$$

so that its magnitude is driven by coherence and relative volatility, while its sign is recovered from the phase. Averaging Eq. (19) across the admissible scales for each date yields the scale-averaged wavelet beta:

$$\bar{\beta}_t^{TF} = \frac{1}{|\mathcal{T}_t|} \sum_{\tau \in \mathcal{T}_t} \beta(\tau, t), \quad \mathcal{T}_t = \{\tau: (\tau, t) \notin \text{COI}\}, \quad (20)$$

where $\mathcal{T}_t$ collects the scales lying outside the cone of influence (COI) at date t . Equations (17) and (20) both produce a single time series of betas and are therefore directly comparable, yet they aggregate information in very different ways.

3.4.2. Why the Two Estimators Differ

The difference between the two estimators can be made precise. By the additivity of the wavelet variance, the within-window covariance and variance in Eq. (17) decompose across scales as $\widehat{Cov}_{t,w}(r_i, r_m) = \sum_{\tau} \widehat{Cov}_{\tau,t}$ and $\widehat{Var}_{t,w}(r_m) = \sum_{\tau} \widehat{Var}_{\tau,t}(r_m)$, so that the rolling beta can be rewritten as a variance-weighted combination of scale-specific betas:

$$\hat{\beta}_t^{roll} = \sum_{\tau} \omega_{\tau,t} \beta_{\tau,t}, \quad \omega_{\tau,t} = \frac{\widehat{Var}_{\tau,t}(r_m)}{\sum_{\tau'} \widehat{Var}_{\tau',t}(r_m)}, \quad \sum_{\tau} \omega_{\tau,t} = 1. \quad (21)$$

The rolling estimator is thus a weighted blend rather than a simple average: each horizon enters with a weight proportional to the share of market variance it carries locally. In a thin, shock-prone market, this share is dominated by the high-frequency component, so that $\hat{\beta}_t^{roll}$ inherits its volatility and overshoots during turbulent episodes. By contrast, the scale-averaged beta in Equation (20) assigns an equal weight $1/|\mathcal{T}_t|$ to every admissible scale, so that no single frequency mechanically dominates the aggregate. Comparing $\omega_{\tau,t}$ with uniform weights makes the gap between the two series interpretable: their common trend identifies the horizon-invariant component of systematic risk, whereas their divergence, which is widest in stress periods when the weights $\omega_{\tau,t}$ shift most sharply towards short scales, measures the extent to which a conventional rolling beta misrepresents risk by ignoring its scale structure [10, 13, 34].

3.4.3. The Cone of Influence

Because the CWT is computed on a finite sample, wavelets at large scales extend beyond the series endpoints, where the data are padded with zeros. This padding attenuates the transform near the edges, so that power and coherence estimates in these regions are biased downwards and unreliable. The boundary between the reliable interior and the edge-affected region is the cone of influence, defined as the locus at which the wavelet power of an edge discontinuity has fallen by a factor e^{-2} from its peak value [11]. The COI widens towards the low-frequency (long-period) end of the plane, where the wavelet is longest and edge contamination reaches deepest into the sample. All estimates inside the COI are treated as unreliable and are excluded from the significance analysis, from the reliability index (Eq. (24)), and from every time- and scale-averaged beta reported below. Only the out-of-cone subdomain $\mathcal{V}$ is used for economic interpretation.

3.5. Complementary Time-Domain Estimators

To place the time-frequency beta in context, we also report two time-domain estimators: the static OLS beta of Eq. (1), which serves as the benchmark, and the 60-day rolling beta of Eq. (17), which captures temporal instability only. Comparing the rolling beta with the scale-averaged wavelet beta shows the consistency of the two dynamic approaches, while the multiscale beta adds the horizon dimension that neither the static nor the rolling estimator can provide.

4. Data and Descriptive Statistics

4.1. Sample and Sources

The empirical analysis uses daily data from the Casablanca Stock Exchange covering the period from January 2013 to June 2026. The market proxy is the Moroccan All Shares Index (MASI), a free-float capitalisation-weighted index of all listed securities. Four financial stocks are selected to cover both sub-sectors and the three usual risk profiles: two banks, Attijariwafa Bank (ATW) and Banque Centrale Populaire (BCP), and two insurers, Wafa Assurance (WAA) and AtlantaSanad (ATL). This design follows the contrasted-profile logic of Mestre and Terraza [13] while extending it to a comparative banking-versus-insurance reading in an emerging market. Prices are obtained from the Casablanca Stock Exchange, and returns are computed in logarithmic form:

$$r_t = \ln(P_t) - \ln(P_{t-1}), \quad (22)$$

This stabilises the variance and ensures the temporal additivity of returns. The trading calendars of the individual stocks are synchronised with that of the MASI, and public holidays and missing observations are removed through common-date matching. The effective sample lengths range from 1,978 observations for Wafa Assurance to 3,256 for Attijariwafa Bank, reflecting differences in liquidity and listing history.

4.2. Descriptive Statistics

Table 1 reports the descriptive statistics of daily returns. Mean returns are very small and positive for all series, consistent with the low drift of daily equity data. Standard deviations reveal markedly heterogeneous risk levels: the insurers (WAA and ATL) are roughly twice as volatile as the large-cap banks (ATW and BCP), reflecting thinner trading and greater exposure to firm-specific shocks. All four stocks display negative skewness, indicating a higher probability of large negative returns than of large positive returns, and exhibit kurtosis well above the Gaussian value of 3, ranging from 4.64 (WAA) to 12.40 (BCP), which points to leptokurtic, fat-tailed distributions. These are the standard stylised facts of financial returns, and they imply that risk measures based on the normal distribution would understate tail risk.

The Jarque-Bera statistic rejects the null hypothesis of normality at the 1% level for every series ($p < 0.001$). The augmented Dickey-Fuller (ADF) test rejects the null of a unit root for all series, with statistics far below the 1% critical value of -3.43 ; the return series are therefore stationary, as required for the wavelet and regression analyses. The market index shares these properties (near-zero mean, low volatility, non-normality and stationarity) and serves as the common benchmark throughout the analysis.

Table 1.

Descriptive statistics of daily logarithmic returns (2013–2026).

Series	Sector	N	Mean	Std. dev.	Skewness	Kurtosis	ADF
MASI	Market	3256	0.00030	0.00858	−0.62	8.90	−26.3
ATW	Banking	3256	0.00027	0.01134	−0.27	9.15	−41.5
BCP	Banking	3235	0.00011	0.01196	−0.54	12.40	−42.1
WAA	Insurance	1978	0.00029	0.02544	−0.08	4.64	−38.5
ATL	Insurance	3171	0.00016	0.02037	−0.07	5.41	−47.9

Note: N = number of observations. ADF = Augmented Dickey-Fuller test statistic (1% critical value ≈ -3.43). The Jarque-Bera test rejects normality ($p < 0.001$) for every series. Returns are daily log returns; the MASI is the free-float capitalisation-weighted market index.

Overall, the descriptive evidence sets the stage for the time-frequency analysis in two ways. First, the stationarity of returns validates their use in the wavelet decomposition and in the market-model regressions. Second, the sharp volatility gap between banks and insurers already hints at the sectoral heterogeneity in systematic risk that the coherence and the time-frequency beta will formalise: the low-volatility, actively traded banks are candidates for strong market integration, whereas the high-volatility, thinly traded insurers are likely to be more idiosyncratic. This intuition is confirmed in the following section.

5. Results and Discussion

This section reports the empirical findings from an economic and portfolio management perspective. We first present the static benchmark and then interpret each of the four assets by jointly reading the coherence magnitude (colour), the phase relationship (arrows), and the time-frequency beta, systematically linking these patterns to the Moroccan macro-financial context over 2013–2026, notably the COVID-19 shock and the monetary response of Bank Al-Maghrib (BAM), the 2022–2023 inflation surge and subsequent disinflation, recurrent droughts, and the September 2023 earthquake [14, 15]. A comparative synthesis then contrasts the banking and insurance sub-sectors, and a final subsection assesses the statistical reliability of the estimates.

