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When volatility turns, recessions follow☆

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ABSTRACT

Do shifts into high stock-market volatility foreshadow recessions rather than merely accompany them? Prior work shows volatility rises in downturns and can help short-horizon forecasts, but the timing of discrete volatility regime changes relative to business-cycle turning points is less understood. Using quarterly data for the United States, United Kingdom, Japan, Germany, Italy, and France (1960–2019; country-specific start dates), we estimate a bivariate Markov-switching model that jointly classifies high/low output growth and high/low return volatility, and tests restrictions on the transition structure. In the United States, United Kingdom, Japan, and France, entry into the high-volatility state typically precedes recession onset by one to two quarters. For Germany and Italy, the output and volatility state processes are approximately independent. These results suggest that volatility-regime switches are a medium-horizon early-warning signal, consistent with uncertainty and risk-premium repricing that tighten funding conditions in more market-based financial systems.

1. Introduction

Financial market volatility typically increases during periods of economic weakness, yet whether it serves as a reliable and timely leading indicator of regime changes in real activity remains an open question. Beyond contemporaneous comovement, the central issue is whether discrete transitions in volatility, rather than marginal changes in conditional variance, tend to precede shifts between expansion and recession phases in output. Establishing this timing is crucial for real-time monitoring by policymakers and investors, as recent episodes, including the Global Financial Crisis, have featured sharp volatility spikes around turning points. Our focus on regime-dependent dynamics addresses this practical need and the conceptual gap between high-frequency predictability and low-frequency phase-shift detection. While real-time forecasting is not our objective, the timing results have practical implications for the quarterly early-warning practice. In four of six economies, entries into the high-volatility state occur earlier than the recession onset, so we interpret volatility-regime switches as medium-horizon signals.

The relationship between financial market volatility and real economic activity has long been central to both academic research and policy debate. Early contributions, such as Schwert (1989), show that stock market volatility systematically rises during recessions and financial crises, suggesting a strong link between asset-price instability and macroeconomic downturns. Schwert (2011) extends this analysis to the Global Financial Crisis, showing that heightened volatility tends to accompany, though not always precede, contractions in output. These studies emphasise the empirical regularity that volatility increases around recessions and may contain valuable information about macroeconomic stress. Building on these insights, researchers have increasingly asked whether asset-price volatility contains predictive information for fluctuations in output. Annaert et al. (2001) find that financial volatility improves business-cycle forecasts for the United States, Germany, and Japan. In contrast, Vu (2015), using a broader panel of 27 countries, reports that stock market volatility predicts output growth at one- and two-quarter horizons. Berg and

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Vu (2019) further document significant spillover effects from U.S. volatility to international output growth, underscoring the global transmission of volatility shocks and their macroeconomic consequences. Related evidence shows that volatility and uncertainty measures can add information about subsequent macroeconomic conditions when the economy is under stress. In related work, Bellégo and Ferrara (2012) show that macro-financial information can sharpen business-cycle prediction in a factor-augmented probit framework, reinforcing the idea that financial conditions embed forward-looking signals about regime changes. For example, Ferrara et al. (2014) show that financial volatility improves growth forecasts during the Great Recession, while Houari (2022) provides evidence that uncertainty shocks are a distinct driver of U.S. business-cycle fluctuations.

Evidence also indicates that volatility and real activity are jointly determined. Choudhry et al. (2016) show bidirectional Granger causality between stock market volatility and output across the United States, Canada, Japan, and the United Kingdom, with U.S. volatility exerting a notable influence abroad. These findings suggest complex feedback mechanisms rather than simple one-way causality, a feature increasingly relevant in a financially integrated world. Several theoretical channels help explain these empirical regularities. Rising volatility is often interpreted as heightened uncertainty, which leads firms to delay investment and households to postpone durable consumption in a "wait-and-see" manner, dampening real activity (Bernanke, 1983; Bloom, 2009). Volatility also raises risk premia and widens credit spreads, tightening financing constraints and amplifying downturns through the financial accelerator (Bernanke et al., 1999). On the household side, greater volatility increases income and wealth uncertainty, prompting higher precautionary savings and weaker aggregate demand (Carroll, 1997). In addition, volatility shocks reduce equity valuations, weaken balance sheets, and lower collateral values, thereby reinforcing borrowing constraints and depressing investment, particularly among smaller firms reliant on external finance. These mechanisms underscore that volatility is not merely noise but an economically meaningful signal that interacts with real activity through multiple channels.

Using a time-varying VAR that jointly identifies equity- and bond-volatility shocks, Kumar et al. (2023) show that these volatility shocks are contractionary and disinflationary, leading to monetary easing. Our contribution is complementary: instead of tracing impulse responses to volatility shocks, we examine whether discrete switches in equity volatility systematically precede output-regime changes, and we test this timing within a bivariate Markov-switching framework across six economies. From a different angle, Ghiaie (2024) emphasises that the effectiveness of quantitative easing hinges on housing and bank-balance-sheet channels. At the same time, we do not model policy transmission; our timing results help identify when volatility-based indicators are most informative for real-time monitoring and when such policy channels are more likely to be engaged.

A related body of research has shifted attention from short-run predictability to the timing of regime shifts. Hamilton (1989) pioneers the use of Markov-switching models to capture nonlinear dynamics in output growth and financial volatility, while Chauvet and Piger (2005) develop methods for dating business-cycle turning points in real time. At a broader level, Camacho and Martínez-Martín (2015) propose methods to monitor the world business cycle, highlighting the value of real-time regime-tracking tools when growth dynamics are nonlinear and internationally synchronised. Evidence from these approaches shows that large shifts in volatility often coincide with, or precede, major business-cycle transitions. Huang and Startz (2020) find that incorporating stock market volatility into Markov-switching models further improves the identification of U.S. business-cycle turning points. Schwert (1989) demonstrates that financial turbulence closely aligns with recessions, while Schwert (2011) highlights the prominent role of equity volatility during the 2008 crisis. Hansen (2024) argues that combining volatility measures with the yield-curve spread substantially improves recession forecasting, underscoring the importance of volatility in identifying regime changes rather than short-run fluctuations. Further studies extend these insights across different settings: Daly (1999) shows that in Australia, financial volatility transmits to real variables such as output and inflation; Levin and De Veirman (2018) find that firm-level earnings volatility rises during recessions, albeit unevenly across sectors; and Martínez-García (2018) models time-varying parameters with stochastic volatility, showing that macroeconomic dynamics evolve with the business cycle. Together, these studies demonstrate that the volatility–real activity connection is pervasive across countries, levels of aggregation, and modelling frameworks.

Despite this extensive literature, important gaps remain. Most existing research emphasises short-run forecasting, testing whether changes in conditional volatility predict output growth at short horizons. By contrast, relatively little is known about whether large, discrete regime shifts in volatility, such as transitions from low to high volatility or from bull to bear markets, systematically precede major macroeconomic turning points such as booms and recessions. Moreover, while international spillovers from U.S. financial markets are well documented, less attention has been devoted to whether volatility regime shifts in major economies systematically precede turning points in domestic or global business cycles.

