

# Interactions between business cycles, financial cycles and monetary policy: stylised facts<sup>1</sup>

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## Introduction

The spectacular rise in asset prices up to 2000 in most developed countries has attracted a great deal of attention and reopened the debate over whether these prices should be targeted in monetary policy strategies. Some observers see asset price developments, in particular those of stock prices, as being inconsistent with developments in economic fundamentals, ie a speculative bubble. This interpretation carries with it a range of serious consequences arising from the bursting of this bubble: scarcity of financing opportunities, a general decline in investment, a fall in output, and finally a protracted contraction in real activity. Other observers believe that stock prices are likely to have an impact on goods and services prices and thus affect economic activity and inflation.

These theories are currently at the centre of the debate on whether asset prices should be taken into account in the conduct of monetary policy, ie as a target or as an instrument.<sup>3</sup> However, the empirical link between asset prices and economic activity on the one hand, and the relationship between economic activity and interest rates or between stock prices and interest rates on the other, are not established facts. This study therefore sets out to identify a number of stylised facts that characterise this link, using a statistical analysis of these data (economic activity indicators, stock prices and interest rates).

More specifically, we study the co-movements between stock market indices, real activity and interest rates over the business cycle. Assuming that there is no single definition of the business cycle, we adopt an agnostic approach in our methodology.

The traditional approach characterises the cycle as a series of phases of expansion and contraction. Formally, expansion phases are defined as the periods of time separating a trough from a peak; conversely, contraction phases correspond to periods separating a peak from a trough. In this respect, it is vital to define and accurately identify peaks and troughs.

Although this view of the cycle fell out of fashion after the 1970s, it has recently come back into focus thanks to a number of studies, in particular by Harding and Pagan (2002a,b), who proposed a simple method for analysing the concordance between macroeconomic variables.<sup>4</sup> By definition, the concordance index represents the average number of periods in which two variables (eg GDP and a stock market index) coincide at the same phase of the cycle.

The traditional approach defines the business cycle directly by analysing changes in the level of a variable, eg GDP. The modern approach (mentioned above), using the appropriate statistical filtering techniques, enables us to split a variable into two components, one cyclical or short-term, and the other structural or permanent. As its name suggests, the cyclical component has no trend and can be associated with the business cycle. Consequently, we can calculate the correlations between the cyclical components of two variables in order to study the degree of their co-movement (ie the similarity of their profile). However, we show that the structural component of a variable is driven by a

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<sup>3</sup> A large amount of theoretical literature has recently been published on this subject. See Bernanke and Gertler (2001), Bullard and Schalling (2002), Filardo (2000) and other references cited in these papers.

<sup>4</sup> For a recent application on euro area data, see Artis et al (2003).

trend. Hence, to avoid spurious relationships, we study the growth rate of the structural components. We can also calculate the correlations between the growth rate of the structural components of two variables in order to study their co-movement.

As the notions of concordance and correlation do not have an identical scope, it is useful to use both of these tools when attempting to characterise the stylised facts relating to the business cycle.

The first part of this study is devoted to the empirical analysis of the concordance indicator; the second part starts off by describing changes in the variables studied (real activity, stock prices and interest rates) by separating the cyclical (or short-term) components from the structural (or long-term) components, and then compares the variables using the dynamic correlations of their corresponding components (ie cyclical/cyclical and structural/structural).

In both parts, we compare the results obtained on the business and stock market cycles to the monetary policies applied over the period studied: first, we analyse the behaviour of short-term interest rates over the phases of expansion and contraction of real activity and stock prices; and second, we calculate the correlations between the cyclical components of real activity, stock prices and interest rates on the one hand, and the correlations between the structural components of these variables on the other.

## 1. Concordance between business cycles and stock market cycles: an empirical analysis

As a concordance indicator, we use a descriptive statistic recently developed by Harding and Pagan (2002a,b) and implemented at the IMF by Cashin et al (1999) and McDermott and Scott (2000). Cashin et al applied this method to an analysis of the concordance of goods prices while McDermott and Scott used it to study the concordance of business cycles in major OECD countries.

The underlying method is based on studies by the National Bureau of Economic Research (NBER) and consists in dating the turning points in cycles. On the basis of these points, we can associate a contraction period with the lapse of time that separates a high point (peak) from a low point (trough). We follow the procedure advocated by Harding and Pagan (2002a,b) to identify turning points. This procedure states that a peak/trough has been reached at  $t$  when the value of the studied series at date  $t$  is superior/inferior to the previous  $k$  values and to the following  $k$  values, where  $k$  is a positive integer that varies according to the type of series studied and its sampling frequency. A procedure is then implemented to ensure that peaks and troughs alternate, by selecting the highest/lowest consecutive peaks/troughs. Additional censoring rules are implemented, which, for example, restrict the minimal phase and cycle durations.<sup>5</sup>

### 1.1 The concordance index

We can now define the contraction and expansion phases for one or more variables and thus define the concordance statistic that indicates the (standardised) average number of periods in which two variables (eg GDP and a stock market index) coincide at the same phase of the cycle. There is a perfect concordance between the series (perfect juxtaposition of expansions and contractions) if the index is equal to 1 and perfect discordance (a marked lag or out of phase) if the index is equal to 0.

Once the turning points of a variable  $y$  have been identified, we can define the binary variable  $s_{y,t}$  such that:

$$s_{y,t} = \begin{cases} 1 & \text{if } y \text{ is in expansion at } t \\ 0 & \text{otherwise} \end{cases}$$

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<sup>5</sup> See Appendix A for further details on the determination of business cycle dates.

We proceed in the same fashion with  $x$ , by defining  $s_{x,t}$ . The concordance index between  $x$  and  $y$ ,  $c_{xy}$ , is then defined as the average number of periods where  $x$  and  $y$  are identified simultaneously in the same phase, and is expressed as follows:

$$c_{xy} = \frac{1}{T} \sum_{t=1}^T [s_{x,t}s_{y,t} + (1-s_{x,t})(1-s_{y,t})]$$

Thus,  $c_{xy}$  is equal to 1 if  $x$  and  $y$  are always in the same phase and to 0 if  $x$  and  $y$  are always in opposite phases. A value of 0.5 indicates the lack of any systematic relationship in the dynamics of the two variables.

As McDermott and Scott (2000) observed, it is only possible to compute analytically the statistical properties of  $c_{xy}$  in a handful of particular cases. For example, if the processes  $x$  and  $y$  are independently drawn from the same Brownian motion, assuming that no censoring rules have been enforced in defining the turning points, then  $c_{xy}$  has mean 1/2 and variance  $1/[4(T-1)]$ .

Note that if  $T$  is very large, the variance of  $c_{xy}$  converges to 0 ( $c_{xy}$  is asymptotically constant).

However, in general, the distribution properties of  $c_{xy}$  are unknown, especially when the censoring rules have been enforced. In order to calculate the degrees of significance of these indices, we use the method suggested by Harding and Pagan (2002b) given below. Let  $\mu_{s_i}$  and  $\sigma_{s_i}$ ,  $i = x, y$ , denote the empirical average and the empirical standard deviation of  $s_{i,t}$ . If  $\rho_s$  denotes the empirical correlation between  $s_{x,t}$  and  $s_{y,t}$ , it can be shown that the concordance index obeys:

$$c_{xy} = 1 + 2\rho_s\sigma_{s_x}\sigma_{s_y} + 2\mu_{s_x}\mu_{s_y} - \mu_{s_x} - \mu_{s_y} \quad (1.1)$$

According to equation (1.1),  $c_{xy}$  and  $\rho_s$  are linked in such a way that either of these two statistics can be studied to the same effect. In order to calculate  $\rho_s$ , Harding and Pagan estimate the linear relationship:

$$\left( \frac{s_{y,t}}{\sigma_{s_y}} \right) = \eta + \rho_s \left( \frac{s_{x,t}}{\sigma_{s_x}} \right) + u_t \quad (1.2)$$

where  $\eta$  is a constant and  $u_t$  an error term.

The estimation procedure of equation (1.2) must be robust to possible serial correlation in the residuals, as  $u_t$  inherits the serial correlation properties of  $s_{y,t}$  under the null hypothesis  $\rho_s = 0$ . The ordinary least squares method augmented by the HAC procedure is therefore used here.

Note that equation (1.1) makes it clear that it is difficult to assess a priori the significance of  $c_{xy}$  relative to 0.5. Indeed, in the case of independent, driftless Brownian motions,  $\rho_s = 0$ , and  $\mu_{s_x} = \mu_{s_y} = 0.5$ , so that  $c_{xy} = 0.5$ . Now, assume that  $x$  and  $y$  are drawn from the same Brownian motion, though characterised by drifts, so that  $\mu_{s_x} = \mu_{s_y} = 0.9$ . In this case, using equation (1.1), it must be the case that  $c_{xy} = 0.82$ . However,  $x$  and  $y$  have been sampled independently, and should not be characterised by a high degree of concordance. Thus, a high value for  $c_{xy}$  relative to 1/2 is not synonymous with a high degree of concordance.

## 1.2 Presentation of the data

We set out to study the relationship between business cycles and stock market cycles in France, Germany, Italy, the United Kingdom and the United States.

Stock prices are obtained from composite indices calculated by Morgan Stanley (MSCI), deflated by the consumer price index. These variables are available at a quarterly and a monthly frequency. We use three variables to define the business cycle: at the quarterly frequency, market GDP and household consumption (these variables are taken from the OECD database over the study period from the first quarter of 1978 to the third quarter of 2002); and at the monthly frequency, retail sales (in volume terms, over the period January 1978-December 2002). This series is only available as of 1990 for Italy. We therefore do not take this country into account in our analysis of monthly data. Moreover, the monthly sales index displays a highly erratic pattern that could conceal some turning points. We

strip out the most erratic parts of these series by prefiltering and focus the analysis on an adjusted version of these variables.<sup>6</sup>

The data sources are detailed below:

- *Financial data*: Morgan Stanley Capital International (MSCI) indices obtained from Datastream. In order to calculate excess returns, we use the nominal interest rate on government bonds (annualised) for France, the United Kingdom and the United States, the interbank rate for Germany and the money market rate for Italy. For all of these countries, we use the three-month money market rates as indicators of monetary policy. These data are obtained from the IMF database.
- *Real data*: real market GDP and real private consumption are expressed in 1995 prices. Real sales are obtained from the real retail sales index (1995 base year). These data are obtained from the OECD database. We also use the consumer price index from the same database to deflate the stock market indices.