5.1. Static Benchmark and Preliminary Diagnostics

Table 2 reports the parameters of the static market model $r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t}$, estimated by OLS over 2013–2026, together with the time averages of the two dynamic betas. Three regularities stand out and motivate the time-frequency analysis. First, as shown in Table 1, the return distributions are far from Gaussian: all series exhibit negative skewness and fat tails, which warn against inference

that relies on normality. Second, the ADF statistics are strongly negative for all series and confirm that log returns are stationary. Third, and most importantly, the static market model reveals differences in the quality of each asset's market exposure, not only in its level. ATW has a moderately aggressive slope ($\beta_{OLS} = 1.10$, $t = 60.3$) and a high coefficient of determination ($R^2 = 0.53$), the signature of a systemic anchor that tracks the index closely. BCP has a near-unit slope ($\beta_{OLS} = 0.97$) but a much weaker fit ($R^2 = 0.37$). The two insurers differ sharply: WAA has an apparently aggressive slope ($\beta_{OLS} = 1.04$) but an R^2 of only 0.12, while ATL is clearly defensive ($\beta_{OLS} = 0.69$) with an almost negligible R^2 of 0.06. In other words, similar OLS betas can conceal very different degrees and modes of market linkage. This gap between the magnitude of beta and the reliability of the linear relationship cannot be resolved within the static CAPM, and it is precisely what the wavelet coherence and time-frequency beta address below.

Table 2.

Static CAPM estimates and time-averaged dynamic betas for the four core assets (2013–2026).

	ATW (Bank)	BCP (Bank)	WAA (Insurer)	ATL (Insurer)
Panel A. Static CAPM				
α	0.0000298	−0.000110	−0.0000242	0.0000256
t-stat (α)	0.218	−0.657	−0.045	0.073
β (OLS)	1.1017	0.9703	1.0448	0.6890
t-stat (β)	60.28	43.46	16.74	14.79
R^2	0.5276	0.3687	0.1242	0.0646
Correlation	0.7264	0.6072	0.3524	0.2541
Panel B. Dynamic betas (Time averages)				
Mean rolling β	1.1493	0.9138	1.2879	0.5227
S.D.	0.2965	0.3429	0.6922	0.4729
Mean wavelet β (TF)	0.9914	0.8454	0.9428	0.6029
s.d.	0.7897	0.9091	1.8793	1.6597

Note: t_α and t_β are the Student statistics of the intercept and slope. β_{roll} is the time average of the 60-day rolling beta (Eq. (17)) and β_{TF} the time average of the scale-averaged wavelet beta (Eq. (20)); s.d. denotes their standard deviations over time.

Panel B of Table 2 already shows that the dynamic estimators diverge from the static benchmark. For the banks, the time-averaged rolling and wavelet betas remain close to their OLS values, but their standard deviations are large. For the insurers, the dispersion of the wavelet beta (1.88 for WAA and 1.66 for ATL) is several times larger than its mean, a first indication that their systematic exposure changes not only in magnitude but also in sign.

5.2. Attijariwafa Bank (ATW): The Systemic Banking Core

5.2.1. Coherence Magnitude

The coherence field (Figure 1a) shows a strong asymmetry across scales that becomes more structured after 2015. In the medium-to-long band (about 64 to 512 days), the squared wavelet coherence approaches unity over most of the sample, indicating a quasi-structural co-movement between ATW and the MASI. This near-saturation is economic rather than accidental: as the largest capitalisation on the Casablanca exchange, ATW accounts for a large share of the benchmark against which it is regressed, so that a substantial part of its long-run variance is, by construction, common variance. The relationship is nevertheless not uniform over time. Before 2015, coherence at the 64–256-day scales is intermittent, with green-to-blue pockets (coherence of about 0.4–0.6), and a conspicuous low-coherence area appears around 2016–2018 near the 64-day scale, when stock-specific events such as dividend adjustments and capital operations temporarily decoupled the bank from the index. At high frequencies (below 8 days), the field breaks into alternating warm and cold vertical filaments, the signature of intermittent, idiosyncratic microstructure noise (order-flow imbalances, block trades and liquidity gaps) that characterises a thin frontier market. Coherence at these scales is episodic rather than

persistent, which underlines the importance of the low-frequency estimates of systematic risk discussed below.

5.2.2. Phase

Within the large coherent core, the phase field is consistent with a positive, contemporaneous relationship: arrows cluster in the right and lower-right quadrants, indicating that ATW and the market move in phase, with at most a marginal lead of the bank over the index at longer scales. This is the phase geometry expected of a constituent that is itself a principal component of the benchmark, namely co-movement without a systematic information lag. Two qualifications sharpen this interpretation. First, the absence of a stable lead rules out any market-timing strategy based on ATW anticipating the index. Second, our signed time-frequency beta preserves the sign of the relationship, not only its intensity: by mapping the local phase into the sign of $\beta(\tau, t)$, the estimator distinguishes genuine positive exposure from regions of high coherence in which the two series are locally out of phase, a distinction that unsigned coherence-based measures cannot make. The stability of the rightward orientation in the very low-frequency band (above 512 days) confirms that the long-run sign of the relationship is invariant over the sample.

5.2.3. The COVID-19 Signature

The most prominent feature of all the maps is a vertical plume of high coherence and common power extending from the 16-day to the 256-day scales around 2020 (Figure 1a), which coincides with the COVID-19 shock. During the pandemic, Bank Al-Maghrib cut its policy rate twice, to a historic low of 1.5%, and provided exceptional liquidity support to the banking system [15]. The episode is best read not merely as a mechanical rise in beta but as a case of systemic risk transmission through the banking channel: a common macro-monetary shock compressed the cross-sectional dispersion of returns and synchronised ATW with the market at all but the shortest scales, widening the significant region at that date. This is the time-frequency analogue of the crisis-driven rise in correlations documented in the contagion literature, whereby diversification benefits disappear when they are most needed [30, 31]. Quantitatively, the mean beta rises from 0.92 in the pre-COVID sub-period to 1.25 during the pandemic.

5.2.4. Time-Domain Dynamics: Rolling versus Scale-Averaged Beta

The comparison between the 60-day rolling beta and the scale-averaged wavelet beta (Figure 1c) is instructive in two respects. Both series follow a common low-frequency trajectory (subdued exposure in 2013–2014, elevated exposure over 2020–2022 and a normalisation towards unity thereafter), but the rolling estimator is systematically more volatile, spiking above 2.0 in early 2016 and again in late 2020, whereas the scale-averaged measure dampens these excursions. This divergence is not noise. As shown in Eq. (21), the rolling beta weights each horizon by its share of local market variance and is therefore dominated by whichever scale happens to carry most of that variance, whereas the scale-averaged beta aggregates the frequency-specific contributions with equal weights. The gap between the two is widest during stress episodes, exactly when the frequency composition of risk is most unstable. This shows that a single-window dynamic beta, although an improvement on static OLS, still misrepresents the horizon structure of systematic risk. The post-2023 convergence of both series towards unity coincides with the disinflation phase and the gradual monetary easing of 2024 [16], as idiosyncratic bank fundamentals reasserted themselves over macro-driven co-movement.

5.2.5. Horizon Dimension: The Multiscale Beta

Averaged over time, ATW's beta is markedly non-monotonic across frequencies (Figure 1d) and traces a distinctive W-shaped profile. It stands at $\beta \approx 1.28$ at the shortest horizon (2–3 days), falls to a first local trough near unity around the weekly-to-fortnightly scale, recovers to a secondary peak close to the monthly horizon, and then declines sharply to a defensive trough of $\beta \approx 0.65$ at the quarterly

scale (70–90 days), its minimum systematic exposure. Beyond this point, beta climbs steeply to a global maximum of $\beta \approx 1.35$ in the 200–350-day band, before declining again to $\beta \approx 0.87$ at the longest horizons, around one year and beyond. This profile illustrates the scale dependence of systematic risk anticipated by Gençay, et al. [10] and is incompatible with the constant-beta postulate of the classical CAPM. Interpreted through the heterogeneous market hypothesis, each horizon corresponds to a distinct clientele: high-frequency traders and market makers, who dominate the intraday-to-weekly scales, bear an amplified exposure to ATW; portfolio managers rebalancing quarterly experience it, paradoxically, as a relatively defensive holding; and long-horizon, buy-and-hold institutional investors again bear above-market risk. Crucially, the single OLS beta of 1.10 is a variance-weighted blend, not a simple average, of these regimes, and therefore misprices ATW's risk at almost every horizon. The cost of this misspecification is horizon-specific: it understates the tail exposure of short-horizon liquidity providers and overstates the risk borne by quarterly rebalancers.

