How Do Financial Cycles Interact? Evidence from the US and the UK

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Are financial cycles an international phenomenon, and, if so, how do financial cycles interact? This letter provides new evidence for the US and the UK. Considering the properties of the data in both the time and the frequency domains, we find a strong relation between the financial cycles of the US and the UK. US financial cycles have a significant impact on the UK, but not the other way around. The relation is clearly most pronounced for cycles between 8 and 30 years, which is also the frequency range that explains almost all variation of the data.

Keywords: Financial Cycle, Vector Autoregressions, Indirect Spectrum Estimation, Coherency, Granger Causality

JEL classification: C22, E32, E44

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1 Introduction

The recent 2007-08 financial crisis has led to a renewed interest in the study of financial cycles and their role in macroeconomic activity. There is strong evidence that financial cycles operate at lower frequencies and feature larger amplitudes than business cycles. This is documented by a turning point analysis of Claessens et al. (2011) and through frequency-based filter methods by Drehmann et al. (2012). Using an indirect spectrum estimation approach, Strohsal et al. (2015) find that financial cycles in the US and the UK have a length of about 15 years, which is significantly longer than that of a business cycle. Claessens et al. (2012) analyze the relation between the business and the financial cycle and show that recessions are much deeper and longer when occurring at the same time as financial disruptions; see also Breitung and Eickmeier (2014).

Borio (2014) points out a further important aspect of financial cycles: they seem, to a large extent, an international phenomenon. Linkages between financial cycles of different countries are, however, not yet at the focus of empirical studies.

This paper contributes to fill this gap by providing a comprehensive picture of the linkage between financial cycles in the US and the UK. We show that to fully understand the cross-country interaction, it is crucial to consider the properties of the data in both the time and the frequency domains. In the time domain, we estimate vector autoregressive (VAR) models and analyze the corresponding impulse response functions and variance decompositions as well as conduct traditional Granger causality tests. Then, we transform the estimated models into the frequency domain in order to examine whether the financial indicators and their relation are indeed mostly driven by low frequencies in the financial cycle range. We study spectral densities, the coherency and a measure of frequency-wise Granger causality discussed in Geweke (1982) and Breitung and Candelon (2006).

During the period of financial liberalization, starting in 1985, we find a strong relation between US and UK financial variables. Significant Granger causality from the US to the UK, but not the other way around, indicates the leading role of the US financial cycle for the UK. Most importantly, the interaction is clearly strongest at low frequencies between 8 and 30 years, which is also the frequency range that explains almost all variation of the data. In the pre-1985 period, we only find a relation in the business cycle range of 2 to 8 years. This relation is, however, very weak.

The paper is structured as follows. Section 2 presents the methodology in the time and frequency domains. In Section 3 we briefly describe the data, particularly the construction of the financial indicators, and the model specification procedure. The empirical results are discussed in detail in Section 4. Section 5 provides concluding remarks.

2 Methodology

2.1 Time Domain: Vector Autoregression

Our starting point is a stable VAR model of order p for two variables $(y_t, \;\; x_t)' = z_t$,

$$z_t = A_1 z_{t-1} + \cdots + A_p z_{t-p} + u_t \tag{1}$$

where A_j, $j = 1, 2, \ldots, p$ are (2×2) coefficient matrices; for the following see e.g. Kirchgässner et al. (2013, ch. 4). While we ignore deterministic terms in the theoretical representation, we include constant terms and linear trends in the empirical analysis where we use level data. Applying ordinary least squares to (1) yields consistent estimates, even in the case of non-stationary time series; see Hamilton (1994). The two-dimensional error vector u_t is assumed to be white noise with $\mathrm{E}(u_t) = 0$ and the positive definite (2×2) variance-covariance matrix $\mathrm{E}(u_t u_t') = \Sigma$.

Since (1) is a reduced form, the cross-correlated u's cannot be used for economic interpretation. Therefore, we introduce the innovations w_t which are uncorrelated and have unit variances. They are obtained from the linear transformation

$$u_t = P w_t \quad \text{with} \quad PP' = \Sigma \;. \tag{2}$$

We consider a Choleski decomposition of Σ that uniquely determines P as a lower triangular regular matrix and implies a recursive structural system.

The moving average representation of (1) in terms of the innovations w_t is suitable for economic interpretation in the time domain. Using the lag operator L defined as $L^k z_t = z_{t-k}$, $k = \cdots - 1, 0, 1, \ldots$ and the transformation defined in equation (2) we get

$$z_t = (I - A_1 L - \cdots - A_p L^p)^{-1} P w_t \;. \tag{3}$$

In the time domain, equation (3) represents the basis for the analysis of impulse response functions, error-variance decompositions and Granger causality.

