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THE FINANCIAL CYCLES IN FOUR EAST ASIAN ECONOMIES

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Abstract

This paper characterizes proxy measures of financial cycles using available data on four East Asian economies, viz., Hong Kong, Malaysia, the Philippines and Thailand. Spectral analysis is adopted to characterize the financial cycles and these cycles are compared with the business cycles of the four East Asian economies. The empirical findings indicated that with the exception of the equity price growth in Hong Kong, the period of the proxy measures for financial cycles is slightly longer than the period of the business cycle. More to the point, there is no evidence to show that the period of the proxy measures for financial cycles in these economies are operating at low frequencies similar to the period of the cycles of between 8 to 32 years observed for advanced economies such as the US, UK and Germany. Taking one step further, the paper finds that the financial cycles of these four economies are better captured by a band-pass filter estimated using the periods obtained in the paper as opposed to using long period cycles of between 8 to 32 years. These findings imply that one needs to be careful in making an a priori assumption on the frequency range the financial cycle is believed to operate.

JEL Classification: C22, E32, E44

Keywords: Financial Cycle, Business Cycle, Frequency-Domain, Periods, Frequency, ARMA Modeling, Spectral Densities

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By

Victor Pontines

1. Introduction

The experience of Japan in the 1980s, 1990s and the recent Great Recession of 2007-2008, clearly indicated that unsustainable buildups of credit and leverage lie at the heart of financial fragility. The debilitating consequences of the significant economic bust on the real sector that followed the long period of economic boom have placed financial factors front and center, not just in theoretical macroeconomic models, but also on the macroeconomic radars of policymakers. In this context, interest has emerged on the modeling of financial factors. In particular, a growing body of literature has sought to understand the empirical regularities of the so-called financial cycle.

There is so far, no consensus on the definition of the financial cycle. Borio (2014), for instance, defined it as, “the self-reinforcing interactions between perceptions of value and risk, attitudes towards risk, and financing constraints, which translate into booms followed by busts”. The crucial implication coming out of this definition is that correctly determining the current phase of the financial cycle is vital for successfully identifying emerging risks as rising asset prices, for instance, can be driven by excessive leverage which would have serious macroeconomic consequences once the cycle turns. Thus, the correct management of the financial cycle through precise and timely policy actions on the part of the authorities, carried out through monetary or prudential policy, or a combination of the two, should increase the resilience of the economy, in general, and the financial system, in particular.

While a consensus definition on the concept has appeared elusive, two key empirical findings have emerged from recent studies that sought to characterize the financial cycle (Claessens et al., 2011; Drehmann et al., 2012; Borio, 2014; Aikman, 2015). First, the financial cycle is best described by the behavior of credit and property prices. The other is that it has a much lower frequency than the traditional business cycle. The traditional business cycle involves periods of between 2 to 8 years, whereas the financial cycle operates at lower frequencies with periods of between 8 and 32 years. It is also based on this latter finding that Borio (2014) argued that “equity prices can be a distraction - they exhibit shorter cycles and tend to be more closely related to the fluctuations in GDP”. Considerably longer financial cycles compared to the traditional business cycles suggests that financial vulnerabilities take some time to grow. This divergence in duration between the financial cycle and the business cycle can make policymakers fall into a sense of complacency. Failing to take into account the longer period of the financial cycle and only focusing on containing recessions in the near or immediate term, could be at the expense of larger and deep recessions later on.

One must note that these two key findings on the characterization of financial cycles were obtained using data on advanced economies, including the US. These findings may not be applicable for emerging economies. Furthermore, these findings were obtained using standard approaches that have been similarly applied to characterize business cycles, that is, either the turning-point approach (Claessens et al., 2011; Drehmann et al., 2012) or frequency-based filter methods such as the Baxter and King (1999) band-pass filter and the Christiano and Fitzgerald (2003) band-pass filter (Drehmann et al., 2012; Aikman et al., 2015). The limitations of these two approaches are obvious. The turning point approach requires a pre-specified rule which is applied to an observed time series in order to find the local maxima and minima, while frequency-based filter methods require a pre-specified frequency range at which the financial cycle is assumed to operate (Strohsal et al., 2015).

More recently, Strohsal et al. (2015) characterizes the business and financial cycles in the US, UK and Germany via spectral analysis. Specifically, they estimated time-series models of the autoregressive moving average (ARMA) class of the business cycle and proxy measures of the financial cycles and used the estimated models to compute their corresponding spectral densities. Compared to the turning point approach and frequency-based filter methods, they showed that their approach offers the major advantage of the non-requirement of an a priori assumption on the frequency range at which the financial cycle is assumed to operate. They then found that financial cycles have increased in recent times in the US and the UK by about 15 years, while slightly less so in the case of Germany. Moreover, strong statistical evidence points to a longer duration and larger amplitude of the financial cycle in comparison to the business cycle in these countries.

This paper provides a characterization using spectral analysis of the business and financial cycles in the context of emerging economies, with particular reference to the East Asian region. Subject to available data, the empirical regularities of the business and financial cycles are undertaken for four emerging economies, namely Hong Kong, Malaysia, the Philippines and Thailand. Following Strohsal et al. (2015), the cyclical properties of the various time-series of these four economies were derived from ARMA models which are estimated for a given sample period and subsequently transformed through the estimation of their corresponding spectral densities. As earlier mentioned, the approach allows one to take into account all possible cycles without an a priori assumption of the different frequency ranges for the business and financial cycles. Specifically, the approach can detect cycles of any duration between 2 quarters and infinity (Strohsal et al. 2015).

The main findings of this paper are as follows. The paper confirms recent evidence provided by Strohsal et al. (2015) that credit and housing price growth in the UK and US, as well as housing price growth in Germany have periods of cycles that are much longer than 8 years. Second, the business cycles measured in terms of GDP growth of the four East Asian economies have periods of between 3 to 6 years. Third, with the exception of the equity price growth in Hong Kong, the cycle periods for the proxy measures of financial cycles are slightly longer than the periods of the business cycle measured in terms of GDP growth. More importantly, the paper finds that the periods of the proxy measures for financial cycles do not operate at low frequencies similar to the periods for advanced economies such as the US, UK and Germany. More specifically, the period of the proxy measures for financial cycles do not substantially exceed the rule-of-thumb cut-off of 8 years, with the longest cycle at 8.1 years in the case of housing price growth in Hong Kong. Finally, taking one step further, this paper finds that the financial cycles of the four East Asian economies are better captured and depicted by a band-pass filter estimated using the periods obtained in our analysis as opposed to using long periods of the cycles equivalent to between 8 to 32 years.

The rest of the paper is organized as follows. Section 2 briefly provides a review of the related literature. Section 3 discusses the main method used in this study. Section 4 discusses the data and the empirical results. The last section concludes.

