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Characterizing the financial cycle: evidence from a frequency domain analysis

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Non-technical summary

Research Question

Since the 2007-08 financial crisis, the literature pays increasing attention to the cyclical behavior of financial markets. Especially at the Bank of International Settlements (BIS) and the International Monetary Fund (IMF) a considerable amount of recent research is devoted to the *financial cycle*. A key aspect in the current literature is to measure duration and amplitude of fluctuations in financial variables. Studies usually find that, compared to the business cycle, the duration and amplitude have increased considerably, particularly since 1985. The most common empirical approaches are the analysis of turning points and band-pass filters. While the analysis of turning points requires a pre-specified rule to identify minima and maxima, band-pass filters require to pre-specify the frequency range where the financial cycle is assumed to operate. For these reasons, both approaches are quite descriptive and testing existing hypotheses on the financial cycle is not possible.

Contribution

The main objective of the current paper is to establish the empirical regularities of the financial cycle on the basis of straightforward time series *econometric* methods. In particular, our contribution is twofold. First, we provide a complete characterization of the properties of the financial cycle *in the frequency domain*. To this end, we estimate univariate time series models for the usual financial variables and use the estimated models to compute their corresponding frequency domain representations. Compared to frequency-based filter methods and the turning point analysis, our approach has the advantage that no a priori assumption on the cycle length is needed. Moreover, also very long cycles can be detected, even if the sample period is limited. Second, a distinguishing feature of our estimation approach is that it allows us to test existing hypotheses on various characteristics of the financial cycle by statistical means. In this respect, we address the following questions: At what frequency does the financial cycle mostly operate? Does the financial cycle indeed have a longer duration, as well as a larger amplitude than the classical business cycle? Have the characteristics of the financial cycle changed over time?

Results

Our main results are as follows. We find that the typical duration of the financial cycle has increased in recent times in the United States and the United Kingdom, currently being about 15 years. Also, compared to the business cycle in these countries, we find strong statistical evidence in support of a longer duration and a larger amplitude of the financial cycle. In the case of Germany – the third representative country we analyze in this paper – distinct characteristics of the financial cycle are, if at all, much less visible.

Nichttechnische Zusammenfassung

Fragestellung

Seit der Finanzkrise 2007-08 gibt es in der Literatur ein erhöhtes Interesse am zyklischen Verhalten von Finanzmärkten. Insbesondere beschäftigen sich Forschergruppen an der Bank für Internationalen Zahlungsausgleich (BIZ) und am Internationalen Währungsfonds (IWF) mit dem sogenannten *Finanziellen Zyklus*. Ein Kernaspekt in der aktuellen Literatur ist die Bestimmung der Dauer und der Intensität von Schwingungen in Finanzmarktvariablen. Häufig zeigt sich in den Analysen, dass Länge und Stärke der Zyklen in Relation zum Konjunkturzyklus, insbesondere seit 1985, deutlich zugenommen haben. Dabei benutzen die vorliegenden Arbeiten hauptsächlich die zur Bestimmung von Konjunkturzyklen entwickelten Wendepunktanalysen und Bandpassfilter. Während Wendepunktanalysen ein a priori festgelegtes Abzählkriterium zur Bestimmung von Minima und Maxima voraussetzen, muss bei der Anwendung von Bandpassfiltern a priori die für den Finanziellen Zyklus vermeintlich relevante Frequenz angegeben werden. Aus diesen Gründen sind die Methoden weitestgehend deskriptiv und erlauben es nicht, die bestehenden Hypothesen bezüglich der Eigenschaften des Finanziellen Zyklus zu testen.

Beitrag

Das Ziel des vorliegenden Papiers ist es, unter Verwendung zeitreihenökonomischer Methoden, die Eigenschaften des Finanziellen Zyklus empirisch fundiert aufzuzeigen. Unser Beitrag zur Literatur bietet *erstens* eine vollständige Charakterisierung des Finanziellen Zyklus im Frequenzbereich. Dazu schätzen wir zunächst univariate Zeitreihenmodelle für die in der Literatur gängigen finanziellen Variablen, um dann deren Darstellung im Frequenzbereich analytisch zu bestimmen. Im Vergleich zu den Wendepunktanalysen und Bandpassfiltern hat unser Ansatz den Vorteil, dass wir keine Annahmen über die Länge des Finanziellen Zyklus treffen müssen. Außerdem ist es uns möglich, auch sehr lange Zyklen nachzuweisen, selbst wenn der Untersuchungszeitraum begrenzt ist. *Zweitens* ist es ein zentrales Unterscheidungsmerkmal unseres Ansatzes, dass wir bestehende Hypothesen über die Eigenschaften des Finanziellen Zyklus mittels formaler Tests statistisch überprüfen können. Diesbezüglich gehen wir folgenden Fragen nach: Was ist die typische Dauer des Finanziellen Zyklus? Weist der Finanzielle Zyklus tatsächlich längere und stärker ausgeprägte Schwingungen auf als der Konjunkturzyklus? Haben sich die Eigenschaften des finanziellen Zyklus über die Zeit geändert?

Ergebnisse

Wir kommen zu den folgenden Hauptergebnissen. Die Länge des finanziellen Zyklus in den USA und in Großbritannien ist in jüngerer Zeit auf etwa 15 Jahre angestiegen. Im Vergleich zum Konjunkturzyklus in diesen Ländern zeigen unsere Ergebnisse eindeutig, dass der Finanzielle Zyklus signifikant länger und stärker ausgeprägt ist. In Deutschland, dem dritten Land in der vorliegenden Untersuchung, sind die typischen Eigenschaften des Finanziellen Zyklus, wenn überhaupt vorhanden, sehr viel weniger deutlich.

Characterizing the Financial Cycle: Evidence from a Frequency Domain Analysis

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July 6, 2015

Abstract

A growing body of literature argues that the financial cycle is considerably longer in duration and larger in amplitude than the business cycle and that its distinguishing features became more pronounced over time. This paper proposes an empirical approach suitable to test these hypotheses. We parametrically estimate the whole spectrum of financial and real variables to obtain a complete picture of their cyclical properties. We provide strong statistical evidence for the US and slightly weaker evidence for the UK validating the hypothesized features of the financial cycle. In Germany, however, the financial cycle is, if at all, much less visible.

Keywords: Financial Cycle, Business Cycle, Indirect Spectrum Estimation, Bootstrapping Inference.

JEL classification: C22, E32, E44.

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1 Introduction

Fluctuations in financial markets play a key role in the macroeconomic dynamics of modern economies, often leading to either significant economic booms or severe economic crises, see e.g. [Kindleberger and Aliber \(2005\)](#) and [Schularick and Taylor \(2012\)](#). The last twenty years provide several examples, from Japan's lost decade following the asset market crash in the early 1990s to the 2007-08 global financial crisis which led the world economy to the brink of a new Great Depression. Against this background, a renewed interest in financial market dynamics is emerging. A growing body of literature argues that the cyclical behavior of financial aggregates may be understood not only as a pure reflection of the real side of the economy, but also as the result of underlying changes in the general perception and attitudes towards financial and macroeconomic risk (see [Caballero, 2010](#) for a survey).

The distinctive feature of the financial cycle, as put forward in recent studies, is that its duration and amplitude are considerably longer and larger than those of the classical business cycle (e.g. [Claessens et al., 2011](#)). [Borio \(2014\)](#) suggests that the financial cycle operates at lower, medium-term frequencies, with a cycle length between eight and thirty years. This extended length of the financial cycle is often considered to reflect the build-up of macro-financial instability, most recently contributing to the 2007-08 financial crisis. Despite its crucial importance for macroeconomic developments, however, it is not clear how the financial cycle should be empirically analyzed.

Most of the existing insights into the characteristics of the financial cycle are based on either the analysis of turning points (e.g. [Claessens et al., 2011, 2012](#)) or frequency-based filter methods (e.g. [Drehmann et al., 2012](#)). The turning point approach requires a pre-specified rule which is applied to an observed time series in order to find local maxima and minima. Frequency-based filter methods require a pre-specified frequency range at which the financial cycle is assumed to operate. Therefore, both approaches are quite descriptive and do not allow to test the hypothesized characteristics of the financial cycle. Indeed, while there is a broad consensus concerning the fundamental characteristics of the business cycle (see [Diebold and Rudebusch, 1996](#) for a survey), this is not yet true for the financial cycle.

The main objective of the current paper is to establish the empirical regularities of the financial cycle on the basis of straightforward time series econometric methods. In particular, our contribution is twofold. First, we provide a complete characterization of the properties of the financial cycle in the frequency domain. To this end, we exploit the fact that any covariance-stationary stochastic processes can be equivalently represented in the time and in the frequency domain. More specifically, we estimate time series models of the autoregressive moving average (ARMA) class for standard financial cycle indicators and use the estimated models to compute their corresponding frequency domain representations. Compared to frequency-based filter methods (e.g. [Baxter and King, 1999](#)) and the turning point analysis ([Bry and Boschan, 1971](#), [Harding and Pagan, 2002](#)), our approach has the advantage that no a priori assumption on the cycle length is needed. Moreover, also very long cycles can be detected, even if the sample period is limited.

Second, a distinguishing feature of our estimation approach is that it allows us to test existing hypotheses on various characteristics of the financial cycle by statistical means. Based on the computed spectral densities and their bootstrap standard errors, we address the following questions: At what frequency does the financial cycle mostly operate? Does the financial cycle indeed have a longer duration, as well as a larger amplitude than the classical business cycle? Have the characteristics of the financial cycle changed over time?

Our main results are as follows. We find that the typical duration of the financial cycle has increased in recent times in the United States and the United Kingdom, currently being about 15 years. Also, compared to the business cycle in these countries, we find strong statistical evidence in support of a longer duration and a larger amplitude of the financial cycle. In the case of Germany – the third representative country we analyze in this paper – distinct characteristics of the financial cycle are, if at all, much less visible.

The remainder of this paper is organized as follows. [Section 2](#) motivates and discusses our methodology in detail. [Section 3](#) contains our empirical results on the financial cycle in the US, the UK, and Germany. Finally, we draw some concluding remarks in [Section 4](#).