5.2.6. Synthesis

Taken together, the four representations identify ATW as the systemic anchor of the Moroccan market: its exposure is contemporaneous and positive at every horizon, structurally high at medium- and long-term scales, defensive only at the quarterly frequency and sharply amplified by macro-monetary shocks transmitted through the banking channel. As an investment, ATW delivers faithful and highly liquid market exposure but offers virtually no diversification. It is best managed with a horizon-contingent hedge ratio that increases at both the high-frequency and long-horizon ends of the spectrum, where its systematic exposure is greatest.

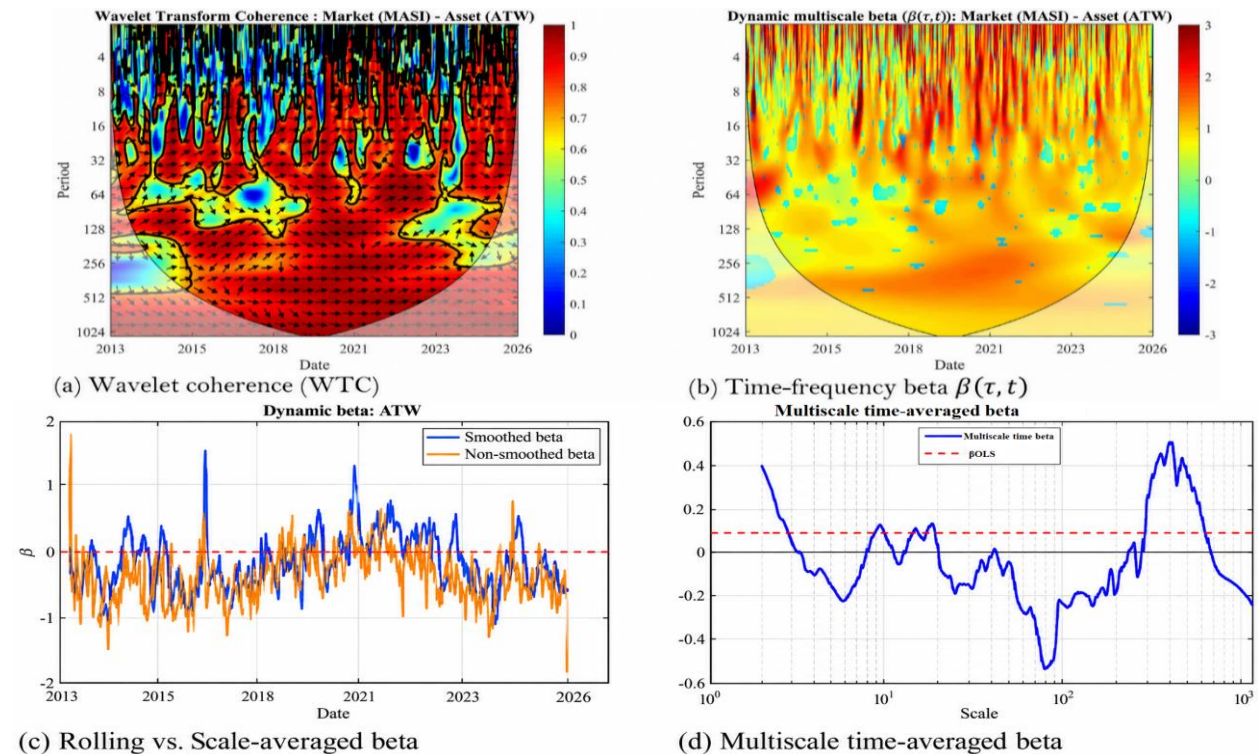


Figure 1.

ATW-MASI coherence and beta dynamics (2013–2026). In panel (a), warm (red) colours denote high coherence, black contours enclose regions significant at the 95% level, the shaded area marks the cone of influence, and rightward arrows denote in-phase (positive) co-movement. Panel (a) shows near-saturated coherence at medium-to-long horizons and a plume around 2020 associated with the COVID-19 shock; panel (b) maps the signed time-frequency beta; panel (c) compares the 60-day rolling beta

with the scale-averaged wavelet beta; panel (d) reveals a non-monotonic, W-shaped frequency profile compared with the OLS beta (Dashed line).

5.3. *Banque Centrale Populaire (BCP) : The Unstable Market Core*

5.3.1. *Coherence Magnitude*

BCP's coherence field (Figure 2a) is dominated by warm tones across the 32–512-day band, signalling robust medium-to-long-run integration with the MASI, yet this integration is visibly less complete and less homogeneous than that of ATW. The high-frequency region is markedly noisier, with frequent cold intrusions and fragmented significance contours, and the long-horizon band contains recurrent green-to-blue areas of depressed coherence, most visibly around 2015 near the 64–128-day scale and again after 2023. This granular texture is the time-frequency expression of a moderate global fit: the static regression yields a near-unit slope ($\beta_{OLS} \approx 0.97$) but explains only about one-third of BCP's return variance ($R^2 = 0.37$). The two figures are not contradictory, since the slope measures the intensity of the systematic response while R^2 measures its tightness, and their combination is economically informative: on average BCP behaves as a textbook unit-beta “market” stock, yet a substantial share of its variation is idiosyncratic. This profile is consistent with BCP's mutualist, retail-oriented franchise, whose regionally anchored deposit base and cooperative governance loosen the mechanical link to the capitalisation-weighted index that binds the internationalised ATW.

5.3.2. *Phase*

Within the significant coherent core, the phase field is again predominantly oriented to the right, confirming a positive and broadly contemporaneous relationship between BCP and the market, with no stable or exploitable lead or lag. As for ATW, the sign stability preserved by the phase-based construction of $\beta(\tau, t)$ is what justifies the economic reading of the systematic risk maps: the positive co-movement is genuine rather than an artefact of high but out-of-phase coherence.

5.3.3. *Time-Frequency Beta Map*

The $\beta(\tau, t)$ surface (Figure 2b) is predominantly warm, but its most instructive feature is the concentration of deep-red streaks ($\beta > 3$) in discrete, recurrent episodes rather than in a continuous ridge. Intense high-frequency bursts cluster in 2014, 2016–2017 and 2023, and a broad warm plateau in the 64–128-day band covers 2016–2017 and re-emerges over 2023–2024. Between these episodes, the surface cools towards moderate values. This intermittency, in which systematic exposure flares and subsides rather than persisting, distinguishes BCP from the structurally saturated ATW and foreshadows the regime-switching behaviour observed in the time domain.

5.3.4. *Time-Domain Dynamics: A Regime-Switching Beta*

The 60-day rolling beta (Figure 2c) is the more volatile of the two banks, covering almost the entire admissible range over the sample. It peaks close to 2.0 in late 2014, collapses to near zero in early 2016 (a state of almost complete decorrelation from the market), and thereafter alternates between prolonged defensive phases (2013 and 2018–2019) and aggressive phases (2016–2017 and 2022). Such wide, low-frequency regime switches are characteristic of a retail bank whose systematic risk is governed by slow-moving fundamentals: successive drought cycles that periodically weaken the agricultural loan book, the disinflation and monetary-easing cycles of Bank Al-Maghrib [15], and changes in the cooperative group's exposures. The scale-averaged wavelet beta follows the same broad trajectory but, by aggregating frequency-specific contributions with equal weights, smooths the extreme excursions of the fixed-window estimator. This again illustrates that a single-window rolling beta overstates the instability of systematic risk by conflating heterogeneous horizons into a single projection.

5.3.5. *Horizon Dimension: An Erratic Multiscale Profile*

Averaged over time, BCP's beta (Figure 2d) is not merely non-monotonic but distinctly erratic across frequencies, in sharp contrast to ATW's comparatively smooth W shape. It starts near $\beta \approx$

0.93 at the shortest horizon, falls to a trough of $\beta \approx 0.67$ around the weekly scale (7–8 days), oscillates within a defensive 0.75–0.90 corridor across intermediate scales, and then rises in a saw-toothed pattern to a global maximum of $\beta \approx 1.20$ near the 150–200-day horizon, with a secondary peak of about 1.11, before falling below 0.65 near the 300-day scale and recovering at the longest horizons. The economic message is clearer than for ATW: BCP's systematic risk is predominantly a low-frequency, business-cycle phenomenon. A high-frequency trader faces a defensive, below-unit-beta stock, whereas a long-horizon, buy-and-hold investor bears above-market risk. This scale dependence, anticipated by Gençay, et al. [10], exposes the failure of the aggregate estimator with particular force: a single OLS beta of 0.97 compresses a profile ranging from 0.65 to 1.20 into a misleading unit-beta verdict, mispricing BCP as a neutral “market” stock at virtually every horizon at which it is actually traded. The jaggedness of the long-horizon segment further indicates that BCP's above-market exposure, while real, is itself unstable across scales, a second-order fragility that no single-number risk measure can reveal.