2.2 Frequency Domain: Multivariate Spectral Analysis

Since we are especially interested in getting information about the relationship of financial cycles, we transform the VAR system into the frequency domain.[1] This allows us to analyze at which frequencies most of the interaction takes place.

The (2×2) spectral matrix is obtained from (2) and (3) and has the form

$$F_z(\lambda) = (I - A_1 e^{-i\lambda} - \cdots - A_p e^{-ip\lambda})^{-1} \frac{\Sigma}{2\pi} (I - A_1 e^{i\lambda} - \cdots - A_p e^{ip\lambda})^{-1'} \tag{4}$$

[1] The spectral methods are presented in detail by e.g. Wolters (1980) and applied by Kirchgässner and Wolters (1994).

with $i^2 = -1$ and $0 \leq \lambda \leq \pi$. It includes the spectra and cross-spectra of the time series y_t and x_t

$$F_z(\lambda) = \begin{pmatrix} f_{yy}(\lambda) & f_{yx}(\lambda) \\ f_{xy}(\lambda) & f_{xx}(\lambda) \end{pmatrix} \quad . \tag{5}$$

The real valued spectra $f_{yy}(\lambda)$ and $f_{xx}(\lambda)$ represent orthogonal decompositions of the variances of y and x in cyclical components. Normalizing the spectra by the process variances yields the spectral densities which include information about the variance contributions of cycles at different frequencies.

The off-diagonal elements of $F_z(\lambda)$ are the complex valued cross-spectra $f_{yx}(\lambda)$ and $f_{xy}(\lambda) = \overline{f_{yx}}(\lambda)$. For measuring the strength of the relation between y and x, we consider the squared coherency

$$K^2_{yx}(\lambda) = \frac{|f_{yx}(\lambda)|^2}{f_{yy}(\lambda) f_{xx}(\lambda)} = K^2_{xy}(\lambda) \tag{6}$$

with $0 \leq K^2_{yx}(\lambda) \leq 1$. It is the analogon to the coefficient of determination R^2 for a linear relation between the cycles of y and x at frequency λ. In contrast to the R^2, however, the coherency is invariant to different linear transformations applied to y and x. It does not change when regressing y on x or x on y. If x and y are cointegrated, the squared coherency at frequency zero equals one; see Granger and Weiss (1983).

To analyze Granger causality at different frequencies, we apply a measure proposed by Geweke (1982, 1984) and Breitung and Candelon (2006). Defining the (2×2) matrix

$$B(L) = (I - A_1 L - \cdots - A_p L^p)^{-1} P \tag{7}$$

we can rewrite (3) as

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} B_{yy}(L) & B_{yx}(L) \\ B_{xy}(L) & B_{xx}(L) \end{pmatrix} \begin{pmatrix} w_{y_t} \\ w_{x_t} \end{pmatrix} \quad . \tag{8}$$

As the innovations are uncorrelated, from (8) we get

$$f_{yy}(\lambda) = \frac{1}{2\pi} (|B_{yy}(e^{-i\lambda})|^2 + |B_{yx}(e^{-i\lambda})|^2) \quad . \tag{9}$$

This representation separates the contributions of y (i.e. B_{yy}) and x (i.e. B_{yx}) to the spectrum of y and therefore allows us to test for Granger causality at any frequency λ. The null hypothesis is that x is not Granger causal to y, meaning $B_{yx}(e^{-i\lambda}) = 0$, and implies that no lagged values of x influence y_t.

The causality measure used in the frequency domain is

$$M_{x \to y}(\lambda) = \ln \left(\frac{2\pi f_{yy}(\lambda)}{|B_{yy}(e^{-i\lambda})|^2} \right) \quad , \tag{10}$$

which leads to

$$M_{x \to y}(\lambda) = \ln \left(1 + \frac{|B_{yx}(e^{-i\lambda})|^2}{|B_{yy}(e^{-i\lambda})|^2} \right) \quad . \tag{11}$$

$M_{x \to y}(\lambda) = 0$ if $|B_{yx}(e^{-i\lambda})|^2 = 0$, i.e., x_t does not Granger cause y_t at frequency λ.