2 Methodology

2.1 Existing Approaches: Analysis of Turning Points and Frequency-Based Filters

The first important empirical approach to assess the financial cycle is the traditional turning point analysis. The method goes back to [Bry and Boschan \(1971\)](#) and is adapted to quarterly data by [Harding and Pagan \(2002\)](#). While originally used to analyze business cycles, recent studies of [Claessens et al. \(2011, 2012\)](#) and [Drehmann et al. \(2012\)](#) adopted it to investigate financial cycles. The turning point analysis requires a pre-specified rule which defines a complete cycle in terms of the minimum number of periods of increases (expansion phase) and decreases (recession phase). Therefore, this method is descriptive in nature and hypotheses testing is not possible.

The second prominent approach is to work with frequency-based filters ([Drehmann et al., 2012](#)) which are usually based on [Baxter and King \(1999\)](#) or refinements thereof, see e.g. [Christiano and Fitzgerald \(2003\)](#). When filters are used to analyze cycles, a crucial point is that the frequency range has to be pre-specified by the researcher. This may lead to results biased into the direction of the pre-defined range. The intuition behind this difficulty is best described by briefly discussing the general functioning of filters.

In the time domain, any linear filter can be written in the form of a two-sided moving average

$$y_t = \sum_{j=-m}^n a_j x_{t-j} . \quad (1)$$

The filtered series y_t depends simultaneously on the properties of the filter (the coefficients a_j) and the data (the observed series x_t). To convert equation (1) into the frequency domain, one uses the corresponding filter function

$$C(\lambda) = \sum_{j=-m}^n a_j e^{-i\lambda j} , \quad i^2 = -1 , \quad (2)$$

and its transfer function

$$T(\lambda) = |C(\lambda)|^2, \quad (3)$$

where $\lambda \in [-\pi, \pi]$ denotes the frequency range, see e.g. Wolters (1980a, 1980b). The relationship between the spectra of the original and the filtered series is given by

$$f_y(\lambda) = T(\lambda)f_x(\lambda). \quad (4)$$

When compared to the time domain, a major advantage of the representation in (4) is that now the filter effect $T(\lambda)$ is separated from the data $f_x(\lambda)$. For the spectrum of the filtered series $f_y(\lambda)$ to accurately identify cycles in the spectrum of the observed series $f_x(\lambda)$, a so-called band pass filter is used. Such a filter has the value 1 at the frequency range of interest $[\lambda_{\text{low}}, \lambda_{\text{high}}]$ and 0 otherwise. In view of equation (4), this implies $f_y(\lambda) = f_x(\lambda)$ for $\lambda \in [\lambda_{\text{low}}, \lambda_{\text{high}}]$ and $f_y(\lambda) = 0$ for $\lambda \notin [\lambda_{\text{low}}, \lambda_{\text{high}}]$. Theoretically, the ideal time domain filter can be achieved by moving averages of infinite order. Yet, in practice, this is not possible since only a limited number of observations is available.

The main idea of frequency-based filters is to pre-specify a range from λ_{low} to λ_{high} and to choose finite values for m and n in equation (1) to find the weights a_j which approximate the ideal filter as good as possible. Due to the approximation, the spectrum of the filtered series is in general different from the one of the observed series in $[\lambda_{\text{low}}, \lambda_{\text{high}}]$ and reflects a mixture of filter and data properties in the form of $T(\lambda)f_x(\lambda)$. More precisely, it can be shown that any filter has the tendency to overstate the contributions of cycles in the pre-defined frequency range $[\lambda_{\text{low}}, \lambda_{\text{high}}]$ to the overall variance of the underlying time series. Because of this tendency, artificial cycles may be produced even if the true data generating process has no cycles.¹

In this study, we emphasize that the appropriate λ_{low} and λ_{high} are unknown. Indeed, while there seems to be general consensus in the literature about the relevant frequency range for the business cycle (2 to 8 years), the relevant frequency range for the financial cycle is

¹This issue has been raised already in the 1950's and 1960's. For a discussion of the general problem see e.g. König and Wolters (1972), Baxter and King (1999), Christiano and Fitzgerald (2003) and Murray (2003).

less clear. For instance, [Drehmann et al. \(2012\)](#) construct their financial cycle measure from the underlying series with *a priori* chosen cycle length between 8 and 30 years.

2.2 An Alternative Approach: Indirect Estimation of Spectral Densities

This paper proposes a simple method to characterize cycles in the frequency domain. Instead of focusing on certain frequency ranges, we analyze the complete spectrum which provides information of all possible cycles from periods of two units to infinity. Hence, our approach seeks to use statistical methods to exploit all the information included in the data.

It is known that any covariance-stationary process has a time domain and a frequency domain representation which are fully equivalent.² However, when compared with the time domain representation, the frequency domain representation is more suited to the analysis of cyclical features, as the importance of certain cycles for the total variation of the process can be easily derived from the spectrum.³ This is possible because the spectrum represents an orthogonal decomposition of the variance of the process.

The starting point of the indirect spectrum estimation is to specify the DGP of the underlying time series as an ARMA model:

$$A(L)x_t = \delta + B(L)u_t \quad , \quad u_t \sim \text{WN}(0, \sigma^2) \quad . \quad (5)$$

In equation (5), $A(L)$ and $B(L)$ denote polynomials in the lag operator L of order p and q , respectively. For stable processes, the MA(∞) representation has the form

$$x_t - \mu = \frac{B(L)}{A(L)}u_t \quad , \quad \mu = \frac{\delta}{A(1)} \quad . \quad (6)$$

Equation (6) shows that an ARMA representation can be interpreted as an estimated filter that transforms the white noise process u_t into the observed time series x_t . This filter is of infinite length but depends only on a finite number of parameters. The ARMA model is

²This was first discussed in [Wiener \(1930\)](#) and [Khintchine \(1934\)](#).

³Technically, the spectrum is the Fourier transformation of the autocovariance function.

in fact a filter which captures the whole dynamics of the observed process x_t in form of its complete spectrum from $-\pi$ to π . In direct analogy to equation (4) it holds that

$$f_x(\lambda) = \frac{|B(e^{-i\lambda})|^2}{|A(e^{-i\lambda})|^2} f_u(\lambda) \quad , \quad (7)$$

where $|B(e^{-i\lambda})|^2/|A(e^{-i\lambda})|^2 = T(\lambda)$ and $f_u(\lambda) = \frac{\sigma^2}{2\pi}$ as the spectrum of the white noise process. Equation (7) represents the *indirect spectrum estimation* and allows us to derive the cyclical properties of x_t .⁴

From $f_x(\lambda)$ we can identify, without any *a priori* assumptions, which frequency range is most relevant for the dynamics of the time series under consideration in terms of its variance contribution. The spectrum will exhibit a peak at a given frequency if cyclical variations occurring around that frequency are particularly important for the overall variation of the process. Also, if spectral mass is more concentrated in a given range around the peak, the corresponding cycle will show a larger amplitude causing more regular process fluctuations in the time domain. Normalizing the spectrum by the process variance⁵, one obtains the spectral density which provides the *relative* contributions of particular frequencies to the total variance of the process.

To statistically assess the characteristics of the financial cycle across variables and different sample periods, the inference in the empirical part will be based on bootstrap methods.⁶ We apply the following bootstrap procedure, see e.g. [Benkwitz et al. \(2001\)](#).

1. Estimate the parameters of the ARMA model in equation (5).
2. Generate bootstrap residuals u_1^*, \dots, u_T^* by randomly drawing with replacement from the set of estimated residuals.
3. Construct a bootstrap time series recursively using the estimated parameters from step 1 and the bootstrap residuals from step 2.

⁴This is a valid approach, as “If the model is correctly specified, the maximum likelihood estimates [of the ARMA(p,q) model] will get closer and closer to the true values as the sample size grows; hence, the resulting estimate of the population spectrum should have this same property” ([Hamilton, 1994](#), p.167).

⁵The process variance is calculated by numerically integrating the spectrum.

⁶To the best of our knowledge, analytical expressions for such standard errors are not available.

4. Reestimate the parameters from the data generated in step 3.
5. Repeat step 2 to step 4 5000 times.
6. From the bootstrap distributions of the statistics of interest, e.g., cycle length, amplitude etc., we compute the standard errors and the corresponding 95% confidence intervals.

An obvious alternative to the indirect parametric estimation would be the direct non-parametric estimation of the spectrum, see e.g. [Fishman \(1969\)](#).⁷ In order to get consistent estimates, however, one has to use a kernel estimator. Such estimates depend heavily on the chosen kernel and its bandwidth parameter M , implying that a large amount of observations is required to have the necessary degrees of freedom. For instance, if we estimate the spectrum from T observations by transforming the first M estimated autocovariances, we have $C \cdot \frac{T}{M}$ degrees of freedom. The constant C is kernel-specific and usually takes on values of around 3. A small value of M decreases the variance but increases the bias of the estimator. Having in mind the data in our empirical analysis below, let us consider a sample size of $T = 100$. In that case, a reasonable choice for M maybe 20, leading to only about 15 degrees of freedom. In contrast, the indirect estimation approach, starting from an ARMA model with e.g. 5 parameters, leaves us with 95 degrees of freedom and hence implies a strong efficiency gain.

3 Empirical Analysis

3.1 Data Description: Indicators of Financial and Real Developments

As perceptions and risk attitudes are not directly observable it is unclear which particular financial indicator or set of financial variables might reflect the financial cycle best.⁸ In the

⁷For an empirical analysis of US business cycles via directly estimated spectra see [Sargent \(1987\)](#).

⁸On the one hand, in [Drehmann et al. \(2012\)](#) and [Borio \(2014\)](#) it is argued that the financial cycle can be most parsimoniously described in terms of credit and property prices. Similarly, according to [Claessens et al. \(2011\)](#), the core of financial intermediation should be well captured by the three distinct market segments of credit, housing and equity. On the other hand, studies such as [English et al. \(2005\)](#), [Ng \(2011\)](#), and [Hatzius et al. \(2010\)](#) have used principal components and factor analysis to identify the common factors of a number of financial price and quantity variables for the characterization of the financial cycle. To extract the main

following analysis we use the most common proxy variables for the financial cycle; quarterly, seasonally adjusted aggregate data on credit volume, the credit to GDP ratio, house prices and equity prices, see Claessens et al. (2011, 2012) and Drehmann et al. (2012). Real GDP is taken as a proxy for the business cycle. We study three industrialized countries: the United States (US), the United Kingdom (UK), and Germany. The US is not only the largest economy in the world, but it also has the most important financial sector. As representative countries for Europe, we consider the UK with its leading financial sector and Germany as the largest EMU country.⁹

To allow for a meaningful comparison to existing studies, we employ data transformations similar to those found in Drehmann et al. (2012). All series are measured in logs, deflated with the consumer price index and normalized by their respective value in 1985Q1 to ensure comparability of units. Growth rates are obtained by taking annual differences of each time series.¹⁰ The only exception is the credit to GDP ratio which is expressed in percentage points and measured in deviations from a linear trend.¹¹ We use the longest possible sample for each individual time series which is mostly 1960Q1 until 2013Q4 for the US and the UK, see Figures 7 and 8. Due to data availability the German time series start only in 1970Q1, see Figure 9.