5.3.6. Synthesis

BCP emerges as an unstable market core: nominally a unit-beta stock, it is in reality a regime-switching, business-cycle-sensitive asset whose systematic risk is defensive at high frequencies and aggressive over the credit cycle. Its moderate R^2 , wide rolling-beta swings, and erratic multiscale profile jointly caution against treating it as a passive market proxy. For a horizon-aware investor, it offers genuine, if intermittent, diversification at short scales but requires a higher, periodically re-estimated hedge ratio as the investment horizon lengthens into the business-cycle band, where its market exposure is concentrated.'

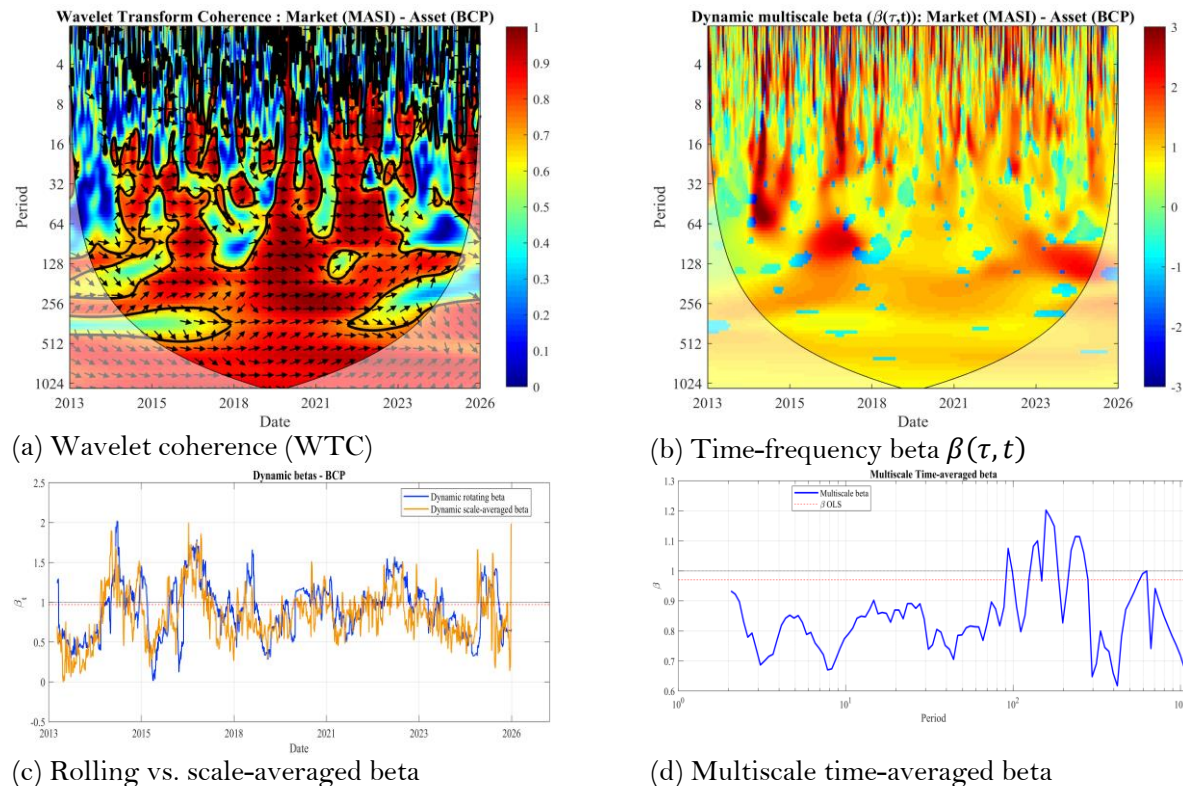


Figure 2.

BCP-MASI coherence and beta dynamics (2013–2026). Colour, contour and arrow conventions as in Figure 1. Panel (a) shows strong medium-to-long-run coherence that is less uniform than for ATW; panel (b) shows recurrent, episodic bursts of high beta; panel (c) reveals a regime-switching rolling beta; and panel (d) shows a long-horizon beta rising above unity.

5.4. *Wafa Assurance (WAA): The Trap of the Misleading Beta*

5.4.1. *Why WAA Is the Decisive Case*

WAA is the case that most clearly vindicates the time-frequency approach. Its static CAPM regression yields a slope of $\beta_{OLS} \approx 1.04$, which at first sight describes an aggressive, above-market stock. However, the fit is very poor ($R^2 = 0.12$): almost seven-eighths of the variance of WAA's return is idiosyncratic. A conventional analysis would stop at this point and treat WAA as a market-tracking asset. The wavelet decomposition shows that this single number is not merely imprecise but qualitatively misleading: WAA's relationship with the MASI is weak, intermittent, scale-dependent and, most strikingly, unstable in sign.

5.4.2. *Coherence and Phase*

In contrast to the warm maps of the banks, WAA's coherence field (Figure 3a) is predominantly cold. Significant coherence is essentially confined to a single low-frequency ridge (about 64–256 days) extending from 2015 to 2023 and concentrated over 2016–2022; elsewhere, only small, scattered red islands appear in a high-frequency region that is mainly blue. Only 27.9% of the out-of-cone time-frequency plane is statistically significant at the 95% level, the second-lowest share in the sample after ATL (Section 5.6). This reliability measure makes explicit what the OLS R^2 only suggests: the systematic risk estimate for WAA is trustworthy in a limited low-frequency region and largely uninformative elsewhere. The phase geometry reinforces this picture. Within the low-frequency ridge, arrows point mostly to the right (positive, in-phase co-movement), but over the scattered high-frequency patches they rotate freely and often point to the left, revealing short-term anti-phase linkages. This is the signature of an insurer whose equity return is driven by its underwriting cycle, claims experience and investment portfolio, factors that are largely unrelated to and at times opposed to the banking-dominated index.

5.4.3. *An Unstable, Sign-Switching Beta*

The time-domain estimators (Figure 3c) reveal a risk that no constant can measure. The 60-day rolling beta ranges from about 0.1 in the mid-2020s to a peak of about 3.45 in late 2017. The scale-averaged wavelet beta fluctuates even more widely, falling to about -0.8 in 2013 and to about -1.0 at the end of the sample. A systematic risk coefficient that moves from below zero to above three cannot describe a stable linear relationship, and the OLS value of 1.04 is merely the average of a sign-changing series rather than a meaningful measure of risk. The $\beta(\tau, t)$ map (Figure 3b) shows this instability clearly: at high frequencies, the surface alternates between deep-red ($\beta > 3$) and deep-blue ($\beta < 0$) cells throughout the sample, a sign-switching pattern absent from both banks, and only the low-frequency band settles at a moderate and stable value of about $\beta \approx 1.5$. The phase-signed construction of $\beta(\tau, t)$ is essential here: an unsigned, coherence-based measure would record a spurious positive “exposure” in regions where WAA actually moves against the market, whereas the signed estimator captures these local reversals. The practical implications are serious: a hedge based on a fixed beta is not only imprecise but potentially wrong in direction, because the sign of WAA's market exposure depends on both horizon and time.

5.4.4. *The Stress-Period Ridge*

The only region of strong coherence, the low-frequency ridge over 2016–2022, coincides with periods of market stress: the pre-pandemic tensions, the COVID-19 shock and the 2022–2023 inflation wave. During these episodes, an otherwise weakly correlated insurer was drawn into the common downturn, with a low-frequency beta of about 1.0–1.5. This is the time-frequency fingerprint of contagion: linkages that are absent in normal times emerge at long horizons under stress and fade as normal conditions return.

5.4.5. Horizon Dimension

Averaged over time, WAA's multiscale beta (Figure 3d) shows a pronounced high-low-high profile with sharp discontinuities. It starts at an aggressive $\beta \approx 1.87$ at the shortest horizon (2–3 days), falls through a short plateau near 1.1 to a $\beta \approx 0.67$ around the weekly scale (7–8 days), remains in a defensive range of $\beta \approx 0.55$ – 0.90 over intermediate horizons, with successive minima near 0.52 and 0.51 around 180 days, and then rises irregularly beyond 200 days to $\beta \approx 1.43$ around 300–350 days before receding. Through the lens of the heterogeneous market hypothesis, WAA amplifies market risk for high-frequency traders, acts as a diversifier at intermediate and quarterly horizons where its beta is well below 1, and again represents above-market risk for long-horizon holders. These three regimes cannot be summarised by a single coefficient: the OLS value of 1.04, which corresponds to none of them for long, is a clear example of the aggregation fallacy highlighted by Gençay, et al. [10].