3 Data and Model Specification

Borio (2014) argues that the most parsimonious description of the financial cycle can be obtained from credit and house prices series. Credit represents a direct financing constraint and house prices are seen as a proxy variable for the average perception of value and risk in the economy.

As Strohsal et al. (2015) found, the cyclical properties of credit and housing are remarkably similar. Thus, in order to obtain a single measure of the financial cycle, we create a financial cycle index for each country by computing the first principal component of the two series.[2] We split the quarterly data into two subsamples, 1970Q1-1984Q4 and 1985Q1-2013Q4, to analyze possible changes in the characteristics of the financial cycle over time. The break point at 1985Q1 is specified following Claessens et al. (2011, 2012) and Drehmann et al. (2012) and is considered the starting point of the financial liberalization phase in mature economies. For the US, the first principal component explains 91% (95%) of the total variation in the pre-1985 (post-1985) period. In the case of UK, it explains 79% (98%).[3]

The time series are measured in logs, deflated by the consumer price index and normalized by their value in 1985Q1 to ensure comparability of units. The financial cycle indices are presented in Figure 1. Both series are trending with cycles and show a remarkable comovement.

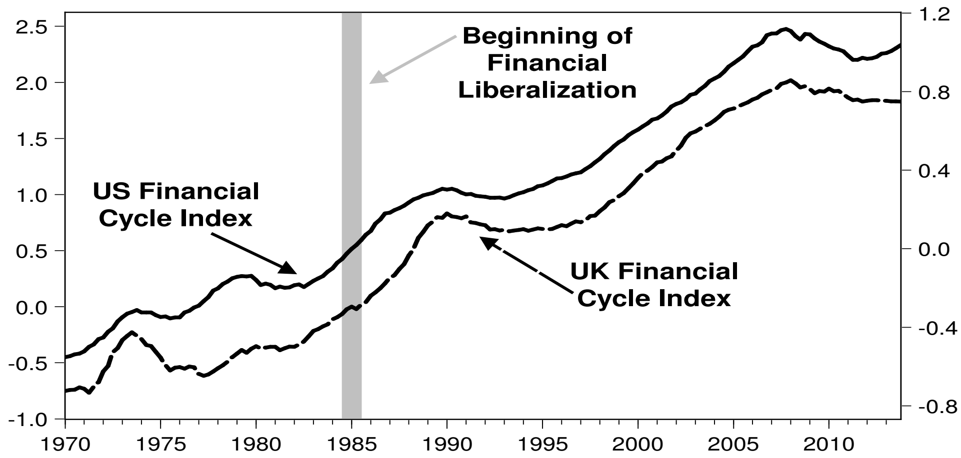

Figure 1 US (solid line, right axes) and UK (dashed line, left axis) Financial Cycle Indices.
Note: The US and UK financial cycle indices are obtained as the first principal component of national credit (source: Datastream) and house price index series (source: OECD.Stat). The gray bar denotes the beginning of the financial liberalization phase, 1985Q1, and indicates the sample split.

Table 1 provides information on the structure of the estimated VAR models for both sample periods. Portmanteau Q-tests show that up to order 24 no significant autocorrelation is left in the residuals. To interpret impulse response functions and variance decompositions,

[2] The empirical results are very similar when considering credit or house prices separately.

[3] US indicators are constructed as $0.94 \cdot \text{credit} + 0.34 \cdot \text{housing}$ and $0.95 \cdot \text{credit} + 0.31 \cdot \text{housing}$ in the first and second sample period, respectively. For the UK, the indicators are $0.82 \cdot \text{credit} + 0.57 \cdot \text{housing}$ and $0.78 \cdot \text{credit} + 0.62 \cdot \text{housing}$.

we use a recursive structural form where we allow for a contemporaneous effect of the US on the UK. The idea being that the US is the natural candidate for the origin of a global financial cycle.

Table 1 Estimated VARs: Included Lags, Deterministic Terms and Autocorrelation Tests

	lags														diagnostics	
sample	1	2	3	4	5	6	7	8	9	10	11	12	c	t	Q(24)	p-value
1970Q1-1984Q4	×	×			×								×	×	87.12	0.39
1985Q1-2013Q4	×	×	×	×	×	×	×		×				×	×	63.20	0.50

Notes: The specification procedure of the reduced form VARs is as follows. We allow for a maximum lag number of 12, include a constant term c, a linear trend t, and use standard information criteria (Akaike, Schwarz and Hannan-Quinn) to obtain the optimal lag length. The model is then refined by including additional lags if necessary to guarantee white noise residuals. This property is checked after each modification by the Portmanteau Q-test with the null of no residual autocorrelation. In the same way, insignificant lags and deterministic terms are removed. Table 1 provides information on the structure of the models for both sample periods. The lags and deterministic terms which are included in the final VAR specification are indicated by $\times$. Q(24) represents the Portmanteau Q-test with the null hypothesis of no residual autocorrelation up to order 24 and the corresponding p-value.

