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# ASSESSING THE CROSS-COUNTRY INTERACTION OF FINANCIAL CYCLES: EVIDENCE FROM A MULTIVARIATE SPECTRAL ANALYSIS OF THE US AND THE UK

August 18, 2017

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## ABSTRACT

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# Assessing the Cross-Country Interaction of Financial Cycles: Evidence from a Multivariate Spectral Analysis of the US and the UK

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In recent times, a large number of studies has investigated the empirical properties of financial cycles within countries, mainly based on band-pass filter techniques. The contribution of this paper to the literature is twofold. First, in contrast to most existing studies in the financial cycle literature, we perform a multivariate parametric frequency domain analysis which takes the complete (cross-) spectrum into account and not only certain frequencies. And second, we provide evidence on the cross-country interaction of financial cycles. We focus on the US and UK and use frequency-wise Granger causality analysis as well as structural break tests to obtain three main results. The relation between cycles has recently intensified. There is a significant Granger causality from the US financial cycle to the UK financial cycle, but not the other way around. This relationship is most pronounced for cycles between 8 and 30 years.

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

*JEL classification*: C32, E32, E44

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## 1. Introduction

The 2007-08 financial crisis has led to a renewed interest in the study of financial cycles and their role in macroeconomic activity. For the conduct of monetary and macro-prudential policy it is crucial to understand the dynamics of financial market fluctuations (see e.g. ECB, 2014). So far, most of the literature focuses on properties of financial cycles within different countries. The evidence shows 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) and Aikman et al. (2015). Using a univariate frequency domain 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 lasting when occurring at the same time as financial disruptions (see also Breitung and Eickmeier, 2014).

A further important aspect of financial cycles that has gained special attention in recent times is that they seem, to a large extent, an international phenomenon (Borio, 2014 and Aikman et al., 2015, among others). Also, as stressed e.g. by Rey (2015), the global financial cycle seems to be driven by US financial market dynamics and, particularly, US monetary policy, see also Forbes and Chinn (2004) and Ehrmann et al. (2011). Against this background, a better understanding of the linkages between financial cycles of different countries may provide valuable information for monetary and macro-prudential policy decisions. For instance, quantifying the impact of foreign financial cycle movements for domestic financial markets is of great importance for setting domestic countercyclical capital buffer rates.

The present paper offers two contributions. Since most of the existing literature studies cycles within countries, the first contribution is to provide new evidence on cross-country interaction of financial cycles. The second contribution is that, compared to the usual approach of filtering the data, this paper performs a parametric frequency analysis taking the complete (cross-) spectrum into account. We use the multivariate indirect spectrum estimation technique which has the distinguishing feature to be efficient enough to allow for possible changes in the relation of cycles over time.

We focus on the US and the UK since their advanced financial sectors play an important role for the economy in both countries and are historically closely connected. 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 at which frequencies the interaction of financial cycles takes place. We study spectral densities, the coherency and a measure of frequency-wise Granger causality discussed in Geweke (1982) and Breitung and Candelon (2006).

We obtain the following main results. The relation between US and UK financial cycles changed over time and is particularly pronounced during the last decades. We use exogenous and endogenous break point tests to statistically establish a structural break around 1985. 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 frequency domain analysis reveals that the interaction is clearly strongest at low frequencies between 8 and 30 years. This 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, relatively 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 $(2 \times 2)$ coefficient matrices; for the following see e.g. Kirchgässner et al. (2013, ch. 4). The two-dimensional error vector $u_t$ is assumed to be white noise with $\mathrm{E}(u_t) = 0$ and the positive definite $(2 \times 2)$ variance-covariance matrix $\mathrm{E}(u_t u_t') = \Sigma$.

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. This is a crucial point since our data are clearly trending. Therefore, in case of cointegration, a deterministic trend may be necessary to capture possibly different drifts in the univariate representations of the time series. If there was no cointegration, we would also need time trends because it is not clear from the outset whether the trending is of stochastic or deterministic nature. In any case, applying ordinary least squares to (1), including appropriate deterministic terms, yields consistent estimates, no matter whether the time series are (trend) stationary, non-stationary or cointegrated; see Hamilton (1994).