This paper contributes by shifting the focus from high-frequency forecasts to low-frequency, regime-based dynamics. Specifically, we examine whether significant transitions in stock market volatility tend to precede changes in business-cycle phases. Our approach builds on the class of Markov-switching models developed by Hamilton (1988) and Hamilton (1989) and extended by Phillips (1991) and Ravn and Sola (1995). Sola et al. (2002) allow us to test formally whether regime changes in one variable precede those in another. Unlike Phillips (1991), who analyses cross-country output dynamics, or Sola et al. (2002), who study volatility spillovers, we focus within a single economy: do large shifts in stock return volatility precede transitions in output growth regimes? We then extend the analysis to an international comparison across six major economies: the United States, the United Kingdom, Germany, France, Japan, and Italy.

Our model distinguishes four possible states of nature: high or low output growth (expansion and recession) and high or low stock market volatility. The filtered probabilities identify these regimes clearly across all countries, enabling formal tests of independence, precedence, or feedback between them. Across the sample, we reject the hypothesis that recessions systematically precede volatility shifts. Instead, the evidence generally supports the interpretation that volatility transitions tend to precede output-regime changes, although the strength of this relationship varies across countries. This pattern is most pronounced for the United States, the United Kingdom, Japan, and France, and weaker for Germany and Italy. Overall, our results suggest that significant shifts in financial market volatility frequently signal impending recessions, though the strength of the linkage depends on financial structure and market depth.

This paper makes two contributions. First, it develops a tractable bivariate Markov-switching framework that jointly characterises output-growth and stock-volatility regimes and allows formal tests of independence, precedence, and feedback between the two state processes. This approach moves beyond linear or single-series models by focusing on regime timing rather than short-horizon forecasting. Second, it provides a systematic international comparison for six advanced economies, documenting how the informational role of equity-market volatility differs across financial structures. The evidence indicates that volatility transitions often precede output regime changes, especially in more market-based systems, highlighting volatility's value as an early warning signal.

Our results have a direct monitoring interpretation at the quarterly frequency. When the filtered probability of the high-volatility regime rises sharply and remains elevated, the historical record suggests a higher likelihood of a recession onset within the next one to two quarters in more market-based economies (U.S., U.K., Japan, France).

Operationally, this signal can be used as a *triage trigger* rather than a point forecast: it provides an objective criterion for intensifying nowcasting, conducting scenario analysis, and stress-testing funding and credit conditions when markets reprice risk. At the same time, the cross-country heterogeneity is itself policy-relevant: in more bank-based systems (Germany, Italy), equity-volatility regime switches carry less early-warning content, implying that surveillance should place relatively more weight on credit spreads, bank-funding indicators, and lending conditions. In this sense, our framework complements widely used recession indicators (e.g., yield-curve measures and composite leading indexes) by adding a regime-based, medium-horizon market signal and clarifying where that signal is informative.

The remainder of the paper is structured as follows. Section 1 outlines the background and motivation for studying the relationship between volatility and the business cycle. Section 2 presents preliminary evidence on short-run and rolling correlations between volatility and output. Section 3 introduces the bivariate Markov-switching framework; Section 4 details the estimation procedure; Section 5 discusses the empirical results; and Section 6 concludes.

Finally, to link this timing perspective to concrete historical episodes without making causal claims, we compile Table 4 (Appendix), which, for each economy, associates the nearest volatility-regime transition with the recession onset and reports the relative timing in quarters (negative values indicate that the volatility switch occurred earlier), together with a brief historical context.

2. Preliminary analysis

This section explores the relationship between stock market volatility and real economic activity. We highlight two phenomena that illustrate varying perspectives on the relationship between output growth and stock market volatility. First, we present evidence of the short-run relationship between output growth and stock market volatility. We achieve this by analysing lead and lagged correlations of output growth and volatility, using squared returns as a proxy. Second, we examine the relationship during significant fluctuations in the data through rolling correlations, which analyse a series of observations of output growth and squared returns. This approach helps us identify larger swings in the data. Consistent with the paper's focus on the cycle, we treat squared equity returns as a tractable proxy for stock-return variance and real GDP (or industrial production) growth as economic activity at business-cycle frequency. The correlations and rolling windows below are descriptive and motivate the regime-based analysis; they are not taken as causal evidence.

2.1. Data description

We use quarterly data for the USA, Japan, the United Kingdom, Germany, Italy, and France to explore the potential interrelation between real economic activity and stock price volatility. For the USA, we use data on an index of real stock prices (from Robert J. Shiller's website) and real output growth data (from the Federal Reserve Bank of St. Louis) covering the period from 1960 Q1 to 2019 Q4. We use data on the share price index of the OECD's main economic indicators for other countries. For the UK, we supplement this with nominal GDP (from the Federal Reserve Bank of St. Louis) and CPI data from the UK's Office for National Statistics from 1958 Q1 to 2019 Q4. Nominal GDP and CPI data for Japan, Germany, Italy, and France are also sourced from the Federal Reserve Bank of St. Louis. For Germany, we analyse data from 1991 Q1 to 2019 Q4; for Japan, from 1994 Q1 to 2019 Q4; for France, from 1980 Q1 to 2019 Q4; and for Italy, from 1995 Q1 to 2019 Q3. We use annual real output growth as our measure of output, and in the preliminary analysis, we use squared returns as a proxy for volatility.

Table 1
Correlations between output growth and squared returns: $\mathrm{Corr}(y_t, x_{t+k})$.

k	USA	UK	Japan	France	Italy	Germany
−5	−0.0127 (0.847)	−0.148 (0.020)	0.097 (0.337)	0.154 (0.056)	0.091 (0.381)	−0.059 (0.533)
−4	−0.079 (0.228)	−0.215 (0.001)	0.012 (0.903)	0.099 (0.217)	0.069 (0.501)	0.075 (0.429)
−3	−0.089 (0.173)	−0.216 (0.001)	0.033 (0.743)	0.048 (0.549)	0.130 (0.203)	0.152 (0.109)
−2	−0.073 (0.263)	−0.323 (0.000)	−0.012 (0.901)	0.007 (0.922)	−0.117 (0.252)	−0.175 (0.064)
−1	−0.031 (0.627)	−0.309 (0.000)	−0.199 (0.044)	0.065 (0.413)	−0.202 (0.045)	−0.283 (0.002)
0	0.149 (0.021)	−0.435 (0.000)	−0.046 (0.640)	0.163 (0.039)	−0.064 (0.527)	0.003 (0.969)
1	0.181 (0.005)	−0.213 (0.001)	−0.214 (0.030)	0.184 (0.020)	−0.150 (0.138)	−0.020 (0.830)
2	0.157 (0.015)	−0.320 (0.000)	−0.150 (0.133)	0.091 (0.257)	0.002 (0.983)	−0.234 (0.013)
3	0.074 (0.255)	−0.194 (0.002)	0.051 (0.615)	−0.003 (0.963)	−0.027 (0.790)	−0.029 (0.755)
4	0.075 (0.252)	−0.151 (0.018)	−0.089 (0.381)	0.052 (0.513)	0.101 (0.327)	0.057 (0.551)
5	0.061 (0.357)	−0.190 (0.003)	−0.044 (0.665)	0.035 (0.665)	0.093 (0.367)	−0.052 (0.587)

The variable y_t denotes output growth and x_t squared returns.
The figures in parentheses are p-values where $H_0: \rho = 0$ and $H_1: \rho \neq 0$.
Sign convention: $\mathrm{Corr}(y_t, x_{t+k})$ with $k < 0$ means volatility leads output; $k > 0$ means output leads; $k = 0$ is contemporaneous.