4 Results: How Financial Cycles Interact

4.1 Time Domain: Impulse Response Analysis, Forecast Error Variance Decomposition and Granger Causality

The impulse response functions in the upper part of Figure 2 refer to the pre-1985 period and show that there is only a marginal and temporary reaction of the UK financial indicator to that of the US. In the reverse direction, there is no response at all. From the lower part of Figure 2, however, it is clear that the interaction between the two countries increases substantially during the post-1985 period. Short and medium-term reactions of the UK to US are now significant over extended time intervals.

The variance decompositions in Figure 3 are in line with the impulse response evidence. In both periods, the UK explains only about 20% of the forecast error variance of the US. The influence of the US on the UK, however, is much stronger. In the long-run, up to 40% of the UK variance is explained by US shocks in the first period and as high as 70% in the second period.

These results are further supported by Granger causality tests. Over the pre-1985 sample, the null hypothesis of no Granger causality from the US to the UK is rejected only with a p-value of 0.09 and a test statistic of $\chi^2(4) = 8.06$, reflecting the weak effect seen in the impulse response. In the second sample, the test statistic increases to $\chi^2(9) = 45.98$ which is significant at any conventional confidence level. Causality from the UK to the US cannot be found in either period. The corresponding statistics and p-values are $\chi^2(3) = 3.08$, $p = 0.38$ and $\chi^2(8) = 11.63$, $p = 0.17$, respectively.

While the time domain results are clearly in favor of a significant relation between the financial indicators, it is not possible to infer at which frequencies most of the interaction takes place.

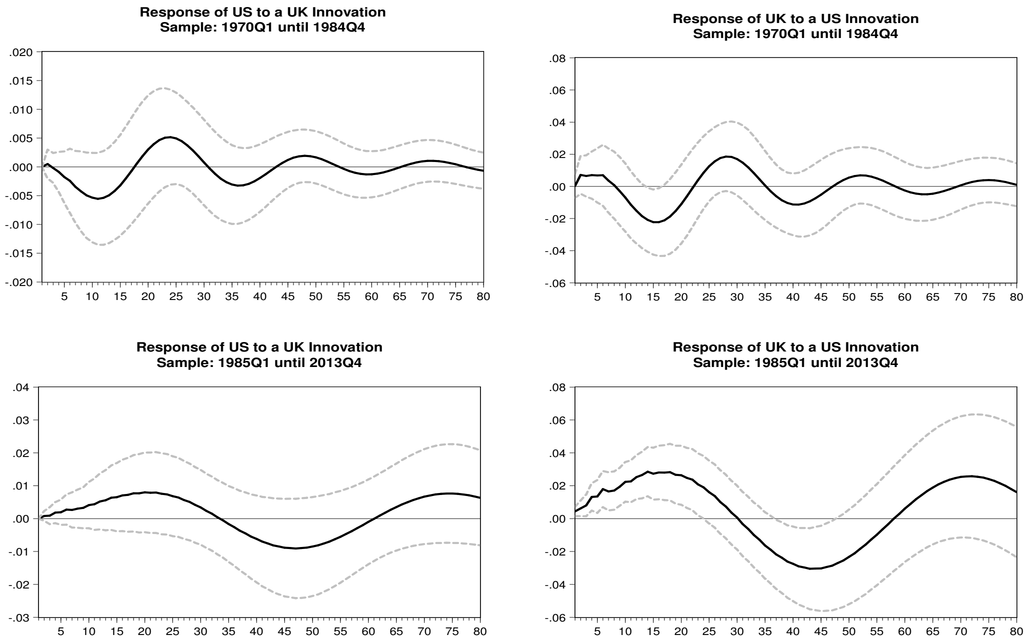

Figure 2 Impulse Response Functions

Note: The asymptotic 95%-confidence intervals are represented by dotted gray lines. The maximum period of 80 quarters equals 20 years.