We split the data into two subsamples to analyze possible changes in the characteristics of the financial cycles over time. According to Claessens et al. (2011, 2012) and Drehmann et al. (2012), the break point is specified at 1985Q1 for the US and UK.¹² In the case of Germany, we choose the break point close to the German reunification, 1990Q2.¹³

driving forces behind business and financial cycles, Breitung and Eickmeier (2014) have recently applied a multi-level dynamic factor model to a large international data set of macroeconomic and financial indicators.

⁹A more detailed description of the definition and sources of the variables can be found in Appendix A.

¹⁰This implies that we investigate cycles in growth rates.

¹¹Unit root tests of the level series indicate that, with the exception of the credit to GDP ratios which are found to be trend-stationary, all other time series can be considered as integrated of order one. Therefore, working with annual growth rates for GDP, credit, housing and equity, i.e., annually differencing the data, is in line with the unit root test results. In the case of the credit to GDP ratio, we eliminated a deterministic linear trend. Results are available upon request.

¹²This is often seen as the starting point of the financial liberalization phase in mature economies. Moreover, during this period monetary policy regimes being more successful in controlling inflation are established, see Borio (2014).

¹³From 1990Q2 on, official data for the unified Germany are available.

All data used in the analysis are shown in Figures 1 to 3, where the vertical gray line highlights the sample split. A first visual inspection of the data shows that the credit and house price growth rates exhibit more pronounced swings than GDP growth, particularly in the US and the UK. In Germany, this is only true for housing. In view of equity, the figures illustrate that these series not only feature a high volatility, but their dynamics seem to be very different from the previous proxy variables for the financial cycle, credit and housing.

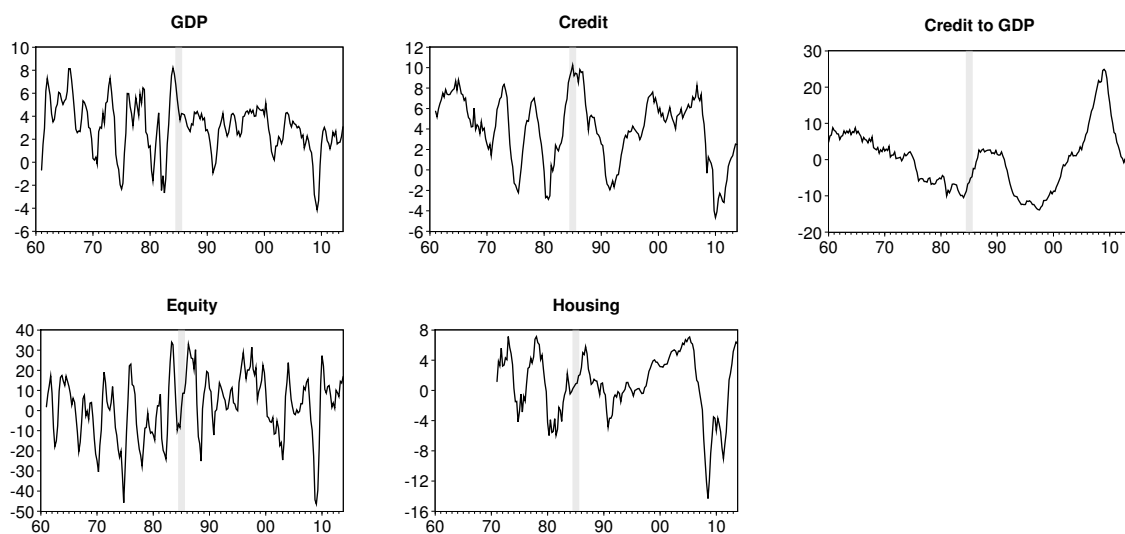


Figure 1: Real GDP and Financial Cycle Proxy Variables in the United States. Note: All series are annual growth rates, except the credit to GDP ratio, which represents deviations from a linear trend measured in percentage points. The vertical gray line shows the sample split.

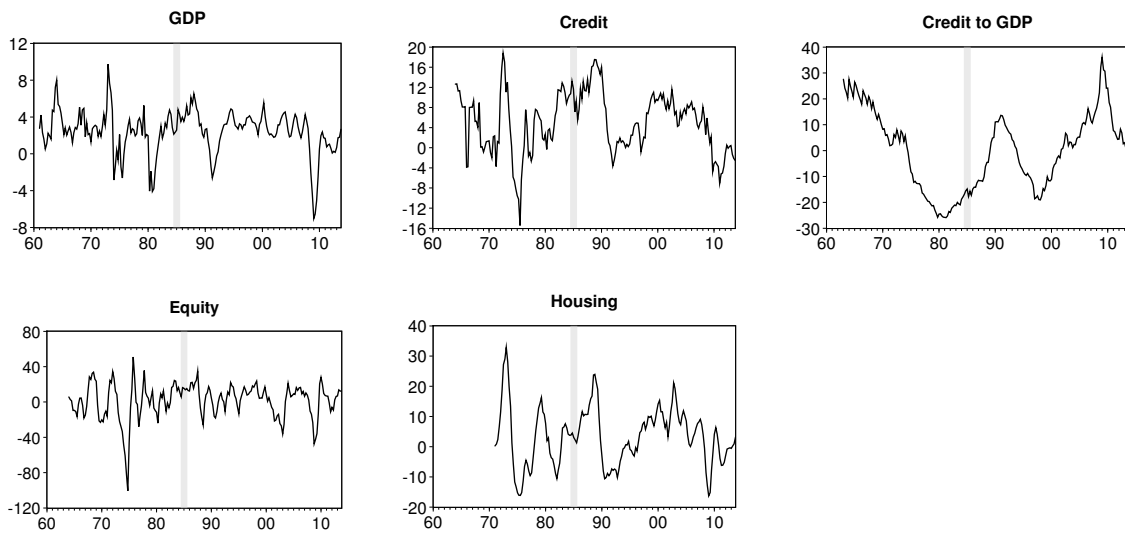


Figure 2: Real GDP and Financial Cycle Proxy Variables in the United Kingdom. Note: All series are annual growth rates, except the credit to GDP ratio, which represents deviations from a linear trend measured in percentage points. The vertical gray line shows the sample split.

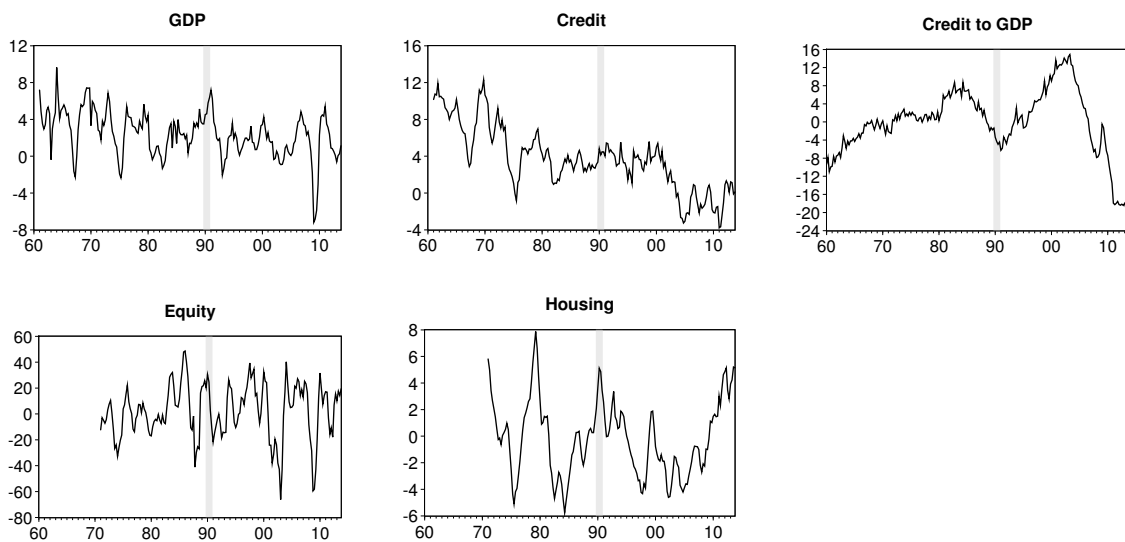


Figure 3: Real GDP and Financial Cycle Proxy Variables in Germany. Note: All series are annual growth rates, except the credit to GDP ratio, which represents deviations from a linear trend measured in percentage points. The vertical gray line shows the sample split.

3.2 Time Domain Estimation Results and Frequency Domain Representation

The empirical estimates of the spectral densities are based on the ARMA models reported in Tables 7 to 9 in Appendix B.¹⁴ The model specification procedure follows the principle of parsimony. We initially allow for a maximum autoregressive order of 5 and subsequently remove any remaining residual autocorrelation by the inclusion of appropriate moving average terms. As reported in Tables 7 to 9, all parameters in the final specifications are statistically significant at standard confidence levels and the estimated residuals are free from autocorrelation according to the Lagrange multiplier (LM) test.