2.2. Short run relationship between output growth and returns volatility

Table 1 presents the cross-correlations between output growth and squared returns. For the USA, volatility has no observed effect on output at any lag. However, there are positive, contemporary first- and second-lag effects from output to volatility, which is counterintuitive. In the UK, we identify significant bidirectional effects with negative signs, which are economically meaningful. Conversely, there is little evidence of any relationship between these variables for Japan, France, and Italy. Germany also exhibits some bidirectional effects.

While further investigation into the short-term relationship between these variables could utilise more advanced econometric tools, this fundamental analysis highlights the challenges in drawing firm conclusions based solely on short-run relationships. It is not always evident that changes in one variable consistently affect the other across all time periods. Therefore, in the following subsection, we will analyse average effects, highlighting that the relationship tends to become clearer during significant movements.

2.3. Rolling correlations between output growth and returns volatility

It is well established that correlations among stock returns tend to rise during periods of financial turmoil, with elevated co-movement often serving as a signal of economic distress (Longin and Solnik, 2001). Building on this insight, we investigate whether a similar pattern emerges between the correlation of volatility and output growth, and whether shifts in this correlation can be interpreted as regime changes. This approach aligns with the literature that links financial market volatility to the real economy. Early studies, such as Schwert (1989), documented that increases in stock market volatility often accompany recessions, while more recent contributions show that volatility contains information about future real economic activity (Campbell et al., 2001).

Research using regime-switching models further suggests that financial variables can serve as leading indicators of shifts in macroeconomic conditions (Hamilton and Lin, 1996; Ang and Bekaert, 2002). The intuition is that financial markets, by incorporating expectations, may signal transitions between economic regimes before they become evident in output data. Our analysis extends this line of inquiry by focusing on the correlation between squared returns, used as a proxy for volatility, and output growth.

Specifically, we examine the time-varying correlation between these series using rolling windows to identify periods when their co-movement intensifies. This exercise provides independent evidence on whether large changes in volatility and output growth coincide, and whether their correlation rises in absolute value during such episodes. Consistent with our expectations, Fig. 1 shows that correlations tend to increase in absolute value across all countries in the sample during periods of pronounced fluctuations. In several instances, strong negative correlations reveal that heightened stock market volatility coincides with severe recessions.

Importantly, our analysis does not focus on high-frequency interactions; rather, it evaluates correlations across observation windows, capturing recurrent large-scale swings. This evidence underpins and motivates our empirical strategy, which characterises such extreme episodes as distinct regimes in the joint dynamics of output growth and volatility.

3. A bivariate Markov-switching model

Consider the following model for the 2×1 vector $z_t = [y_t, r_t]'$,

$$z_t = \mu_{s_t} + \Phi_{s_t'} u_t, \tag{1}$$

where $\mu = [\mu_{y_{s_t}}, \mu_r]'$ and u_t is a Gaussian process with zero mean and covariance matrix the identity I; $\{s_t, s_t'\}$ are modelled as a time-homogeneous Markov chain, independent of $\{u_t\}$, with $\{s_t, s_t'\}$ indicating the state that the system is in state j at time t. The time series $\{z_t\}$ (the vector of output growth and stock market returns, respectively y_t and r_t) satisfies, therefore, a four-state Markov process

$$z_t|(s_t = s, s_t' = s') \sim N(\mu_{s_t}, \Omega_{s_t'}), \tag{2}$$

for $s = 1, 2$ and $s' = 1, 2$ with $\Omega_{s_t'} = \Phi_{s_t'}' \Phi_{s_t'}$. Accordingly, the means and the variance–covariance matrices are:

$$\mu_{s=1} = \begin{bmatrix} \mu_{yh} \\ \mu_r \end{bmatrix}, \mu_{s=2} = \begin{bmatrix} \mu_{yl} \\ \mu_r \end{bmatrix}, \tag{3}$$

$$\Omega_{s'=1} = \begin{bmatrix} \sigma_y^2 & \sigma_{y,rh} \\ \sigma_{rh,y} & \sigma_{rh}^2 \end{bmatrix}, \Omega_{s'=2} = \begin{bmatrix} \sigma_y^2 & \sigma_{y,rl} \\ \sigma_{rl,y} & \sigma_{rl}^2 \end{bmatrix}. \tag{4}$$

where the indices h and l refer to high or low mean or volatility, respectively. In this way, we model booms and recessions (for output growth) and high and low volatility for the stock markets.[1] In the general case, the transition matrix will be given by a 4×4 matrix, Π (with elements $\Pi_{ij} = \Pr(l_t = i | l_{t-1} = j)$, $(i, j = 1, 2, 3, 4)$), where each column sums to unity; all elements are nonnegative, and $l_1 = \{s = 1, s' = 1\}$, etc. Since the system must move to one of the four states in the next period, each of the four columns of the transition matrix sums to unity; thus, the general unrestricted model has a transition matrix of 12 free probabilities to be estimated.

We can impose various restrictions on the transition matrix to test particular hypotheses.[2] For example, if the mean of the output growth and the volatility of the stock market follow an Independent regime-shifting process, there are only four free probabilities to be estimated, referring to high growth, high volatility, low growth, and low volatility. The four-state transition matrix will then be given by:

$$\Pi^{indep} = \begin{pmatrix} \pi_{yh}\pi_{rh} & \pi_{yh}(1-\pi_{rl}) & (1-\pi_{yl})\pi_{rh} & (1-\pi_{yl})(1-\pi_{rl}) \\ \pi_{yh}(1-\pi_{rh}) & \pi_{yh}\pi_{rl} & (1-\pi_{yl})(1-\pi_{rh}) & (1-\pi_{yl})\pi_{rl} \\ (1-\pi_{yh})\pi_{rh} & (1-\pi_{yh})(1-\pi_{rl}) & \pi_{yl}\pi_{rh} & \pi_{yl}(1-\pi_{rl}) \\ (1-\pi_{yh})(1-\pi_{rl}) & (1-\pi_{yh})\pi_{rl} & \pi_{yl}(1-\pi_{rh}) & \pi_{yl}\pi_{rl} \end{pmatrix} \tag{5}$$

where $\pi_{yh} = \Pr(s_t = 1|s_{t-1} = 1)$, $\pi_{yl} = \Pr(s_t = 0|s_{t-1} = 0)$, $\pi_{rh} = \Pr(s_t' = 1|s_{t-1}' = 1)$ and $\pi_{rl} = \Pr(s_t' = 0|s_{t-1}' = 0)$. We can then test the validity of the restricted version by using a likelihood ratio (LR) test under the null hypothesis, which is distributed as $chi^2(8)$. We will refer to this as the hypothesis of independence between the states that dictate the changes in y and r.