2. Review of Related Literature

Prior to the Great Recession of 2007-2008, the role of finance in the macroeconomy was treated with less importance compared to the role of the business cycle. In fact, the study of business cycles has a long history in economics – there was an explosion of studies on this topic in the aftermath of World War II starting with the seminal work of Burns and Mitchell (1946). Some of the later studies which characterize business cycles were Mintz (1972); Lucas (1977); Kydland and Prescott (1990); Backus and Kehoe (1992); Diebold and Rudebusch (1992); King and Plosser (1994); Watson (1994); Artis et al. (1997); Layton (1997); Baxter and King (1999); Canova (1998, 1999); Narayan (2008); and, Tawadros (2011). While the above-mentioned studies are exclusively concerned with developed countries, there were also some that characterized business cycles in developing countries such as Rand and Tarp (2002) which looked at the case of 15 developing countries; du Plessis (2004) which examined the case of South Africa (2004); Aiolfi et al. (2011) which characterized business cycles in Latin American countries; Caraiani (2012) which examined the case of the transition economy of Romania.

The financial crisis of the late 2000s has confirmed that there is another cycle that operates in the macroeconomy, which prompted an increased focus on the role of financial variables. For instance, recent papers have shown that, financial variables after a prolonged period of credit and housing booms, can cause deep and severe economic dislocations manifested through credit crunches and asset price busts (Reinhart and Rogoff, 2009). Indeed, the historical evidence suggests that financial crises have been preceded by credit and housing price booms (Jorda et al., 2016). The important role of financial variables in driving economic activity has also spurred another line of research that attempts to understand, in isolation, the time-series dynamics of these series. For instance, Narayan and Thuraisamy (2013) examined the role of permanent and transitory shocks in explaining variations in the S&P 500, Dow Jones and the NASDAQ and found that permanent shocks explain the bulk of the variations in stock prices over short horizons. Zheng et al. (2017) found that investors' speculative behavior is an important factor in explaining house price evolution and dynamics.

Also in the aftermath of the crisis, financial stability has become an important goal for central banks in advance and emerging economies. While there is a rich literature that examines the macroeconomic effects of a monetary policy shock in the context of advance and emerging economies (Christiano et al., 2005; Sims and Zha (2006); Sousa (2010); Mallick and Sousa (2012, 2013a),[1] it is only recently that researchers focused on the macroeconomic impact of shocks coming from the financial sector (Jermann and Quadrini, 2012; Mallick and Sousa, 2013b). One of the notable findings from this emerging literature is that financial stress conditions plays an important role in explaining output fluctuations. A large and growing body of evidence has also borne out the view that monetary policy interacts with financial variables (Granville and Mallick, 2009; Adrian et al., 2010; Bruno and Shin, 2015; Juselius et al., 2016). This interaction derives from the powerful influence that monetary policy can exert on incentives for risk-taking (Praet, 2016).

A separate strand of literature has also emerged which seeks to characterize the financial cycle and uncover how distinct the financial cycle is from the traditional business cycle. For instance, Claessens et al. (2011) employed a cycle-dating algorithm for a large number of advanced countries to identify peaks and troughs in credit, house prices and equity prices, and found that these series have long cycles. Drehmann et al. 2012 used a turning-point approach and a frequency-based filter to characterize cycles in credit, house prices and equity prices and found that the period of the cycles in these three series substantially exceed those of the business cycle. Aikman et al. (2015) also used a frequency-based filter and found that a distinct credit cycle exists, which has a length and amplitude that is greater than the business cycle. However, all these studies mentioned above are all concentrated on advanced economies. The question then is whether these results can be generalized to the financial cycle of emerging economies. To the best of our knowledge, no evidence has so far been advanced on the characterization of financial

[1] For studies that examine the macroeconomic effects of fiscal policy, see, for instance, Mountford and Uhlig (2009) and Jha et al., (2014).

cycles and how distinct the financial cycles is from the traditional business cycle in the context of emerging economies.

3. Methodology

This paper uses spectral analysis, a simple but powerful tool, to characterize cycles in the frequency domain. Spectral analysis represents an alternative way to examine and interpret the information contained in the second-order moments (i.e., variance) of the series. Specifically, the interest is centered on the contribution made by various periodic components in the series. This is achieved by estimating and analysing the spectrum of the series. The spectrum of a series is the distribution of the variance of the series as a function of frequency. In other words, unlike the standard time domain graph, which shows how a series changes over time, the spectrum in the frequency domain graph shows how much of the movement in the series lies within each given frequency band over a range of frequencies.

One approach to estimate the spectrum of a series is to employ an ARMA model. An ARMA(p,q) process can be written as[2]:

$$x_t + a_1 x_{t-1} + \cdots + a_p x_{t-p} = \epsilon_t + b_1 \epsilon_{t-1} + \cdots + b_q \epsilon_{t-q} \qquad (1)$$

where ϵ_t is a purely random process, thus a sequence of independent identically distributed variable with zero mean and variance σ_ϵ^2 . It is a pure AR process if $q = 0$, while a pure MA process if $p = 0$. The spectrum $f(\omega)$ of the ARMA(p,q) process is for frequencies between
$-\pi$ and π and given by:

$$f(\omega) = \frac{\sigma_\epsilon^2}{2\pi} \frac{\left|1 + \sum_{i=1}^{q} b_i \exp(-j\omega i)\right|^2}{\left|1 + \sum_{i=1}^{p} a_i \exp(-j\omega i)\right|^2} \qquad (2)$$

The first step of the procedure is to estimate the coefficients of the ARMA(p,q) process and these estimates are then substituted for the a_i's and b_i's in equation (2). The shape of the spectrum is entirely determined by the ARMA parameters, but they do not change the relative contribution of the variance over frequency. A plot of the spectrum against frequency (ω) is essentially a plot of the variance of a series as a function of the frequency. A peak in the spectrum represents relatively high variance in that frequency range, which is centered on the peak.[3]

[2] See, for instance, Broersen (2002).
[3] For an introductory yet exhaustive treatment of spectral analysis, please refer to Chatfield (2004).

4. Data and Empirical Results

4.1 Data

In line with previous studies, quarterly aggregate data on total credit, house and equity prices were used as the proxy measures for financial cycles (Claessens et al., 2011, 2012; Drehmann et al., 2012). Typical of studies on business cycles, real GDP was used as a proxy measure for the business cycle. The longest available sample period for each individual quarterly time series for the four emerging economies of Hong Kong, Malaysia, the Philippines and Thailand was used. In addition, to have a meaningful comparison with the business cycle measure, the sample period of the three proxy measures for financial cycles (credit, house and equity prices), were at the same time, aligned with the available quarterly data on GDP of these four economies.

The house price and total credit data were taken from the Bank of International Settlements (BIS) statistics.[4] The former was taken from the residential property price statistics, while the latter was from the recently released data by the BIS on credit to the non-financial sector. The GDP and equity prices data were taken from the International Monetary Fund (IMF) - International Financial Statistics (IFS) database. It should also be mentioned at this point that there were some limitations on the available data, particularly, on the proxy measures for financial cycles. First, for credit, only Malaysian data was used in the analysis as quarterly credit data for the other three economies were not considered sufficiently long.[5] Meanwhile, for the housing data, due to a similar constraint, only Hong Kong data on house price was considered in the analysis.[6] Data transformations were employed similar to Drehmann et al., (2012) and Strohsal et al., (2015). That is, the time series were measured in logs, deflated by the consumer price index and normalized by their respective value in 1993Q1 to ensure comparability of units.[7] Growth rates were then obtained by taking the annual differences of each time series. The period of analysis for the individual emerging economies were as follows: Hong Kong (1980Q4-2016Q1), Malaysia (1991Q1-2016Q1), the Philippines (1981Q1-2016Q1) and Thailand (1993Q1-2016Q1).