### 1.3 Results

The turning points in real GDP, real consumption and MSCI indices are shown in Graphs 1, 2 and 3, respectively. Those for the retail sales index and the MSCI indices at the monthly frequency are given in Graphs 4 and 5, respectively.

At the quarterly frequency, results derived from the graphs relating to real activity variables (Graphs 1 and 2) are compatible overall and consistent with the analysis of McDermott and Scott (2000) and with that of Artis et al (2003). Naturally, we do not detect a perfect identity between the cycles described by GDP and real consumption. In France, for example, a short contraction can be observed in 1995 when we study private consumption data, whereas the French economy was in a phase of expansion according to GDP data. When studying the turning points observed in stock markets, we note in particular that they are more frequent than in the real economy, irrespective of the country considered in our sample. The long phase of expansion in the 1990s is clearly visible in all countries. Some pronounced lags are observed between the phases of the business and stock market cycles, in particular in Europe, and especially at the start of the 2000s.

We note that the retail sales index is a more or less reliable indicator of private consumption and is more volatile than the latter. Nevertheless, these are the two indicators that must be compared. We therefore compare the turning points derived from the analysis of these two variables. Overall, in sales indices we observe the same marked contractions as in consumption, as well as more occasional contractions, consistent with the high volatility of these indices. We can carry out the same analysis on stock market indices at two frequencies: all pronounced contractions at a quarterly frequency can also be observed at a monthly frequency; here, too, more contractions are detected at the monthly frequency.

These initial findings obtained from analysing the graphs naturally call for a more in-depth study of the co-movements of real economy and stock market variables. Table 1 lists the intra-country index of concordance between the MSCI indices and the three real activity indicators used.

The United States appears to be characterised by a significant concordance between the level of real activity and stock prices. Indeed, this is the case for all three real activity indicators used, which is not surprising in view of the role of stock markets in the investment and financing behaviour of US economic agents. However, the same is not true of the other countries in the sample.

Stock market and business cycles do not occur at the same frequencies and furthermore may be uncorrelated, with the exception of the United States. Indeed, an analysis of Graphs 1 (or 2) and 3 shows that the duration of a stock market expansion is generally shorter than one in GDP or consumption. This difference naturally contributes to reducing the degree of concordance between real activity and stock markets. Nevertheless, the lack of significant concordance in most countries under review does not necessarily mean that business and stock market cycles are different or

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<sup>6</sup> See Watson (1994).

uncorrelated phenomena. The result obtained simply highlights the fact that the periods of expansion and contraction of GDP and stock prices (for example) do not coincide.

We observe that the start of US stock market contractions (ie the dates of peaks) precede contractions in real activity measured by real GDP.<sup>7</sup> The lag oscillates between one and four quarters. However, we also note that not all stock market contractions result in contractions in real activity. In particular, when they are very short (like in 1987), they do not seem to spill over into real activity. A similar phenomenon can be detected in European countries such as France and Italy. Like in the United States, but to a lesser degree, GDP contractions are preceded by stock market contractions, although most stock market contractions in these two countries do not lead to contractions in real activity. However, this rule does not apply to Germany and the United Kingdom. Stock market contractions may precede or follow contractions in real activity by more than a year. Therefore, contrary to received wisdom, it does not always appear relevant to use negative turning points in stock markets as leading indicators of the start of a contraction phase of GDP or consumption.

Turning now to the relationship between monetary policy and business and stock market cycles, we observe a relative decoupling between certain contraction periods of real activity or stock markets and money market rate developments, used here as indicators of monetary policy (Graph 6). No clear rule emerges from a comparison between stock markets and money markets: for the business cycle, a decline in rates more or less coincides with a contraction but, here too, it is difficult to establish a general rule. This graph suggests that the reaction of money market rates to turnarounds in real activity or stock markets is not systematic or correlated in the countries studied. This corresponds in theory to the mandate of monetary authorities as well as to the way we have modelled monetary policy rules in recent macroeconomic studies.<sup>8</sup>

Concordance indices have enabled us to measure the degree of “juxtaposition” between two chronological series, without having to consider whether there is a trend in the variables (non-stationarity). It should nevertheless be noted that only one aspect of the notion of cycles is taken into account here.

It could therefore be useful to broaden the study by retaining the concepts of phase and duration, but without limiting ourselves to such restrictive indicators as concordance indices. To do this, in Part two we decompose the different series studied in order to isolate the long-term (or structural) and the short-term (or cyclical) components; the latter correspond to the business cycle concept put forward by the NBER.

## 2. Correlation of cyclical and structural components

On the basis of NBER studies, we identify business cycles with all movements whose recurrence period is between six and 32 quarters.<sup>9</sup> This corresponds to the frequency of business cycles. Furthering this approach, it has become common in macroeconomics to split a variable ( $y_t$ ) according to the frequencies band over which its components are concentrated. The one corresponding to the business cycle is determined as the residual obtained after stripping out long movements, imputable to structural economic factors ( $\tau_t$ ).<sup>10</sup> By construction, the residual variables ( $y_t - \tau_t$ ) obtained by robust statistical techniques (filtering) are detrended (stationary). We can thus calculate the correlations between the corresponding components of the series in the hope of isolating a set of statistical regularities or stylised facts that characterise the business cycle.

The analysis of these components is based on the assumption that it is possible to isolate them from each other. To this end, we use two complementary non-parametric methods. First, we take the band pass filter recently put forward by Christiano and Fitzgerald (2003) (CF filter). For each country and

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<sup>7</sup> To date, statistics for testing the significance of these lags do not exist.

<sup>8</sup> See, in particular, studies in the collective work edited by Taylor (1999).

<sup>9</sup> Estrella (2003) uses a slightly different definition of business cycle frequencies.

<sup>10</sup> This is the approach generally adopted following Kydland and Prescott (1982).

each variable ( $y_t$ ), we thus define the short-term (or cyclical,  $y_t^{st}$ ) components and the long-term (or structural,  $y_t^{lt}$ ) components and calculate the correlations between the corresponding components. Second, we compute the dynamic correlations between the studied variables, following the work by Croux et al (2001).

The following section briefly reviews the methodological tools used.

## 2.1 A brief review of spectral analysis

### 2.1.1 The band pass filter

The ideal band pass filter used to isolate cyclical movements whose recurrence periods are in the interval  $[b_l, b_u]$ , is defined by the following equation:

$$y_t^{st} = B(L)y_t, \quad B(L) = \sum_{k=-\infty}^{k=+\infty} B_k L^k, \quad L^k y_t = y_{t-k},$$

where  $B_k$  is expressed as:

$$B_k = \frac{\sin(2k\pi/b_l) - \sin(2k\pi/b_u)}{\pi k}.$$

In order to interpret the role played by the filter, we introduce the concept of *spectral density*. The spectral density of the stationary stochastic process  $y_t$ , denoted  $S_y(\omega)$ , is interpreted as the decomposition of the variance of  $y_t$  in the frequency domain. As  $y_t$  can be decomposed into a sum of orthogonal cyclical movements that each appear at a different frequency, we can interpret  $S_y(\omega)$  as the variance of  $y_t$  explained by the cyclical movements operating at frequency  $\omega$ .

A classic result of spectral analysis shows us that, under certain conditions, the equation  $y_t^{st} = B(L)y_t$  implies that the spectral density of the process  $y_t^{st}$ ,  $S_{y^{st}}(\omega)$ , is deduced from that of  $y_t$ ,  $S_y(\omega)$ , using the formula:

$$S_{y^{st}}(\omega) = \|B(e^{-i\omega})\|^2 S_y(\omega),$$

where  $\|B(e^{-i\omega})\|^2$  is the squared modulus of  $B(e^{-i\omega})$ . Given the definition of  $B_k$ , a direct calculation shows that:

$$B(e^{-i\omega}) = \begin{cases} 1 & \text{for } \omega \in ]2\pi/b_u, 2\pi/b_l[ \cup ]-2\pi/b_l, -2\pi/b_u[ \\ 0 & \text{otherwise} \end{cases}.$$

From this formula it can be observed that the spectral density of  $y_t$  is not 0 on the frequency band  $]2\pi/b_l, 2\pi/b_u[ \cup ]-2\pi/b_l, -2\pi/b_u[$ , and 0 everywhere else in the interval  $]-\pi, \pi[$ . In other words, all the variance of  $y_t^{st}$  is explained by cyclical movements whose recurrence periods are between  $b_l$  and  $b_u$ .

The definition of the filter  $B(L)$  imposes a major limitation, as it requires a data set of infinite length. In practice, we work with a finite sample and must therefore make an appropriate approximation of  $B(L)$ . Starting from a finite number of observations  $\{y_1, \dots, y_T\}$  of the stochastic process  $y_t$ , Christiano and Fitzgerald (2003) define the optimal linear approximation  $\hat{y}_t^{st}$  of  $y_t^{st}$  as the solution to the problem:

$$\min E \left[ \left( y_t^{st} - \hat{y}_t^{st} \right)^2 \middle| \{y_1, \dots, y_T\} \right] \quad (2.1)$$

The method therefore consists in minimising the mathematical expectation of the square error between the ideally filtered series and the approximately filtered series, where the expectation is conditioned on all the available data.

### 2.1.2 Dynamic correlation

Consider a bivariate stationary stochastic process  $(x_t, y_t)'$ . The classical notion of correlation is a static measure of the linear relation between  $x_t$  and  $y_t$ . In contrast, the dynamic correlation between  $x_t$  and  $y_t$ , denoted  $\rho_{xy}(\omega)$ , permits us to decompose the correlation between these series in the frequency domain. In particular, it allows us to quantify the amount of covariation between the cyclical components of  $x_t$  and  $y_t$  at frequency  $\omega$ .

Let us define formally the notion of dynamic correlation. Let  $S(\omega)$  denote the spectral density of  $(x_t, y_t)'$ :

$$S(\omega) = \begin{pmatrix} S_x(\omega) & S_{xy}(\omega) \\ S_{yx}(\omega) & S_y(\omega) \end{pmatrix}, \quad \omega \in [-\pi, \pi],$$

where the cross-spectrum  $S_{xy}(\omega)$  is a complex number, such that  $S_{xy}(\omega) = S_{yx}(\omega)'$  (where “ ’ ” denotes the transpose-conjugate operation). The dynamic correlation  $\rho_{xy}(\omega)$  associated with  $(x_t, y_t)'$  is defined by the relation:

$$\rho_{xy}(\omega) = \frac{C_{xy}(\omega)}{\sqrt{S_x(\omega)S_y(\omega)}}, \quad \omega \in [0, \pi[,$$

where  $C_{xy}(\omega)$  is the real part of  $S_{xy}(\omega)$ . Thus, this statistic is nothing more than the correlation coefficient between real waves of frequency  $\omega$  appearing in the spectral decomposition of  $(x_t, y_t)'$ .

