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The declining explanatory power of interest rates for stock market and business cycle dynamics

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ABSTRACT

This study applies a multivariate wavelet framework to examine the time-varying relationship between stock market cycles and business cycles in Germany, Japan, the UK, and the USA from 2000 to 2025. Prior to 2020, stock market cycles generally led business cycles at medium- to longterm frequencies. Around 2020, this pattern reversed, indicating a structural shift. Controlling for key interest rates reduces regions of significant coherence during the Global Financial Crisis, but not around 2020, suggesting a diminished role of interest rates in explaining the joint dynamics of stock markets and business cycles in recent years.

1. Introduction

Traditionally, the stock market has been regarded as a leading indicator of the business cycle, with stock price changes, under rational expectations and market efficiency, often cited among the best single-variable predictors of economic activity (Fischer and Merton, 1984). In this context, wavelet analysis tools, such as wavelet coherence, phase differences, and wavelet gain, have proven effective in analyzing co-movement between stock market cycles and business cycles across both time and frequency domains. Wavelet analysis decomposes time series into time–frequency components, allowing detection of dynamic patterns, lead–lag structures, and structural breaks.

One of the first and most influential applications in this context is Crowley (2007), who used wavelet coherence to analyze the evolving relationship between GDP and stock market indices. Subsequent studies, including Aguiar-Conraria and Soares (2011) and Aguiar-Conraria and Soares (2014), extended this to multivariate settings, detecting phase shifts and lead–lag relationships across countries and economic regimes.

Several country-specific applications of wavelet analysis have investigated the relationship between stock markets and business cycles. Gallegati (2008), using discrete wavelet transformation, showed that the relationship between US stock returns and US industrial production is frequency-dependent, with stock returns typically leading industrial production growth, but only at the lowest frequencies. Durai and Bhaduri (2009) found a long-term negative relationship for India, with stock prices leading at lower frequencies, while Tiwari et al. (2018) showed that GDP shocks, especially negative ones, strongly affect US stock prices. Si et al. (2019) conducted a similar study for China, finding that the stock market cycle tends to lead during economic expansions and lag during recessions, often reacting counter-cyclically. Wang and Li (2020) found a positive correlation between Chinese stock returns and industrial production from 1995 to 2018, with stock returns tending to lead in the medium term and lag in the long term. For

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Germany, Krüger (2021) applied continuous wavelet transformation and found a positive correlation between industrial production and four selected leading indicators, including a stock market index, at lower frequencies.

This study is motivated by the recent, unprecedented shifts in key interest rates. In 2022–2023, the US Federal Reserve raised its benchmark rate by 5.25 percentage points, one of the fastest increases on record. Similar hikes occurred in the Eurozone and the UK. In March 2024, the Bank of Japan raised interest rates for the first time since 2007. Such changes can affect both real economic activity and stock markets, as emphasized in early work by Bernanke and Gertler (1995), Taylor (1995), King and Watson (1996), and Mishkin (1996). More recent empirical studies, such as Alam and Uddin (2009), Bjørnland and Leitemo (2009), or Marfatia (2014), confirm that interest rates influence both business cycles and stock markets. Moreover, rate changes may not only affect these dynamics individually, but also influence the dynamic interaction between them.

This paper contributes to the literature by being the first to analyze the joint dynamics of industrial production and stock markets in a multivariate wavelet setting that incorporates interest rates as a control variable across several major economies. Our analysis covers Germany, Japan, the UK, and the USA from 2000 to 2025. We apply wavelet coherence to measure co-movements, phase differences to capture lead–lag relationships, and wavelet gain to evaluate the influence of stock markets on business cycles, extending the framework with partial wavelet analysis to control for interest rates. Unlike existing country-specific studies (e.g., Si et al., 2019), this study provides the first systematic comparison across several major economies during the recent period of drastic interest rate changes.

We present three key findings. First, the relationship between economic and stock market cycles varies over time and across frequencies, with weak and country-specific correlations at high frequencies and stronger co-movements in the medium- to long-term frequency ranges. Second, we identify a structural break around 2020: while stock market cycles lead across coherence regions before 2020, this pattern reverses thereafter, accompanied by significant increases in the wavelet gain. Third, including interest rates has a strong effect on the medium- to long-term coherence structure: coherence regions around 2008 disappear in all countries once interest rates are controlled for, while coherence regions around 2020 remain largely unchanged, suggesting a declining explanatory role of interest rate policy since 2020.