In order for one to clearly see how the financial cycles of the four emerging economies are different from those of the advanced economies, the results obtained for them were then

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[4] Available at: http://www.bis.org/statistics/index.htm?m=6%7C37

[5] Quarterly data on credit for Hong Kong, the Philippines and Thailand were only available from the late 1990s.

[6] Quarterly data on housing for Malaysia was only available from the late 1990s, while data for the Philippines and Thailand were only available from the late 2000s.

[7] It can be noted that in the case of Drehmann et al., (2012) and Strohsal et al., (2015), 1985Q1 was used as the period to normalize their time series data.

compared to the advanced economies examined in Strohsal et al. (2015), i.e., Germany, UK and US. Data for these three advanced economies were similarly obtained from the BIS (for the residential property and total credit data) and the International Monetary Fund (IMF)-International Financial Statistics (IFS) database (for the GDP and equity price data).[8] Similar data transformations were employed and the various time series were also normalized by their respective value in 1993Q1 to ensure comparability of units. Growth rates were also obtained by taking the annual differences of each time series. To facilitate comparison in the results, the sample period considered for these three advanced economies were around the same period considered in the analysis for our four economies, i.e., Germany (1991Q1-2016Q1), UK (1984Q4-2016Q1) and US (1984Q4-2016Q1).[9]

4.2 Empirical Results: Four East Asian Economies (Hong Kong, Malaysia, the Philippines and Thailand)

In this sub-section, the results of the spectral analysis applied to available data on GDP growth and proxies of financial cycles for the four emerging economies are presented. The plots of the data used in the analysis are shown in Figures 1 to 4. A visual inspection of the data shows that house price growth in Hong Kong and credit growth in Malaysia exhibit more pronounced swings than their respective GDP growth. Equity growth, while showing a high volatility, exemplifies time-series dynamics that closely resembles the time-series behavior of GDP growth in all the four economies.

The estimates of the coefficients of the final ARMA models for these economies are reported in Table 1. The selection of these final ARMA models follows the principle of parsimony in line with the usual practice in the time-series literature. As reported in this Table, all the estimated coefficients of the final ARMA models are statistically significant at the standard significance levels and the estimated residuals do not exhibit autocorrelation according to the Lagrange Multiplier (LM) test.

Once the coefficients of the final ARMA models were obtained, these were then substituted in equation (2) to obtain the spectrum of the individual series. As an example, consider the final estimated ARMA model for Malaysian GDP growth with *t*-values in parentheses and following the notation in equation (1):

[8] With the exception of the housing price data for Germany, the data for which was obtained from Till Strohsal.

[9] It is noted that the sample period for the housing price data for Germany starts from 1991Q1 and ends on 2013Q4.

$$x_t = 0.514 + 1.267x_{t-1} - 0.423x_{t-2} - 0.891\epsilon_{t-4} + 0.095\epsilon_{t-7}$$

(13.56) (13.42) (-4.44) (-18.46) (1.96)

These estimates are then substituted in equation (2) to obtain the corresponding spectrum for Malaysian GDP growth and following the notation in equation (2):

$$f(\omega) = \frac{\sigma_\epsilon^2}{2\pi} \frac{|1 - 0.891\text{exp}(\text{-}j4\omega) + 0.095\text{exp}(\text{-}j7\omega)|^2}{|1 + 1.267\text{exp}(\text{-}j1\omega) - 0.423(\text{-}j2\omega)|^2}$$

Dividing the spectrum by the variance of the individual series, one obtains the spectral density of the individual series. These spectral densities are presented in Figures 5 to 8 plotted against the frequency in the range of [0, π/4], which for quarterly data, is equivalent to periods of ∞ to 2 years. Since $f(\omega)$ is symmetric around ω = 0, it is customary to limit the analysis to this frequency range of 0 ≤ ω ≤ π/4.[10] In other words, the calculated spectral densities equivalent to periods of 2 years to half-a-year[11] are not included since almost no spectral mass is observed. Indeed, the plots of the spectral densities in Figures 5 to 8 bear this out. The frequency π/16 corresponds to 8 years and separates what is considered in existing studies as the period of the financial cycle (8 to 32 years) from the period of the business cycle (2 to 8 years). One will arrive at the following notable findings from a visual inspection of Figures 5 to 8 for the four individual economies:

- In all the series considered for the four economies, there are observed peaks. However, the location of these peaks varies in some of the series.
- In the case of Hong Kong, the location of the peaks in GDP and equity price growth is almost similar, located at slightly longer than the frequency π/8 (or slightly longer than 4 years). However, the location of the peak in house price growth is more shifted to the left at around the frequency π/16 (or around 8 years).
- In the case of Malaysia, the shape and the location of the observed peak in equity price growth is similar to Hong Kong's peak location, which is slightly longer than the frequency π/8. Meanwhile, the shape and location of the peak in Malaysian credit growth is also quite similar to those of housing price growth in Hong Kong, that is, the location of the peak is also more shifted to the left at around the frequency π/16. The slight difference is that for Malaysia, the location of the peak in GDP growth is slightly shorter than the frequency π/8.
- In the case of the Philippines, the observed peak in GDP growth has a shape that is quite similar to Hong Kong's and is located at slightly longer than the frequency π/8.

[10] For annual data, it is noted that the customary frequency interval can be expressed as 0 ≤ ω ≤ π.
[11] Or, the frequency range π/4 ≤ ω ≤ π.

However, the observed peak in equity price growth is more shifted to the left and closer to the frequency π/16.

- In the case of Thailand, the shape and location of the peaks in its GDP growth and equity price growth are quite identical and the peaks in both series are located quite close to the frequency π/16.

To reinforce the analysis from the visual inspection of the spectral densities, formal statistics recently proposed in Strohsal et al., (2015), are presented for the individual series in Table 2. The first column of the results shows the *period of the main cycle* measured in years, while the second and last columns show the *spectral mass* (measured in percentages) at the pre-defined medium-term frequencies with periods of between 2 to 8 years and low-frequencies with periods of between 8 to 32 years, respectively. The values in brackets below the point estimates of these statistics are the 95% bootstrap confidence intervals. As a technical note, these bootstrap confidence intervals were obtained using the following steps: (i) a bootstrap time series was recursively constructed using the earlier estimated parameters from the final ARMA model as well as the generated bootstrap residuals that were randomly drawn with the replacement from the estimated residuals of the final ARMA model; (ii) the final ARMA model is re-estimated from the constructed bootstrap time series; (iii) steps (i) and (ii) are repeated 5000 times; and, (iv) from these bootstraps, the statistics are computed with their corresponding standard errors and 95% confidence intervals obtained.[12]

As can be observed from the period of the main cycle measured at the peak of the spectrum[13] in Table 2, the business cycle measured in terms of GDP growth have periods of 4.7, 3.5, 4.4 and 5.9 years in Hong Kong, Malaysia, the Philippines and Thailand, respectively. For these four economies, the period of the GDP growth cycle is between 3 to 6 years, which is consistent with the finding in the existing literature that the period of the business cycle is typically between 2 to 8 years. In terms of the proxy measures for financial cycles, the period of the cycles are longer than the period of the business cycle measured in terms of GDP growth. The only exception is the equity price growth in Hong Kong, where GDP growth and equity price growth are almost similar (4.7 years vis-à-vis 4.5 years). Nonetheless, the periods of the cycles of the proxies for financial cycles in the four economies do not substantially exceed the rule-of-thumb cut-off of 8 years[14] (the longest cycle observed is in the case of housing price growth in Hong Kong at 8.1 years).