5.4.6. Synthesis

WAA is, in every respect, the opposite of the systemic anchor. Whereas ATW combines saturated coherence, a sign-stable positive beta and a structurally high long-run exposure, WAA displays sparse coherence, a low share of significant coefficients, a beta that switches sign and a large idiosyncratic component. This combination makes WAA a valuable diversification instrument, able to move independently of and at times against the market, but also a difficult one to hedge, since no fixed-beta instrument can track an exposure whose magnitude and sign both change across horizons and over time. WAA thus demonstrates that, in a thin, bank-dominated frontier market, a single OLS beta can be not only noisy but fundamentally misleading, which is the central methodological claim of this study.

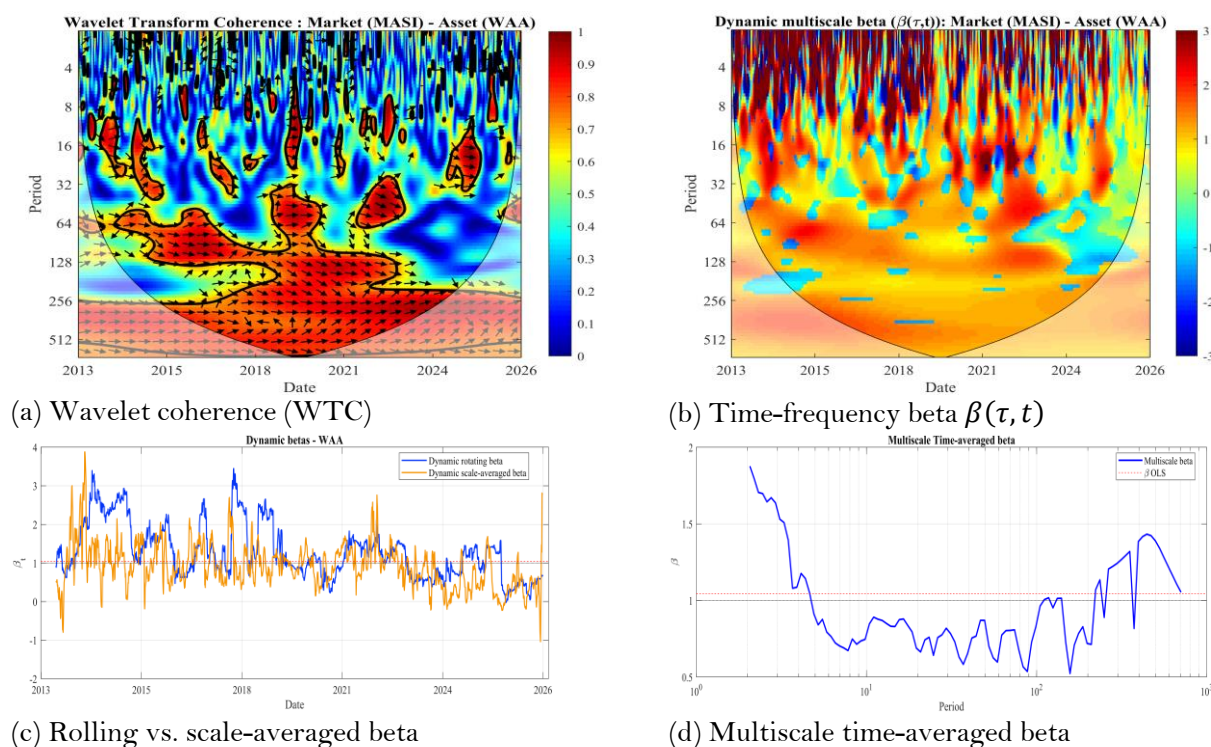


Figure 3.

WAA-MASI coherence and beta dynamics (2013–2026). Colour, contour and arrow conventions as in Figure 1. Panel (a) shows predominantly low (blue) coherence outside a long-horizon band; panel (b) reveals sign-switching short-run betas; panel (c) shows an unstable dynamic beta that takes negative values; and panel (d) displays a high-low-high frequency profile, the hallmark of a diversifying, weakly integrated stock.

5.5. AtlantaSanad (ATL): The Defensive, Decoupled Insurer

5.5.1. The Least Coupled Asset

ATL completes the risk typology at the opposite pole from ATW. Its static regression yields a clearly defensive slope ($\beta_{OLS} \approx 0.69$) and the poorest fit in the sample ($R^2 = 0.06$): only 6% of ATL's return variance is explained by the market. Whereas WAA's misleading beta appears aggressive, ATL's appears defensive, but the two insurers share the same underlying feature: a link to the market that is so weak and unstable that no single coefficient can represent it. The wavelet evidence shows that ATL is even more decoupled than WAA, with the smallest significant share of the time-frequency plane among the four assets.

5.5.2. Coherence and Phase

ATL's coherence field (Figure 4a) is the coldest in the sample, a predominantly blue surface with only a few red islands. Significant coherence is organised around three main episodes: the 64–256-day band from 2013 to 2015, a prominent vertical plume over 2018–2020 reaching down to the 32-day scale, and a further region in 2021–2022, together with scattered, short-lived high-frequency islands. Outside these episodes, ATL is essentially unrelated to the index. Within the significant regions, the phase arrows point mostly to the right, so that, when coupling occurs, it is positive and largely contemporaneous; however, the small area covered by these regions shows that such coupling is the exception rather than the rule. ATL is a mid-capitalisation insurer with a modest free float and relatively low trading volume, and its price is driven mainly by firm-specific developments and episodic liquidity rather than by market-wide forces, which provides the microstructural basis for its weak and intermittent integration.

5.5.3. A Low and Often Negative Beta

The time-domain estimators (Figure 4c) show that ATL's exposure is not only low but also repeatedly negative. The 60-day rolling beta fluctuates around a small mean and turns negative on several occasions, most markedly reaching about -1.3 in 2014 and again in 2016 and 2021. The scale-averaged wavelet beta also becomes strongly negative, reaching about -1.3 in early 2014. A systematic risk coefficient that repeatedly changes sign cannot be captured by any constant: over these windows, ATL moves against the market and temporarily acts as a natural hedge. The $\beta(\tau, t)$ map (Figure 4b) shows an even more fragmented patchwork of warm ($\beta > 0$) and cyan ($\beta < 0$) cells than for WAA, with scattered, short-lived deep-red bursts and no persistent positive ridge. Here again, the phase-signed construction of $\beta(\tau, t)$ is crucial, since it records the local sign reversals that an unsigned coherence measure would misreport as ordinary positive exposure.

5.5.4. Horizon Dimension

ATL's multiscale beta (Figure 4d) is strongly non-monotonic and turns negative at an intermediate-to-long horizon. It is clearly defensive at short and intermediate horizons, oscillating between 0.2 and 0.6, and rises to a peak of $\beta \approx 1.22$ near the 70-day horizon, falls to about 0.47 near 130 days, recovers to $\beta \approx 1.2$ around 200–250 days, then drops to a negative trough of $\beta \approx -0.28$ near the 400-day horizon before returning to a long-horizon peak of $\beta \approx 1.34$. The negative long-horizon segment is particularly striking: it implies that, even at low frequencies, ATL can at times offset market movements rather than amplify them. This cannot be reconciled with the defensive but positive OLS constant of 0.69, and it shows how strongly ATL's systematic risk depends on the investment horizon considered.

5.5.5. Synthesis

ATL is the strongest diversifier in the sample, the defensive mirror image of WAA's apparently aggressive profile. With the lowest R^2 , the coldest coherence field, a rolling beta that falls to -1.3 and a multiscale profile that turns negative at long horizons, it reduces portfolio market exposure on average and occasionally reverses it. However, the features that make ATL valuable for diversification also make

it a poor market proxy and difficult to hedge, since an exposure whose sign is uncertain across horizons and over time cannot be neutralised with a fixed beta. Like WAA, ATL displays significant low-frequency coherence mainly during market-wide stress episodes. This leads to a central conclusion of the study: the diversification provided by Moroccan insurers is real in calm periods but erodes precisely when it would be most valuable, that is, during periods of stress.