In order to provide an example of how we use the estimated ARMA models to obtain the spectral densities, consider the following process of US real GDP growth during the pre-1985 period with t -values in parentheses (cf. Table 7) and the notation as in equation (5):

$$x_t = 0.002 + 1.144x_{t-1} - 0.224x_{t-3} - 0.985u_{t-4} + u_t \quad .$$

(2.97) (19.21) (-4.37) (-42.04)

These estimates are applied to equation (7) to calculate the corresponding spectrum as

$$f_x(\lambda) = \frac{|1 - 0.985 e^{-i4\lambda}|^2}{|1 - 1.144 e^{-i\lambda} + 0.224 e^{-i3\lambda}|^2} \frac{\sigma^2}{2\pi} \quad ,$$

with $e^{-i\lambda} = \cos(\lambda) - i \cdot \sin(\lambda)$ by Euler's relation and $i^2 = -1$. According to this procedure, we calculated the spectra for all countries and sample periods under consideration. Dividing $f_x(\lambda)$ by the variance of x_t yields the spectral densities.

The estimated spectral densities are shown in Figures 4 to 6 in the range $[0, \pi/4]$, i.e., for periods of ∞ to 2 year.¹⁵ We do not show frequencies in $[\pi/4, \pi]$ since almost no spectral mass is located in this range. The frequency $\pi/16$ corresponds to 8 years and separates the

¹⁴To statistically double-check the specified break dates, we also estimated ARMA models for the full sample. Chow breakpoint tests show overwhelming evidence for a break at 1985Q1 for the US and the UK. For Germany, the statistical support for a break at 1990Q2 is weaker, but for GDP and credit we clearly reject the null hypothesis of no break. Nonetheless, the German reunification is a natural break date from an economic point of view.

¹⁵When using quarterly data, all cycles of length infinity to half a year are described by the spectrum in the range from 0 to π because $f_x(\lambda)$ is an even symmetric continuous function. We approximate the continuous spectrum by 1000 equally spaced frequency bands from 0 to π .

financial cycle range from the business cycle range. An initial visual inspection of Figures 4 to 6 delivers at least two noteworthy results.

First, especially for the US and UK the spectral densities of credit, credit to GDP and house prices are substantially shifted to the left in the later period compared to the first one, indicating - at least superficially - that longer cycles became present, see Figures 4 and 5. Moreover, the peaks of the spectral densities are much more pronounced, suggesting that these longer cycles are also more important for the variation of the process. For Germany, as illustrated in Figure 6, this is only true for house prices. We obtain no clear results for German credit and credit to GDP. Therefore, German data do not provide much evidence in favor of the postulated financial cycle properties.

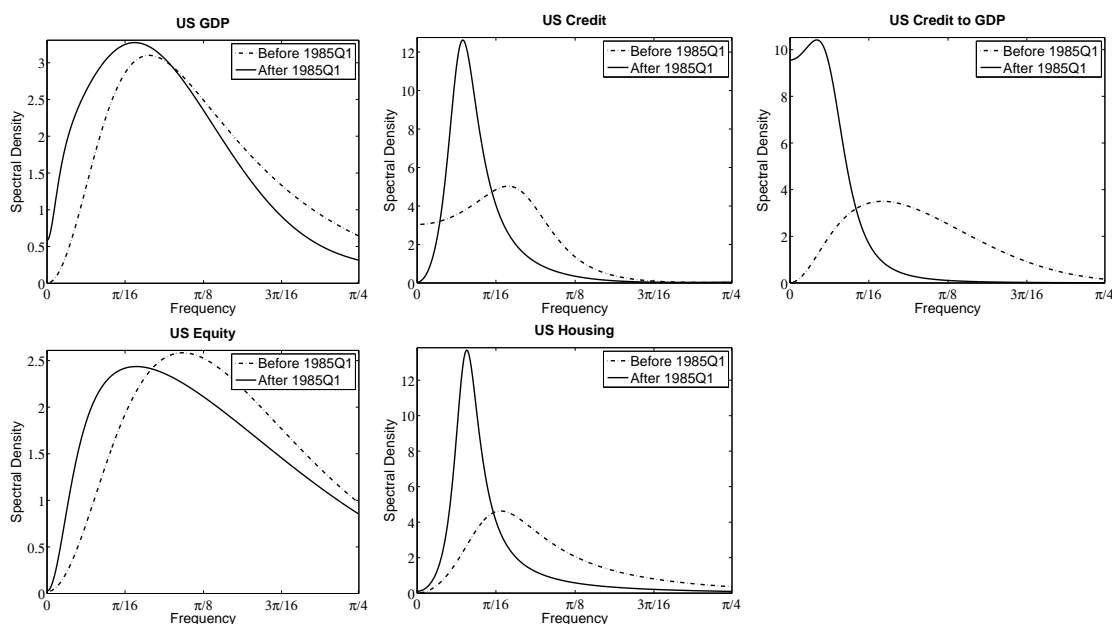


Figure 4: Spectral Densities in the US. Note: Spectral densities from frequency zero to $\pi/4$, corresponding to a cycle length of infinity to 2 year. Frequency $\pi/16$ corresponds to 8 years. Densities are denoted in thousands.

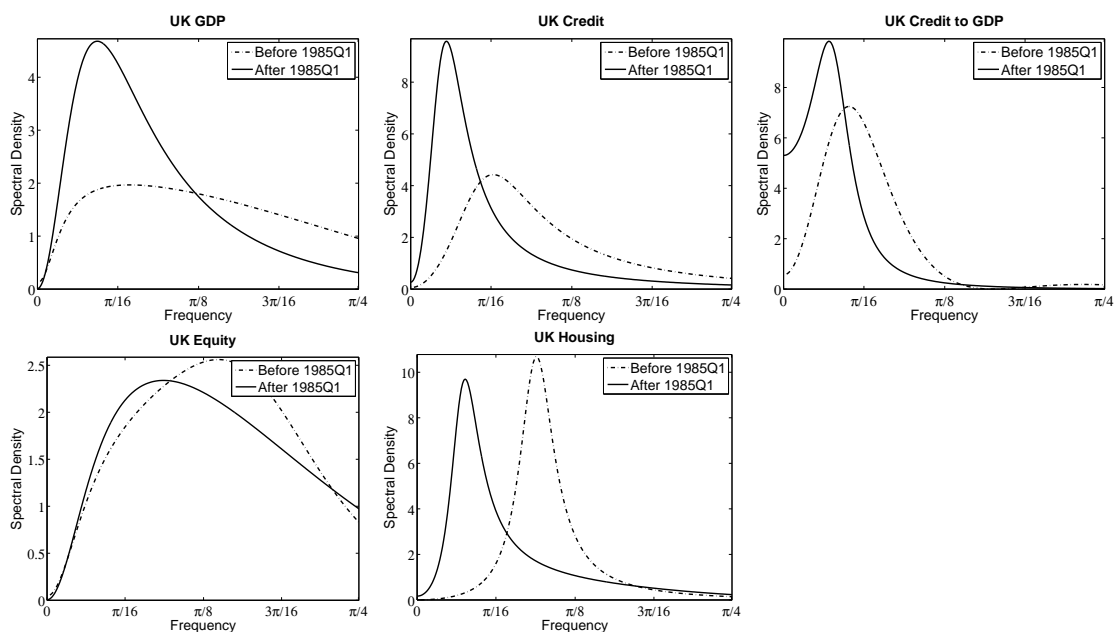


Figure 5: Spectral Densities in the UK. Note: Spectral densities from frequency zero to $\pi/4$, corresponding to a cycle length of infinity to 2 year. Frequency $\pi/16$ corresponds to 8 years. Densities are denoted in thousands.

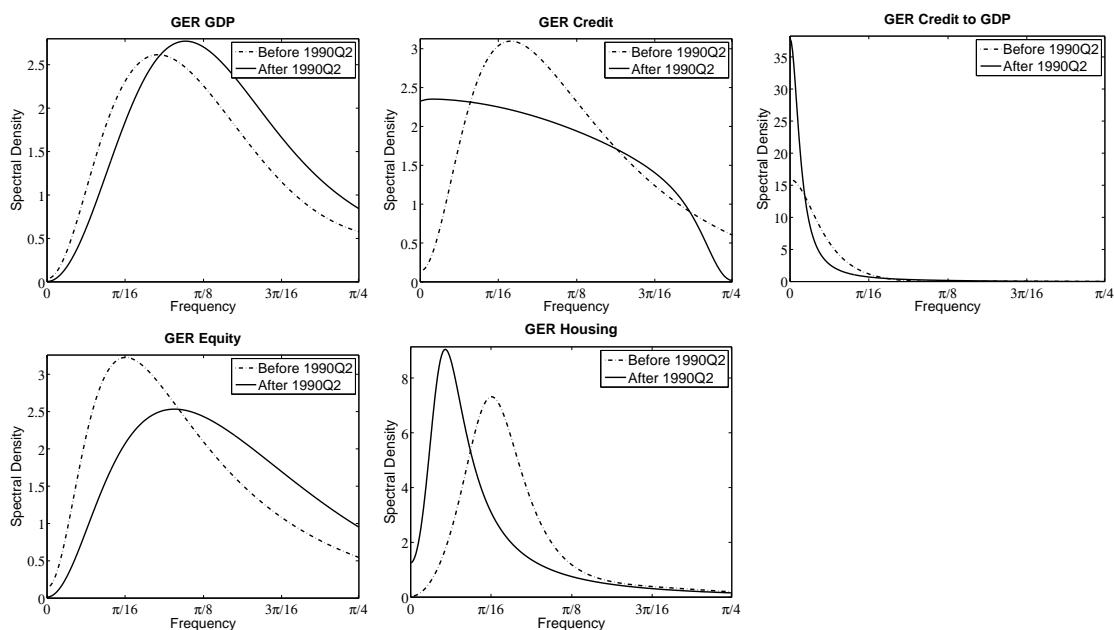


Figure 6: Spectral Densities in Germany. Note: Spectral densities from frequency zero to $\pi/4$, corresponding to a cycle length of infinity to 2 year. Frequency $\pi/16$ corresponds to 8 years. Densities are denoted in thousands.

Second, Figures 4, 5 and 6 clearly show that in all three countries, the spectral densities of both GDP and equity changed very little from the period before the sample split to the one thereafter. The interesting exception is the spectrum of UK GDP growth which may indeed have experienced a change. The general impression, however, is that in almost all cases GDP and equity show very similar spectral shapes with less pronounced peaks compared to the other variables.

Having obtained a frequency representation of the time series under consideration which is particularly suitable for the analysis of their cyclical properties, we continue in the next section by statistically testing various hypotheses concerning key features of the financial cycle which have been postulated in recent studies.