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[12] For further elaboration, see also Benkwitz et al., (2001) and Strohsal et al., (2015).

[13] Given by $2\pi/\omega_{max}$, with ω_{max} the frequency where the spectral density has its unique maximum (Strohsal et al., 2015).

[14] The literature considers 8 years as the typical cut-off or separation between the periods corresponding to the medium-term frequencies with that of the periods corresponding to the low frequencies.

The respective set of statistics based on the spectral mass at the pre-defined medium-term frequencies with periods of between 2 to 8 years (column 2) and low frequencies with periods of between 8 to 32 years (column 3) in Table 2 provide confirmatory results. Since the spectral mass provides an approximation of the variance contribution at a particular frequency range (Strohsal et al., 2015), a higher spectral mass at that frequency range suggests a relatively higher variance contribution at the said frequency range. The results reported in the last two columns of Table 2 indicate that for all the available series considered in the four economies, the variance contribution of the medium-term frequencies is higher than the variance contribution of the low frequencies, suggesting that all the series considered belong to cycles that have periods of between 2 to 8 years.

4.3 Empirical Results: Three Advanced Economies (Germany, UK and US)

The results of the spectral analysis applied to available data on GDP growth and proxies of financial cycles for the three advanced economies are presented next. The plots of the data used in the analysis are shown in Figures 9 to 11. These plots show that the proxies of the financial cycles for Germany, UK and US exhibit much more pronounced swings than GDP growth, although the plots of the equity growth for these three economies exhibit different time-series dynamics compared to the other financial cycle proxies. The estimates of the coefficients of the final ARMA models for these three advanced economies are presented in Appendix Table 1 (US), Appendix Table 2 (UK) and Appendix Table 3 (Germany). As reported in these Tables, the estimated coefficients of the final ARMA models are statistically significant at the standard significance levels and the estimated residuals from these models do not exhibit autocorrelation according to the Lagrange Multiplier (LM) test. The spectral densities are presented in Figures 12 to 14.

It is clear from visual inspection that the spectral densities of credit growth and growth in housing prices in the US (Figure 12) and UK (Figure 13) are more pronounced and the location of the peaks is substantially shifted to the left. In the case of Germany (Figure 14), this is only true for the spectral density of growth in housing prices. Similar to Strohsal et al., (2015), the paper did not obtain a clear result for German credit growth. Another noteworthy observation from the Figures is the similar shape of the spectral densities of GDP growth and equity price growth in all three advanced economies.

Formal statistics recently proposed in Strohsal et al., (2015) are presented in Table 3 for the individual series of the three advanced economies. As before, the first column of the results shows the *period of the main cycle* measured in years, while the second and last columns show the *spectral mass* (measured in percentages) at the pre-defined medium-term frequencies with periods of between 2 to 8 years and low-frequencies with periods of between 8 to 32 years, respectively. The values in brackets below the point estimates of these statistics are the 95% bootstrap confidence intervals.[15]

As presented in Table 3 (column 1), the period of the cycles of credit growth in the US and UK at 15.6 and 18.5 years, respectively, are longer than the period of cycles of their GDP growth at 8.8 and 9.1 years, respectively. A similar observation is obtained in the case of housing price growth in the US, UK and Germany where the periods of the cycles are 12.8, 10.6 and 19.9 years, respectively. These findings support the evidence advanced in recent studies that the periods in the cycles of these two proxies for financial cycles are longer than 8 years. However, the observation does not apply in the case of equity price growth for these three advanced economies. Specifically, the period of cycles for equity price growth in the US, UK and Germany at 7.5, 5.8 and 4.9 years, respectively, are well within the period of 2 to 8 years, and they are either shorter (US and UK) or slightly longer (Germany) than the period of the cycle for GDP growth. The results of the spectral mass reported in the last two columns of Table 3 reinforce these findings. The columns indicate that the variance contribution of the low frequencies for credit and housing price growth in the US and UK as well as housing price growth in Germany is higher than the variance contribution of the medium-term frequencies of these same set of series. This suggests that these series belong to cycles that have periods of between 8 to 32 years. On the other hand, the variance contribution of the medium-term frequencies for GDP growth and equity price growth is higher than the variance contribution of the low frequencies for these same series in all three economies. This suggests that GDP growth and equity price growth belong to cycles that have periods of between 2 to 8 years. These findings for the three advanced economies are in line with the earlier evidence obtained by Strohsal et al., (2015).

4.4 Band-pass Filter and Peaks and Troughs in the Four East Asian Economies

This sub-section takes a step further by examining the implication of the earlier finding of the paper that the period of the proxies for the financial cycles in the four East Asian economies are just slightly longer than the periods of their business cycles. This is done by using our estimates of the periods of the proxies for the financial cycles for the same four economies to perform a band-pass filter and obtain estimates of their financial cycles. These estimates of the cycles are then compared to the case in which the cycles are obtained from assuming that their periods are longer at low frequencies equivalent to between 8 to 32 years. In each case, the peaks and troughs of these cycles are examined, particularly, in relation to identified peaks around the time of a crisis.

[15] Refer to sub-section 4.2 on how these bootstrap confidence intervals were obtained.

The paper uses the Corbae-Ouliaris (2006) ideal band-pass filter to extract the cyclical component from the available data on proxies for the financial cycles. This procedure uses frequency domain techniques and spectral regression in estimating deviations from trend of a given periodicity. As Corbae-Ouliaris (2006) demonstrated, their procedure has superior statistical properties, i.e., no finite sampling error, superior end-point properties, lower mean-squared error, compared to the Hodrick-Prescott (1997) and Baxter-King (1999) time-domain based filters. Moreover, it was also shown that in comparison to the Baxter-King, it is consistent in that the filtered series asymptotically converges to the true cycle.

Figures 15 to 18 depict the cycles of the available proxies for financial cycles using the Corbae-Ouliaris (2006) (C-O) band-pass filter for the four East Asian economies. The discontinuous or broken lines in each Figure are the cycles using the estimates of the periods according to the spectral analysis conducted earlier. In contrast, the solid, squared lines in each Figure are the cycles assuming that the period is at low frequencies equivalent to between 8 to 32 years. Each Figure suggests that the choice of the periods in the band-pass filter can generate substantially different estimates of the cycles. The cycles presented in solid, squared lines, because of the assumption of a much longer periodicity, are visibly longer and identify few peaks and troughs. In contrast, the cycles presented in discontinuous or broken lines, because a relatively shorter period was used, that is, just slightly longer than the estimated periods of the business cycles of these four economies, clearly exhibited more pronounced swings and identified several peaks and troughs.