Cointegration transforms non-stationary data into a stationary system. Therefore, we do not need alternative detrending methods to detect cyclical properties. The advantage is that we thereby circumvent the problem that different data filtering can lead to quite different cyclical properties; see the discussion in Canova (1998a, 1998b) and Burnside (1998).

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 $\Sigma$ 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 the relationship between the cyclical components of financial variables, we transform the stable VAR system into the frequency domain.[1] This allows us to analyze at which frequencies most of the interaction takes place.

The $(2 \times 2)$ spectral matrix is obtained from (2) and (3) and has the form

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

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

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

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 $\lambda$. 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 $y$.

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

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

we can rewrite (3) as

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

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

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 $\lambda$. The null hypothesis is that $x$ is not Granger causal to $y$, meaning $B_{yx}(e^{-i\lambda}) = 0$ and implying 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 $\lambda$.

Compared to other approaches to investigate cycles, as e.g. the turning point analysis (Claessens et al., 2011) or direct spectrum estimation (Aikman et al., 2015, Schüler et al., 2015), the parametric indirect spectrum estimation provides reliable estimates already for a moderate sample length. Hence, changes in cyclical properties can be analyzed by investigating estimates over different time periods.

## 3. Data and Model Specification

According to a common finding in the literature, Borio (2014) argues that the most parsimonious description of the financial cycle can be obtained from credit and house prices series.[2] 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 create a single measure of the financial cycle, we construct a financial cycle index for each country by computing the first principal component of the two series.[3]

To analyze possible changes in the characteristics of the financial cycle over time, we split the quarterly data into two subsamples, 1970Q1-1984Q4 and 1985Q1-2013Q4.[4] The break

[2]The variable *credit* represents the outstanding volume of credit, measured in national currency, to the private non-financial sector from all sectors. The data are provided by Datastream with identifiers *USBLCAPAA* and *UKBLCAPAA*. The variable *housing* represents a national house price index. These data are collected by OECD.Stat and made available for each country under the general identifier *House Prices*.

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

[4]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%). 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 $0.78 \cdot \text{credit} + 0.62 \cdot \text{housing}$.

point at 1985Q1 is specified following the literature (Claessens et al., 2011, 2012, Drehmann et al., 2012) and is considered the starting point of the financial liberalization phase in mature economies. Statistical support for this break date is provided by a Chow break point test and an endogenous break point search. The Chow test clearly rejects the null of no break at 1985Q1 with a $\chi^2(16)$-distributed test statistic of 117.09. The break point search with impulse indicator saturation (IIS) techniques according to Hendry (2011) and Ericsson (2013) strongly points to a break around mid to late 1980's as well. Detailed results are provided in Appendix B, Figure 5.

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 upward trending with cycles.

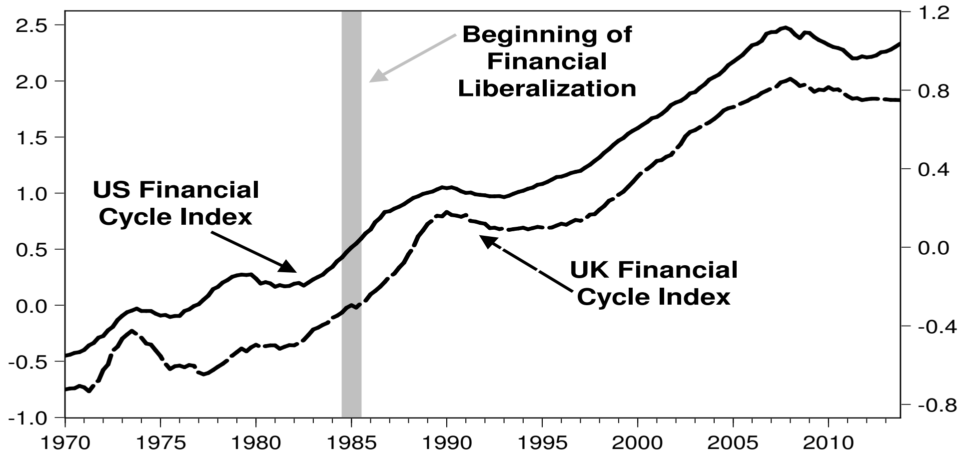


Figure 1 US and UK Financial Cycle Indices

Note: The US (solid line, right axis) and UK (dashed line, left axis) 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.