We analyse restrictions on the evolution of the states, rather than independence, that occur whenever one of the two variables leads (or lags) the other into and out of periods of high or low volatility, or into a boom or a recession. For example, this would be the case if r is always in the same state that y was one period before. In this case, there are only two free probabilities to be estimated: the probability of the leading variable staying in the high state and the probability of the leading variable staying in the low state (i.e., what drives the system is the probability of the leading variable staying in the high or low states). Accordingly, the appropriateness of this hypothesis can be verified by testing (using LR tests distributed as $\chi^2(10)$) if we can reduce the general transition matrix to:

$$\Pi^{ylr} = \begin{pmatrix} \pi_{yh} & \pi_{yh} & 0 & 0 \\ 0 & 0 & (1-\pi_{yl}) & (1-\pi_{yl}) \\ (1-\pi_{yh}) & (1-\pi_{yh}) & 0 & 0 \\ 0 & 0 & \pi_{yl} & \pi_{yl} \end{pmatrix} \tag{6}$$

where Π^{ylr} indicates y leads r one period. Conversely, when r leads y, the transition matrix reduces to:

$$\Pi^{rly} = \begin{pmatrix} \pi_{rh} & 0 & \pi_{rh} & 0 \\ (1-\pi_{rh}) & 0 & (1-\pi_{rh}) & 0 \\ 0 & (1-\pi_{rl}) & 0 & (1-\pi_{rl}) \\ 0 & \pi_{rl} & 0 & \pi_{rl} \end{pmatrix} \tag{7}$$

It is worth noting that when the number of states is three or more, a zero in any transition probability merely implies that a particular sequence of state movements is never observed, and has no further implications. Moreover, equations (6) and (7) restrict the evolution of the joint movement of the states. Under these restrictions, all transition probabilities are well-defined, so there are no nuisance parameters. Finally, we test whether a structure such as (5), (6), or (7) provides a valid restriction on the general transition probability matrix.

Whenever the results are inconclusive, and more than one restricted model is not rejected, they can be compared using selection criteria. The following section employs two popular criteria, the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). Psaradakis et al. (2009) found that complexity-penalised likelihood criteria reliably select the appropriate nonlinear models.

To avoid label switching in estimation, we impose weak sign/ordering constraints consistent with the economic interpretation of regimes: $\mu_{yh} > \mu_{yl}$ (booms vs. recessions) and $\sigma_{rh}^2 > \sigma_{rl}^2$ (high vs. low volatility). These restrictions pin down the mapping between latent states and economic regimes without affecting the likelihood maximisation over the remaining free parameters. As in Ravn and Sola (1995), testable hypotheses on the transition structure (independence; y leads r; r leads y) are implemented as linear restrictions on Π and evaluated via LR tests against the unrestricted four-state model. Information criteria (AIC, SBC) are then used to discriminate among non-rejected specifications.

[1] In what follows, "business cycle" refers to recession/expansion phases (Burns and Mitchell, 1946; Bry and Boschan, 1971; Hamilton, 1989), and "economic activity" denotes aggregates such as real GDP or industrial production growth (Stock and Watson, 1989; King et al., 1991; Harding and Pagan, 2002; Chauvet, 1998).

[2] Ravn and Sola (1995) test restrictions that inquire whether changes in the stochastic process that dictates the state of output growth lead to or lag the changes in the stochastic process that dictates the state of consumption price growth.

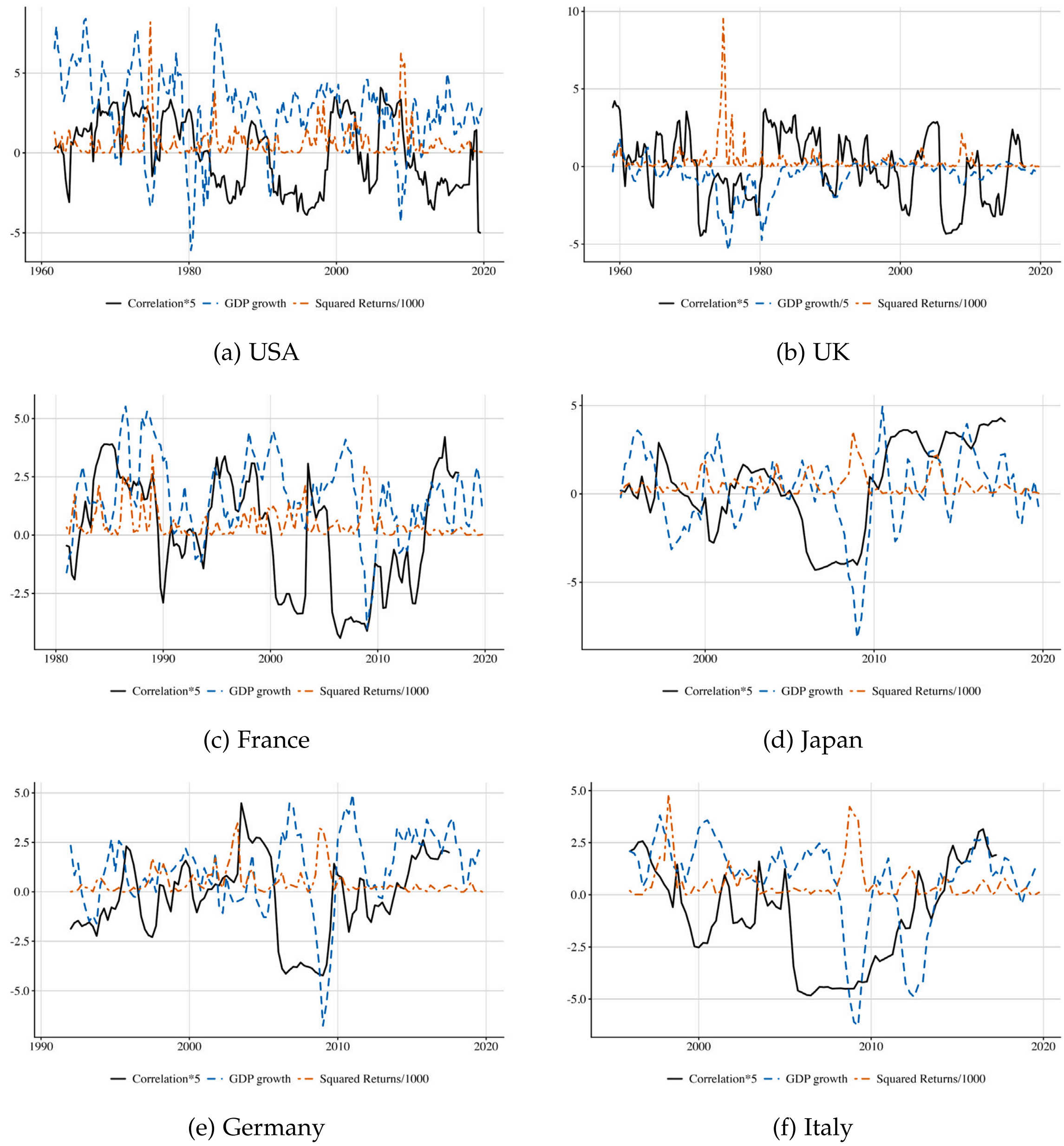


Fig. 1. Rolling correlations of GDP growth and squared returns.
Notes. Each panel shows the 12-quarter rolling Pearson correlation between quarterly real GDP growth y_t and squared equity returns r_t^2. Each point is dated at the *end* of the window. GDP growth is computed as $100 \times \Delta \log(\text{real GDP})$; r_t is the log return on the broad market index for each country. (Sample as in the data section.).