To estimate  $\rho_{xy}(\omega)$  we first estimate  $S(\omega)$  through the well known relation:

$$S(\omega) = \sum_{k=-\infty}^{k=+\infty} \Gamma_k e^{-i\omega k}, \quad \omega \in [-\pi, \pi].$$

Here,  $\Gamma_k = E z_t z_{t-k}'$  is the  $k$ -th autocovariance of  $(x_t, y_t)'$ . In practice, the  $\Gamma_k$  are not known and are replaced by their sample counterparts:

$$\hat{\Gamma}_k = \frac{1}{T} \sum_{t=k+1}^T z_t z_{t-k}'$$

where  $T$  is the sample size. Finally,  $S(\omega)$  is replaced by its empirical estimate, denoted  $\hat{S}(\omega)$ , which is obtained by smoothing the empirical covariogram with a Bartlett window of width  $q$ :

$$\hat{S}(\omega) = \frac{1}{2\pi} \left[ \hat{\Gamma}_0 + \sum_{k=1}^q \left( 1 - \frac{k}{q+1} \right) \left( \hat{\Gamma}_k e^{-i\omega k} + \hat{\Gamma}_k' e^{i\omega k} \right) \right].$$

Finally, to compute the confidence intervals reported below, we used a traditional block-bootstrap approach.

## 2.2 Empirical results

Here, the analysis is limited to quarterly frequencies. The different real activity indicators are logarithms of real market GDP and private consumption; for the financial sphere, we consider the excess returns on stocks relative to the risk-free interest rate.<sup>11</sup>

<sup>11</sup> Excess returns are defined as the difference between the nominal interest returns on stocks and on three-month government bonds.

We propose two applications. First, for each country, we calculate the correlation between the cyclical (short-term) components of the variables studied and the correlation between the structural (long-term) components. In the latter case, we do not deal with real activity indicators and measures of returns in the same way. Indeed, real activity indicators are characterised by trends and therefore do not have the required statistical properties (they are not stationary) for calculating the correlations.

We show that their long-term components are non-stationary too. Consequently, we focus on the growth rate of the structural components that are, in general, stationary (in particular, they are not characterised by a trend). Conversely, the excess returns on stocks relative to the risk-free interest rate and their components are stationary. We can therefore study these variables in level form.

In order to determine the cyclical components, we adopt the traditional definition of the cycle presented above. For all the variables studied, the business cycle is identified with all movements whose recurrence period is between six and 32 quarters. In order to isolate the structural components, we apply the CF filter so as to strip out the cyclical movements with a recurrence period of less than 32 quarters. We then calculate the difference between the initial series and the filtered series to obtain the structural component.

Let  $y_t$  denote the log of real GDP at  $t$ , and  $x_t$  the excess return at  $t$ . For each country  $i$  ( $i$  = France, Germany, Italy, the United Kingdom and the United States), we calculate the following correlations:

- the correlation between the cyclical component of GDP and excess returns,  $y_{t+k}^{st}(i)$  and  $x_t^{st}(i)$ , for  $k = -3, \dots, 3$ ;
- the correlation between the growth rate of the structural component of GDP,  $\Delta y_{t+k}^{lt}(i)$ , and the structural component of excess returns,  $x_t^{lt}(i)$ , for  $k = -3, \dots, 3$ ;

where  $\Delta$  is the first difference operator ( $\Delta a_t = a_t - a_{t-1}$ ). We establish  $k$  as ranging from  $-3$  to  $3$  as is the usual practice in studies of US data. For the purposes of symmetry, we adopt the same horizon for the other countries. As mentioned above, the exponent  $st$  denotes the short-term component and the exponent  $lt$  denotes the long-term component. We estimate these correlations using the Generalised Method of Moments (GMM) completed with the HAC procedure developed by Andrews and Monahan (1992). We use the same methods for real private consumption, replacing  $y_t$  by  $c_t$ , the logarithm of consumption.

Second, for each country, we calculate the dynamic correlation between excess returns and either GDP growth or consumption growth. We decide to study growth rates of trending variables for the same reasons as those outlined above. Thus, it is important to keep in mind that the dynamic correlation between output growth and excess returns at low frequencies does not exactly cover the same phenomenon as the simple correlation between the structural component of excess returns and the growth rate of the structural component of output.

From Tables 2 and 3, we cannot conclude that there is a strong link between the cyclical components of GDP or consumption and those of excess returns in the different countries reviewed.

However, in France, Germany and the United States, the correlation between  $y_{t+k}^{st}$  and  $x_t^{st}$  is significantly positive for  $k = 2$  or  $3$  quarters. This means that a positive variation of the cyclical component of GDP at  $t+2$  or at  $t+3$  is associated with a positive variation of the cyclical component of excess returns at  $t$ . In other words, a positive variation of the cyclical component of GDP follows an increase in the cyclical component of excess returns with a lag of two or three quarters.<sup>12</sup>

Even though the share of equities in household wealth differs across the Atlantic<sup>13</sup> the reactions of the three economies display a certain convergence. A similar link is observed for the cyclical component of consumption, although the lag in the correlation appears to be closer to three quarters.

<sup>12</sup> This result must, however, be considered with caution as the sign of the correlation coefficient sometimes changes with  $k$  in some countries (see the line corresponding to the United States).

<sup>13</sup> See Odonnat and Rieu (2003).



However, the correlations between the growth rate of the structural component of GDP and the structural component of excess returns are significantly positive for all countries, at a fairly short horizon (Tables 4 and 5). The structural determinants of excess returns appear to covary positively with those of real activity. This result is borne out overall when consumption is used as a real activity indicator, at least for short horizons.<sup>14</sup>

The previous results are partly confirmed by the dynamic correlation analysis. Figure 7 reports the dynamic correlation between GDP growth and excess returns. The graph clearly shows that, in most countries, this correlation is significantly positive at low frequencies while not always significantly different from 0 at higher frequencies. This confirms our analysis: excess returns and real activity are strongly linked at low frequencies, because they share possibly common structural determinants; conversely, at shorter horizons, the determinants of these variables can differ. Graph 8 reports the dynamic correlation between consumption growth and excess returns. Once again, we obtain similar results, even though the dynamic correlation appears to be higher at higher frequencies for some countries.

If we compare the cyclical and structural components of the real activity indicator, stock prices and interest rates, we see that in most countries studied (Table 6), with the notable exception of France, the correlation between the cyclical component of GDP and that of the nominal interest rate is positive for negative  $k$  and negative for positive  $k$ . These results seem to point to a stabilising monetary policy: temporary rises in the level of real activity are followed by temporary increases in the money market rate, which precede a decline in the cyclical component of GDP. The difference in the French case may be due, *inter alia*, to the implementation of the “strong franc” policy at the start of the 1980s, which introduced a break.

We do not, however, detect a significant relationship between the cyclical component of excess returns and that of money market rates (Table 7), except in the United Kingdom: overall, short-term fluctuations in excess returns appear in some respects to be independent of those in money market rates. If we use these rates to represent monetary policy, this analysis does not rule out the possibility that monetary authorities may have reacted to some stock market events, but it indicates that, in general, stock price fluctuations do not play a determining role in the conduct of their policy. In results not reported here, we obtain confirmation of this conclusion with the dynamic correlation approach. The latter is not found statistically significant at business cycle frequencies.

Table 8 suggests that there is a negative relationship between the long-term component of the money market rate and that of real GDP in the United States, France and Germany (where we observe a lag).<sup>15</sup>

This relationship means that a lasting rise in the money market rate results in a fall in the growth rate of the long-term component of GDP. We could enhance the interpretation of this result by comparing the long-term components of real activity with those of real interest rates, calculated *ex ante*, in keeping with economic theory. However, this exercise is not easy because no simple and reliable measurement of this interest rate is available.

Lastly, we do not detect a significant link between the long-term component of the money market rate and that of excess returns (Table 9), except in the United Kingdom and to a lesser extent in the United States. The long-term component of interest rates therefore does not appear to react to the structural component of excess returns, except in the United Kingdom and the United States, no doubt owing to the weight of equities in household wealth that characterises these countries.

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<sup>14</sup> We can compare these conclusions with those of Daniel and Marshall (1998). These authors show that it is not possible to reject the augmented C-CAPM models when consumption and excess returns have been stripped of their short-term cyclical movements.

<sup>15</sup> Once again, we obtain similar results with the dynamic correlation approach.

## Conclusion

In order to understand the link between business cycles and stock market cycles and use it to improve the conduct of monetary policy, it is first necessary to identify the stylised facts underlying this relationship.

In practice, we set out to study the links between business and stock market cycles by using two complementary approaches that enable us to measure the co-movements between these phenomena.

First, in the tradition of the NBER, we defined the business cycle as a succession of phases of expansion and contraction in order to compare the cycles based on two variables by calculating their concordance index. Above all, this exercise allowed us to identify significant concordance between the business and stock market cycles in the United States.

Second, using the predominant methodology in applied macroeconomics, we analysed this link by decomposing the variables studied into short- and long-term components and by calculating the correlations between corresponding components (ie cyclical/cyclical and structural/structural).

We draw two conclusions from the various analyses carried out: (i) there does not seem to be a strong dependence link between stock prices and the level of real activity at business cycle frequencies, except in the United States; and (ii) in the longer term, it appears that real activity and stock prices share the same determinants. At any rate, we cannot clearly identify an impact of asset prices on three-month interest rates, used to represent monetary policy in the countries studied. In general, we do not detect a significant relationship between the cyclical components of excess returns and money market rates, nor do we observe a significant link between the structural components of these same variables.

These conclusions appear to be robust. However, it may be useful to further investigate the dichotomy between the short and long term using an approach based on a behavioural analysis of agents (or a microeconomic analysis of markets). In particular, we will attempt to identify the transmission mechanisms that enable us to detect links between business and stock market cycles.

Table 1

**Concordance between real and financial cycles**

	United States	France	Germany	United Kingdom	Italy
GDP	0.68687*	0.61616	0.62626	0.58586	0.54545*
Consumption	0.64646*	0.60606	0.66667*	0.59596	0.53535
Sales	0.73874*	0.54655	0.56456	0.62462*	...