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 the Akaike information criterion 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 estimated VAR models for both sample periods. Up to order 24, no significant autocorrelation is left in the residuals. To interpret impulse response functions and variance decompositions, we use a recursive structural form where we allow for a contemporaneous effect of the US on the UK. As in Rey (2015), the idea is that the US is the natural candidate for the origin of a global financial cycle. Note that, even though it is unintuitive, we also tried the opposite Cholesky ordering. This changes only the very short term interaction of the two time series, whereas the main results remain almost unchanged.[5]

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

| sample | lags | | | | | | | | | | | | | | diagnostics | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 lags and deterministic terms which are included in the final VAR specification are indicated by ×. 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

We start our analysis of financial cycles in the time domain, looking at both subsamples. This allows us to get an overall impression of the existence of Granger causality, the direction of effects (through impulse response analysis) and the strength of interaction (through variance decomposition). [6]

**Granger causality tests** over the pre-1985 sample, show that 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 rather weak evidence. In the second sample, the test statistic increases to $\chi^2(9) = 45.98$ which is significant at any conventional confidence level.[7] 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.

**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.

[5] Another piece of evidence which maybe interpreted in favor of our Cholesky ordering is the weak exogeneity property of the US index. We find that only the UK adjusts to deviations from the long-run relation. With a test statistic of $\chi^2(1) = 1.33$ and a $p$-value of 0.25 weak exogeneity cannot be rejected for the second sample period. However, theoretically this result does not imply any Cholesky ordering and should therefore be interpreted with caution. But intuitively, the non-adjustment of the US at time $t$ to deviations from the equilibrium at $t - 1$ makes it more plausible that the US does not react contemporaneously to UK innovations than the other way around.

[6] Johansen (1995) cointegration test results can be found in Table 3 in Appendix A. Since these test statistics suggest that there may actually exist a cointegration relation between the two synthetic indices, a time and frequency-domain analysis of a vector error correction model of these two time series would be an equivalent approach for the analysis of the properties of the financial cycle in the US and the UK.

[7] As an anonymous referee pointed out, the existence of Granger causality in at least one direction is already implied by the existence of a cointegration relation, see Table 3 in Appendix A.