3.3 Statistics to Characterize Cycles in the Frequency Domain

We propose four different statistics derived from the spectral densities to describe the main features of business and financial cycles. Table 1 summarizes the statistics for all countries under consideration and the two estimation subsamples. The first two columns of Table 1 include the *main cycle length* in years measured at the peak of the spectrum. It is given by $\frac{2\pi}{\lambda_{\max}}$ with λ_{\max} as the frequency where the spectral density has its unique maximum. The remaining columns include three statistics that provide information about the distribution of the spectral mass. To approximate the variance contribution of the main cycle's amplitude, we report the spectral mass, measured in percentage points, located around λ_{\max} . We choose a symmetric frequency band with length of about $\frac{\pi}{20}$.¹⁶ The last four columns present estimates of the spectral mass for pre-defined ranges which are often used in the literature, i.e., 8 to 40 years for the financial cycle and 2 to 8 years for the business cycle. The values in brackets below the point estimates are the 95% bootstrap confidence intervals.

¹⁶This band is defined as $\lambda_{\max} \pm \frac{\pi}{1000} \cdot 25$.

Table 1: Frequency Domain: Length and Variance Contribution of Cycles

		length of main cycle <i>in years</i>		spectral mass <i>in percent</i> located...					
				... at the amplitude of the main cycle		... at longer-term cycles (8 to 40 years)		... at shorter-term cycles (2 to 8 years)	
		pre	post	pre	post	pre	post	pre	post
US	GDP	6.2 [4.6, 7.2]	7.1 [4.9, 17.2]	29.9 [22.3, 35.8]	31.9 [27.2, 42.3]	17.4 [10.0, 23.4]	27.9 [11.4, 41.5]	71.4 [66.6, 74.9]	63.3 [45.1, 77.7]
	credit	6.9 [5.7, 12.2]	13.9 [12.8, 14.7]	46.1 [39.1, 59.7]	75.4 [71.9, 78.6]	39.6 [17.0, 51.4]	77.3 [72.5, 80.5]	51.4 [34.9, 80.6]	19.3 [15.4, 23.3]
	credit to GDP	6.8 [5.1, 9.4]	23.8 [14.7, 45.4]	33.7 [27.8, 36.7]	86.4 [75.2, 91.2]	23.7 [13.7, 32.3]	67.9 [56.3, 76.2]	66.0 [54.7, 71.0]	6.8 [4.1, 12.8]
	housing	7.6 [4.0, 9.6]	12.8 [10.2, 14.7]	41.4 [20.6, 72.3]	73.0 [61.4, 81.0]	26.2 [3.3, 38.0]	73.2 [56.2, 81.1]	66.2 [53.5, 89.9]	24.9 [17.5, 41.3]
	equity	4.6 [3.3, 5.6]	7.0 [5.4, 8.5]	25.3 [21.7, 30.9]	23.9 [21.0, 27.1]	10.7 [3.9, 15.3]	19.5 [14.3, 23.0]	74.2 [67.5, 82.0]	65.4 [61.6, 69.3]
UK	GDP	6.9 [6.2, 8.1]	10.9 [8.2, 12.5]	19.4 [19.3, 19.5]	41.8 [32.0, 47.0]	16.8 [15.3, 18.1]	39.1 [26.4, 46.8]	58.6 [57.3, 59.6]	55.8 [48.3, 65.2]
	credit	7.8 [4.6, 9.4]	17.8 [15.1, 20.0]	39.5 [21.4, 54.3]	60.6 [53.7, 64.9]	26.4 [8.2, 38.9]	65.1 [57.0, 68.9]	63.5 [53.5, 77.3]	27.6 [23.0, 35.3]
	credit to GDP	9.8 [5.7, 13.9]	14.3 [8.8, 31.2]	62.1 [46.5, 79.4]	73.2 [52.0, 87.1]	55.6 [18.3, 64.5]	72.0 [46.8, 85.2]	39.7 [29.5, 76.6]	13.1 [6.3, 41.3]
	housing	5.3 [3.7, 6.4]	13.1 [11.1, 14.3]	69.2 [35.0, 96.8]	58.1 [33.5, 72.2]	5.1 [0.3, 16.7]	58.8 [30.1, 73.5]	93.0 [76.8, 99.4]	37.8 [24.9, 63.0]
	equity	3.6 [2.4, 6.4]	5.4 [3.3, 6.8]	25.2 [20.7, 47.9]	23.0 [20.6, 27.1]	12.4 [2.2, 20.0]	14.1 [4.4, 18.6]	75.3 [61.5, 89.5]	68.4 [62.8, 77.2]
GER	GDP	5.6 [5.0, 7.8]	4.5 [2.9, 5.7]	25.4 [20.7, 32.1]	27.0 [21.7, 33.1]	14.0 [11.3, 23.7]	9.5 [3.0, 15.7]	62.2 [58.0, 62.8]	74.2 [66.0, 81.6]
	credit	6.9 [6.1, 8.5]	45.4 [−, −]	29.8 [25.2, 36.9]	23.3 [−, −]	21.0 [16.7, 29.1]	23.6 [−, −]	67.9 [63.6, 69.3]	56.6 [−, −]
	credit to GDP	∞ [−, −]	∞ [−, −]	86.9 [69.7, 94.5]	91.4 [45.2, 96.5]	53.0 [34.9, 57.8]	29.5 [13.0, 58.7]	4.1 [1.7, 10.4]	5.7 [2.2, 41.2]
	housing	7.9 [4.9, 12.8]	18.5 [11.6, 20.8]	59.8 [33.2, 72.8]	60.6 [35.8, 70.3]	39.6 [11.4, 56.8]	63.6 [34.4, 72.4]	59.4 [38.7, 84.4]	27.7 [19.6, 55.0]
	equity	7.9 [4.8, 10.2]	4.9 [3.0, 6.4]	30.7 [18.6, 40.7]	24.9 [21.5, 31.4]	24.3 [10.6, 33.7]	12.2 [3.0, 17.8]	63.0 [56.0, 71.1]	72.5 [65.3, 82.3]

Notes: The terms *pre* and *post* refer to the sample periods 1960Q1 until 1984Q4 and 1985Q1 until 2013Q4, respectively, for the US and the UK. In the case of Germany the samples are 1970Q1 until 1990Q1 and 1990Q2 until 2013Q4. The cycle length is defined as $\frac{2\pi}{\lambda_{\max}}$, where λ_{\max} is the frequency where the spectral density has its unique maximum. The amplitude of the main cycle is defined as the spectral mass in the frequency band symmetric around λ_{\max} with a length of about $\frac{\pi}{20}$. 95% bootstrap confidence intervals are given in brackets. By "−" it is indicated that there is no distinct solution (maximum and percentiles) in the frequency range $0 < \lambda \leq \pi$.

As it can be observed from the estimates of the *main cycle length* in Table 1, the duration of the financial cycle increased strongly from the first to the second subsample. Averaging over the four financial variables, we find cycles of 6.5, 6.6 and 7.6 years during the first period, and 14.4, 12.7 and 11.7 years during the second period in the US, UK, and Germany, respectively.¹⁷ Hence, the point estimates suggest that the duration of the financial cycle has indeed exceeded the classical business cycle range in both subsamples. With respect to the business cycle as measured in terms of a country's GDP, our results reproduce a common result from the literature. The length of the business cycle has remained roughly constant and, with a single exception, is in line with the standard notion that business cycle fluctuations have a duration between 2 and 8 years, see [Hodrick and Prescott \(1997\)](#).

3.4 Hypotheses Tests

Going beyond the point estimates, let us now turn to the formal hypotheses tests. Detailed testing results are only reported for credit and housing. This is because in none of the countries studied, equity shows any feature usually ascribed to financial cycles. The tests simply confirm the impression from the figures in the last subsection. The cyclical properties of equity are neither significantly different from those of GDP nor do they change over time. For the credit to GDP ratio, the results are very similar to those obtained from credit alone, making use of credit to GDP redundant.¹⁸ Further, following [Borio \(2014\)](#), credit and house prices should capture the most important features of financial cycles. 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. In the following, we address four distinct hypotheses.

Is the financial cycle significantly longer than the business cycle? As a starting point, we test whether the financial cycle tends to be a medium-term phenomenon with a

¹⁷For Germany, cases where finite standard errors could not be found are not taken into account.

¹⁸Note that the results for the other variables can easily be derived from the measures and their standard errors given in Table 1.

significantly longer cycle length than that of the business cycle as suggested by Claessens et al. (2011), Drehmann et al. (2012) and Borio (2014). This addresses the key question, are financial market fluctuations mere reflections of the business cycle, in which case they should operate at similar frequencies, or are financial market fluctuations driven by intrinsic and self-reinforcing forces which would make such fluctuations last longer, and feature a larger amplitude. Table 2 reports the test results of the null hypothesis that the financial cycle and the business cycle are of equal length against the alternative hypothesis that the financial cycle is longer than the business cycle. According to one-sided two-sample t -tests, the null hypothesis cannot be rejected in the first subsample for any of the countries. This is no longer true in the second subsample, where the null is rejected at all conventional confidence levels. With respect to the information given in Table 1 this is not surprising. In the second subsample the average financial cycle is twice as long as the average business cycle.

Table 2: Is the Financial Cycle Longer Than the Business Cycle?

		pre break		post break	
		\hat{t} -stat	p -value	\hat{t} -stat	p -value
US	credit	0.26	0.399	2.45	0.007
	housing	0.76	0.224	1.95	0.025
UK	credit	0.64	0.259	4.28	0.000
	housing	-1.86	0.968	1.72	0.042
GER	credit	1.37	0.085	—	—
	housing	0.90	0.185	5.39	0.000

Notes: \hat{t} -stat represents the estimated value of the t -statistic of a one-sided two-sample t -test. By "—" it is indicated that we could not obtain finite bootstrap standard deviations which implies that it is not possible to conduct a t -test.

Did the financial cycle increase in length over time? We now consider if the medium-term nature of the financial cycle is a recent phenomenon, i.e., whether the length of the cycle increased over time. Statistical evidence is shown in Table 3. The results clearly support the hypothesis that the financial cycle is indeed longer during the second sample period. The mean value of the financial cycle length across the three countries more than doubled, from

about 7 years in the first period, to about 15 years in the second period. These findings, together with the test results reported in Table 2, not only corroborate the insights gleaned from Figures 4, 5 and 6 – where a general left-shift of the spectral densities of credit and housing growth (as well as of the credit to GDP ratio) can be observed – but they also deliver statistical support for the descriptive findings of Claessens et al. (2011), Drehmann et al. (2012) and Borio (2014).