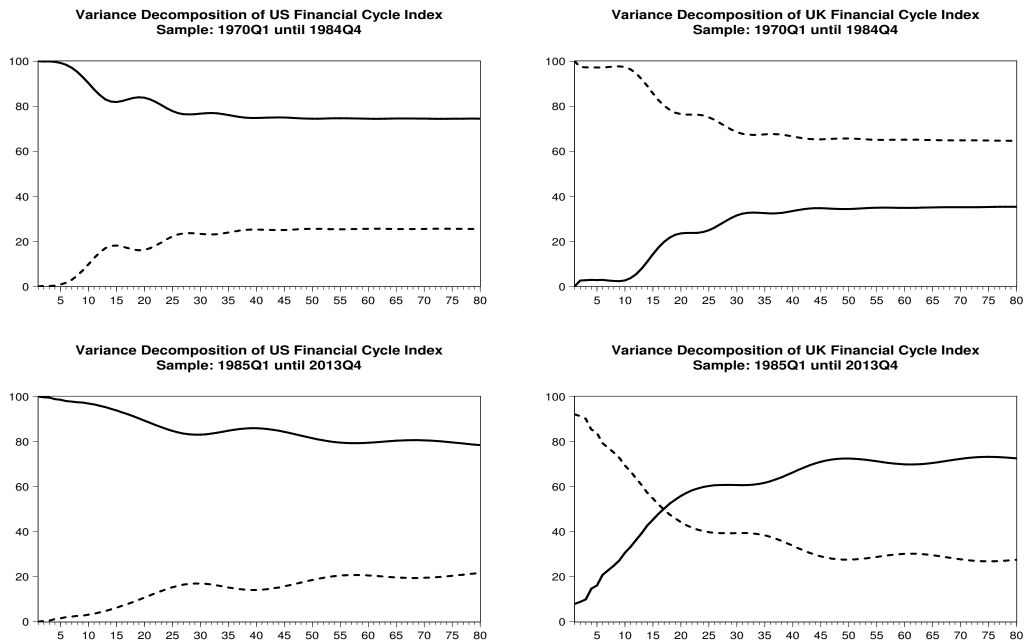

Figure 3 Variance Decompositions

Note: Contributions of US innovations are represented by solid lines, contributions of UK innovations by dashed lines. The maximum period of 80 quarters equals 20 years.

4.2 Frequency Domain: Spectral Density, Coherency and Granger Causality

In order to analyze whether the relation between the US and UK is in fact driven by financial cycles or rather by higher frequencies associated with business cycles, we use the frequency domain representations of the estimated VARs. The results are presented in Figure 4.