4. Model estimation and evaluation

Given observations $\{z_0, z_1, \dots, z_T\}$, inference in the model defined by (1)–(7) can be carried out by using a recursive algorithm analogous to that discussed in Hamilton (1994). This entails iterating on the Eqs. (8) and (9)

$$\boldsymbol{\delta}_{t|t} = [\boldsymbol{\iota}'(\boldsymbol{\delta}_{t|t-1} \odot \boldsymbol{g}_t)]^{-1}(\boldsymbol{\delta}_{t|t-1} \odot \boldsymbol{g}_t), \qquad t = 1, 2, \dots, T, \tag{8}$$

$$\boldsymbol{\delta}_{t+1|t} = \boldsymbol{\Pi}\boldsymbol{\delta}_{t|t}, \qquad t = 1, 2, \dots, T, \tag{9}$$

Where

$$\boldsymbol{\delta}_{t|l} := \begin{bmatrix} \mathrm{P}(l'_t = (1,1)|\mathcal{F}_0^l;\boldsymbol{\theta}) \\ \mathrm{P}(l'_t = (1,2)|\mathcal{F}_0^l;\boldsymbol{\theta}) \\ \mathrm{P}(l'_t = (2,1)|\mathcal{F}_0^l;\boldsymbol{\theta}) \\ \mathrm{P}(l'_t = (2,2)|\mathcal{F}_0^l;\boldsymbol{\theta}) \end{bmatrix}, \qquad \mathbf{g}_t := \begin{bmatrix} g_{00}(z_t|l'_t = (1,1), \mathcal{F}_0^{t-1};\boldsymbol{\theta}) \\ g_{01}(z_t|l'_t = (1,2), \mathcal{F}_0^{t-1};\boldsymbol{\theta}) \\ g_{10}(z_t|l'_t = (2,1), \mathcal{F}_0^{t-1};\boldsymbol{\theta}) \\ g_{11}(z_t|l'_t = (2,2), \mathcal{F}_0^{t-1};\boldsymbol{\theta}) \end{bmatrix},$$

$$\boldsymbol{\Pi} = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} \end{bmatrix}.$$

Here, $\boldsymbol{\theta}$ denotes the vector of all free parameters of the model, $\mathcal{F}_0^t := \{z_0, z_1, \dots, z_t\}$ is the information set available at time t, $g_{ij}(z_t|\mathbf{l}'_t = (i,j), \mathcal{F}_0^{t-1};\boldsymbol{\theta})$, $i, j \in \mathbb{S}$, is the conditional density of z_t given $l'_t = (i,j)$ and $\mathcal{F}_0^{t-1}$, $\boldsymbol{\iota}$ is a four-dimensional all-ones column vector, and $\odot$ denotes element-wise multiplication.[3]

[3] The restrictions presented in the previous section are imposed on the Π general matrix presented above. The filter structure remains unchanged, and we evaluate the estimated maximum across different versions of Π.

Table 2
Maximised Log-Likelihood and Complexity-Penalised Likelihood Criteria.

	Model Specification	Log-L		AIC		SBC	
USA	General	−1020.49		2080.98		2142.11	
	Independent	−1019.89		2063.79		2100.47	
	Stock Volatility leads GDP growth	−1017.63		2055.26	(X)	2086.185	(X)
	GDP growth leads Stock Volatility	−1025.28	(X)	2070.57		2101.13	
UK	General	−1663.668		3367.337		3401.943	
	Independent	−1772.641	(X)	3569.28		3611.249	
	Stock Volatility leads GDP growth	−1670.202		3360.403	(X)	3395.377	(X)
	GDP growth leads Stock Volatility	−1673.485	(X)	3366.971		3401.943	
Japan	General	−637.296		1314.593		1366.697	
	Independent	−639.842		1303.684		1334.946	
	Stock Volatility leads GDP growth	−639.870		1299.740	(X)	1325.791	(X)
	GDP growth leads Stock Volatility	−652.697	(X)	1325.395		1351.447	
France	General	−942.744		1925.489		1986.486	
	Independent	−969.171	(X)	1962.342		1998.940	
	Stock Volatility leads GDP growth	−949.709		1919.419	(X)	1949.917	(X)
	GDP growth leads Stock Volatility	−985.942	(X)	1991.885		2022.383	
Italy	General	−572.338		1184.677		1235.964	
	Independent	−-577.260		1178.521	(X)	1209.293	(X)
	Stock Volatility leads GDP growth	−582.561		1185.123		1210.767	
	GDP growth leads Stock Volatility	−586.659	(X)	1193.318		1218.962	
Germany	General	−693.137		1426.274		1480.644	
	Independent	-681.970		1387.940	(X)	1420.562	(X)
	Stock Volatility leads GDP growth	−689.320	(X)	1398.640		1425.825	
	GDP growth leads Stock Volatility	−704.277	(X)	1428.554		1455.739	

Notes. The countries highlighted in bold are those chosen based on the established criteria. The [X] next to the Log-L column indicates that the model has been rejected. Conversely, the [X] next to the selection criteria indicates which model has been selected according to each specific criterion.

The log-likelihood of θ associated with the observed data can be computed from the iteration of (8)–(9) as

$$\ell(\theta) := \sum_{t=1}^{T} \ln(\iota'[\delta_{t|t-1} \odot g_t]).$$

The ML estimator $\hat{\theta}$ of θ is obtained as the maximiser of $\ell(\theta)$. Furthermore, inferences about the hidden regimes $\{I_t\}$ may be made based on the filtered state probabilities $\delta_{t|t}$, or the smoothed state probabilities $\delta_{t|T}$, evaluated at $\theta = \hat{\theta}$.

We numerically maximise $\ell(\theta)$ using a quasi-Newton routine with multiple random starts drawn from a coarse grid over (Π, μ, Ω) to mitigate local maxima. Filter initial probabilities are set to the stationary distribution of the candidate Π. Hessian-based standard errors are cross-checked with Huber–White sandwich estimates to account for potential misspecification, and we monitor the score and likelihood gradients at the optimum to ensure first-order conditions are met. Finite-sample reliability of ML in MS models is a known concern; see Psaradakis and Sola (1998) for small-sample evidence and Pouzo et al. (2022) for consistency under TVTP—our constant-Π setup nests as a special case. Results relating to the local asymptotic normality of a general class of Markov-switching models with time-varying transition probabilities and to the consistency of ML estimators in such models were recently established by Pouzo et al. (2022). These results ensure that the ML estimator in a model like (1)–(7) has standard large-sample properties under the assumption of correct model specification and suitable regularity conditions.

5. Empirical results

We evaluate three transition-structure hypotheses – independence, "r precedes y", and "y precedes r" – via LR tests against the unrestricted four-state model and then use AIC/SBC for non-rejected cases. To make the timing interpretation transparent across countries, Table 4 (Appendix) lists, for each economy, recession start dates and the nearest volatility-regime transition, indicating the relative timing in quarters (negative = volatility switch earlier), along with a short historical context. This table is descriptive and supports the regime-timing results reported below.

Our research employs Hamilton's non-linear algorithm (Hamilton, 1988, 1989), as outlined in Section 4, to estimate and conduct statistical inference for the Markov-switching models discussed in Section 3. The results are summarised in Table 2, which serves as a guide for selecting appropriate assumptions regarding the transition probabilities. Table 3 shows the estimated parameters for the selected models.

Table 2 presents the maximised log-likelihood values for the various models under consideration. This indicates that the data does not reject any restrictions imposed on the transition matrix for the United States and Japan. However, for the United Kingdom, we reject, at the conventional 5% significance level, the restrictions that output leads volatility and that both states are independent. Nevertheless, the model does not reject the null hypothesis that stock volatility leads GDP growth. The model rejects all tested hypotheses at a 5% significance level for France. The only rejected restriction for Italy is the hypothesis that changes in the state of GDP precede those in stock market volatility. Lastly, for Germany, the model does not reject the hypothesis of independence but does reject the hypothesis that volatility leads growth and that growth leads volatility. These statistical tests indicate that no single model prevails across all countries. However, they notably reject the hypothesis that changes in GDP state precede changes in stock volatility for four of the six countries analysed. Only the independence of the UK and France can be rejected at the 5% significance level.