Note: A star denotes a coefficient significant at the 5% level. These levels are determined according to the method advocated by Harding and Pagan (2002b).

Table 2

**Short-run correlation, GDP-stock prices**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	-0.0097	-0.1872	-0.2940	-0.2835	-0.1528*	0.0493	0.2461*
France	-0.0020	0.1015	0.2178	0.2884	0.2729*	0.1789*	0.0377
Germany	-0.1131	-0.1129	-0.0438	0.0656	0.1666*	0.2357*	0.2625*
United Kingdom	0.1215	0.1276	0.0875	0.0070	-0.0675	-0.1023	-0.0938
Italy	0.1279	0.1631	0.1647	0.1381	0.0997	0.0769	0.0731

Note: Correlation between  $y_{t+k}^{st}(i)$  and  $x_t^{st}(i)$ , where *i* is the country in the first column.

Table 3

**Short-run correlation, consumption-stock prices**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	-0.1076	-0.1958	-0.2181	-0.1530	-0.0165	0.1352	0.2368*
France	-0.2315	-0.0839	0.0949	0.2280	0.2929*	0.2659*	0.1707
Germany	-0.1902	-0.2442	-0.2528	-0.2024	-0.0995	0.0502	0.2125*
United Kingdom	0.0208	-0.0262	-0.0816	-0.0975	-0.0609	0.012	0.0248
Italy	-0.0323	0.0018	0.0369	0.0793	0.1251	0.1830*	0.2362

Note: Correlation between  $c_{t+k}^{st}(i)$  and  $x_t^{st}(i)$ .

Table 4

**Long-run correlation, GDP-stock prices**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	0.6243*	0.6528*	0.6665*	0.6653*	0.6415*	0.6073*	0.5641*
France	0.1872*	0.3062*	0.4179*	0.5197*	0.5997*	0.6650*	0.7143*
Germany	0.0622	0.1381	0.2128	0.2845	0.3265*	0.3663*	0.4029*
United Kingdom	0.6161*	0.6242*	0.6175*	0.5965*	0.5586*	0.5093*	0.4501*
Italy	0.4909*	0.5735*	0.6424*	0.6959*	0.7254	0.7423	0.7462

Note: Correlation between  $\Delta y_{t+k}^{st}(i)$  and  $x_t^{st}(i)$ .

Table 5

**Long-run correlation, consumption-stock prices**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	0.3898	0.4041	0.4091*	0.4054*	0.4060	0.3889*	0.3850*
France	0.0629	0.1698*	0.2714*	0.3653*	0.4580*	0.5369*	0.6006*
Germany	0.0974	0.1675	0.2362	0.3019	0.3425*	0.3804*	0.4149*
United Kingdom	0.3423	0.3855	0.4175	0.4380	0.4556*	0.4602*	0.4522*
Italy	0.3377*	0.4391*	0.5305*	0.6098*	0.6598*	0.6991*	0.7266*

Note: Correlation between  $\Delta c_{t+k}^{st}(i)$  and  $x_t^{st}(i)$ .

Table 6

**Short-run correlation, GDP-money market rates**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	0.5341*	0.6218*	0.6334*	0.5430*	0.3629*	0.1096	-0.1750*
France	0.1775	0.1996	0.1827	0.1188	0.0219	-0.0801	-0.1720
Germany	0.7303*	0.7233*	0.6299*	0.4475*	0.2020*	-0.0585*	-0.2846*
United Kingdom	0.5535*	0.5172*	0.3870*	0.1663	-0.0904	-0.3187*	-0.4740*
Italy	0.5129*	0.5983*	0.5702*	0.4524*	0.2644	0.0973	-0.0137

Table 7

**Short-run correlation, excess returns-money market rates**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	-0.0115	-0.1372	-0.22137*	-0.2298	-0.1842	-0.1009	-0.0007
France	-0.1078	-0.1159	-0.0643	-0.0195	-0.0058	-0.0222	-0.0417
Germany	0.0796	0.0778	0.0580	0.0235	-0.0111	-0.0231	-0.0007
United Kingdom	-0.1632	-0.729	0.1482	0.3792*	0.4989*	0.4289*	0.2083*
Italy	-0.0950	-0.0931	-0.0750	-0.0301	0.0367	0.1051	0.1381*

Table 8

**Long-run correlation, GDP-money market rates**

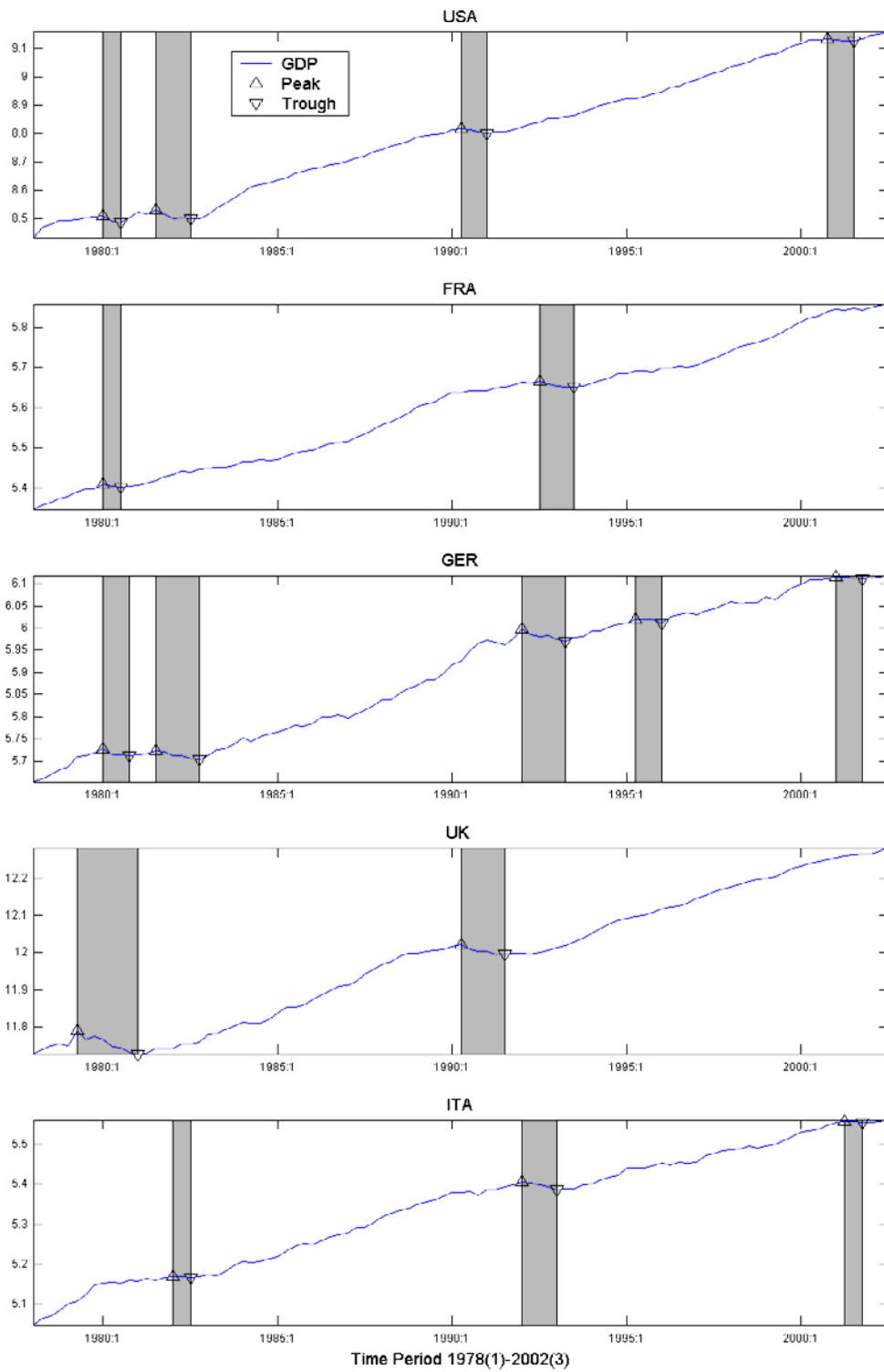
<i>k</i>	-3	-2	-1	0	1	2	3
United States	-0.2332	-0.2493	-0.2600*	-0.2646*	-0.2761*	-0.2776*	-0.2685*
France	-0.2404	-0.2906*	-0.3363*	-0.3764*	-0.4187	-0.4549	-0.4835
Germany	0.1101	0.0233	-0.0612	-0.1417	-0.2272	-0.3044*	-0.3715*
United Kingdom	-0.3266	-0.3582	-0.3824	-0.3986	-0.4026	-0.3929	-0.3691
Italy	0.1183	0.0932*	0.0732	0.0587	0.0309	0.0086	-0.0077