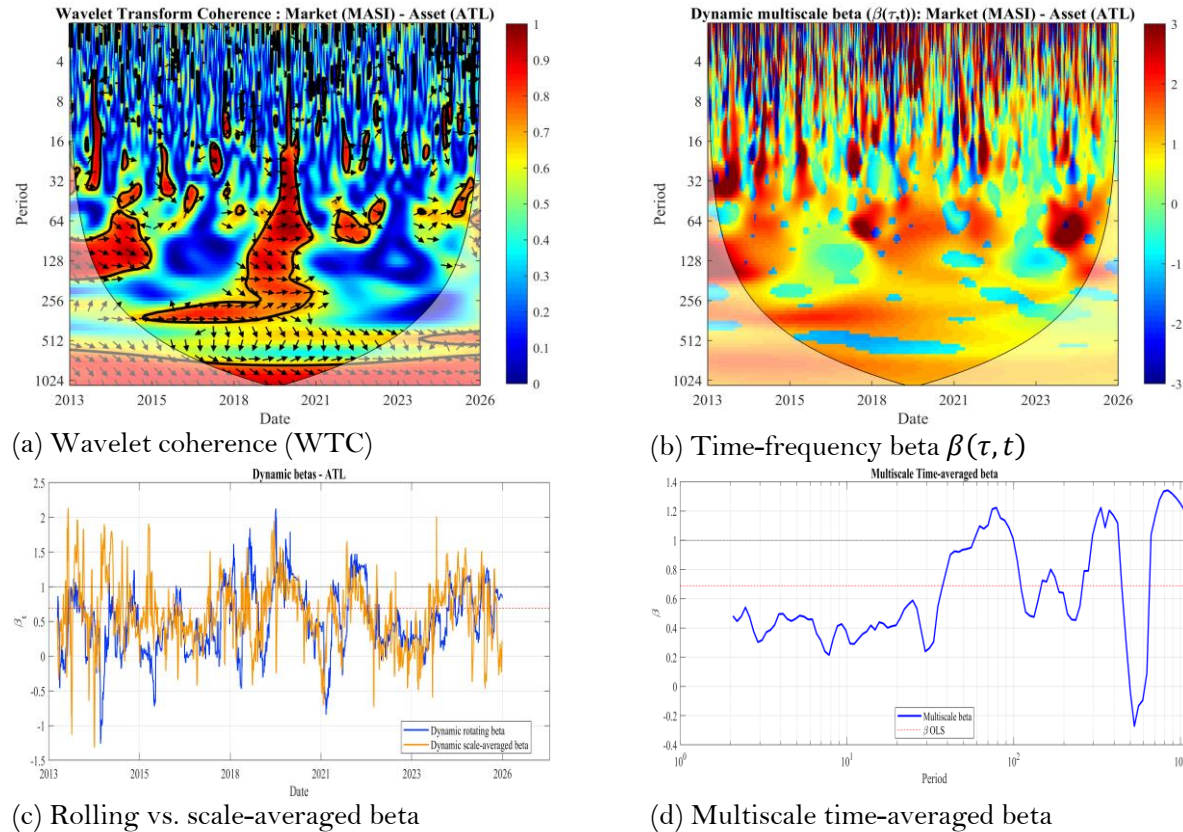


Figure 4.

ATL-MASI coherence and beta dynamics (2013–2026). Colour, contour and arrow conventions as in Figure 1. Panel (a) shows the weakest coherence in the sample, confined to isolated islands; panel (b) shows a fragmented, sign-switching beta surface; panel (c) reveals a low and frequently negative dynamic beta; and panel (d) shows a long-horizon beta that turns negative before rebounding.

5.6. Statistical Significance and Reliability of the Time-Frequency Beta

5.6.1. A Reliability Index for Time-Frequency Systematic Risk

The wavelet coherence and the signed beta $\beta(\tau, t)$ are defined at every point of the time-frequency plane, but not every point carries the same evidential weight. Coherence estimated from a finite sample is subject to sampling variability, and the resulting systematic risk estimate can be considered economically meaningful only where coherence exceeds what red noise would produce by chance [11, 34]. Following the surrogate-based inference standard of the wavelet literature [22, 34], we assess significance against a first-order autoregressive (AR(1)) null through a Monte Carlo experiment with $M = 300$ surrogate series for each asset, which reproduce the autoregressive structure of the data. Because the signed beta is built from the same smoothed cross- and auto-spectra as the coherence, this criterion identifies where the systematic risk estimate reflects genuine co-movement rather than sampling noise. We then summarise the resulting significance mask in a single, cross-sectionally

comparable statistic. Let $\mathcal{V} = \{(\tau, t) \notin \text{COI}\}$ denote the set of time-frequency locations outside the cone of influence, that is, the sub-domain free of edge effects, and let

$$\text{sig}(\tau, t) = \frac{R^2(\tau, t)}{R_{95}^2(\tau, t)} \quad (23)$$

be the ratio of the observed squared wavelet coherence $R^2(\tau, t)$ to its Monte Carlo 95% critical value $R_{95}^2(\tau, t)$, so that $\text{sig}(\tau, t) \geq 1$ indicates significance at the 95% level. We define the reliability index (RI) of an asset as

$$RI = \frac{|\{(\tau, t) \in \mathcal{V} : \text{sig}(\tau, t) \geq 1\}|}{|\mathcal{V}|} \in [0, 1], \quad (24)$$

That is, the fraction of the reliable (out-of-cone) time-frequency plane over which the co-movement between the asset and the market is statistically significant. At the extremes, $RI = 0$ means that no part of the estimated systematic risk surface can be distinguished from noise, whereas $RI = 1$ means that the whole surface is significant.

The reliability index complements, rather than duplicates, the coefficient of determination of the static market model. R^2 compresses the quality of the linear fit into a single number that is time-invariant and frequency-blind: it answers the question “how tight is the relationship on average?” but is silent on where, that is, at which horizons and in which period, the relationship actually holds. The reliability index answers this second question by quantifying the extent of the time-frequency plane over which the systematic linkage is statistically warranted. In this sense, it summarises in one scalar the horizon and time heterogeneity of systematic risk that motivates the wavelet approach [10, 13] and it guards against over-interpreting full-plane beta maps in which apparent exposure may, in low-coherence regions, reflect noise rather than genuine co-movement. Table 3 reports the index for the four core assets, together with the time-frequency beta averaged over the whole out-of-cone plane ($\bar{\beta}_{TF}$) and over the significant region only ($\bar{\beta}_{TF}^{\text{sig}}$).

Table 3.

Reliability of the time-frequency systematic risk estimates.

Asset	Reliability index	Mean β (TF), whole plane	Mean β (TF), significant region	R^2 (OLS)
ATW (bank)	61.9%	0.99	1.21	0.53
BCP (bank)	47.5%	0.85	1.17	0.37
WAA (insurer)	27.9%	0.94	1.53	0.12
ATL (insurer)	15.4%	0.60	1.44	0.06

Note: The reliability index is the share of the out-of-cone time-frequency plane that is significant at the 95% level (Monte Carlo, 300 surrogates, Eq. (24)). $\bar{\beta}_{TF}$ is the beta averaged over the whole out-of-cone plane and $\bar{\beta}_{TF}^{\text{sig}}$ over the significant region only. The R^2 of the static CAPM is reproduced for comparison.

5.6.2. The Reliability Index Recovers the Integration Axis

The most important feature of Table 3 is that the reliability index reproduces, by an entirely different route, the ordering already given by the static R^2 . The significant share declines monotonically from ATW (61.9%) through BCP (47.5%) and WAA (27.9%) to ATL (15.4%), exactly mirroring the R^2 sequence ($0.53 > 0.37 > 0.12 > 0.06$). The fact that two conceptually independent measures, a goodness-of-fit statistic in the time domain and a Monte Carlo significance share in the time-frequency plane, deliver the same integration ranking is a strong internal consistency check: the banks are robustly integrated with the market, and the insurers only marginally so. For ATW, nearly two-thirds of the systematic risk surface is statistically reliable, confirming its status as the systemic anchor; for ATL, barely one-sixth is, confirming its near-decoupling.