To further unravel the implication of the earlier finding of the paper that the period of the proxies for the financial cycles in the four East Asian economies are just slightly longer than the period of their business cycles, as opposed to a longer, low frequency equivalent to between 8 to 32 years, one can dig deeper by examining the cyclical phase of the financial variables around a financial crisis. As argued by Drehmann et al. (2012), it is intuitive that, a priori, a financial crisis should be associated with the onset of the contraction phase of the financial cycle. In terms of the dating of the crisis, the widely cited systemic banking database of Laeven and Valencia (2013) identifies one crisis period (i.e, the Asian Financial Crisis in July 1997) for Malaysia, the Philippines and Thailand and none for Hong Kong.

Table 4 summarizes this relationship between the financial crisis and the cycles identified using the two periods in the band-pass filter. Following the analysis conducted in Drehmann et al. (2012), the Table shows the time distance (in quarters) between the time marking the onset of the crisis and the nearest peak of the proxies for financial cycles. A negative number indicates that the peak in the cycle occurs prior to (after) the quarter in which the crisis begins. Column 1 of the Table shows the distance in quarters between the July 1997 Asian Financial Crisis and the nearest peak of the available financial variable using 32 up to 128 quarters (or 8 to 32 years) in the C-O band-pass filter, whereas Column 2 shows the distance in quarters using the estimated periods from our earlier spectral analysis in the C-O band-pass filter. Hong Kong is excluded from the Table as there was no identified crisis according to the Laeven and Valencia (2013) database. It is clear from this Table that the July 1997 Asian Financial Crisis for the three East Asian economies occurred very close to the peaks identified in the C-O band–pass filter using the estimated periods from our earlier spectral analysis (column 2). The peaks identified, in fact, tend to occur, at least one year away from the actual crisis date. In the case of the peaks identified using the longer, low-frequencies equivalent to 8 to 32 years in the C-O band-pass filter (column 1), the closest is 5 months preceding the actual crisis date (credit growth in Malaysia), while the identified peak in equity price growth for Thailand occurred 31 quarters (or, roughly 8 years!) after the actual crisis date. It is also interesting to note that the peaks identified for credit growth in Malaysia, which closely precedes the actual crisis date, confirm the credit boom that occurred prior to the crisis as recorded in the Laeven and Valencia (2013) database.

These results can also be observed in Figures 16 to 18. The bold, solid vertical lines in these Figures mark the July 1997 crisis date.[16] The cycles presented in discontinuous or broken lines in Figure 16 (for equity price and credit growth in Malaysia), Figure 17 (for equity price growth in the Philippines) and Figure 18 (equity price growth in Thailand) which used the estimates of the periods according to the spectral analysis, all show identified peaks that closely precedes the bold, solid, vertical line that marks the actual crisis. However, the cycles presented in the solid, squared lines for these same Figures which assume that the period is at low frequencies equivalent to between 8 to 32 years, have identified peaks that occur further away from the bold, solid, vertical lines. In fact, the solid, squared line in Figure 18 shows that the cycle for the equity price growth in Thailand is still at the expansion phase, just months before the occurrence of the crisis.

5. Conclusion

Starting as early as the 1940s, studies on the empirical characterization of the business cycle have proliferated. The consensus that emerged from this strand of literature is that the business cycle has a typical period of 2 to 8 years. On the other hand, work on the empirical characterizations of financial cycles has so far been sparse. This is quite unfortunate given the role played by financial factors in the severity of economic booms and busts. The evidence that we have so far on this issue pertain to advanced economies. According to the literature, the financial cycle is best described by the behavior of credit and property prices with equity prices tending to exhibit shorter cycles and more closely related to the fluctuations in GDP. More

[16] To be specific, the horizontal axis in each of the Figures provides the dates of the observations, which is in quarterly frequency. Thus, the bold, solid line in each of the Figures is marked for the third quarter of 1997.

importantly, the financial cycle of advanced economies operates at a low frequency with a cycle period of between 8 and 32 years. The question of whether these findings are applicable to emerging economies is both relevant and interesting.

The empirical characterization of the financial cycles for Hong Kong, Malaysia, the Philippines and Thailand was carried out using spectral analysis, which, unlike standard approaches employed in earlier studies, does not need an a priori assumption on the period of the cycle. In terms of the four East Asian economies, the paper finds that the business cycle measured in terms of real GDP growth have periods of between 3 to 6 years, in line with the stylized evidence. Furthermore, the period of the cycles for the proxy measures of the financial cycles are slightly longer than the period for the business cycle, with the exception of equity price growth in Hong Kong. More importantly, the paper finds that the periods of the proxy measures for financial cycles do not operate at low frequencies similar to the periods found for advanced economies, i.e., US, UK and Germany. The paper also confirms recent evidence that credit and housing price growth in the UK and US, as well as housing price growth in Germany have period cycles that are much longer than 8 years.

One empirical lesson from the findings above is that it may be entirely inappropriate to characterize financial cycles of the East Asian economies using band-pass filters that assume cycles with periods of between 8 to 32 years, akin to periods of financial cycles in advanced economies. Taking one step further, the paper, indeed, finds that the financial cycles of these four East Asian economies are better captured and depicted by a band-pass filter estimated using the periods obtained in the paper as opposed to using long period cycles akin to periods of the financial cycles of advanced economies. For instance, the July 1997 Asian financial crisis occurred very close to the peaks identified in the band–pass filter using the estimated periods obtained in the paper. These results reinforce the argument that the choice of the periods in the band-pass filter can generate substantially different estimates of the cycles and as such, one needs to be careful in making an a priori assumption on the frequency range the financial cycle is believed to operate.

Given that the period of the financial cycles is slightly longer than the period of the business cycle in these group of economies, the case for macroprudential policy as a separate stabilization tool in addition to fiscal and monetary policy is justified. Specifically, given a measure of the financial cycle, the stage at which the economy is located in the cycle can guide the activation of macroprudential policy instruments. Finally, the finding of a slight divergence in periodicity between the financial and business cycles suggests the need for monetary policy to respond systematically to the financial cycle rather than just to output and inflation.