Section 2 outlines the wavelet analysis methodology. Section 3 presents the empirical analysis and discusses the empirical findings. Section 4 concludes.

2. Wavelet analysis

As an extension of Fourier analysis, wavelet analysis, as proposed by Aguiar-Conraria and Soares (2014), allows the estimation of time-dependent spectral properties of a time series, enabling a detailed view of both time and frequency components. Although the discrete wavelet transform focuses mainly on noise reduction and data compression, the continuous wavelet transform is particularly suitable for identifying patterns and hidden information within a time series, as briefly described in the following section.[1]

A mother wavelet $\psi(t)$ that satisfies the admissibility conditions can generate *daughter wavelets* $\psi_{\tau,s}(t)$ via scaling and translation:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad s,\tau \in \mathbb{R},\ s \neq 0. \tag{1}$$

s determines the mother wavelet width; τ shifts it along the time axis.

For a time series $x(t) \in L^2(\mathbb{R})$, the *continuous wavelet transform* with respect to the wavelet $\psi(t)$ is:

$$W_{x;\psi}(\tau,s) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)\mathrm{d}t, \tag{2}$$

where ψ^* is the complex conjugate of ψ. τ locates the daughter wavelet in the time domain; s determines its position in the frequency domain. In the following analysis, we use the *Morlet wavelet* defined as:

$$\psi_{\omega_0}(t) = \pi^{\frac{-1}{4}}\exp\left(i\omega_0 t\right)\exp\left(\frac{-t^2}{2}\right), \tag{3}$$

with the angular frequency parameter $\omega_0 = 6$, a common choice in empirical economics.

2.1. Univariate tools

The *wavelet power spectrum* is defined as:

$$\mathrm{WPS}_x(\tau,s) = |W_x(\tau,s)|^2. \tag{4}$$

It measures the localized variance of a time series $x(t)$ at each time and frequency (or scale).[2]

[1] See Grinsted et al. (2004) for a detailed derivation.

[2] See Aguiar-Conraria and Soares (2014) for a detailed explanation of the scale/frequency relation.

Table 1
Interpretation of the phase difference ϕ_{yx}.

Phase range ϕ_{yx}	Direction	Interpretation
$\phi_{yx} = 0$	In phase	Time series are exactly in phase
$0 < \phi_{yx} < \frac{\pi}{2}$	In phase	$y(t)$ leads $x(t)$
$-\frac{\pi}{2} < \phi_{yx} < 0$	In phase	$x(t)$ leads $y(t)$
$\frac{\pi}{2} < \phi_{yx} < \pi$	Out of phase	$x(t)$ leads $y(t)$ (inverse relationship)
$-\pi < \phi_{yx} < -\frac{\pi}{2}$	Out of phase	$y(t)$ leads $x(t)$ (inverse relationship)

The phase difference ϕ_{yx} describes the lead–lag relationship between two time series across frequencies. A value near 0 indicates synchronous movement; positive (negative) values indicate that $y(t)$ ($x(t)$) leads. Phase differences beyond $\pm\frac{\pi}{2}$ suggest inverse (out-of-phase) relationships.

2.2. Bivariate tools

Note that all the quantities introduced in this subsection are functions of time and frequency. In order to simplify the notation, we follow Aguiar-Conraria and Soares (2014) and describe these quantities for a specific value of the argument (τ, s) and this value of the argument will be omitted in the formulas.

To analyze the relationship between two time series $y(t)$ and $x(t)$, the cross-wavelet transform is:

$$W_{yx} = W_y W_x^*, \tag{5}$$

where, W_y denotes the wavelet transform of $y(t)$, and W_x^* is the complex conjugate of the wavelet transform of $x(t)$. The *cross-wavelet power spectrum* $|W_{yx}|$ measures the local covariance between the two time series at each point in time and frequency.