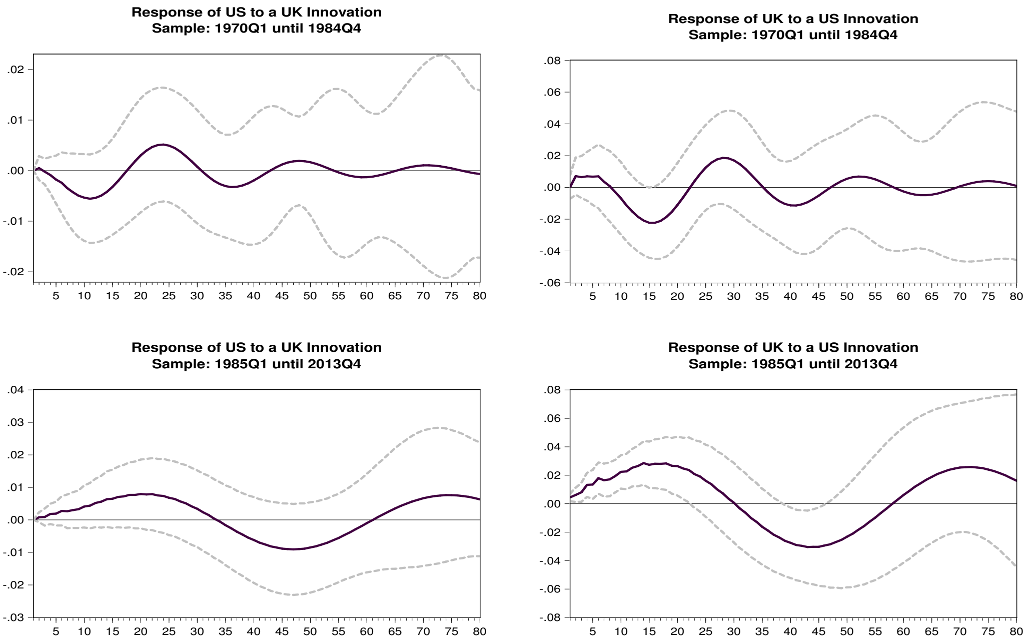


Figure 2 Impulse Response Functions

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

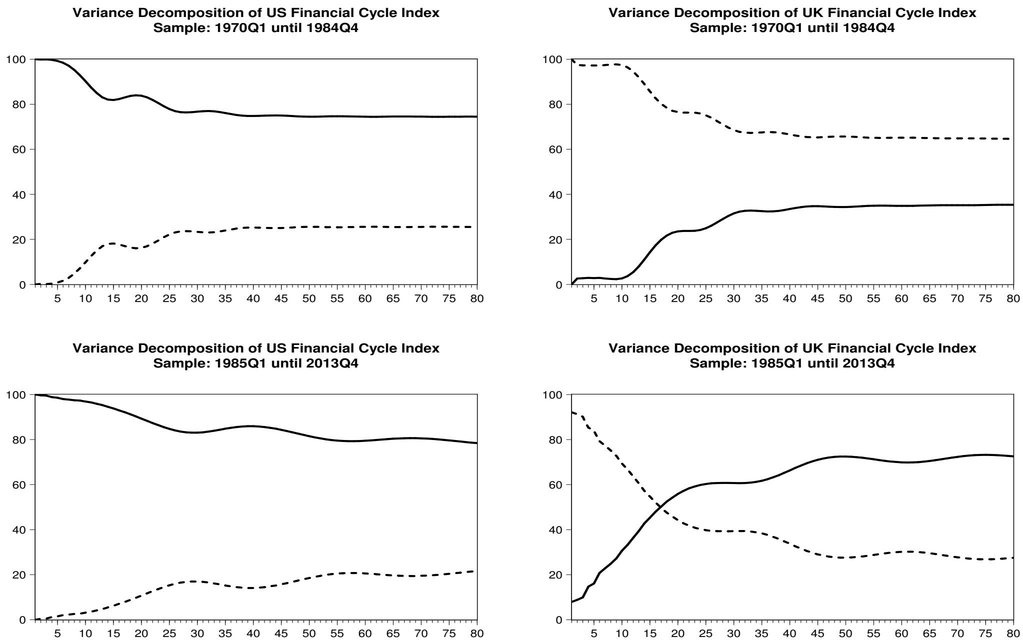


Figure 3 Variance Decompositions

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.

**Variance decompositions** in Figure 3 show that 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. This result adds to the evidence of Ehrmann et al. (2011) who document a dominating role of the US markets for global financial markets.

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.

## 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 frequency components in the financial cycle rage or rather by components in the business cycle range, we use the frequency domain representations of the estimated VARs. The results are presented in Figure 4.