Table 3: Did the Financial Cycle Increase in Length Over Time?

H_0 : The length of the financial cycle has not changed over time.			
H_1 : The length of the financial cycle has increased over time.			
		\hat{t} -stat	p -value
US	credit	2.32	0.010
	housing	2.59	0.005
UK	credit	5.69	0.000
	housing	7.26	0.000
GER	credit	–	–
	housing	3.01	0.001

Notes: \hat{t} -stat represents the estimated value of the t -statistic of a one-sided two-sample t -test that compares the cycle lengths in the pre and post sample period. By "–" it is indicated that we could not obtain finite bootstrap standard deviations which implies that it is not possible to conduct a t -test.

Does the financial cycle have a larger amplitude than the business cycle? Next, we investigate the variance contributions (i.e. the amplitudes) of given frequency ranges to analyze the relevance of the financial cycle. First, we test whether the financial cycle and the business cycle featured the same amplitude in the two subperiods. Table 4 shows somewhat mixed evidence in the first sample period. In most cases we reject the null of equal amplitudes of business and financial cycles. For US house prices and German credit, however, a rejection is not possible. In the second period, the results are much clearer. The null hypothesis is rejected for all variables in all countries. This indicates that, particularly in recent times, the financial cycle is characterized by a larger amplitude than the business cycle.

Table 4: Does the Financial Cycle Have a Larger Amplitude Than the Business Cycle?

		pre break		post break	
		\hat{t} -stat	p -value	\hat{t} -stat	p -value
US	credit	2.64	0.004	6.48	0.000
	housing	0.82	0.207	5.05	0.000
UK	credit	2.27	0.012	3.97	0.000
	housing	3.01	0.001	1.66	0.049
GER	credit	0.96	0.169	—	—
	housing	3.17	0.001	3.54	0.000

Notes: The approximate amplitude is defined as the spectral mass in the symmetric frequency band with a length of about $\frac{\pi}{20}$ around λ_{\max} , where λ_{\max} is the frequency where the spectral density has its unique maximum. \hat{t} -stat represents the estimated value of the t -statistic of a one-sided two-sample t -test. By "—" it is indicated that we could not obtain finite bootstrap standard deviations which implies that it is not possible to conduct a t -test.

Did the importance of the financial cycle increase over time? Finally, we investigate whether the financial cycle has become more important over time in terms of its variance contribution. We address this question by testing whether the main cycle’s amplitude has increased, whether the contribution of longer-term cycles to the overall variation of the process has increased, and whether the variance contribution of shorter-term (business) cycles has decreased. As can be seen from Table 5, the t -tests strongly support the alternative hypothesis of a significant increase for the US using both the credit and housing series. In the UK, the t -test results deliver a significant result only for the credit series. Germany seems again to be characterized by different dynamics, as the main cycle’s amplitude of the house price series does not appear to have changed between the two time periods.

We also find strong statistical evidence supporting the idea that the contribution of longer-term cycles in the dynamics of credit and housing has increased over time, both for the US and the UK, but much less significantly for Germany. This is further supported by the test results in the last two columns in Table 5 which suggest that the variance contribution of shorter-term cycles in credit and housing has significantly decreased in the US and UK, and, to a lesser extent, in Germany. Put differently, these results indicate a significant change of

Table 5: Did the Importance of the Financial Cycle Increase Over Time?

<i>H₀: The relevance of longer-term cycles has not changed over time.</i>							
That is, the variance contribution...							
		... of the main cycle's amplitude remained constant over time.		... of longer-term cycles (8 to 40 years) remained constant over time.		... of shorter-term cycles (2 to 8 years) remained constant over time.	
<i>H₁: Longer-term cycles became more important in recent decades.</i>							
That is, the variance contribution...							
		... of the main cycle's amplitude increased over time.		... of longer-term cycles (8 to 40 years) increased over time.		... of shorter-term cycles (2 to 8 years) decreased over time.	
		\hat{t} -stat	<i>p</i> -value	\hat{t} -stat	<i>p</i> -value	\hat{t} -stat	<i>p</i> -value
US	credit	5.38	0.000	4.25	0.000	2.72	0.003
	housing	2.18	0.015	4.16	0.000	3.39	0.000
UK	credit	2.28	0.011	4.51	0.000	5.03	0.000
	housing	-0.59	0.722	4.86	0.000	5.10	0.000
GER	credit	—	—	—	—	—	—
	housing	0.06	0.478	1.52	0.065	2.04	0.021

Notes: The approximate amplitude is defined as the spectral mass in the symmetric frequency band with a length of about $\frac{\pi}{20}$ around λ_{\max} , where λ_{\max} is the frequency where the spectral density has its unique maximum. \hat{t} -stat represents the estimated value of the *t*-statistic of a one-sided two-sample *t*-test. By "—" it is indicated that we could not obtain finite bootstrap standard deviations which implies that it is not possible to conduct a *t*-test.

the overall shape of the spectral density over time. In more recent times, the largest share of spectral mass of the credit and housing series in the US and UK is clearly located at cycles longer than the business cycle. This conclusion does not seem to bear out for the house price dynamics in Germany. However, medium-term frequencies do seem to have become somewhat more relevant in the second period.

4 Concluding Remarks

What are the main characteristics of the financial cycle?¹⁹ Is it a medium-term phenomenon, meaning it is longer than the business cycle, as suggested in the literature, or does it share similar characteristics with the business cycle? Did its importance increase over time? Or is it tied to the business cycle in a way that makes analysis of the financial cycle a redundant exercise? In this paper we intended to shed some light on these and other related questions. We did that by estimating the data generating processes of financial and business cycle variables using econometric methods, in contrast to the more descriptive approaches pursued by Claessens et al. (2011, 2012), and Drehmann et al. (2012).

Specifically, we made use of the correspondence between the time domain and the frequency domain representation of linear stochastic processes to obtain a complete characterization of the series' DGP. We derived the cyclical properties from ARMA models which are estimated for a given sample period and then analytically transformed into the frequency domain. This approach has a number of appealing features. It allowed us to take into account all possible cycles without *a priori* assuming different ranges for financial and business cycles. Also, while for the usual methods the maximum cycle length is limited to the length of the sample period, our approach can detect cycles of any duration between 2 quarters and infinity. Applying bootstrap methods, we were able to statistically test the characteristics of the financial cycle.

Our results concerning the United States, United Kingdom and Germany can be summarized as follows. First, while the financial and the business cycles had a similar length of about 7 years in the first subsample of our analysis, the duration of the financial cycle has dramatically increased since 1985 or in the case of Germany, 1990. This has indeed turned the financial cycle into a medium-term phenomenon, operating at cycles with an average length of about 15 years. We also found strong statistical evidence supporting the notion

¹⁹At the theoretical level the notion of the existence of such an underlying “financial cycle” is not new: Seminal works by Fisher (1933), Keynes (1936), von Mises (1952), Hayek (1933) and Minsky (1982) stressed the inherently procyclical behavior of the financial system and the role of extrapolative behavior by financial market participants.

that financial cycles have larger amplitudes than business cycles, as suggested in particular by Drehmann et al. (2012) and Borio (2014).

While the main characteristics of the financial cycle have been postulated by the existing literature, the statistical significance of our findings elevates the relevance of these issues from a descriptive exercise to stylized facts. Important to policymakers, our results indicate a decoupling of the dynamics of the financial cycle (measured here in terms of credit and housing dynamics) from those of the business cycle, particularly in the recent decades. Although both cycles have shared similar lengths and amplitudes before the financial liberalization process of the 1980s, the financial cycle has since significantly changed, featuring long and persistent upward movements followed – as the recent financial crisis has shown – by abrupt downward corrections.

At least two interesting extensions of our approach would be straightforward. First, time-varying parameter autoregressive models could provide deeper insight into the question when the financial cycle has developed its distinguishing features. Second, multivariate models could be specified to capture the dynamic interaction between real and financial variables at different frequencies. We intend to do this in further research.

Appendix A Data Sources and Definitions

All series are measured in logs and deflated using the consumer price index. All series are normalized by their respective value in 1985Q1 to ensure comparability of the units. We obtain annual growth rates by taking annual differences of the time series. The only exception is the credit to GDP ratio which is expressed in percentage points.

Table 6: Definition and Sources of the Data

	Source	Identifier	Notes
GDP	OECD.Stat	CARSA	national currency
CPI	OECD.Stat	Consumer Prices	national index
credit	Datastream	USBLCAPAA, UKBLCAPAA, BDBLCAPAA	national currency, credit to private non-financial sector from all sectors
housing	OECD.Stat	House Prices	national index
equity	IMF	USQ62...F, UK62...F, BDQ62.EPC	national index

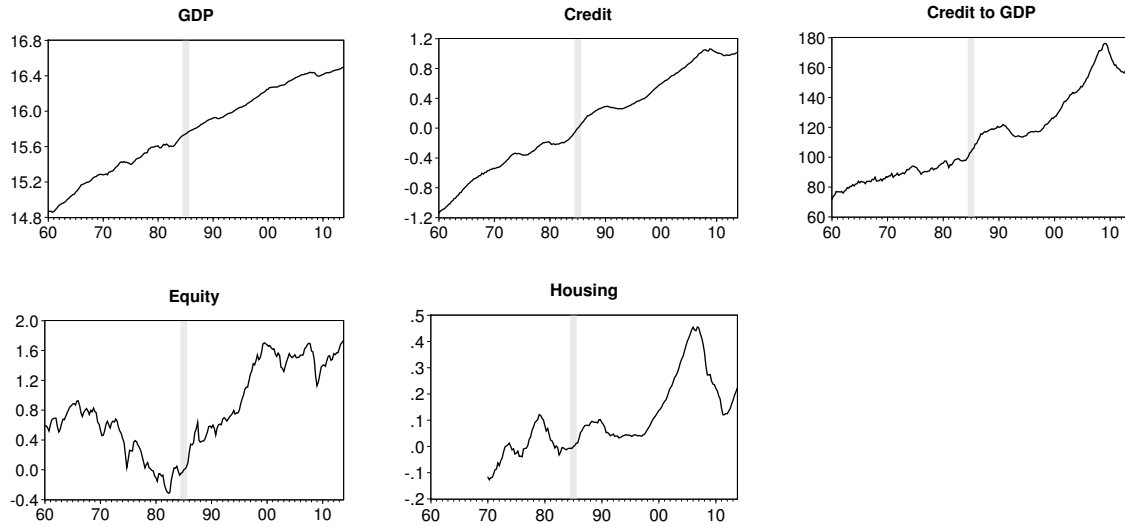


Figure 7: Real GDP and Financial Cycle Proxy Variables in the United States. All series are log levels except the credit to GDP ratio, which is measured in percentage points. The vertical gray line shows the sample split.