Given our interest in the co-movement between business cycles and stock market cycles, wavelet coherence is particularly relevant, as it provides insight into the strength of the co-movement of the two time series at any given time and frequency. The *complex wavelet coherence* is given by:

$$\rho_{yx} = \frac{S(W_{yx})}{\sqrt{S(|W_y|^2)S(|W_x|^2)}}, \tag{6}$$

where $S(\cdot)$ is a smoothing operator in time and frequency.[3] The *wavelet coherence* $\mathrm{R}_{yx} = |\rho_{yx}|$ takes values in $[0, 1]$.

To investigate the temporal lag between business and stock market cycles, the phase relationship of the two time series can be determined by calculating the phase difference. This indicates delays in oscillations between the two time series as a function of time and frequency.

The *phase difference* quantifies the lead–lag relationship between $y(t)$ and $x(t)$ at each time and frequency:

$$\phi_{yx} = \arctan\left(\frac{\mathfrak{I}(S(W_{yx}))}{\mathfrak{R}(S(W_{yx}))}\right), \tag{7}$$

where $\mathfrak{I}$ and $\mathfrak{R}$ denote imaginary and real parts. We employ phase differences because they not only capture the lead–lag structure between two series, but also convey whether their co-movement is positive (in phase) or negative (out of phase). Table 1 summarizes how to interpret different phase ranges.

For economic interpretation, selected phase differences are converted into implied lead–lag lengths (in months) following Aguiar-Conraria and Soares (2011, 2014), using

$$\Delta T_{yx} = \frac{\phi_{yx}}{2\pi f}. \tag{8}$$

Note that this yields frequency-specific ranges rather than point estimates, which are interpreted as approximate lead–lag magnitudes.

2.3. Multivariate tools

To account for the effect of interest rates on the relationship between the business cycle and the stock market cycle, we employ multivariate wavelet tools.

The *complex partial wavelet coherence*, controlling for a third time series $z(t)$, is defined as:

$$\rho_{yx|z} = \frac{\rho_{yx} - \rho_{yz}\rho_{xz}^*}{\sqrt{(1 - R_{yz}^2)(1 - R_{xz}^2)}}, \tag{9}$$

where ρ_{xz}^* denotes the complex conjugate of ρ_{xz}. The *partial wavelet coherence* $R_{yx|z} = |\rho_{yx|z}|$ takes values in $[0, 1]$.

[3] Smoothing is necessary to avoid coherency being identically one; see Aguiar-Conraria and Soares (2014) for details.

Table 2
Descriptive statistics.

(a) Germany			
Statistic	IP index	Stock index	Interest rate
Series used	Index for Germany	DAX	ECB: Main Refinancing Operations Rate
No. of observations	307	307	307
Minimum value	73.30	2423.87	0.00
Maximum value	110.80	23,997.48	4.75
Mean value	95.47	9,251.90	1.70
Standard deviation	8.64	4,512.28	1.60
(b) Japan			
Statistic	IP index	Stock index	Interest rate
Series used	Index for Japan	Nikkei 225	BoJ: Target Rate
No. of observations	307	307	307
Minimum value	78.31	7568.42	−0.10
Maximum value	119.91	40,487.39	0.50
Mean value	101.22	17,741.63	0.06
Standard deviation	7.56	8,139.64	0.17
(c) United Kingdom			
Statistic	IP index	Stock index	Interest rate
Series used	Index for the UK	FTSE 100	BoE: Bank Rate
No. of observations	307	307	307
Minimum value	77.57	3567.40	0.10
Maximum value	118.21	8,809.74	6.00
Mean value	96.76	6,207.39	2.45
Standard deviation	8.23	1,149.34	2.18
(d) United States			
Statistic	IP index	Stock index	Interest rate
Series used	Index for the USA	S&P 500	FED: Federal Funds Effective Rate
No. of observations	307	307	307
Minimum value	79.61	735.09	0.04
Maximum value	108.20	6,204.95	6.86
Mean value	98.17	2,188.05	1.98
Standard deviation	4.31	1,341.02	2.05

The table presents raw data and series names for industrial production indices, stock indices, and interest rates.