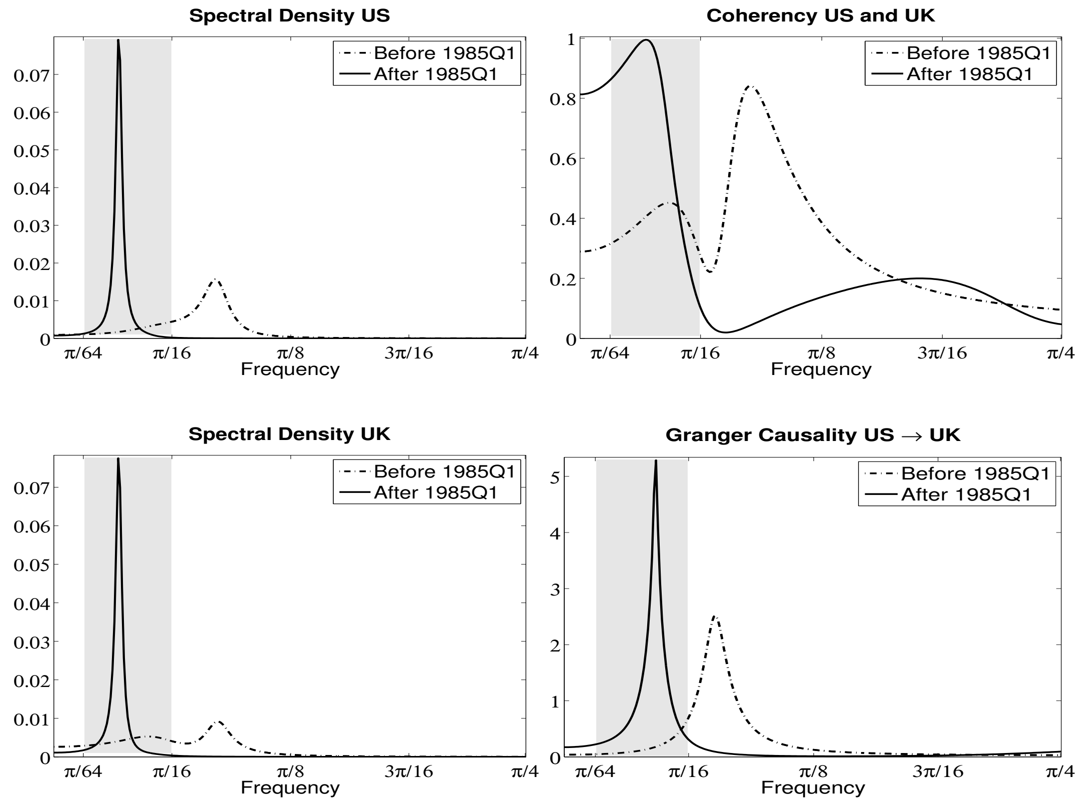


Figure 4 Spectral Densities, Coherency and Granger Causality.

Note: Dashed lines show estimates from 1970Q1 until 1984Q4, solid lines those from 1985Q1 until 2013Q4. For quarterly data, the frequencies $\pi/64$ and $\pi/16$ in the shaded area correspond to long cycles between 32 and 8 years. Frequency $\pi/4$ corresponds to a cycle of length 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 ($\pi/16 > \lambda \geq \pi/64$, shaded area), 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. [8] 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 peaking at 11 years. 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... ...of the financial cycle range (8 to 32 years) | | average coherency... | average causality... |
|---|---|---|---|---|---|---|
| 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).

Looking back at Figure 1, the two times series indeed appear to share a common and long cycle of around 15 years during the second subsample. This time span would roughly correspond to the cycle starting at the common hump at the beginning of the 1990's and ending at next hump around 2007.

## 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. 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

[8] According to equation (11) $M_{x\rightarrow y}(\lambda)$ is a logarithmic measure which describes the strength of the Granger-causality of $x$ on $y$ at a given frequency $\lambda$. Accordingly, the higher the value of $M_{x\rightarrow y}(\lambda)$, the stronger the causality from $x$ to $y$. In particular, if $M_{x\rightarrow y}(\lambda) = 0$, $x$ does not Granger-cause $y$ at the frequency $\lambda$.

much stronger with the US financial cycle influencing the UK cycle. The break date of 1985, which follows the existing literature, is verified by Chow break point tests and impulse indicator saturation (IIS) techniques. 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 suggest that the cross-country transmission of financial shocks has increased considerably in recent times. This implies that an international coordination of macro-prudential policies - which aim at curbing financial cycles - is crucial.

## Appendix A Cointegration Test Results

Table 3 presents the cointegration test results according to Johansen (1995). The evidence suggests that there is a cointegration relation in both sample periods.

Table 3 Results of the Johansen (1995) Test

| sample | lags | deterministic terms | rank | trace test | $\lambda_{\max}$ test |
|---|---|---|---|---|---|
| 1970Q1-1984Q4 | 5 | trend in long-run relation | $r=0$ | 30.56 (0.01) | 25.63 (0.01) |
| | | | $r\leq 1$ | 4.92 (0.61) | 4.92 (0.61) |
| 1985Q1-2013Q4 | 9 | unrestricted constant | $r=0$ | 15.18 (0.06) | 14.26 (0.05) |
| | | | $r\leq 1$ | 0.92 (0.34) | 0.92 (0.34) |

Notes: The number of lags refer to the VAR in levels as specified in Table 1. $p$-values are given in parentheses.