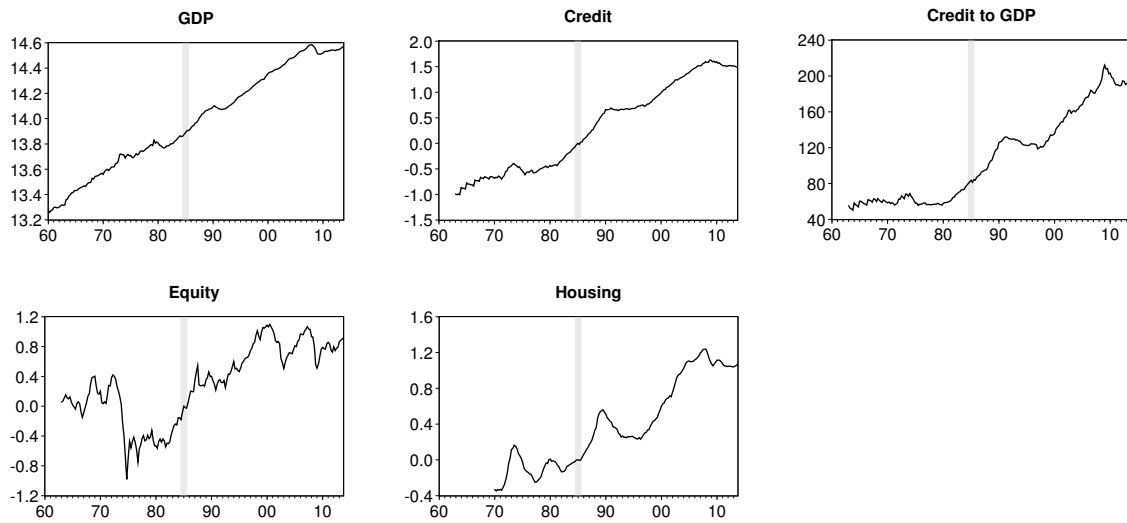


Figure 8: Real GDP and Financial Cycle Proxy Variables in the United Kingdom. All series are log levels except the credit to GDP ratio, which is measured in percentage points. The vertical gray line shows the sample split.

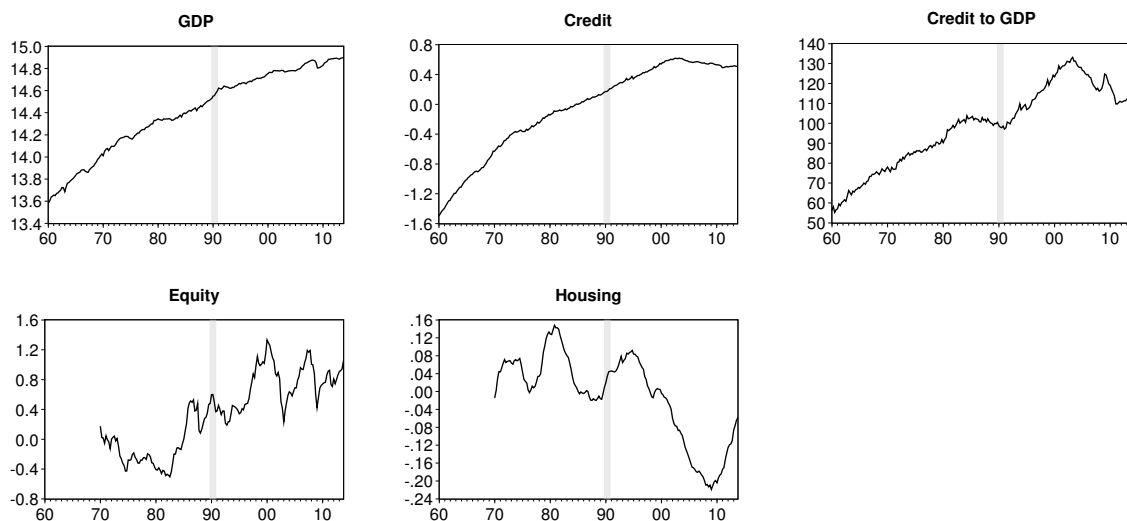


Figure 9: Real GDP and Financial Cycle Proxy Variables in Germany. All series are log levels except the credit to GDP ratio, which is measured in percentage points. The vertical gray line shows the sample split.

Appendix B Time Domain Results: Estimated ARMA Models

Table 7: ARMA Models for the US

<i>parameters</i>	GDP			credit			credit to GDP			housing			equity		
	total	pre	post	total	pre	post	total	pre	post	total	pre	post	total	pre	post
const	0.028 (18.7)	0.031 (21.3)	0.022 (2.95)	0.039 (24.2)	0.044 (5.10)	0.038 (10.5)	-1.180 (-0.50)	0.239 (1.40)	-1.795 (-0.43)	0.009 (4.15)	0.001 (0.14)	0.010 (2.48)	0.050 (2.04)	-0.049 (-5.77)	0.043 (3.25)
AR(1)	1.202 (29.9)	1.144 (19.2)	1.318 (27.1)	1.185 (79.7)	1.237 (19.6)	1.170 (47.3)	1.251 (28.8)	0.873 (18.4)	1.381 (35.8)	1.373 (18.7)	1.130 (17.2)	1.664 (18.5)	1.350 (20.8)	1.302 (13.5)	1.285 (14.3)
AR(2)										-0.332 (-2.58)		-0.827 (-4.66)	-0.365 (-5.64)	-0.410 (-4.33)	-0.333 (-3.77)
AR(3)	-0.230 (-5.76)	-0.224 (-4.37)	-0.328 (-6.64)		-0.346 (-5.69)		-0.600 (-6.49)		-0.402 (-10.3)	0.270 (2.10)		0.484 (2.68)			
AR(4)							0.939 (62.68)			-0.342 (-4.64)	-0.201 (-3.28)	-0.345 (-3.69)			
AR(5)				-0.222 (-14.9)		-0.201 (-7.92)	-0.611 (-10.2)								
MA(3)					0.403 (3.68)		0.360 (3.95)								
MA(4)	-0.978 (-92.2)	-0.985 (-42.0)	-1.144 (-18.1)	-0.904 (-29.5)	-0.374 (-3.75)	-0.929 (-31.6)	-0.429 (-5.65)	0.212 (2.76)		-0.973 (-37.2)	-0.983 (-29.5)	-0.932 (-25.9)	-0.977 (-65.2)	-0.943 (-47.2)	-0.972 (-60.5)
MA(5)					0.241 (2.21)	0.487 (5.95)		-0.516 (-8.47)							
MA(6)					0.302 (2.95)		-0.185 (-2.75)								
MA(7)								-0.429 (-5.87)							
MA(12)			0.182 (3.02)												
<i>diagnostics</i>															
Chow	3.37 (0.01)			1.74 (0.14)			3.66 (0.00)			3.97 (0.00)			3.38 (0.01)		
LM(4)	0.75	0.89	0.35	0.82	0.16	0.21	0.47	0.62	0.28	0.14	0.69	0.83	0.94	0.51	0.99
LM(8)	0.36	0.46	0.42	0.53	0.38	0.14	0.79	0.94	0.54	0.11	0.63	0.69	0.81	0.44	0.99
LM(12)	0.13	0.34	0.17	0.22	0.44	0.35	0.57	0.68	0.63	0.14	0.57	0.56	0.71	0.26	0.93

Notes: The terms *pre* and *post* refer to the sample periods 1960Q1 until 1984Q4 and 1985Q1 until 2013Q4, respectively. *Total* denotes the full sample period. Below the parameter estimates *t*-values are given in parentheses. Chow tests with *p*-values in parentheses refer to a break in parameters at 1985Q1. For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.

Table 8: ARMA Models for the UK

<i>parameters</i>	GDP			credit			credit to GDP			housing			equity		
	total	pre	post	total	pre	post	total	pre	post	total	pre	post	total	pre	post
const	0.024 (23.3)	0.021 (5.95)	0.023 (10.8)	0.057 (12.7)	0.043 (2.71)	0.037 (3.71)	-4.367 (-2.87)	-0.094 (-0.07)	-1.538 (-0.37)	0.037 (7.24)	0.001 (0.16)	0.039 (4.64)	0.032 (3.03)	-0.024 (-0.83)	0.023 (3.05)
AR(1)	1.101 (32.0)	0.941 (27.2)	1.464 (17.2)	1.113 (36.4)	1.174 (39.6)	1.060 (19.6)	1.099 (37.3)	1.046 (17.8)	1.151 (36.0)	1.480 (36.9)	1.321 (33.0)	1.573 (17.1)	1.309 (18.0)	1.372 (11.8)	1.206 (13.3)
AR(2)			-0.291 (-1.98)									-0.291 (-1.65)	-0.400 (-3.37)	-0.571 (-3.05)	-0.289 (-3.32)
AR(3)			-0.198 (-2.33)							-0.596 (-8.03)	-0.446 (-12.1)	-0.300 (-3.17)	0.166 (1.37)	0.446 (2.32)	
AR(4)	-0.135 (-3.82)			0.267 (2.28)			0.479 (4.43)						-0.235 (-1.98)	-0.596 (-3.19)	
AR(5)				-0.400 (-4.00)	-0.192 (-6.34)	-0.137 (-2.29)	-0.589 (-7.04)	-0.120 (-2.01)	-0.192 (-5.99)	0.095 (2.27)			0.123 (1.70)	0.280 (2.40)	
MA(4)	-0.922 (-113.6)	-0.946 (-34.9)	-0.986 (-81.8)	-1.148 (-14.9)	-0.954 (-39.2)	-0.930 (-30.4)	-0.474 (-5.33)			-1.120 (-12.3)	-0.956 (-41.1)	-1.261 (-12.6)	-0.979 (-74.5)	-0.939 (-30.1)	-0.979 (-38.6)
MA(6)							-0.229 (-3.47)		-0.246 (-2.42)						
MA(8)							-0.237 (-3.40)	0.150 (3.02)		0.156 (1.75)		0.317 (3.33)			
MA(12)				0.174 (2.41)				-0.832 (-28.0)							
<i>diagnostics</i>															
Chow	1.86 (0.12)			5.54 (0.00)			1.92 (0.07)			3.24 (0.01)			1.90 (0.07)		
LM(4)	0.83	0.62	0.77	0.88	0.74	0.44	0.83	0.75	0.72	0.15	0.98	0.99	0.95	0.40	0.70
LM(8)	0.39	0.39	0.85	0.41	0.74	0.78	0.83	0.81	0.52	0.18	0.99	0.57	0.85	0.82	0.92
LM(12)	0.43	0.40	0.56	0.51	0.81	0.84	0.71	0.31	0.36	0.30	0.99	0.87	0.94	0.94	0.98