Table 9

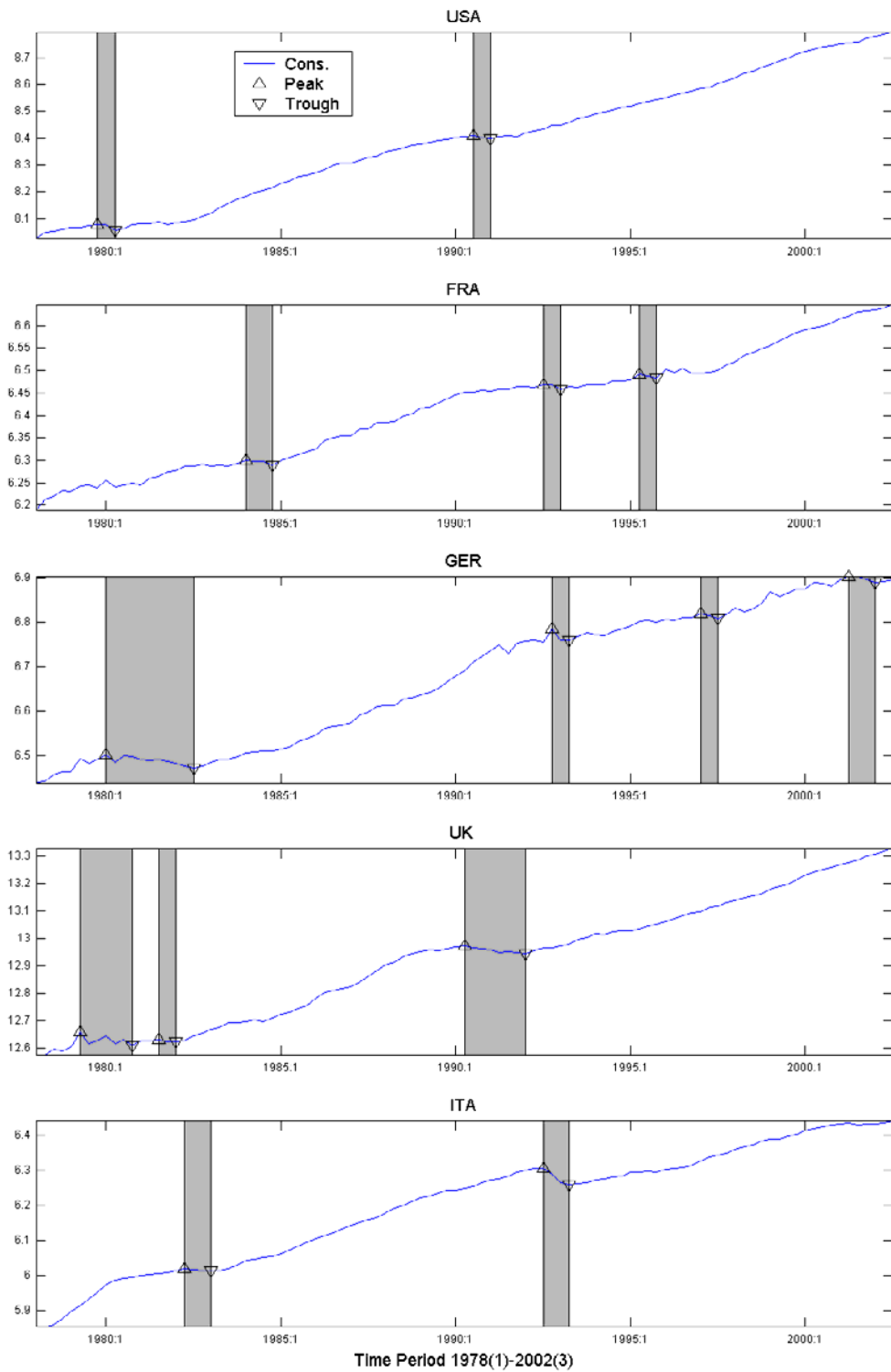
**Long-run correlation, excess returns-money market rates**

<i>k</i>	-3	-2	-1	0	1	2	3
United States	0.0312	0.0615	0.0895	0.1155*	0.0606	0.0112	-0.0316
France	-0.167	-0.1386	-0.0995	-0.0497	-0.0618	-0.0630	-0.0528
Germany	-0.2636	-0.2238	-0.1724	-0.1097	-0.1036	-0.0860	-0.0571
United Kingdom	0.2013*	-0.2068*	0.2163*	0.2305*	0.1796	0.1347	0.0971
Italy	0.0489	0.147	0.1693	0.2421	0.2326	0.2276	0.2270