Turning to the information criteria, both the AIC and SBC favour the model that posits that changes in stock market volatility precede changes in GDP growth in most countries. Only in Germany and Italy do these criteria support the idea that the two Markov chains operate independently. These findings indicate that the unrestricted general model is not preferred based on the information criteria. Notably, no country supports the hypothesis that changes in GDP growth come before changes in stock market volatility. Overall, these results suggest that the model in which changes in stock market volatility lead to changes in output growth is most supported for the majority of the countries analysed.

For the USA, we divided the sample into two periods for clarity. We report results using data up to the fourth quarter of 1985 (Q4) because our primary empirical analysis employs a Markov-switching model, which distinguishes between economic booms, recessions, and periods of high and low return volatility. McConnell and Perez-Quiros (2000)

Table 3
Maximum Likelihood Estimation Results[a].

	USA (M3)	UK (M3)	Japan (M3)	France (M3)	Italy (M2)	Germany (M2)
μ_{yh}	−0.006	−0.0122	0.0051	0.0289	0.0150	0.0234
	(0.0149)	(0.0124)	(0.0078)	(0.0071)	(0.0042)	(0.0065)
μ_{yl}	−0.0963	−0.1519	−0.0411	0.0075	−0.0330	−0.0047
	(0.0437)	(0.0466)	(0.0118)	(0.0066)	(0.0089)	(0.0079)
μ_r	0.0550	0.0157	0.0145	0.0403	0.0874	0.0513
	(0.0008)	(0.1134)	(0.0208)	(0.0847)	(0.0652)	(0.0962)
σ^2_y	0.0048	0.0104	0.0009	0.0002	0.0001	0.0004
	(0.0004)	(0.0009)	(0.0001)	(0.00008)	(0.00005)	(0.0002)
σ^2_{rh}	0.0580	0.1404	0.1340	0.0367	0.1309	0.1716
	(0.0032)	(0.006)	(0.0014)	(0.0006)	(0.0006)	(0.0044)
σ^2_{rl}	0.0182	0.0244	0.0397	0.0641	0.0117	0.0339
	(0.0008)	(0.002)	(0.0008)	(0.0014)	(0.0003)	(0.0008)
$\mathrm{Cov}(y, rh)$	0.0029	0.0013	0.0045	0.0015	0.0020	−0.0037
	(0.0683)	(0.0903)	(0.0664)	(0.0286)	(0.0823)	(0.1095)
$\mathrm{Cov}(y, rl)$	0.0036	0.0061	0.0024	0.0024	0.0004	0.0029
	(0.0090)	(0.0097)	(0.0159)	(0.0309)	(0.0114)	(0.0195)

[a] *Notes*. Figures in parentheses are heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. M3 = the volatility state precedes the output state; M2 = the two Markov chains are independent. y denotes output growth and r denotes stock returns. μ_{yl} (μ_{yh}) is the low (high) mean of y; μ_r is the mean of r. σ^2_y is the variance of y. σ^2_{rl} (σ^2_{rh}) is the variance of r in the low (high) volatility state. $\mathrm{Cov}(y, rl)$ and $\mathrm{Cov}(y, rh)$ are the covariances of y with r conditional on the low and high volatility states, respectively.

demonstrated that the characteristics of the business cycle changed during the latter part of the sample. Incorporating their modifications into our framework would significantly complicate the analysis, resulting in eight possible states. Therefore, we prefer to draw clear conclusions based on separate parts of the sample. Results for Q1 1986 to Q4 2019 support the independence of the chains and are available upon request.

Our findings have three implications. First, the fact that volatility regime shifts tend to precede recessions underscores the informational value of equity markets as real-time, forward-looking aggregators. Volatility-based indicators can complement traditional tools, such as yield-curve spreads or composite leading indexes (Stock and Watson, 1989; Hansen, 2024), to improve the timeliness of recession monitoring and policy assessment. At a quarterly frequency, the operational use of our evidence is triage rather than point prediction: when a volatility-regime transition is inferred and remains elevated, central banks can intensify surveillance, scenario analysis, and funding-stress tests, and investors may rebalance away from cyclical exposures. Table 4 summarises typical relative timing; the signal is informative at a medium horizon and should be combined with other indicators.

Second, the cross-country heterogeneity we uncover suggests that financial structure conditions the strength of the volatility–real activity linkage. In more market-based systems (e.g., U.S., U.K.), equity prices adjust rapidly and embed expectations about macro fundamentals, making volatility a stronger early signal. In more bank-based systems (e.g., Germany, Italy), credit intermediation and institutional features may slow down the transmission of information from stock markets to real activity, attenuating the leading role of volatility.

Third, our results motivate several extensions. Allowing for time-varying transition probabilities (TVTP) linked to financial or policy covariates, in the spirit of Pouzo et al. (2022), could reveal how interventions and shifting financial conditions alter regime persistence and timing. Broadening the financial block to include credit spreads or volatility in the bond market would help to unravel multiple channels of uncertainty transmission. Finally, a real-time exercise that fixes data vintages and evaluates pseudo out-of-sample turning-point performance would quantify the operational value of volatility-based signals for early-warning systems.

In general, the evidence supports the view that financial volatility is not simply a by-product of recessions but an economically meaningful signal that often precedes them. Recognising and quantifying that signal can enhance our understanding of modern business cycles and inform the design of timely, well-targeted macroeconomic policies.