Accordingly, *partial phase difference* is defined as:

$$\phi_{yx|z} = \arctan\left(\frac{\Im(\rho_{yx|z})}{\Re(\rho_{yx|z})}\right). \tag{10}$$

The *partial wavelet gain*, after controlling for $z(t)$, is:

$$G_{yx|z} = \frac{|\rho_{yx} - \rho_{yz}\rho^*_{xz}|}{(1-R^2_{xz})}\frac{\sqrt{S(|W_y|^2)}}{\sqrt{S(|W_x|^2)}}. \tag{11}$$

The interpretation of the partial wavelet gain is analogous to the bivariate case, with the difference that the effect of $z(t)$ is held constant.

3. Empirical analysis

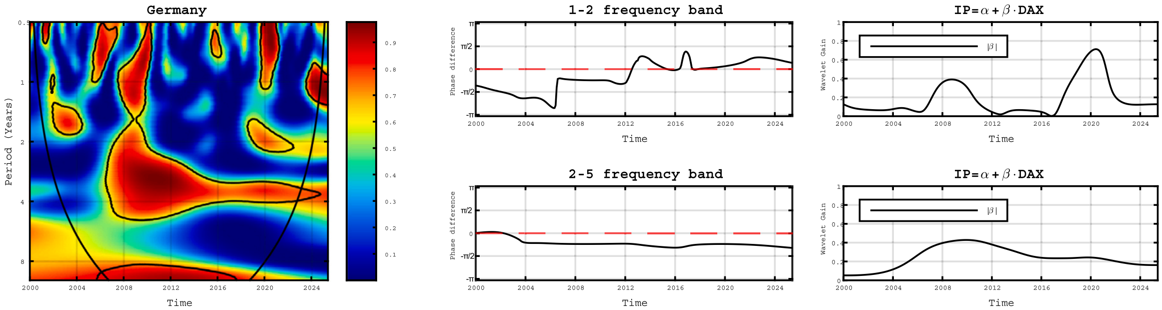
3.1. Data

Our dataset comprises seasonally and calendar adjusted industrial production (IP) indices for the manufacturing sector and stock index data for Germany, Japan, the UK and the USA from January 2000 to July 2025. Production index data are sourced from the OECD and stock prices from Bloomberg. Both series are log-transformed to mitigate heteroskedasticity and scale effects, and their monthly growth rates (log differences) are used for analysis. Key interest rates (European Central Bank Main Refinancing Rate; Bank of Japan Target Rate; Bank of England Bank Rate; and the Federal Funds Effective Rate) are included as control variables in the partial wavelet analysis. Table 2 presents descriptive statistics for all variables used.

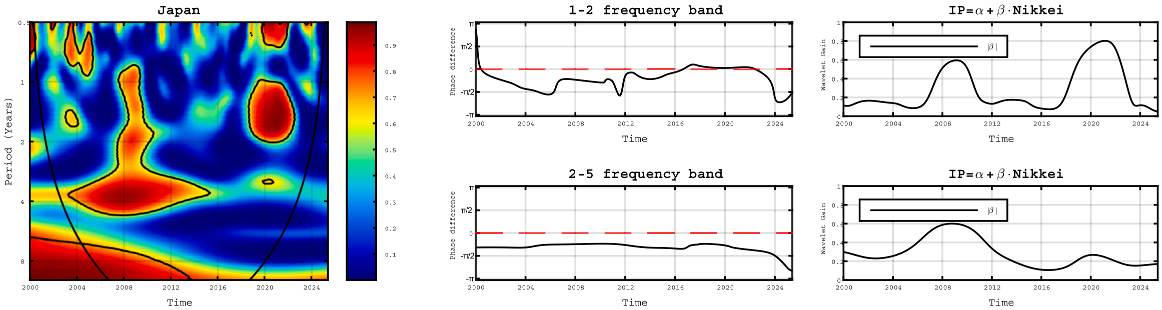
3.2. Bivariate analysis

Fig. 1 presents the results of the bivariate analysis for Germany, Japan, the UK, and the USA. For each country, the left panel displays the wavelet coherence between the business cycle and the stock market cycles. The black contour marks the 10% significance