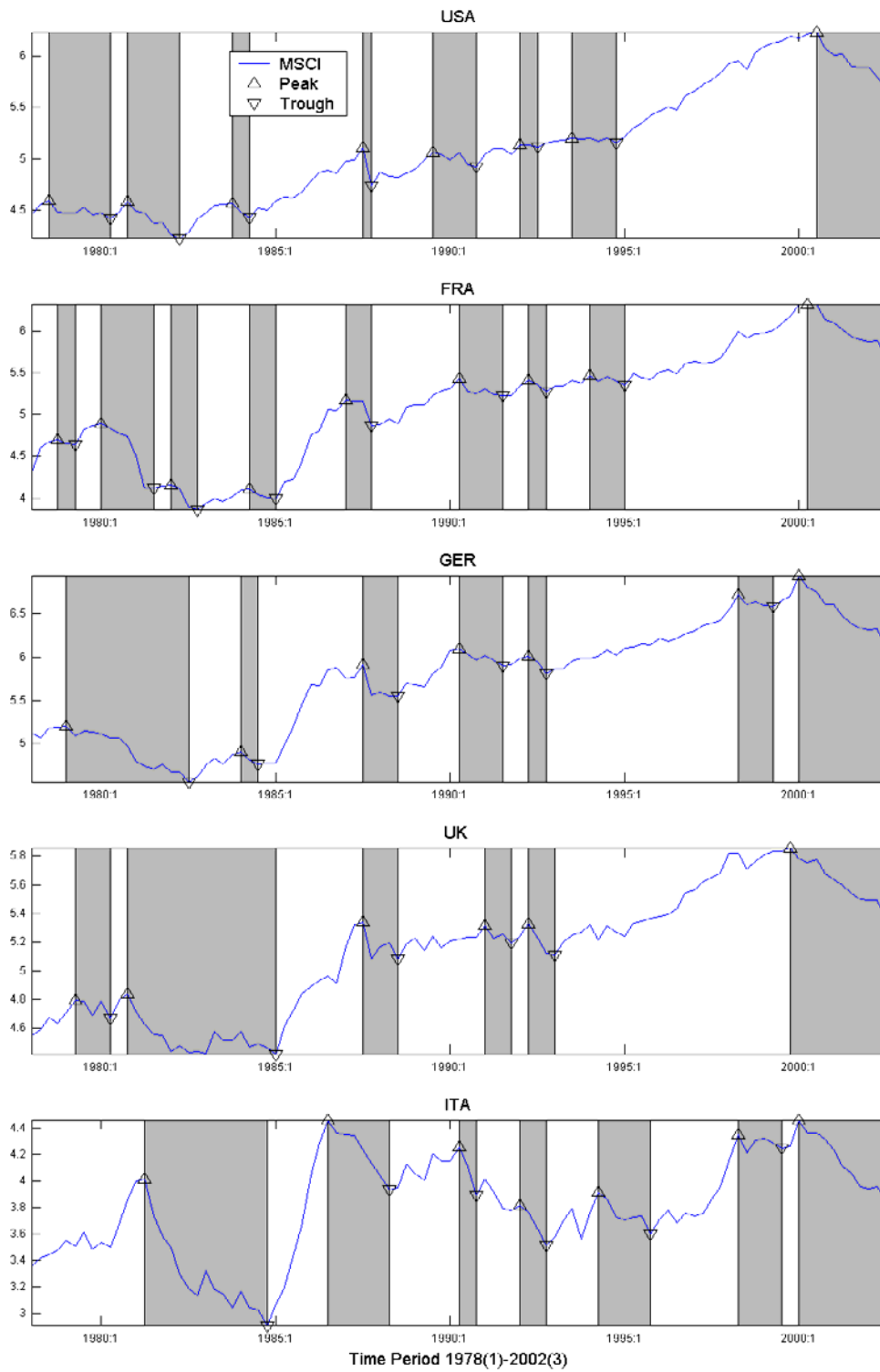
Graph 1  
Turning points of real GDP



Graph 2  
Turning points of real private consumption

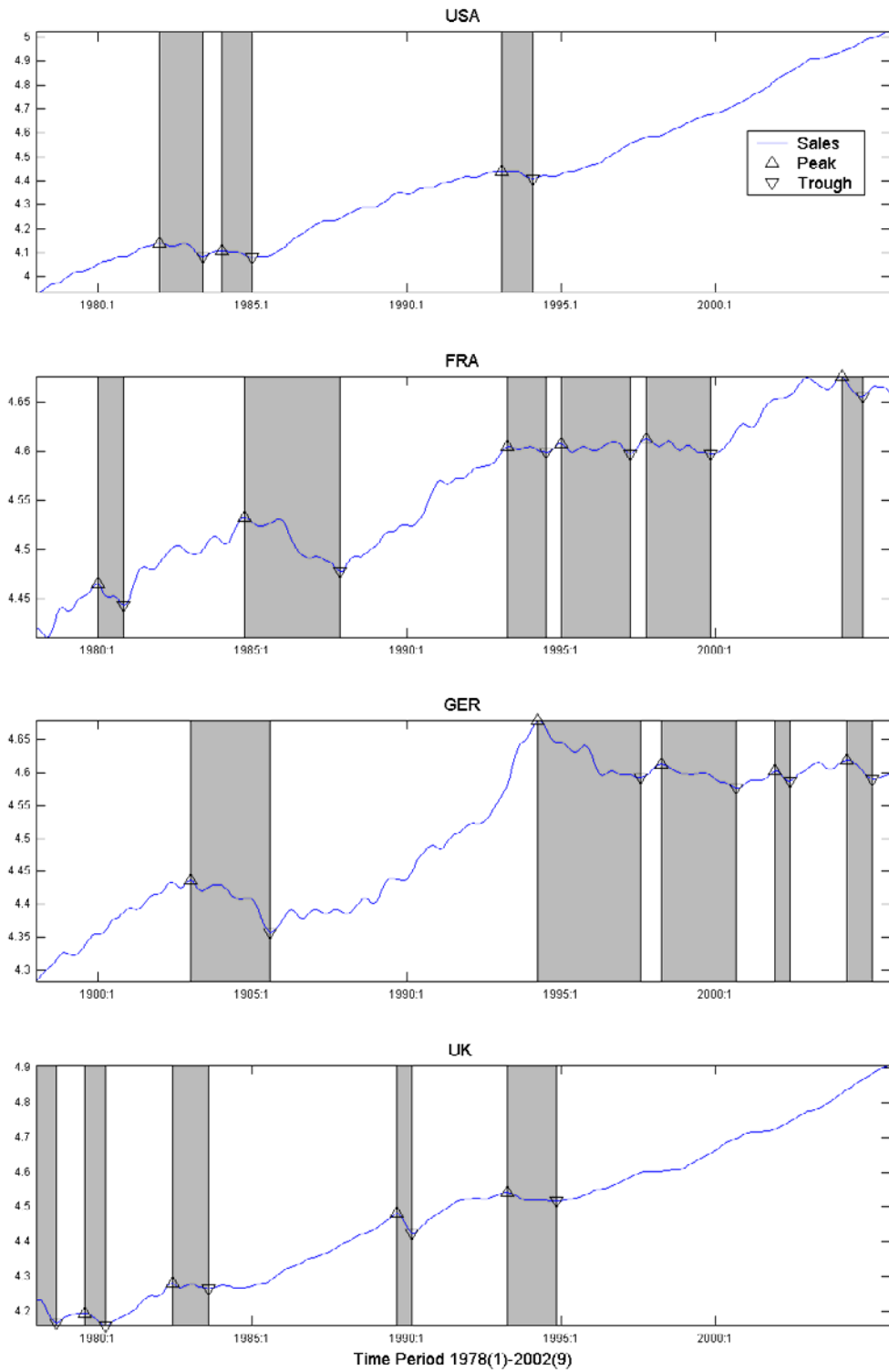


Graph 3  
**Turning points of MSCI return indices**

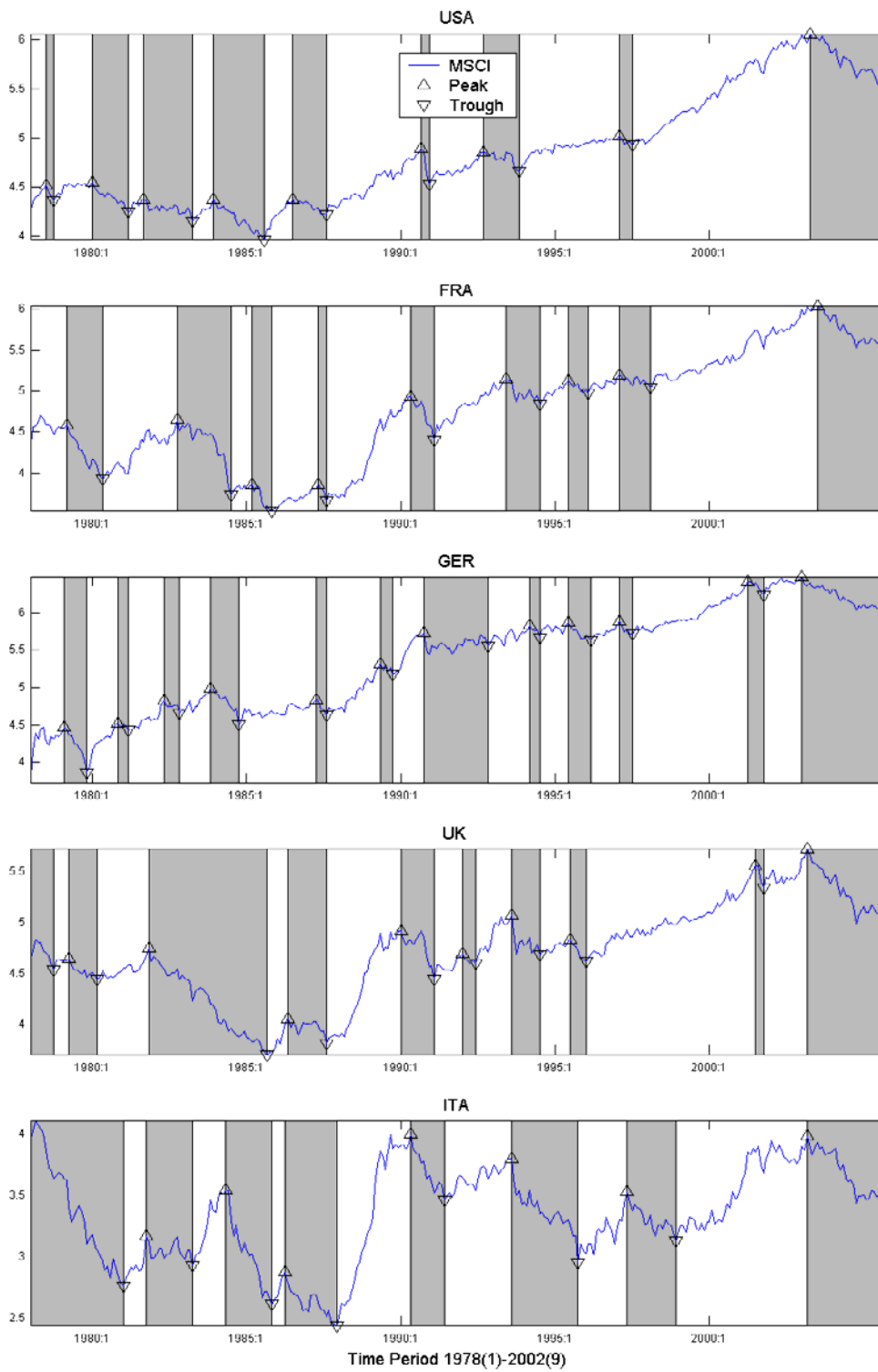




Graph 4  
**Turning points of real retail sales index (filtered)**

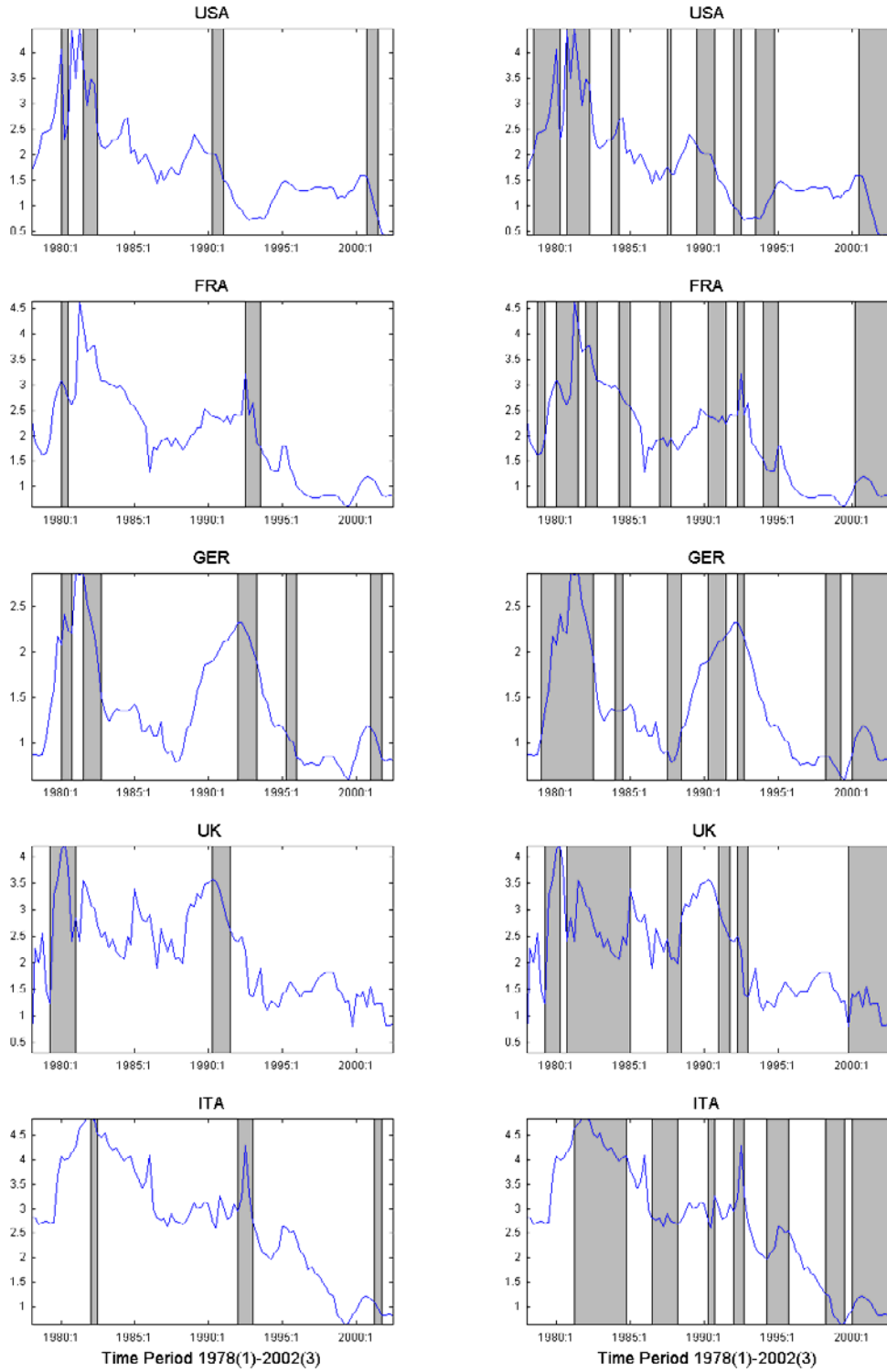


Graph 5  
**Turning points of monthly MSCI indices**



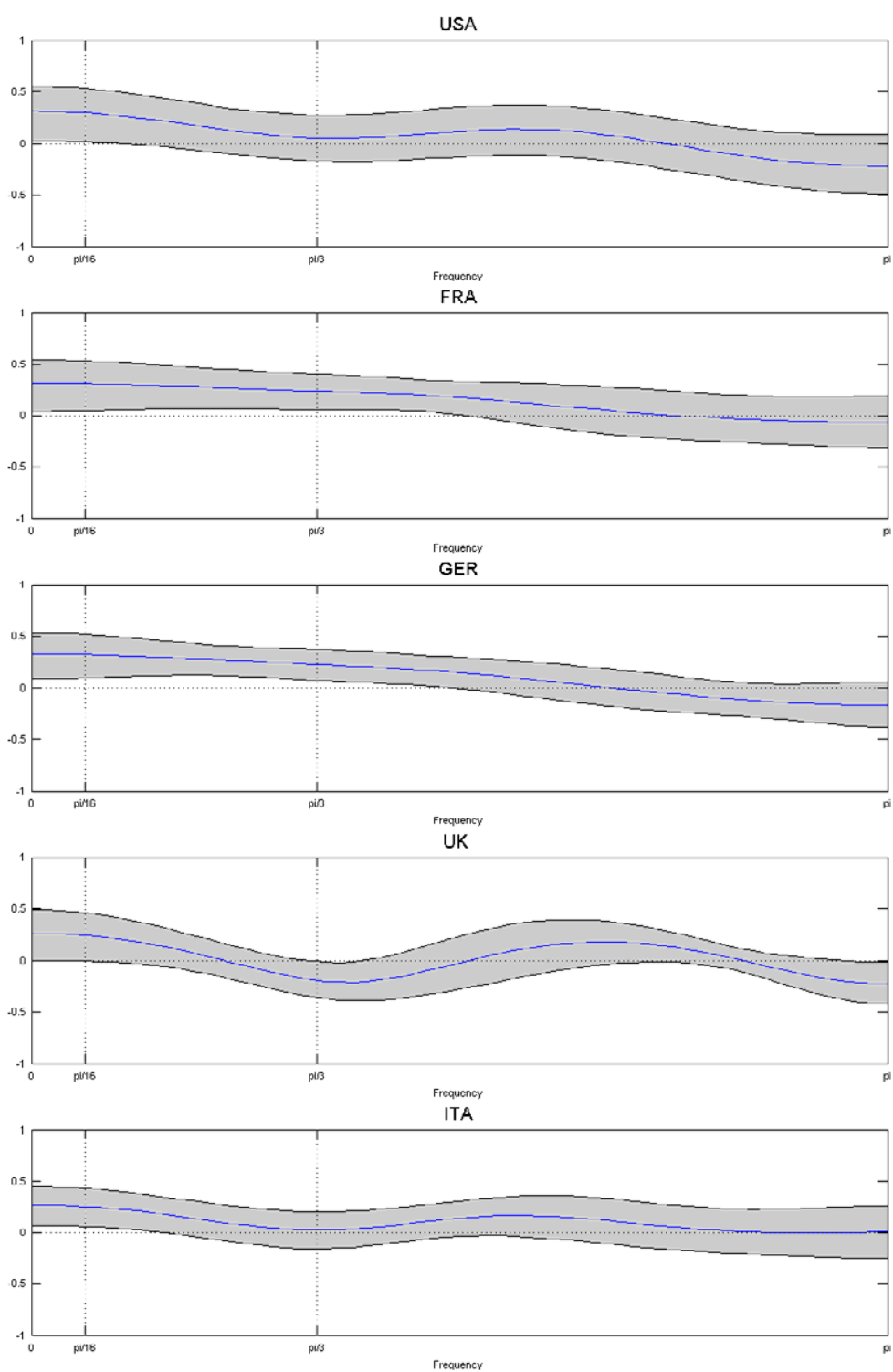
Graph 6

**Money rates and GDP turning points (left-hand column)  
and return index turning points (right-hand column)**



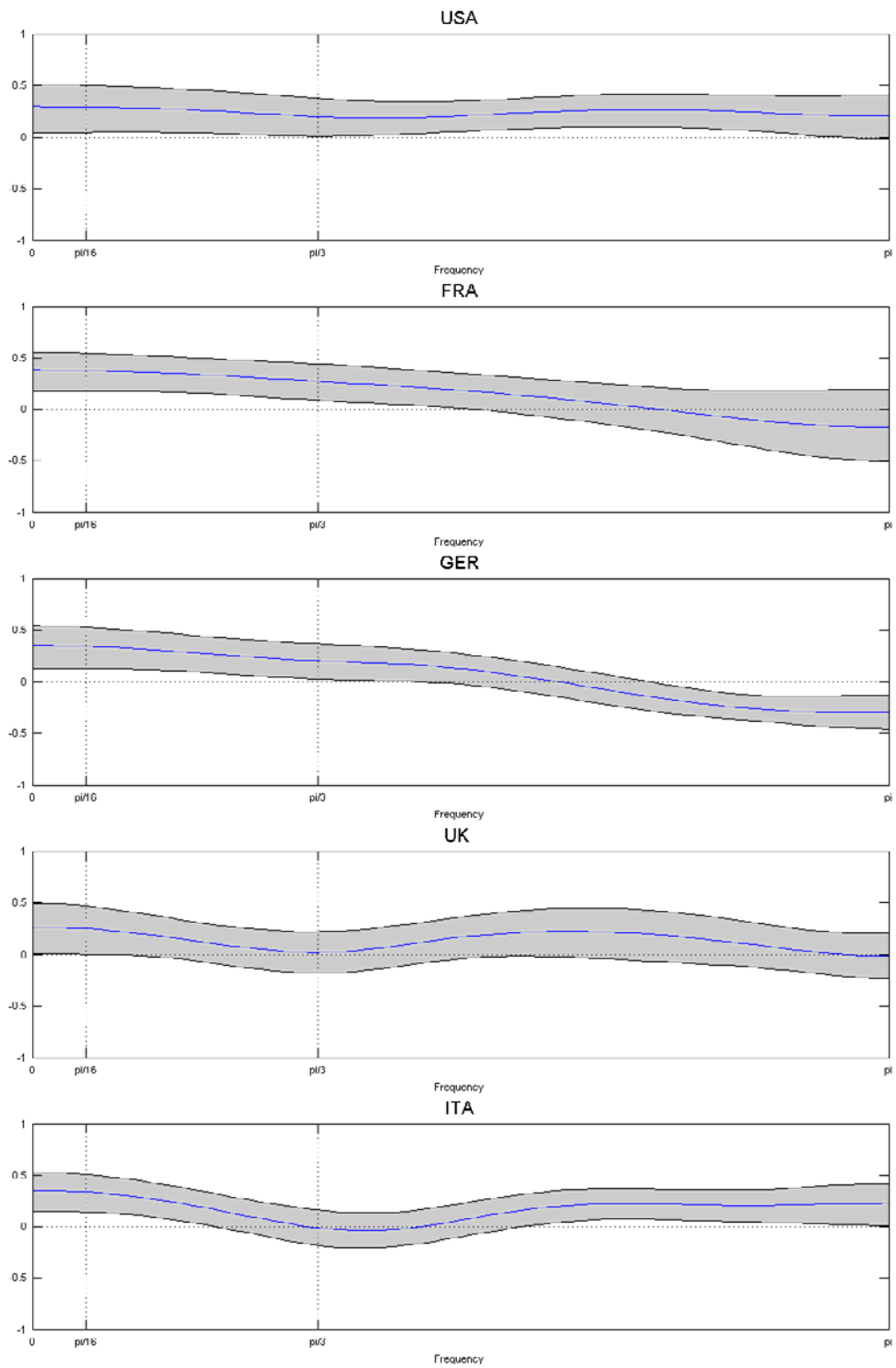
Graph 7

Dynamic correlation between GDP growth and excess returns



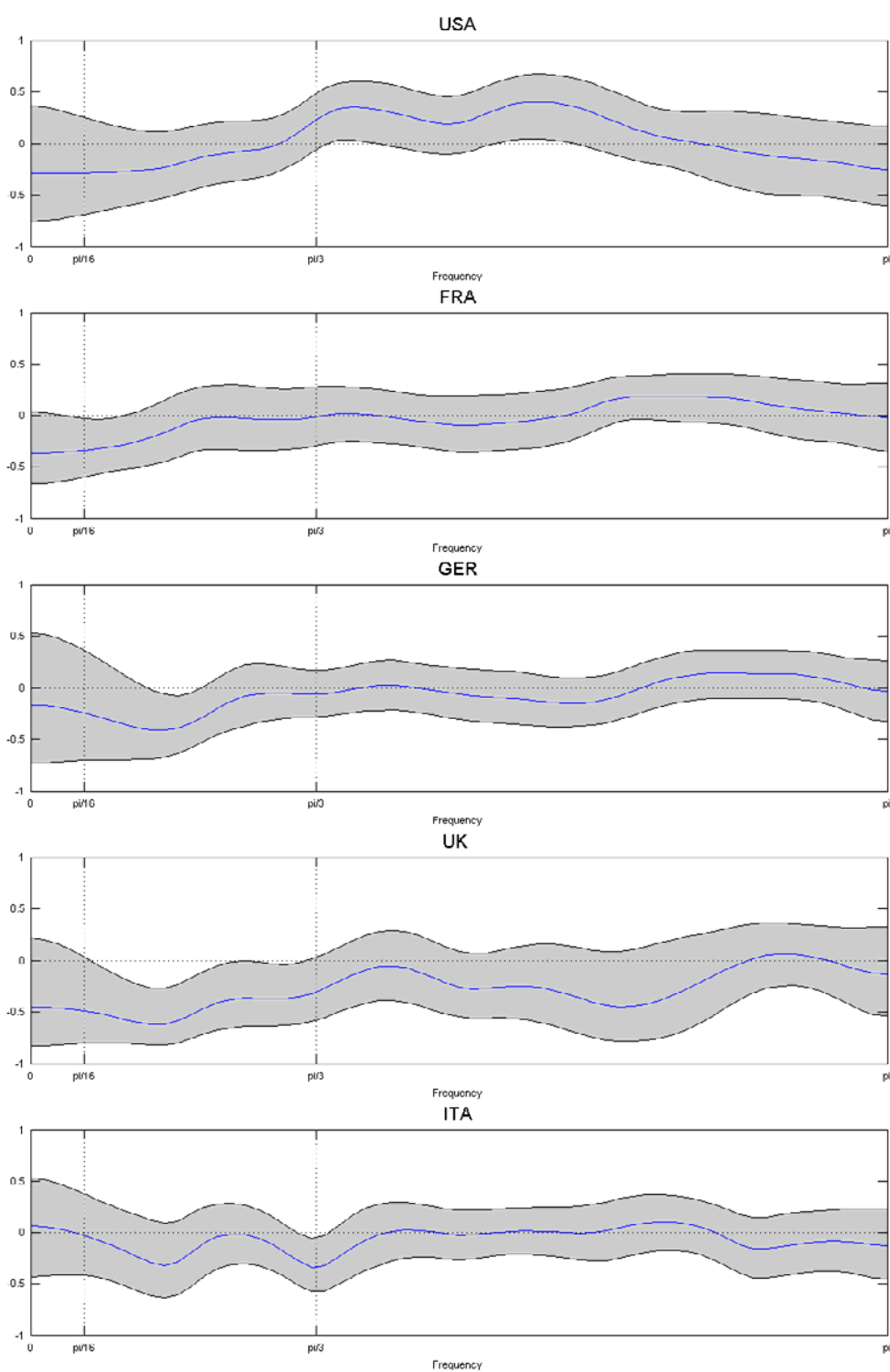
Graph 8

Dynamic correlation between consumption growth and excess returns



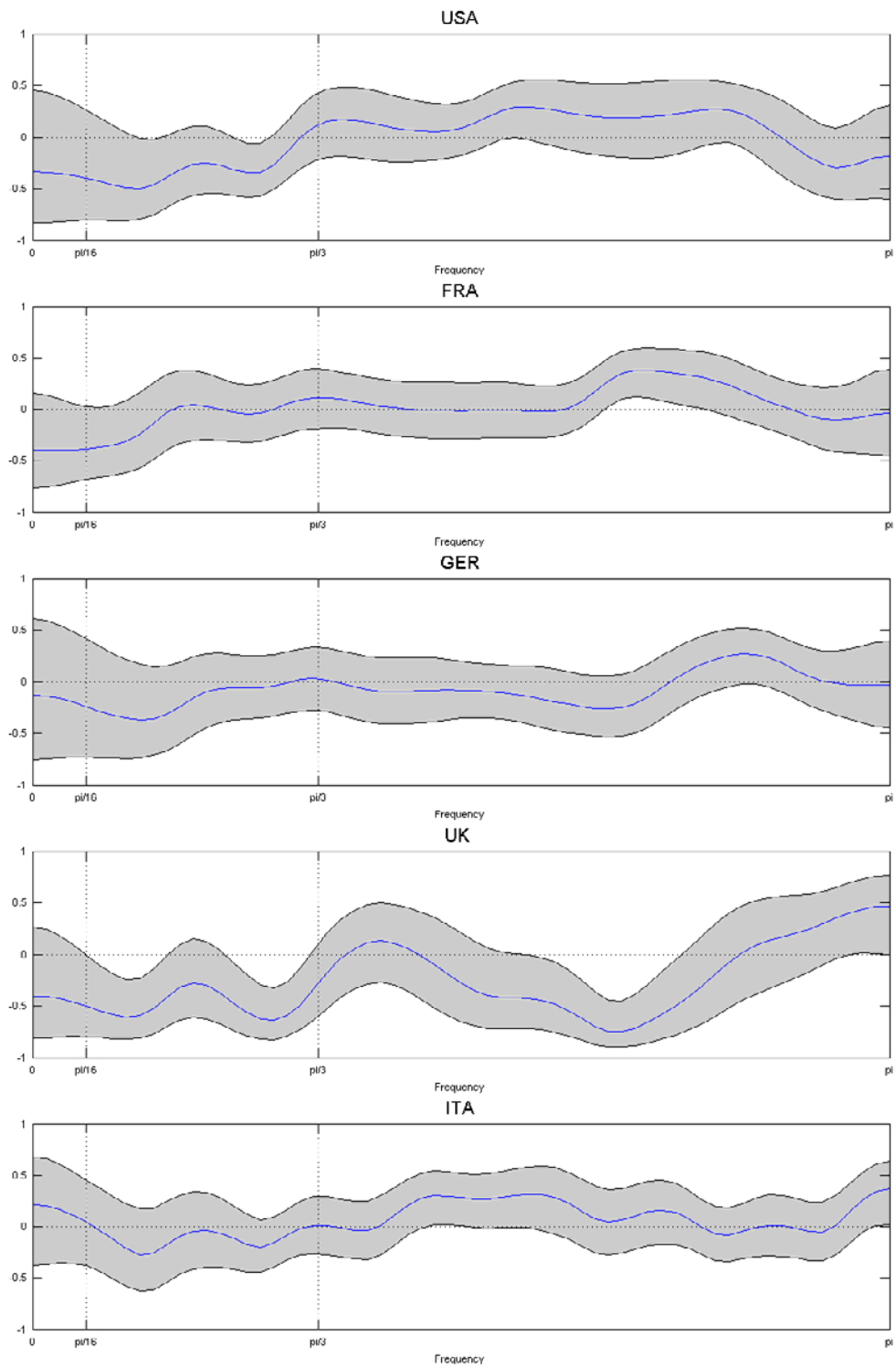
Graph 9

Dynamic correlation between GDP growth and money market rates



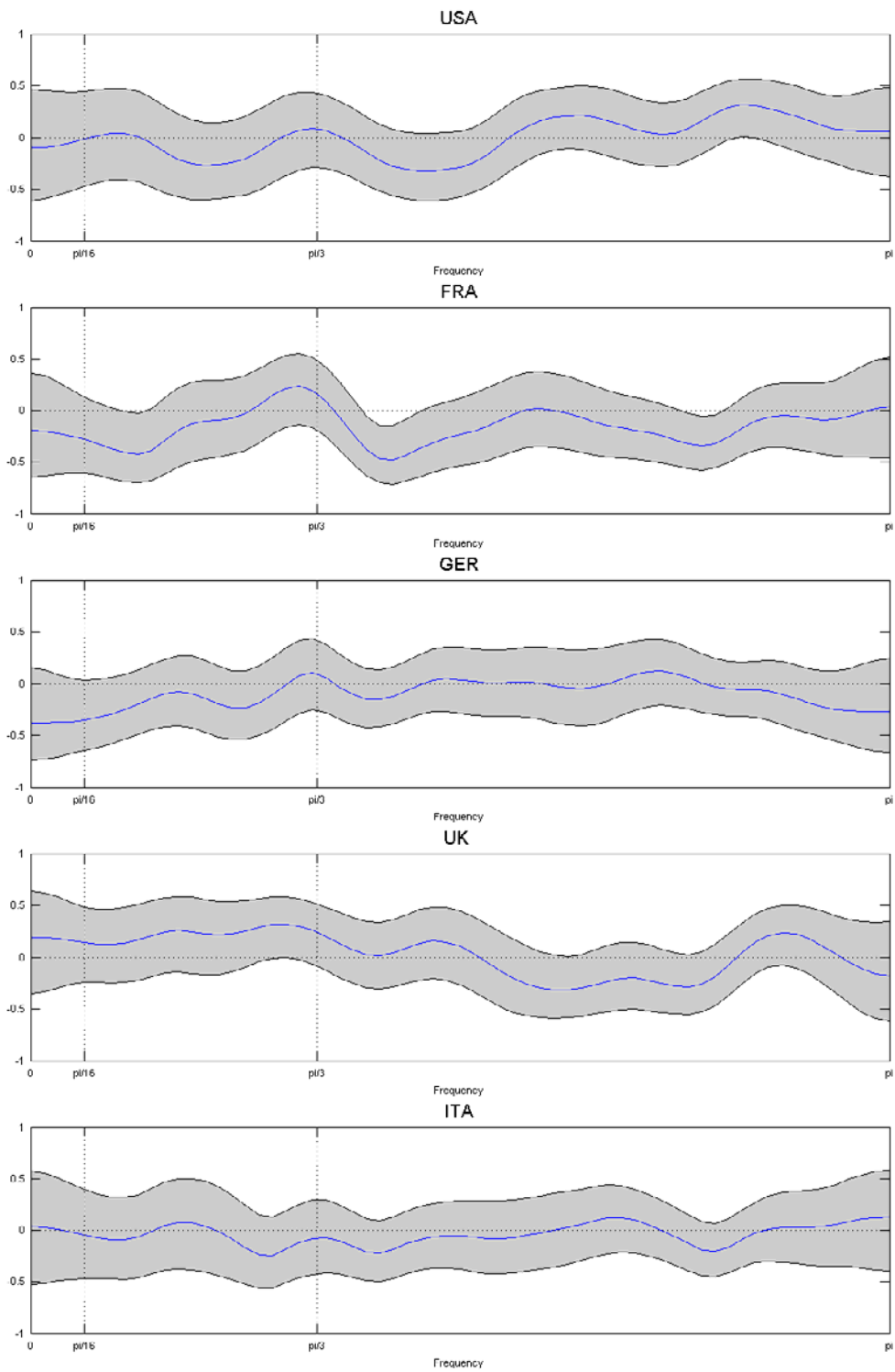
Graph 10

Dynamic correlation between consumption growth and money market rates



Graph 11

Dynamic correlation between excess returns and money market rates





## Appendix A

### Turning points and concordance

Bry and Boschan (1971) determined an algorithm that made it possible to replicate the contraction start dates identified by a committee of experts from the NBER. We used a variation of this algorithm, developed by Harding and Pagan (2002a,b), whose steps are as follows:

1. A peak/trough is reached at  $t$  if the value of the series at date  $t$  is superior/inferior to previous  $k$  values and to the following  $k$  values, where  $k$  is a positive integer that varies according to the type of series studied and its sampling frequency.<sup>16</sup>
2. A procedure is implemented to ensure that peaks and troughs alternate, by selecting the highest/lowest consecutive peaks/troughs.<sup>17</sup>
3. Cycles whose duration is shorter than the minimum time  $m$  are stripped out, as are cycles whose complete recurrence period (number of periods separating a peak from a peak or a trough from a trough) is lower than the prespecified number of periods  $M$ .
4. Complementary rules are applied:
  - (a) the first peak/trough cannot be lower/higher than the first point in the series, and the last peak/trough cannot be lower/higher than the last point in the series;
  - (b) the first/last peak/trough cannot be positioned at less than  $e$  periods from the first/last point in the series.

The monthly sales index is prefiltered using a Spencer curve, in accordance with the usual procedure adopted in the literature. The latter defines the filtered series  $\tilde{x}_t$  from the raw series  $x_t$  according to:

$$\tilde{x}_t = \sum_{i=-7}^7 s_i x_{t+i}, \quad s_i = s_{-i} \quad \text{for } i = 1, \dots, 7$$

$$s_0 = \frac{74}{320}, \quad s_1 = \frac{67}{320}, \quad s_2 = \frac{46}{320}, \quad s_3 = \frac{21}{320}, \quad s_4 = \frac{3}{320}, \quad s_5 = -\frac{5}{320}, \quad s_6 = -\frac{6}{320}, \quad s_7 = -\frac{3}{320}.$$