Cross-country heterogeneity and financial structure

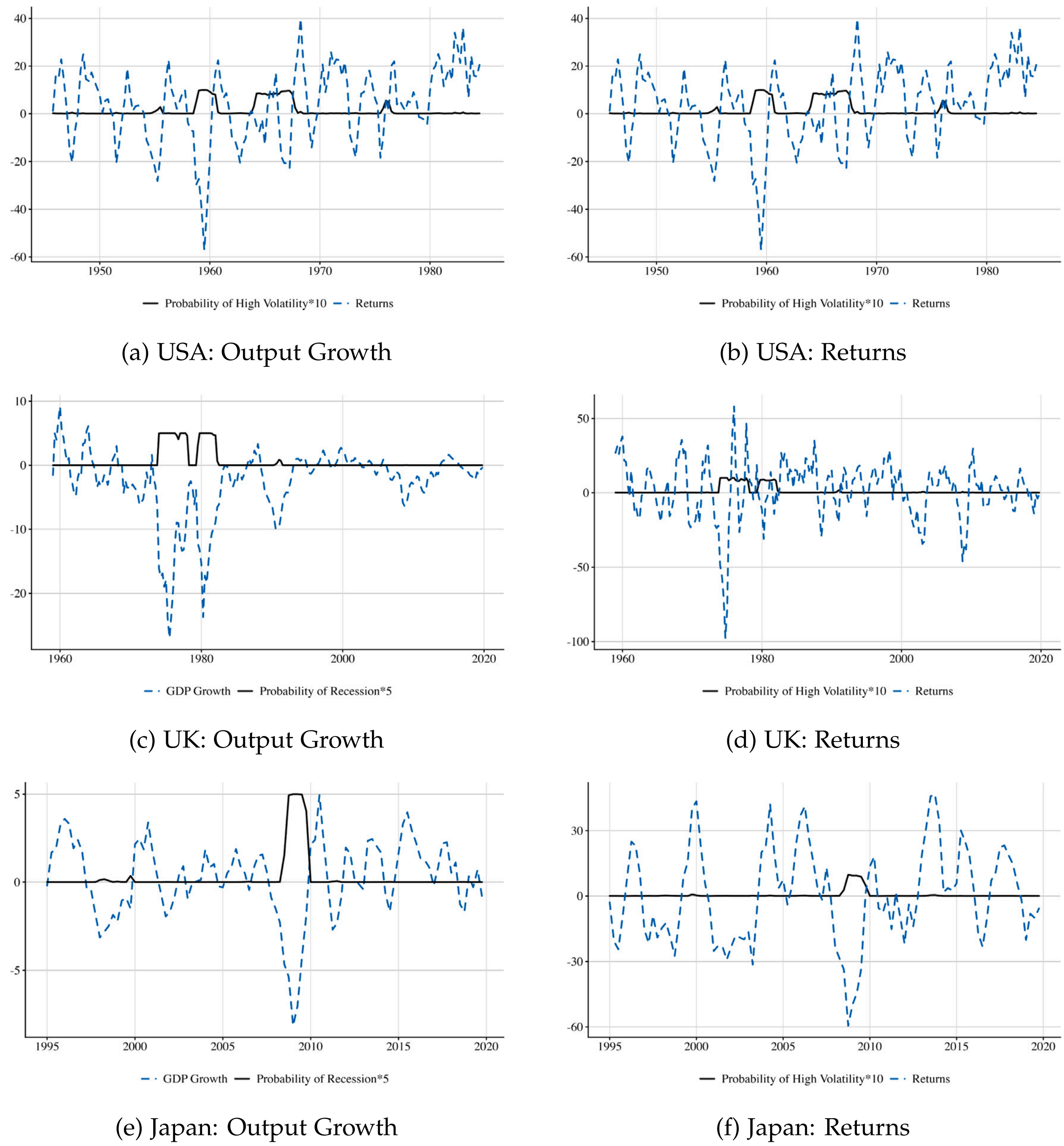
The estimates reported in Table 2 reveal consistent cross-country regularities. The Markov-switching specification successfully differentiates between low- and high-growth regimes in real activity and between low- and high-volatility regimes in financial markets. Across all countries, the estimated parameters are statistically significant, confirming that the model captures systematic shifts in the joint dynamics of output and financial volatility.

For the United States, the United Kingdom, Japan, and France, the estimated state sequences indicate that switches in the volatility regime tend to precede changes in the output-growth regime. This ordering supports the hypothesis that volatility contains early information about turning points in real activity. In contrast, for Germany and Italy, the filtered probabilities suggest a more decoupled evolution of the two processes, consistent with weaker or less synchronised linkages between the financial and real sectors.

Institutional and structural differences in financial systems help explain these asymmetries. In economies with large and liquid equity markets – such as the United States and the United Kingdom – equity price volatility tends to incorporate forward-looking expectations of macroeconomic conditions. France and Japan exhibit similar behaviour, reflecting episodes of financial liberalisation and greater market integration over the sample. Conversely, Germany and Italy, where bank-based intermediation has traditionally dominated, display less sensitivity of real activity to stock-market volatility (Demirgüç-Kunt and Levine, 1999). In these systems, credit channels rather than market volatility drive the transmission of information and shocks.

Finally, the estimated covariances between output growth and equity returns are generally small and not statistically different from zero. This result implies that short-term co-movements are negligible, underscoring the importance of regime-dependent dynamics rather than contemporaneous correlations. Overall, the evidence suggests that while instantaneous financial–real linkages remain weak, changes in volatility states often anticipate real turning points in economies with deeper and more market-based financial structures. These findings are consistent with the broader literature on financial leading indicators of business cycles (Stock and Watson, 1989), which emphasises the predictive content of financial variables for real activity.

Figs. 2 and 3 display the filtered probabilities of being in a recession and in a low-volatility regime, respectively. The estimates are based on the preferred specification, which assumes that volatility regime



(a) USA: Output Growth
(b) USA: Returns
(c) UK: Output Growth
(d) UK: Returns
(e) Japan: Output Growth
(f) Japan: Returns

Fig. 2. Filtered probabilities of output growth and returns.
Notes. Each panel displays filtered probabilities from country-specific Markov-switching models. “Recession” denotes $P(S_t^{(y)} = 2 \mid \mathcal{I}_t)$ for real GDP growth; “High returns volatility” denotes $P(S_t^{(v)} = 1 \mid \mathcal{I}_t)$ for equity returns. The model specification and sample follow the empirical setup for these countries.

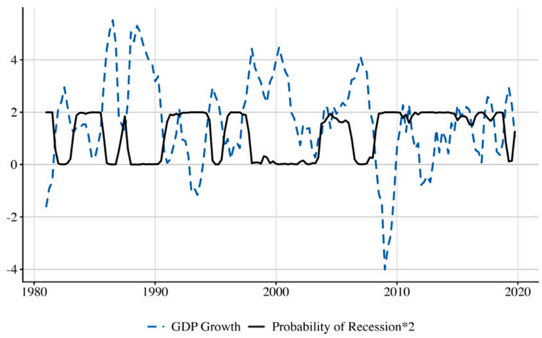
changes precede output growth regime changes for all countries except Italy and Germany, where independence is imposed.

The results show that the periods identified by the filter align closely with the major swings observed in the raw data, underscoring the model’s ability to capture recessionary episodes. In countries where volatility is assumed to lead output growth, the filter probabilities perform particularly well in detecting recessions, consistent with the model’s design. Similarly, in distinguishing between high- and low-volatility regimes, the filter accurately classifies periods of turbulence versus calm, with particularly high precision in Italy and Germany, where independence between the two processes is assumed.

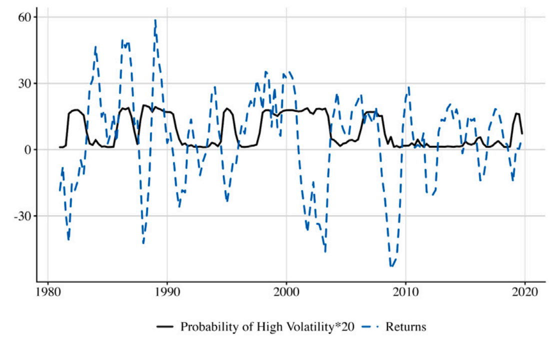
In addition to the overlays, we present Table 4 in the Appendix, which collects episodes in which a recession state follows a volatility state. The table reports the calendar timing, the lag in quarters, and provides a brief snapshot of mechanisms based on well-documented historical events. Two clear patterns emerge.

First, in the United States, United Kingdom, France, and Japan, episodes of volatility tend to cluster around events such as oil-price shocks, credit dislocations, exchange-rate or sovereign-risk turbulence, and external demand or disaster shocks. Typically, a recession follows these volatility episodes within a few quarters. This pattern aligns with the idea that uncertainty and risk-premium repricing, along with tighter funding conditions, impact real economic activity.