The deterministic terms in the VECM differ from the ones included in the unrestricted VAR. The reason is that when estimating a VAR the nature of the trending (stochastic or deterministic) is unclear. Even in the presence of cointegration, a deterministic trend may be necessary to capture different drifts of the times series. Fortunately, OLS estimates of a VAR are consistent in any case. When estimating a VECM, cointegration can be tested and it can also be seen whether a deterministic time trend needs to be included in the cointegration relation. It the current case, it turned out that the series have different drifts in the first subsample but the same drift in second subsample.

## Appendix B Impulse Indicator Saturation Results

As outlined during the Section 3 on data and model selection, we want to analyze possible changes in the characteristics of the financial cycle. Thereby, we follow the literature (Claessens et al., 2011, 2012 and Drehmann et al., 2012), which specifies the break at 1985Q1, seen as the starting point of the financial liberalization. 1985Q1 is also in accordance with a Chow test, see Section 3.

To provide additional statistical support without a priori specifying a break date, we conducted an impulse indicator saturation analysis, see Figure 5. Following Hendry (2011) and Ericsson (2013) (see also the references therein), we use the split-half approach. That is, we include impulse dummies for all data points of the first half of the sample and estimate the model over the full sample. The upper right graph of Figure 5 shows the dummies being significant at the 10%-level. Then we do the same for the second half of the sample, see middle right graph of Figure 5. Finally, we estimate the model including all remaining significant dummies. A considerable amount of dummies [38] remains significant in the first half, but only very few [3] in the second half, see lower right graph of Figure 5. The three dummies in the second half clearly indicate the Lehman bankruptcy. Therefore, the results strongly point to a sample split somewhere around mid to late 1980's.

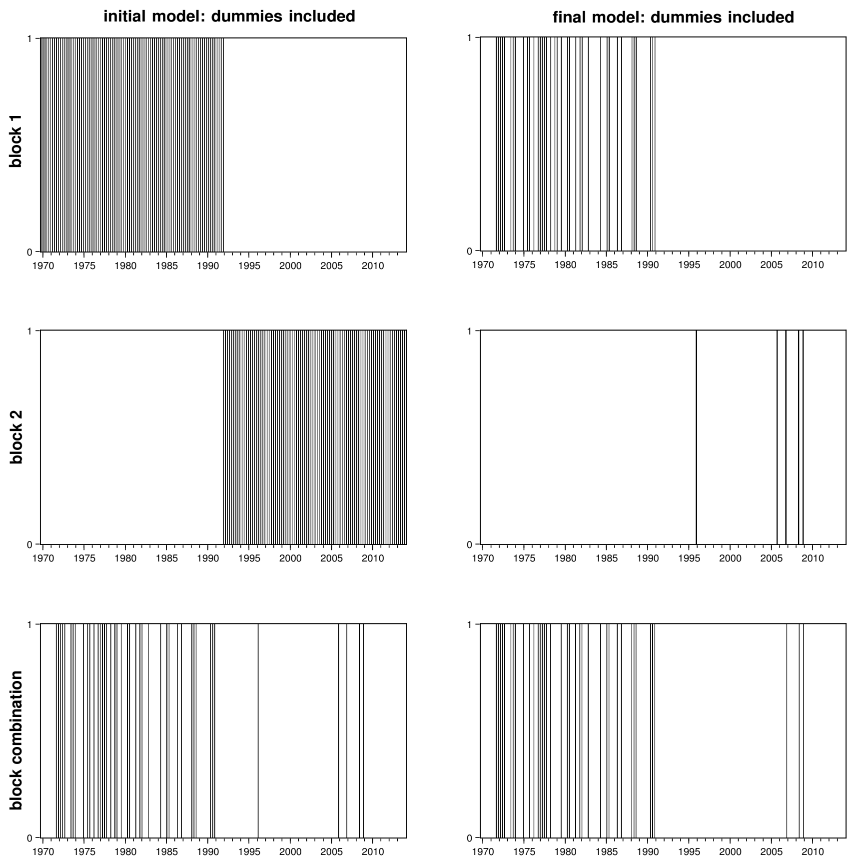


Figure 5 Results of Impulse Indicator Saturation

Note: The figure shows the two blocks of impulse dummies which were included in the first half (upper left figure) and the second half (middle left figure) of the sample. The significant dummies in the first and second period are shown in the upper right and middle right figure, respectively. The combined block of dummies is shown in the bottom left figure. The significant dummies remaining in the very final model are shown in the bottom right figure.

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