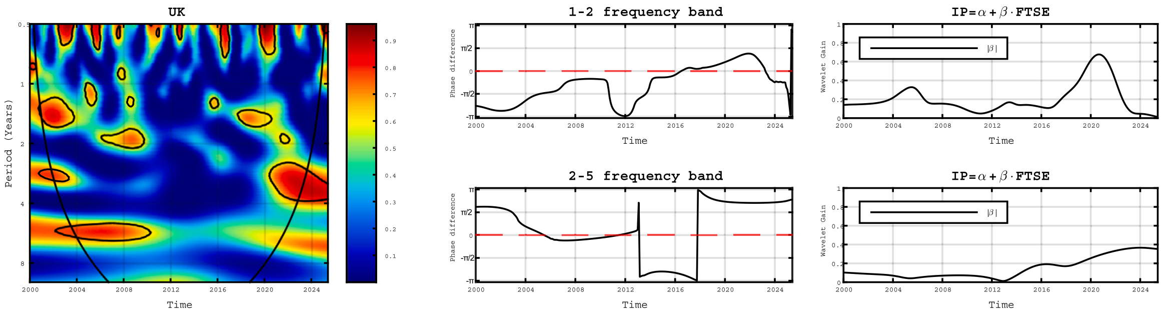
(a) Germany



(b) Japan



(c) UK



(d) USA

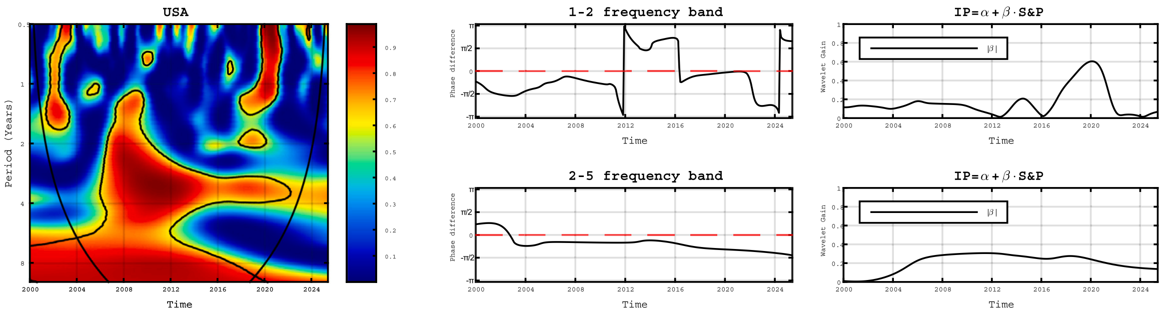


Fig. 1. Bivariate wavelet analysis of Germany, Japan, the UK, and the USA.

level, and the cone of influence is indicated by the black parabola.[4] Coherence ranges from dark blue (low) to dark red (high). In the center panel, the phase differences are shown; the right panel illustrates the wavelet gains. Frequency bands of 1–2 and 2–5 years reflect medium- and long-term dynamics, respectively.

A first major finding from Fig. 1 is that the previously strong pattern, where the stock market cycle led the business cycle, has weakened notably around 2020. Significant wavelet coherence regions appear in all countries during the Global Financial Crisis (GFC) around 2008 in both the 1–2 and 2–5 year periods. During this period, phase differences for all countries lie almost entirely in the interval $(-\frac{\pi}{2}, 0)$, indicating that the stock market cycle leads the business cycle. Quantitatively, the implied stock market lead averages about 2.2 months in Germany, compared with roughly 0.2 months in Japan and 0.5 months in the USA. Around 2020, however, phase differences in the 1–2 frequency band shift to 0 (Japan, USA) or into the interval $(0, \frac{\pi}{2})$ (Germany, UK) during times of significant wavelet coherence, indicating that the business cycle began to lead. In the 2–5 frequency band, results for the UK and the USA slightly contrast with this finding. A second key finding is the appearance of pronounced spikes in wavelet gain during periods of significant coherence since 2020. This implies a larger local regression coefficient β, reflecting a stronger stock market influence on industrial production. Together with the lead–lag reversal, this suggests that the relationship between stock market cycles and business cycles remains strong but has structurally changed. Notably, this finding holds for all countries in the 1–2 year periods.

Overall, our results from the bivariate analysis are consistent with prior studies on co-movement and lead–lag relationships, including those by Tiwari et al. (2018), Si et al. (2019), Wang and Li (2020) and Krüger (2021). The following section extends the analysis by incorporating interest rates using partial wavelet analysis.