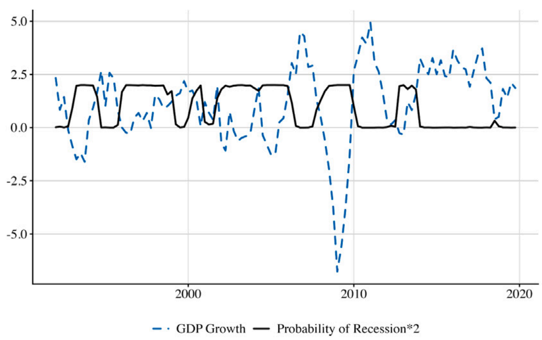
Second, in Germany and Italy, there is no systematic relationship between volatility and recession, suggesting that these two processes operate independently. This distinction sharpens the contrast and indicates that the transmission we document is not merely mechanical. Overall, the table organises the evidence by timing of phase shifts



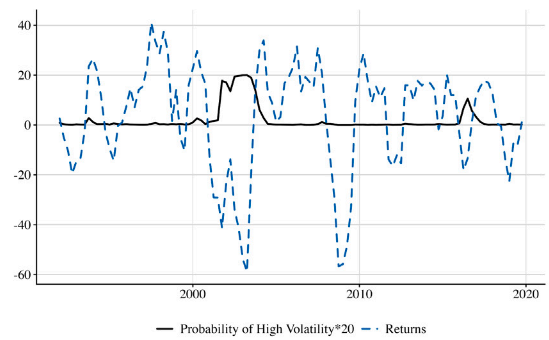
(a) France: Output Growth



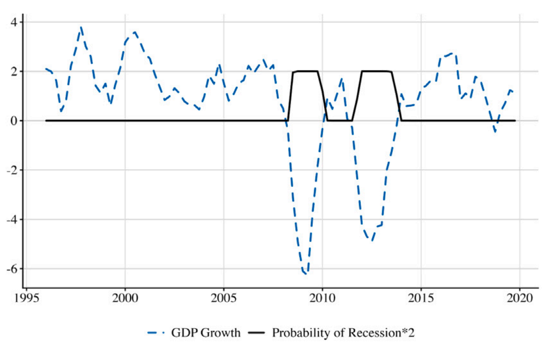
(b) France: Returns



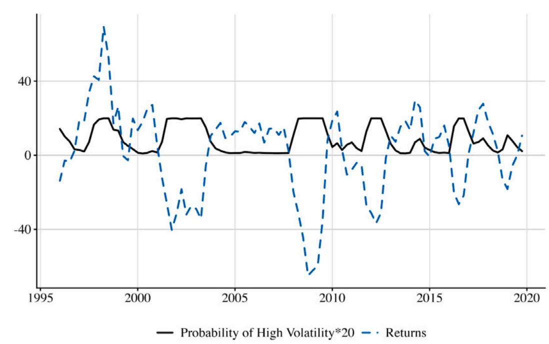
(c) Germany: Output Growth



(d) Germany: Returns



(e) Italy: Output Growth



(f) Italy: Returns

Fig. 3. Filtered probabilities of output growth and returns.
Notes. Each panel displays filtered probabilities from country-specific Markov-switching models. "Recession" denotes $P(S_t^{(y)} = 2 \mid \mathcal{I}_t)$ for real GDP growth; "High returns volatility" denotes $P(S_t^{(v)} = 1 \mid \mathcal{I}_t)$ for equity returns. The model specification and sample follow the empirical setup for these countries.

and utilises historical context to highlight plausible channels without making causal claims.

The results indicate that the model effectively captures distinct periods of economic expansion and contraction, along with transitions between high and low volatility.

6. Concluding remarks

This study examines the interaction between financial markets and real economic activity through the lens of regime-dependent dynamics. Using a Markov-switching framework, we jointly identify phases of output growth and stock market volatility for six advanced economies – the United States, the United Kingdom, Japan, Germany, Italy, and France – over several decades. The approach moves beyond high-frequency co-movements to characterise how persistent changes in financial uncertainty relate to shifts in real activity.

The results show that the model captures distinct periods of expansion and contraction in output, as well as transitions between high- and low-volatility regimes in financial markets. Although there is limited evidence that changes in output growth regimes precede volatility transitions, the opposite ordering is more frequent: volatility regime shifts tend to precede changes in real activity. This pattern suggests that financial markets contain useful information about forthcoming macroeconomic conditions.

The analysis highlights three main implications. First, the finding that volatility shifts often precede recessions underscores the informational value of equity markets as forward-looking aggregators. Volatility-based indicators can complement traditional tools such as yield-curve spreads or composite leading indexes (Stock and Watson, 1989; Hansen, 2024), improving the timeliness of business-cycle monitoring. Second, the cross-country heterogeneity observed in the strength of the volatility-real activity linkage points to the role of

Table 4
Episodes where Recession follows High Volatility (Germany/Italy: independence, not shown)

Country	Episode	VOL entry	R entry	Lag	Mechanism snapshot
United States	1973–1975	1973:Q4	1974:Q2	2	Oil shock → risk-premium jump; investment pullback.
	1979–1982	1979:Q4	1980:Q1	1	Energy shock + tightening → funding costs up; demand compression.
	1981–1982	1981:Q3	1981:Q4/1982:Q1	1	Monetary tightening → “double-dip”.
	2007–2009	2007:Q4	2008:Q1	1	Credit crunch → collateral constraints; capex/employment retrenchment.
United Kingdom	2008–2009	2007:Q4	2008:Q4–2009:Q1	~4	Banking stress → lending contraction; domestic demand fall.
	2011–2012	2011:Q3	2012:Q1	2	Euro-area turmoil → tighter financial conditions; growth dip.
France	1992–1993	1992:Q3	1993:Q1	2	ERM turbulence → uncertainty spike; policy adjustment; slowdown.
	2008–2009	2008:Q4	2009:Q1	1	Global financial shock → external demand drop; output contraction.
	2011–2013	2011:Q3	2012:Q1	2	Sovereign-risk episode → bank funding pressure; growth weakening.
Japan	2008–2010	2008:Q4	2009:Q1	1	External demand collapse → export shock; production adjustment.
	2011	2011:Q1	2011:Q2–Q3	~1–2	Disaster/energy shock → supply disruption; uncertainty; retrenchment.

financial structure. In more market-oriented systems, such as the United States and the United Kingdom, volatility tends to convey early signals of changing fundamentals, whereas in bank-based systems, such as Germany and Italy, the transmission of financial information to the real economy appears slower and less direct. Third, the framework can be extended to explore richer mechanisms. Allowing transition probabilities to depend on financial or policy variables, in the spirit of Pouzo et al. (2022), would shed light on how evolving conditions influence regime persistence and timing. Incorporating other indicators, such as credit spreads or bond-market volatility, could further clarify the multiple channels through which financial shocks affect real activity.

Overall, the evidence supports the view that financial volatility is not merely a consequence of recessions but often a preceding signal of them. Recognising and quantifying this signal improves our understanding of the interaction between the financial and real sectors and can inform the design of timely, well-calibrated macroeconomic policies. Because the signal is a single filtered regime probability from a parsimonious Markov-switching model, it can be updated each quarter mechanically and used to flag episodes that warrant deeper nowcasting and risk assessment.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Table 4.

Data availability

When Volatility Turns, Recessions Follow (Original data) (Mendeley Data)

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