5.6.3. Conditional Exposure: What the Significant Regions Reveal

A less obvious result is the gap between the two beta columns. When the average is restricted to the significant region, the time-frequency beta increases for all assets, and the increase is larger when integration is weaker: it is modest for ATW (0.99 to 1.21) and BCP (0.85 to 1.17) but much larger for the insurers, whose beta rises from 0.94 to 1.53 for WAA and from 0.60 to 1.44 for ATL. This pattern must be interpreted with care. Part of it is mechanical: since the signed beta increases with the square root of coherence, conditioning on regions of high (significant) coherence necessarily selects larger absolute betas. We therefore do not claim that WAA's "true" beta is 1.53. The result does show, however, that the systematic exposure of WAA and ATL is strongly regime-dependent: when, and only when, these insurers are genuinely connected to the market, the link is aggressive rather than defensive, and this occurs mostly in the low-frequency band during the stress episodes identified above (the pandemic and the 2022–2023 inflation surge). The defensive, below-unit betas reported by the unconditional averages and by OLS thus blend two regimes: long periods of near-autonomy and shorter periods of aggressive, crisis-driven co-movement. For risk management, the implication runs contrary to the reassuring message of the static beta: the insurers' market exposure is largest precisely when systemic stress makes diversification most valuable and least attainable.

The reliability analysis completes the empirical argument in two ways. First, it equips the signed time-frequency beta with an explicit significance criterion and a scalar reliability metric, thereby addressing the main objection that a full-plane beta map may display exposure where none is statistically warranted. Second, it confirms the integration ordering from an independent angle and reveals the regime-dependent nature of insurer risk, which neither the static CAPM nor unconditional wavelet averages can capture. The asset-level significance maps, with 95% contours and cone-of-influence masking, are reported in Appendix B (Figures 9 and 10).

6. Conclusion

The CAPM summarises systematic risk in a single number, beta, under two assumptions that empirical evidence seldom supports: that this risk is constant over time and identical across investment horizons. This paper has relaxed both assumptions simultaneously by estimating a time- and frequency-varying beta for the Moroccan financial sector. Building on the continuous wavelet framework of Rua [21], Rua and Nunes [26], and Mestre and Terraza [13], we derived beta from the wavelet coherence between each asset and the MASI index, recovered its sign from the wavelet phase, and compared it with static and rolling betas. The analysis covered four financial stocks (two banks and two insurers) over 2013–2026, a period that includes the COVID-19 shock, Bank Al-Maghrib's monetary easing and tightening, recurrent droughts and the September 2023 earthquake.

The empirical results are clear and economically relevant. First, systematic risk in the Moroccan financial sector is neither constant nor horizon-independent: beta fluctuates over time and varies non-monotonically across scales, so that a single OLS estimate misrepresents risk at almost every horizon. Second, and most importantly, the time-frequency lens reveals a sharp sectoral divide that the static CAPM conceals. The banking stocks, Attijariwafa Bank and Banque Centrale Populaire, are almost fully coherent and in phase with the market at medium and long horizons, and their betas are amplified during crises; they provide market exposure rather than diversification. The insurers, Wafa Assurance and AtlantaSanad, show weak and intermittent coherence and unstable, sometimes negative, betas driven by idiosyncratic risk; they are genuine but hard-to-hedge diversifiers. Third, two cross-cutting regularities emerge: coherence generally strengthens with the investment horizon, and the COVID-19 shock synchronised the whole sector with the market, eroding diversification benefits precisely when they were most valuable. The reliability index confirms this integration ordering independently, falling from 61.9% for ATW to 15.4% for ATL.

The paper makes three contributions. First, it extends the continuous wavelet time-frequency beta to a concentrated emerging market over a recent, crisis-rich period. Second, by contrasting banking and insurance stocks, it documents sectoral heterogeneity in systematic risk that single-asset studies cannot

observe. Third, it provides strong evidence for the heterogeneous-agents hypothesis: short- and long-horizon investors do not face the same systematic risk, and beta is inherently horizon-specific.

The practical implications for portfolio management are direct. Relying solely on the static beta overlooks both the sign-switching short-term exposure of weakly coherent insurers and the crisis-driven amplification of banking risk. The time-frequency framework allows managers to allocate and hedge by horizon: banks should be treated as market proxies requiring dynamically adjusted, horizon-specific hedge ratios, and insurers as tactical diversifiers whose benefits weaken during crises. For regulators and risk managers, the amplification of banking betas during stress periods provides a further signal of the systemic role of the banking sector in transmitting market-wide shocks on the Casablanca Stock Exchange.

The study has limitations that open avenues for future research. The rolling-window length, the wavelet, and the smoothing parameters follow common practice, and a systematic sensitivity analysis would strengthen the robustness of the estimates. The lower liquidity of insurance stocks may also inflate the idiosyncratic component of their returns, so that part of their low coherence may reflect microstructure noise rather than genuine decoupling. Finally, the analysis emphasises coherence and beta more than phase; lead-lag relationships deserve closer examination, and the framework could be extended to other sectors and emerging markets and combined with time-frequency Value-at-Risk measures. Such extensions would make the time-frequency approach more operational for understanding and managing systematic risk in emerging markets.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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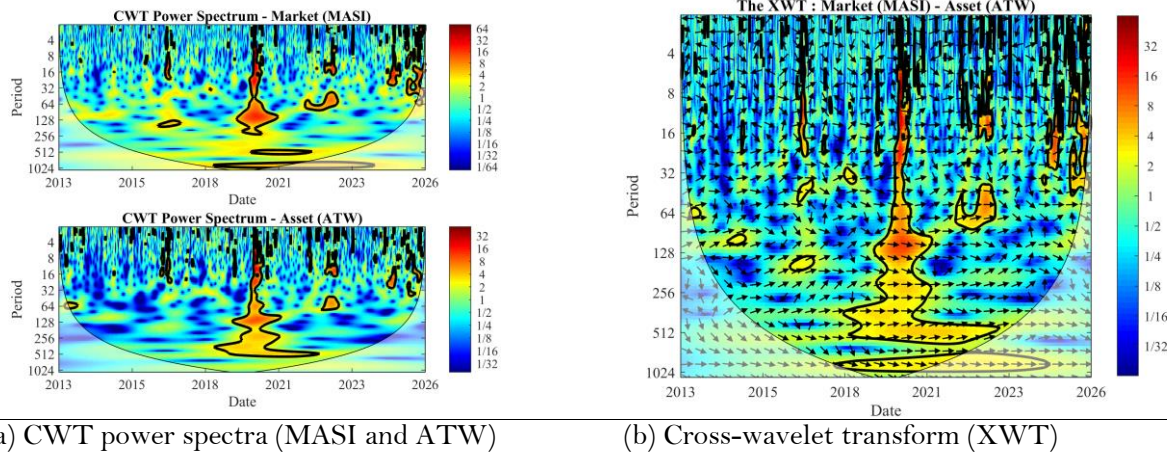
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Appendix A. Supplementary Figures

For each asset, this appendix presents two complementary figures that are not reproduced in the main text: the continuous wavelet power spectra (CWT) of the market and of the asset, and their cross-wavelet transform (XWT). The CWT panels show where each series concentrates its variance; the shared high-power region around 2020 at the 64–256-day scales reflects the COVID-19 volatility common to the market and the banks. The XWT highlights regions of high common power, and its phase arrows corroborate the in-phase co-movement documented by the coherence maps.

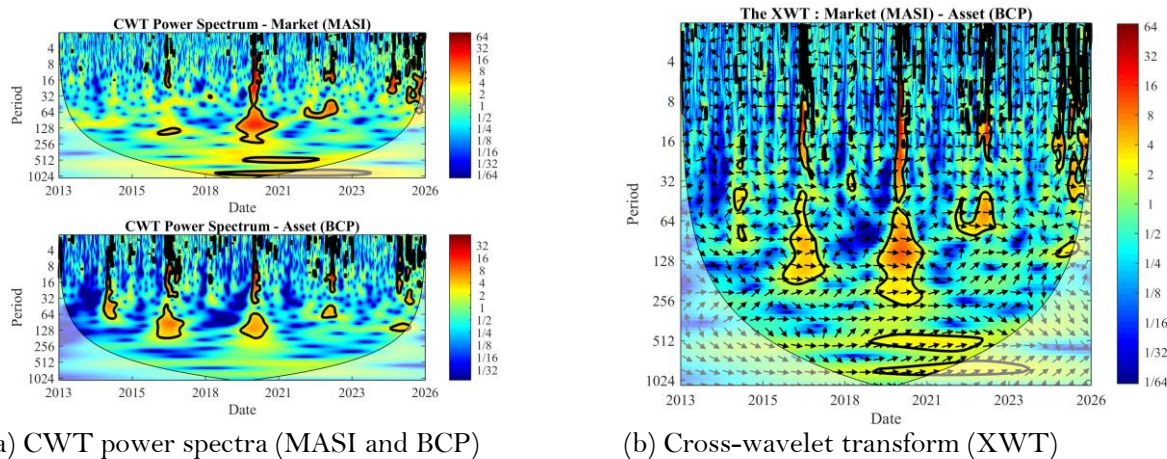


(a) CWT power spectra (MASI and ATW)

(b) Cross-wavelet transform (XWT)

Figure 5.