Note that, like Pagan and Sossounov (2003), we do not prefilter the monthly financial series. Moreover, in the latter case, imposing a minimum phase  $m$  may be restrictive. Pagan and Sossounov therefore propose relaxing the constraint on the minimum phase when a fall or a rise in excess of 20% is present in a period. We adopt this procedure here.

A contraction/expansion phase is thus defined as the time separating a peak/trough from a trough/peak, when the sequence of peaks and troughs meets all the identification rules listed above.

Note that the identification of turning points is very sensitive to the choice of parameters  $k$ ,  $e$ ,  $m$  and  $M$ : if the latter are set to small values, almost all absolute declines in the level of a series will be identified as troughs, all the more so as the original variable is not too smooth. On the other hand, if these are set to large values, the procedure will come up with almost no turning points.

The choice of  $k$ ,  $e$ ,  $m$  and  $M$  depends upon the series under consideration and their sampling frequency. For example, if  $y$  denotes logged real quarterly GDP, one generally sets  $k = 2$ ,  $e = 2$ ,  $m = 2$  and  $M = 5$ . These values allow us to replicate the NBER business cycle dates.

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<sup>16</sup> In this method used for identifying turning points, it is not necessary to assume that the series studied is stationary.

<sup>17</sup> This criterion is not always adopted in the literature (see Canova (1999)).

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