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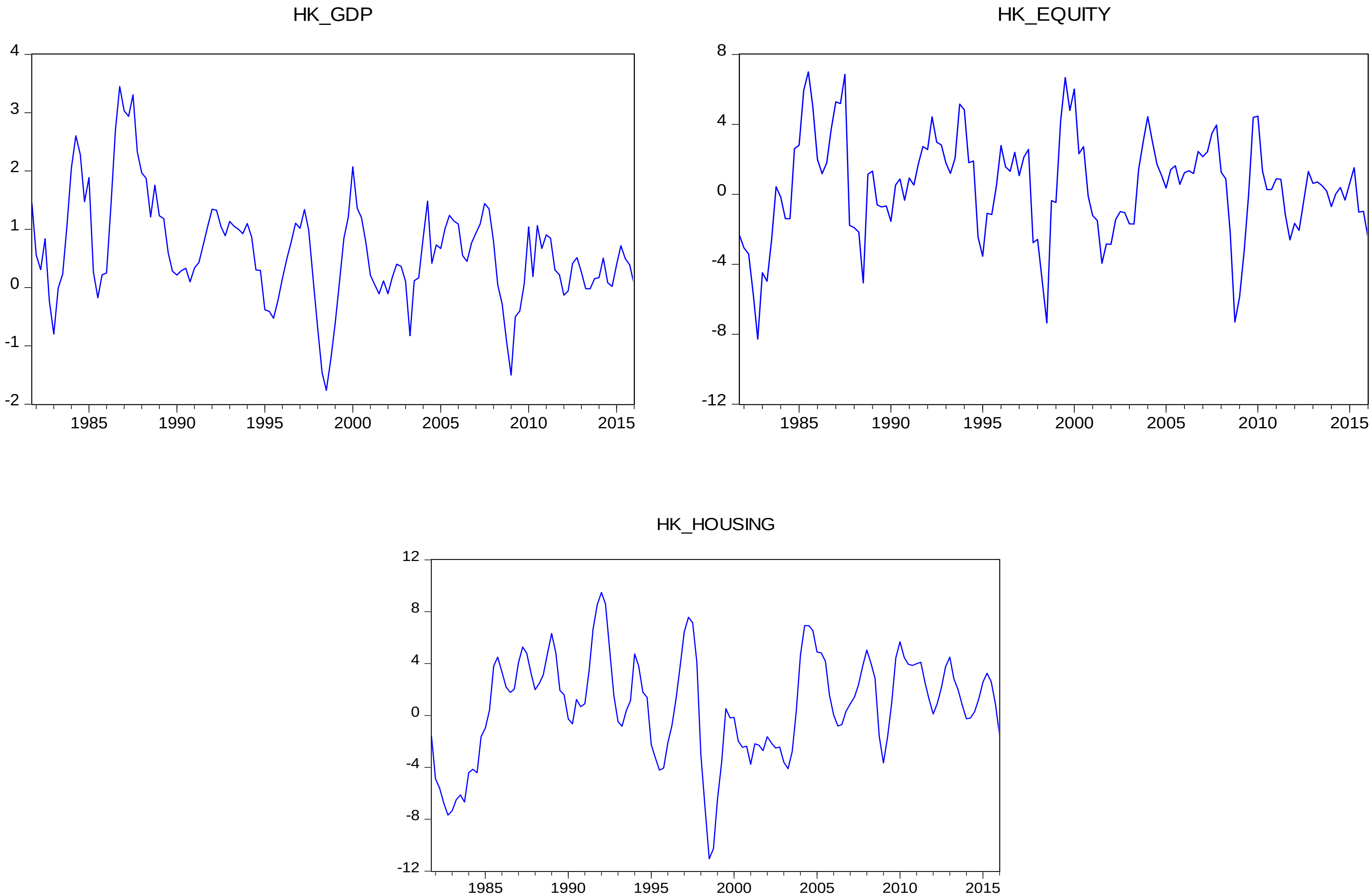
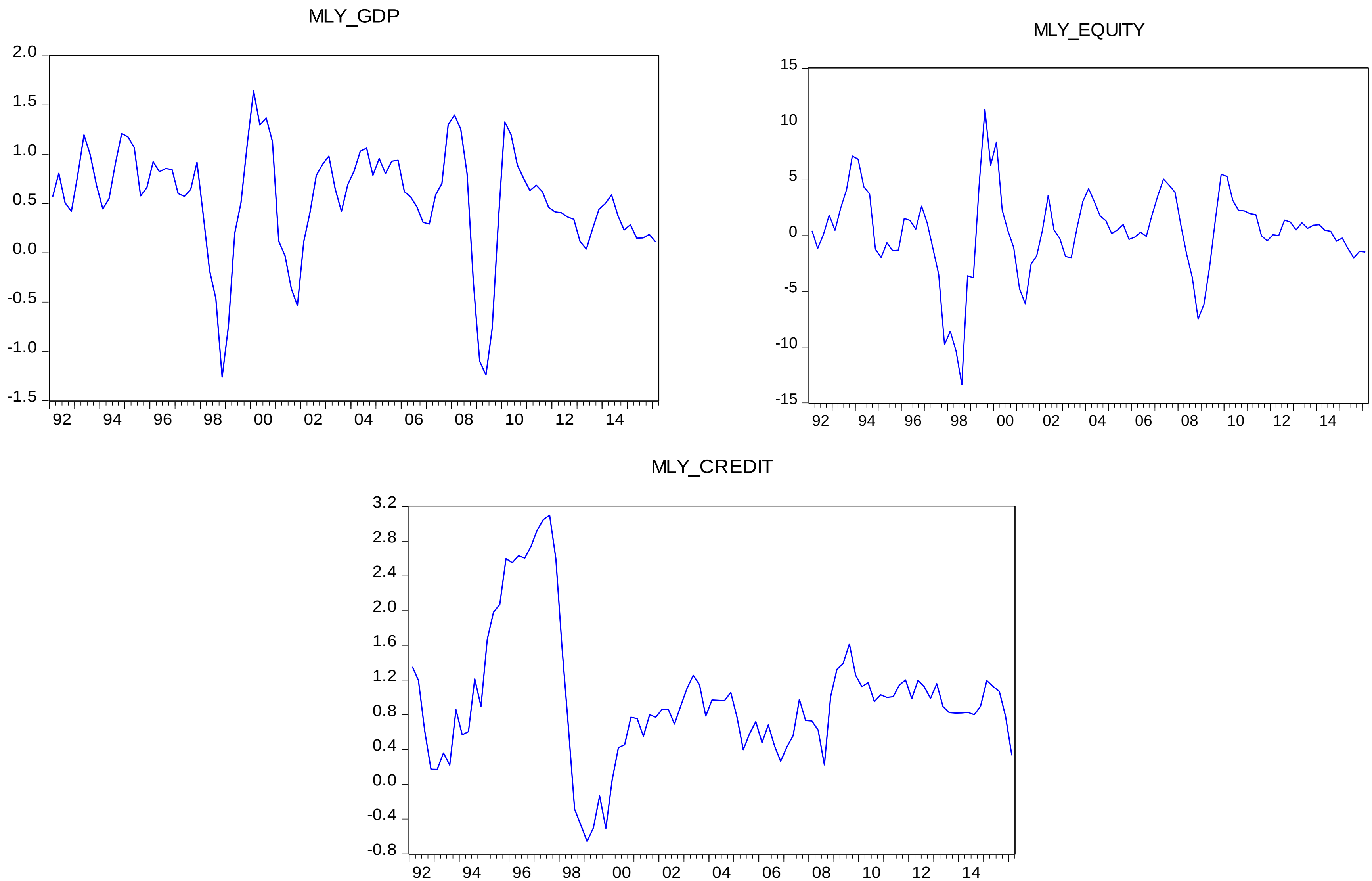
Figure 1: Real GDP, Equity and House Prices – Hong Kong



Note: All series are annual growth rates.

Figure 2: Real GDP, Equity and Credit – Malaysia



Note: All series are annual growth rates.