Continuous wavelet power spectra and cross-wavelet transform for Attijariwafa Bank (ATW) and the MASI. Thick black contours denote the 95% significance level against a red-noise null; the lighter shaded area lies outside the cone of influence.

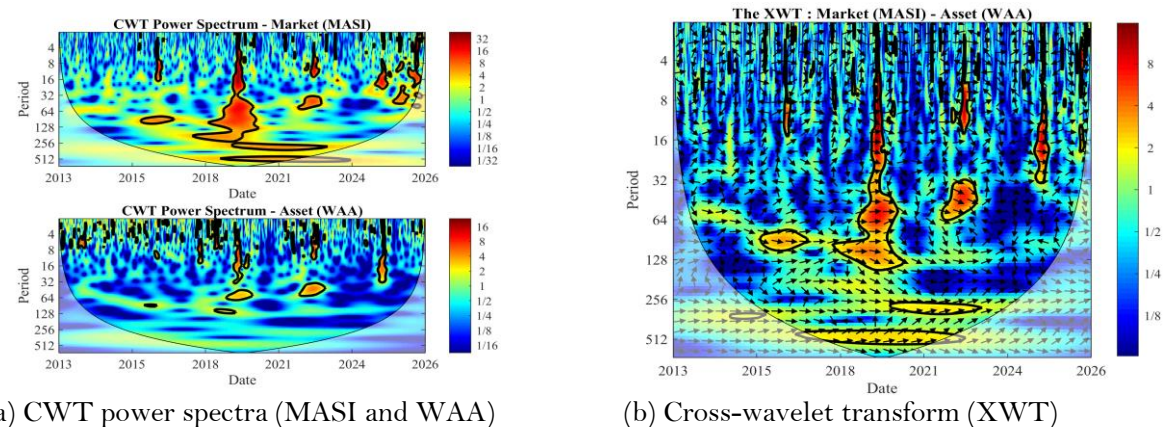


(a) CWT power spectra (MASI and BCP)

(b) Cross-wavelet transform (XWT)

Figure 6.

Continuous wavelet power spectra and cross-wavelet transform for Banque Centrale Populaire (BCP) and the MASI. Conventions as in Figure 5.

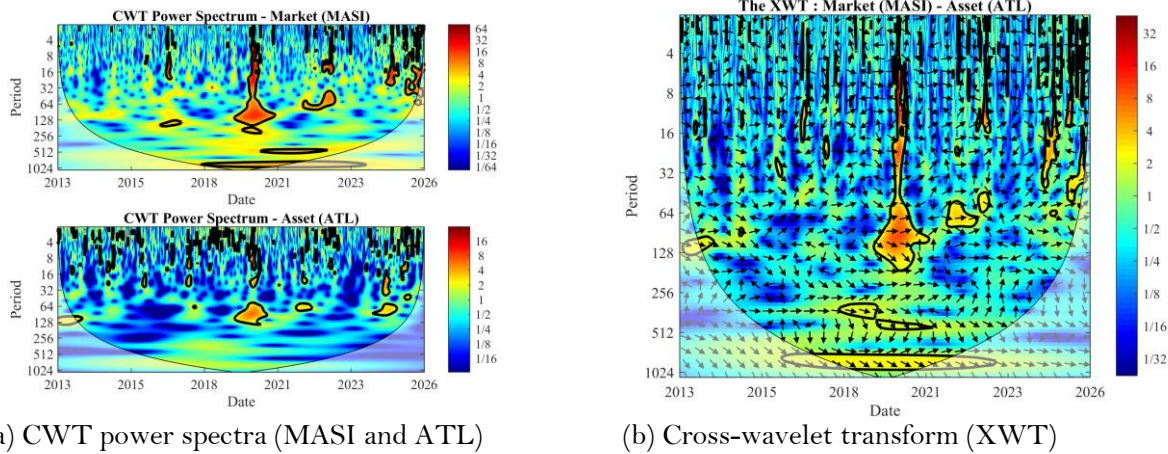


(a) CWT power spectra (MASI and WAA)

(b) Cross-wavelet transform (XWT)

Figure 7.

Continuous wavelet power spectra and cross-wavelet transform for Wafa Assurance (WAA) and the MASI. Conventions as in Figure 5.



(a) CWT power spectra (MASI and ATL)

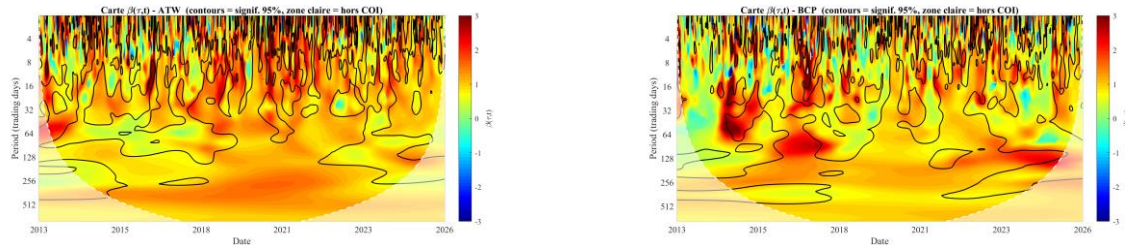
(b) Cross-wavelet transform (XWT)

Figure 8.

Continuous wavelet power spectra and cross-wavelet transform for AtlantaSanad (ATL) and the MASI. Conventions as in Figure 5.

Appendix B. Time-Frequency Significance Maps

This appendix reports, for the four core assets, the signed time-frequency beta $\beta(\tau, t)$ together with its statistical significance. In each panel, the background shows $\beta(\tau, t)$ on a diverging colour scale (blue: $\beta < 0$; green-yellow: $\beta \approx 0$ to 1; red: $\beta > 1$), bounded to $[-3, 3]$ for readability. The solid black lines are the 95% significance contours obtained from the Monte Carlo procedure of Grinsted, et al. [34] so that regions enclosed by a contour are those in which co-movement is significant at the 95% level; the white dashed curve is the cone of influence, and the lighter area outside it marks the edge-affected region excluded from all averages and from the reliability index (Eq. (24)). Read against the reliability shares in Table 3, these maps make the integration ordering visually explicit: significant regions occupy a large, connected share of ATW's plane, shrink for BCP, and reduce to sparse, disconnected islands for the two insurers, WAA and ATL.

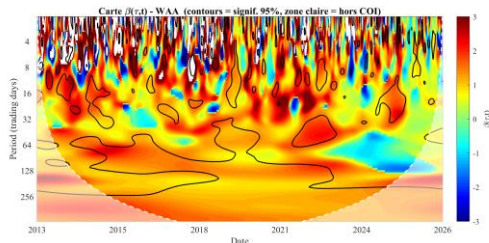


(a) ATW (bank)

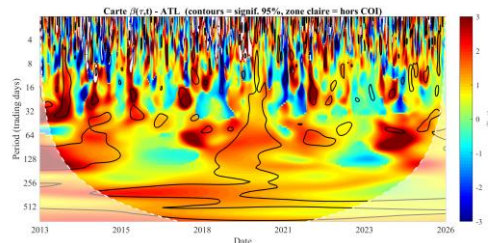
(b) BCP (bank)

Figure 9.

Signed time-frequency beta $\beta(\tau, t)$ with 95% significance contours and cone-of-influence masking: banks. (a) ATW, the systemic anchor, shows significant exposure over a broad, connected region of the plane; (b) BCP shows solid but more fragmented significance than ATW.



(a) WAA (insurer)



(b) ATL (insurer)

Figure 10.

Signed time-frequency beta $\beta(\tau, t)$ with 95% significance contours and cone-of-influence masking: insurers. (a) For WAA, significance is confined to a low-frequency ridge within an otherwise non-significant, sign-switching plane; (b) ATL, the most decoupled asset, shows only sparse, scattered significant islands.