Notes: The terms *pre* and *post* refer to the sample periods 1960Q1 until 1984Q4 and 1985Q1 until 2013Q4, respectively. *Total* denotes the full sample period. Below the parameter estimates *t*-values are given in parentheses. Chow tests with *p*-values in parentheses refer to a break in parameters at 1985Q1. For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.

Table 9: ARMA Models for Germany

<i>parameters</i>	GDP			credit			credit to GDP			housing			equity		
	total	pre	post	total	pre	post	total	pre	post	total	pre	post	total	pre	post
const	0.017 (8.59)	0.022 (14.1)	0.013 (14.2)	-0.159 (-0.16)	0.035 (15.0)	-0.047 (-0.83)	-	-2.168 (-0.71)	-0.933 (-0.10)	-0.005 (-1.93)	-0.001 (-0.30)	-0.004 (-0.31)	0.038 (5.12)	0.065 (1.66)	0.029 (2.06)
AR(1)	1.032 (24.7)	0.820 (12.2)	1.201 (12.4)	1.091 (28.2)	1.159 (16.8)	1.018 (22.3)	0.999 (55.4)	0.586 (5.11)	1.094 (19.7)	1.545 (19.9)	1.769 (23.0)	1.440 (14.0)	1.233 (16.6)	1.076 (16.9)	1.291 (13.2)
AR(2)			-0.363 (-3.80)					0.298 (2.53)		-0.429 (-3.06)	-0.811 (-10.7)	-0.337 (-2.54)	-0.307 (-4.17)		-0.386 (3.97)
AR(3)					-0.223 (-3.75)					-0.139 (-1.77)					
AR(4)	-0.072 (-1.72)			-0.092 (-2.37)		-0.725 (-8.61)			-0.518 (-3.09)					-0.136 (-2.16)	
AR(5)						0.688 (9.74)			0.396 (2.39)			-0.116 (-2.80)			
MA(4)	-0.751 (-9.90)	-0.615 (-5.34)	-0.782 (-6.94)	-0.647 (-8.86)	-0.912 (-28.6)		0.402 (5.74)	0.520 (5.11)	0.764 (5.93)	-0.736 (-10.9)	-0.751 (-7.59)	-0.905 (-24.5)	-0.969 (-74.5)	-0.923 (-21.3)	-0.957 (-45.0)
MA(8)	-0.228 (-3.03)	-0.302 (-2.68)	-0.182 (-1.63)	-0.239 (-3.18)		-0.907 (-38.2)		0.814 (19.3)							
MA(12)								0.563 (6.28)		-0.198 (-3.09)	-0.183 (-1.87)				
<i>diagnostics</i>															
Chow	3.63 (0.00)			3.68 (0.00)			1.74 (0.18)			1.22 (0.30)			0.30 (0.88)		
LM(4)	0.96	0.80	0.15	0.88	0.66	0.32	0.43	0.76	0.83	0.57	0.74	0.58	0.57	0.31	0.86
LM(8)	0.28	0.90	0.58	0.20	0.86	0.19	0.43	0.40	0.92	0.59	0.95	0.75	0.89	0.73	0.87
LM(12)	0.42	0.97	0.86	0.38	0.92	0.31	0.54	0.50	0.59	0.76	0.81	0.81	0.78	0.57	0.80

Notes: The terms *pre* and *post* refer to the sample periods 1970Q1 until 1990Q1 and 1990Q2 until 2013Q4, respectively. *Total* denotes the full sample period. Below the parameter estimates *t*-values are given in parentheses. Chow tests with *p*-values in parentheses refer to a break in parameters at 1990Q2. For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.

References

- Baxter, Marianne and Robert G. King (1999), ‘Measuring business cycles: Approximate band-pass filters for economic time series’, *Review of Economics and Statistics* **81**, 575–593.
- Benkowitz, Alexander, Helmut Lütkepohl and Jürgen Wolters (2001), ‘Comparison of bootstrap confidence intervals for impulse responses of german monetary systems’, *Macroeconomic Dynamics* **5**(01), 81–100.
- Borio, Claudio (2014), ‘The financial cycle and macroeconomics: What have we learnt?’, *Journal of Banking & Finance* **45**(395), 182–98.
- Breitung, Jörg and Sandra Eickmeier (2014), Analyzing business and financial cycles using multi-level factor models, CAMA Working Paper 43/2014, Australian National University, Centre for Applied Macroeconomic Analysis.
- Bry, Gerhard and Charlotte Boschan (1971), *Cyclical Analysis of Times Series: Selected Procedures and Computer Programs*, NBER.
- Caballero, Ricardo (2010), ‘Macroeconomics after the crisis: Time to deal with the pretense-of-knowledge syndrome’, *Journal of Economic Perspectives* **24**(4), 85–102.
- Christiano, Lawrence J. and Terry J. Fitzgerald (2003), ‘The band pass filter’, *International Economic Review* **44**(2), 435–465.
- Claessens, Stijn., M. Ayhan Kose and Marco E. Terrones (2011), Financial cycles: What? how? when?, in R. Clarida and F. Giavazzi, eds, ‘NBER International Seminar on Macroeconomics’, Vol. 7, University of Chicago Press, pp. 303–344.
- Claessens, Stijn, M. Ayhan Kose and Marco E. Terrones (2012), ‘How do business and financial cycles interact?’, *Journal of International Economics* **97**, 178–190.
- Diebold, Francis X. and Glenn D. Rudebusch (1996), ‘Measuring business cycles: A modern perspective’, *Review of Economics and Statistics* **78**, 67–77.

- Drehmann, Mathias, Claudio Borio and Kostas Tsatsaronis (2012), Characterizing the final cycle: Don't lose sight of the medium term!, BIS Working Paper 380, Bank for International Settlements.
- English, William, Kostas Tsatsaronis and Edda Zoli (2005), 'Assessing the predictive power of measures of financial conditions for macroeconomic variables', *BIS Papers* **22**, 228–252.
- Fisher, Irving (1933), 'The debt-deflation theory of great depressions', *Econometrica* **1**, 337–357.
- Fishman, George S. (1969), *Spectral Methods in Econometrics*, Harvard University Press, Cambridge.
- Hamilton, James D. (1994), *Time Series Analysis*, Princeton University Press, Princeton.
- Harding, Don and Adrian Pagan (2002), 'Dissecting the cycle: A methodological investigation', *Journal of Monetary Economics* **49**, 365 – 381.
- Hatzius, J., P. Hooper, F. Mishkin, K. Schoenholtz and M. Watson (2010), Financial conditions indexes: A fresh look after the financial crisis, Working Papers 16150, National Bureau of Economic Research.
- Hayek, Friedrich A. (1933), *Monetary Theory and the Trade Cycle*, Clifton, New Jersey: Augustus M. Kelly reprint 1966.
- Hodrick, Robert J. and Edward C. Prescott (1997), 'Postwar U.S. business cycles: An empirical investigation', *Journal of Money, Credit, and Banking* **29**, 1 – 16.
- Keynes, John M. (1936), *The General Theory of Employment, Interest and Money*, MacMillan, New York.
- Khintchine, Alexander (1934), 'Korrelationstheorie der stationären stochastischen Prozesse', *Mathematische Annalen* **109**(1), 604–615.
- Kindleberger, Charles P. and Robert Z. Aliber (2005), *Manias, Panics and Crashes. A History of Financial Crises*, fourth edn, Cambridge University Press.

- König, Heinz and Jürgen Wolters (1972), ‘Zum Problem langfristiger Wachstumszyklen: Eine Spektralanalyse der englischen Entwicklung von 1700—1913’, *Zeitschrift für die gesamte Staatswissenschaft/Journal of Institutional and Theoretical Economics* pp. 72–96.
- Minsky, Hyman P. (1982), *Can ‘It’ Happen Again?*, Essays on Instability and Finance, M. E. Sharpe., Armonk.
- Murray, Christian J. (2003), ‘Cyclical properties of Baxter-King filtered time series’, *Review of Economics and Statistics* **85**(2), 472–476.
- Ng, Tim (2011), ‘The predictive content of financial cycle measures for output fluctuations’, *BIS Quarterly Review* **June**, 53–65.
- Sargent, Thomas J. (1987), *Macroeconomic Theory*, Vol. 2, Academic Press New York.
- Schularick, Moritz and Alan M. Taylor (2012), ‘Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008’, *American Economic Review* **102**(2), 1029–61.
- von Mises, Ludwig (1952), *The Theory of Money and Credit*, Yale University Press.
- Wiener, Norbert (1930), ‘Generalized harmonic analysis’, *Acta mathematica* **55**(1), 117–258.
- Wolters, Jürgen (1980a), ‘Business cycle stabilization policies in a small econometric model of the FRG’, *European Economic Review* **14**(1), 9–43.
- Wolters, Jürgen (1980b), Stochastic dynamic properties of linear econometric models, *in* M.Beckmann and H.Künzi, eds, ‘Lecture Notes in Economics and Mathematical Systems’, Vol. 182, Springer Berlin Heidelberg, pp. 1–154.