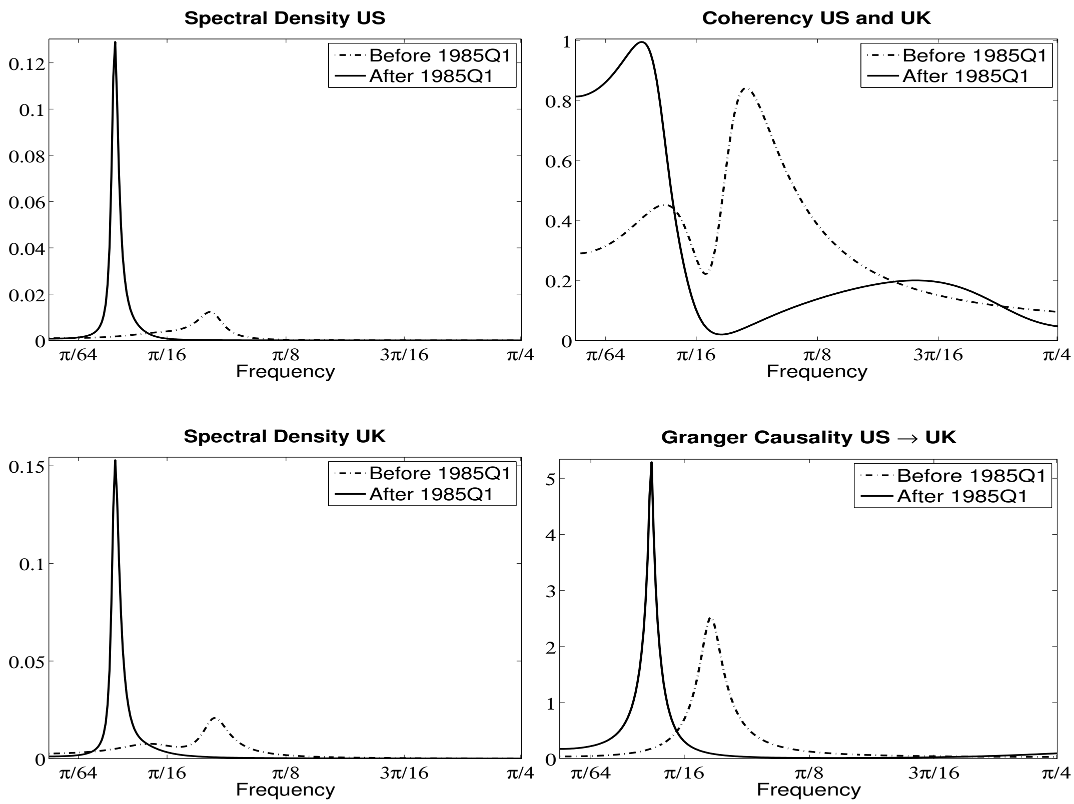

Figure 4 Spectral Densities, Coherency and Granger Causality.

Note: Dashed lines show estimates from 1970Q1 until 1984Q4, solid lines those from 1985Q1 until 2013Q4. For quarterly data, the frequencies $\pi/64$, $\pi/16$, and $\pi/4$ correspond to cycles of lengths 32, 8, and 2 years.

The left part of Figure 4 shows the spectral densities of the US and UK financial indicators. In the pre-1985 period (dashed lines), the peaks of the spectral densities are not very pronounced and imply a main cycle lengths of 5.9 and 5.7 years for the US and the UK, respectively; see also Table 2. These cycles are located in the range between 2 to 8 years ($\pi/4 \geq \lambda \geq \pi/16$) and are therefore usually identified as business cycles. The variance contribution of the financial cycle range, defined by cycles between 8 and 32 years ($\pi/16 > \lambda \geq \pi/64$), amounts to only 21% for the US and 39.2% for the UK. The right part of Figure 4 shows the coherency and causality measures from equations (6) and (11). The average coherency in the financial cycle range amounts to only 0.39 and the Granger causality measure is 0.19. This shows that most of the weak interaction found in the VAR analysis happens in the business cycle rather than in the financial cycle range.

In the second period, the picture totally changes. For both indicators the peaks of the spectral densities (solid lines) are clearly located in the financial cycle area, implying a main cycle length of 14.7 years for both countries. The contributions of the financial cycle range to the overall variances of the variables amounts to 96.3% for the US and to 94.3% for the UK. Hence, the dynamics of the two financial indicators are almost fully explained by financial cycles, highlighting their tremendous importance. The average coherency increased from 0.39 to 0.71 and the Granger causality measure from 0.19 to 1.19. Using 10000 bootstrapped values, see Strohsal et al. (2015), we applied two-sample t-tests and Wilcoxon rank-sum tests to average coherency and average Granger causality. The null hypothesis that the estimated means are equal in both sample periods is rejected with p-values far less than 0.01.

Table 2 Financial Cycle Interaction: Main Cycle, Variance Contribution, Coherency and Granger Causality

	cycle length in years		variance contribution...		average coherency...	average causality...
			...of the financial cycle range (8 to 32 years)			
sample	US	UK	US	UK	US $\leftrightarrow$ UK	US $\rightarrow$ UK
1970Q1-1984Q4	5.9	5.7	21.4%	39.2%	0.39	0.19
1985Q1-2013Q4	14.7	14.7	96.3%	94.2%	0.71	1.19

Notes: Cycle length refers to the frequency, expressed in years, where the spectral density has its unique maximum. For the coherency and causality measures cf. equations (6) and (11).

5 Conclusions

On the basis of the combined use of time domain- and frequency domain analysis tools, we find that the international linkage between the US and UK financial cycles has increased in recent times. Applying standard VAR methods, we show that, if any, there existed only a weak relation between US and UK financial indicators in the pre-1985 period. In the post-1985 sample, this relation became much stronger with the US financial cycle influencing the UK cycle. From the VARs' frequency domain representations we find that the weak relation from the first period occurs mainly at frequencies in the business cycle range, whereas in the second period the interaction and causality from the US to the UK are clearly driven by the financial cycles operating at lower frequencies only.

Our results are of high practical relevance in a variety of dimensions. First, they support the view that the international transmission of financial shocks has dramatically increased in recent times. Second, as financial cycles have increased in length and amplitude, they require more detailed and long-term monitoring mechanisms for the enforcement of macro-financial stability. Finally, our results highlight that it is crucial for monetary policy to take into account not only traditional measures as inflation and output gap operating at business cycle frequencies, but also financial cycle fluctuations operating at lower frequencies.

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