Figure 3: Real GDP and Equity – Philippines

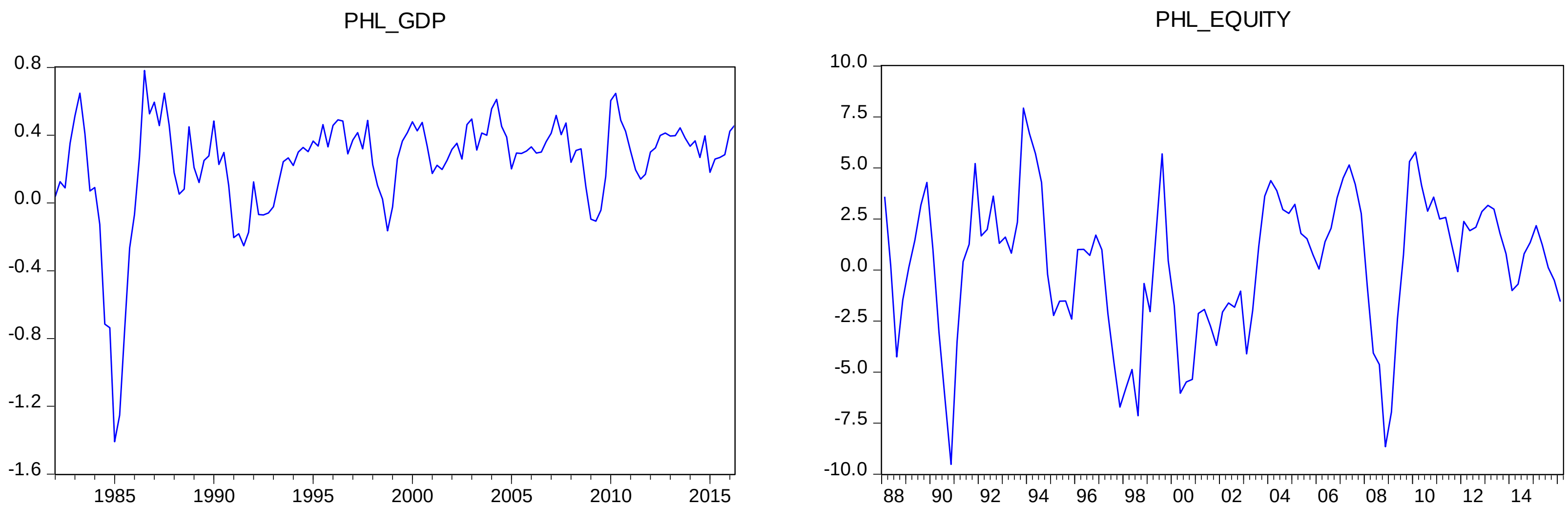
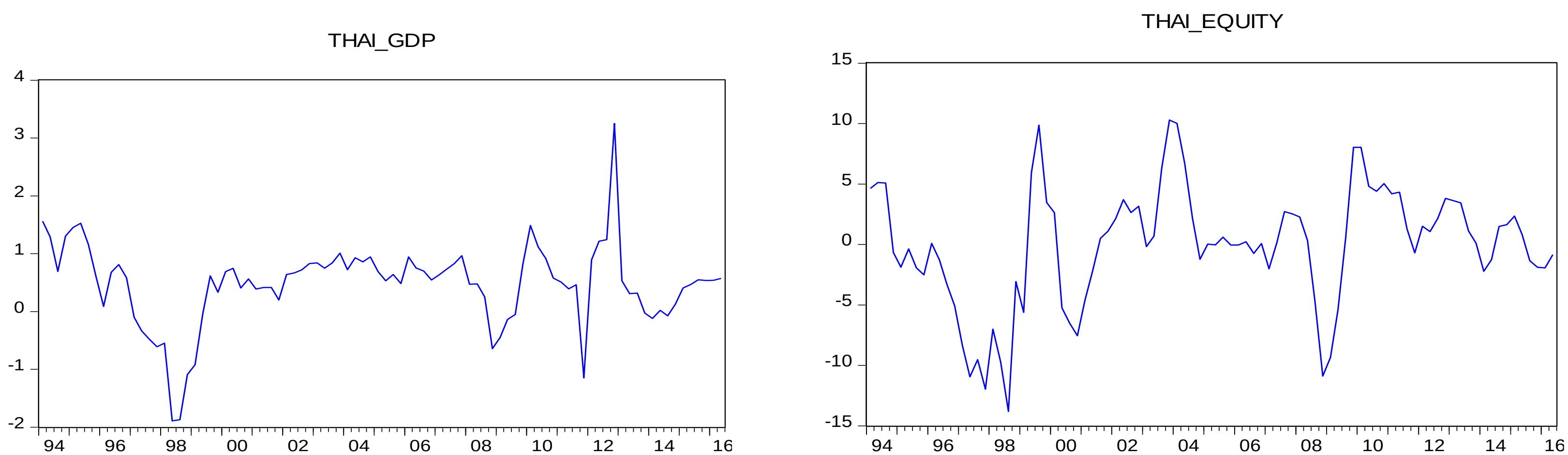
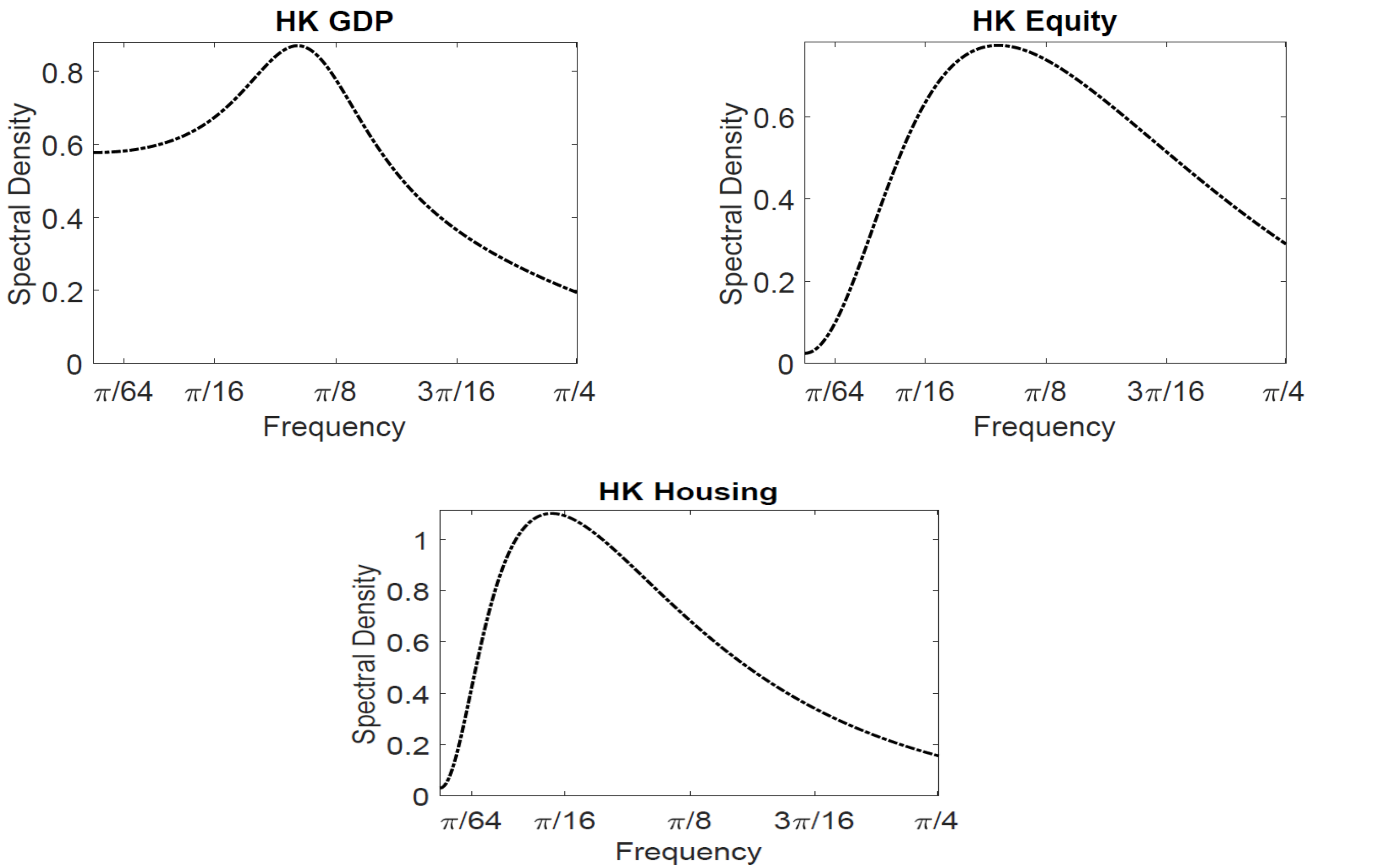