3.3. Partial analysis

Fig. 2 presents the results of the multivariate analysis for Germany, Japan, the UK, and the USA.

A key finding of our analysis emerges when comparing Fig. 2 to Fig. 1. The significant coherence regions observed during the GFC around 2008 largely vanish after including interest rates. In contrast, the coherence regions around 2020 remain largely intact across all countries, even when controlling for interest rates. The patterns in phase differences and wavelet gains during this period, especially in the 1–2 year band, are broadly consistent with those in Section 3.2.

More specifically, after controlling for interest rates, the only consistently significant coherence regions appear in the 1–2 year band around 2020. Phase differences indicate that business cycles lead stock market cycles in Germany and Japan, but that stock markets lead business cycles in the USA. Quantitatively, the implied lead amounts to about 0.5 months in Germany and 0.3 months in Japan, while the stock market leads by roughly 1.9 months in the USA. In the 2–5 year frequency band, the previously significant coherence regions around 2008 largely disappear. In Germany and the USA, distinct 4-year coherence regions persist from 2010 to 2025, separate from both the GFC and 2020 patterns. These results suggest that interest rates largely account for joint movements at lower frequencies, consistent with Si et al. (2019). Consequently, interest rates should be explicitly considered when analyzing the evolving relationship between stock markets and business cycles.

3.4. Robustness checks

To verify the robustness of our findings, we employ two standard methods. First, we estimate bivariate VAR models of monthly industrial production growth and stock returns, including key interest rates as exogenous controls. Each model uses six monthly lags and Monte Carlo impulse responses (1000 replications) up to a 24-month horizon. Granger causality tests assess whether past stock market movements help predict industrial production and vice versa. Second, we estimate GARCH(1,1) models for monthly stock returns to measure average and peak conditional volatility.

The results in Table 3 show that stock markets significantly led industrial production before 2020 in all countries, with bidirectional causality in the USA. After 2020, this relationship weakened or even reversed in several economies. These findings are consistent with the wavelet-based evidence of a structural break in the lead–lag relationship between stock market and business cycle dynamics. GARCH results further show that conditional volatilities were higher before 2020.

4. Conclusion

This paper examines the dynamic relationship between stock market cycles and business cycles in Germany, Japan, the UK, and the USA from 2000 to 2025 using multivariate wavelet methods. A key contribution is the inclusion of interest rates via partial wavelet analysis. The findings show that, prior to 2020, stock market cycles typically led business cycles in the medium- to long-term frequency bands, but this pattern reversed around 2020, indicating a structural shift. Controlling for interest rates reduces coherence regions during the GFC but leaves coherence regions around 2020 largely unchanged, suggesting that interest rate policy has lost explanatory power for recent business and stock market dynamics.

[4] To calculate significance, we generate surrogates by fitting an ARMA(1,1) model with a moving average to each time series. Residuals are drawn from a Gaussian distribution using the estimated variance, and this process is repeated 5000 times. The critical values for the 10% significance level are then extracted. Phase differences and wavelet gains should only be interpreted when wavelet coherence is statistically significant.

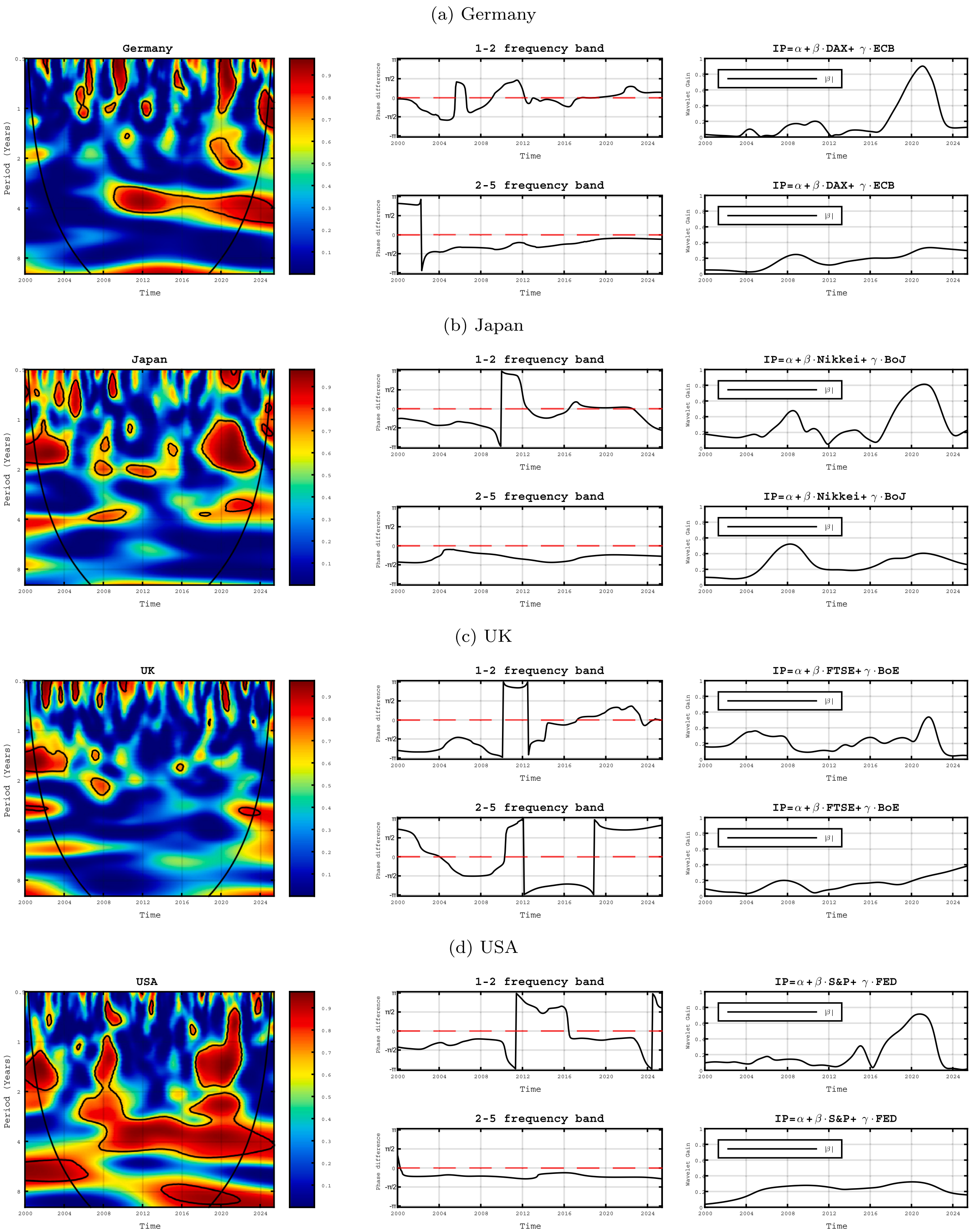


Fig. 2. Partial wavelet analysis of Germany, Japan, the UK, and the USA.

Table 3
VAR and GARCH robustness analysis.

Period	Stock→IP	IP→Stock	Max. IRF (Stock→IP)	Mean Volatility	Max. Volatility (Date)
(a) Germany					
2000–2019	0.0005***	0.8822	0.0037	22%	70% (2002–11)
2020–2025	0.2062	0.0043***	0.0025	17%	21% (2020–05)
(b) Japan					
2000–2019	0.0162**	0.3186	0.0039	21%	52% (2008–12)
2020–2025	0.1571	0.3386	0.0061	16%	18% (2020–01)
(c) United Kingdom					
2000–2019	0.0447**	0.1142	0.0021	14%	30% (2008–12)
2020–2025	0.0170**	0.0009***	0.0022	12%	15% (2020–05)
(d) United States					
2000–2019	0.0000***	0.0013***	0.0018	15%	45% (2008–12)
2020–2025	0.8480	0.4005	0.0015	17%	19% (2020–01)

This table reports Granger causality p-values and impulse response function (IRF) maxima from VAR models together with annualized mean and maximum GARCH(1,1)-based volatility estimates. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

CRediT authorship contribution statement

S. Geissel: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **D. Klein:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization.

Data availability

Data will be made available on request.

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