Figure 4: Real GDP and Equity - Thailand



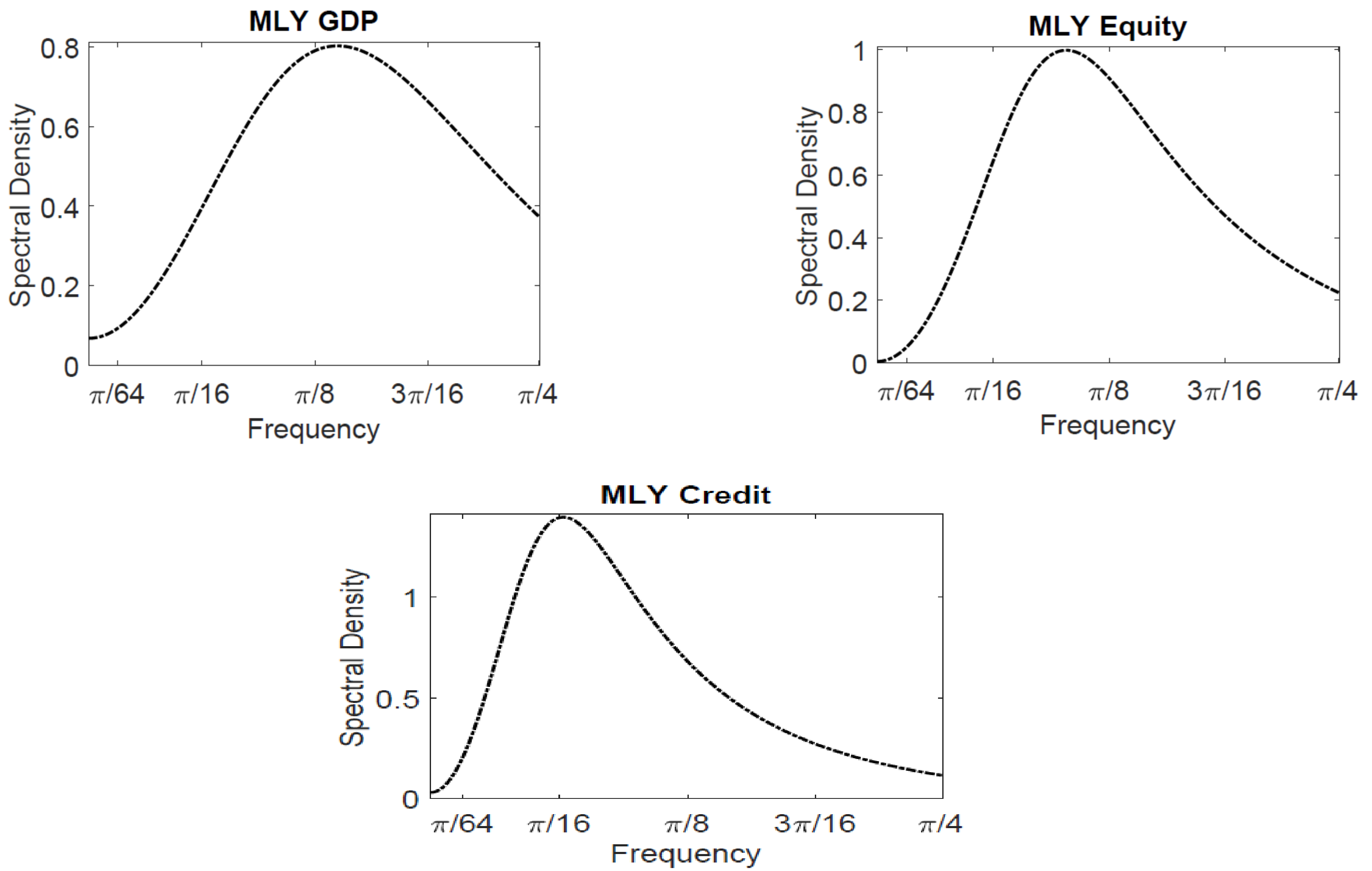
Note: All series are annual growth rates.

Figure 5: Spectral Densities for Hong Kong



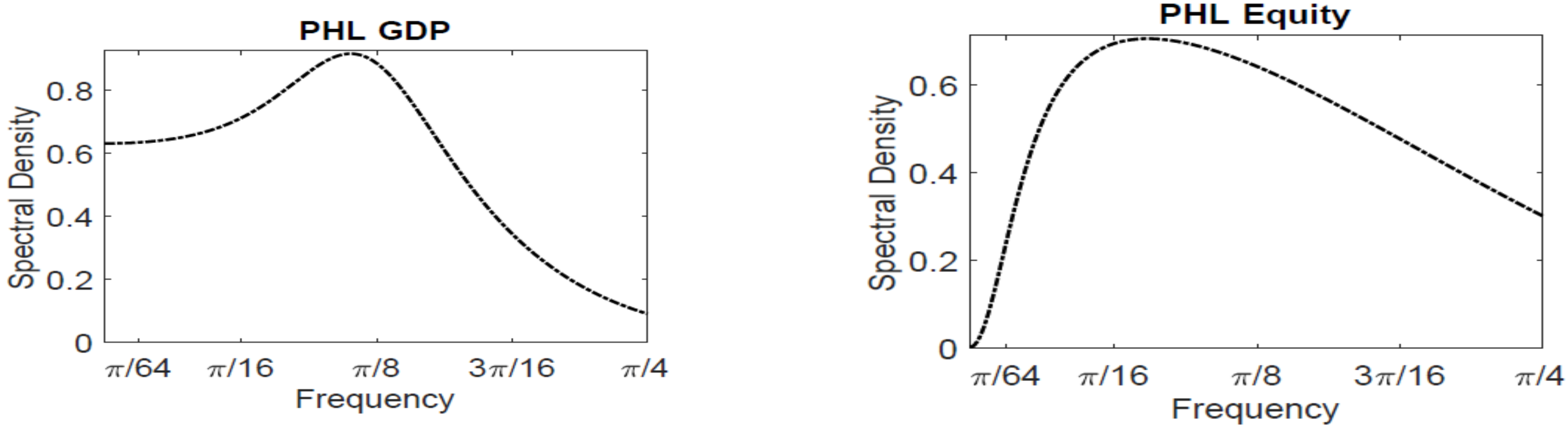
Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

Figure 6: Spectral Densities for Malaysia



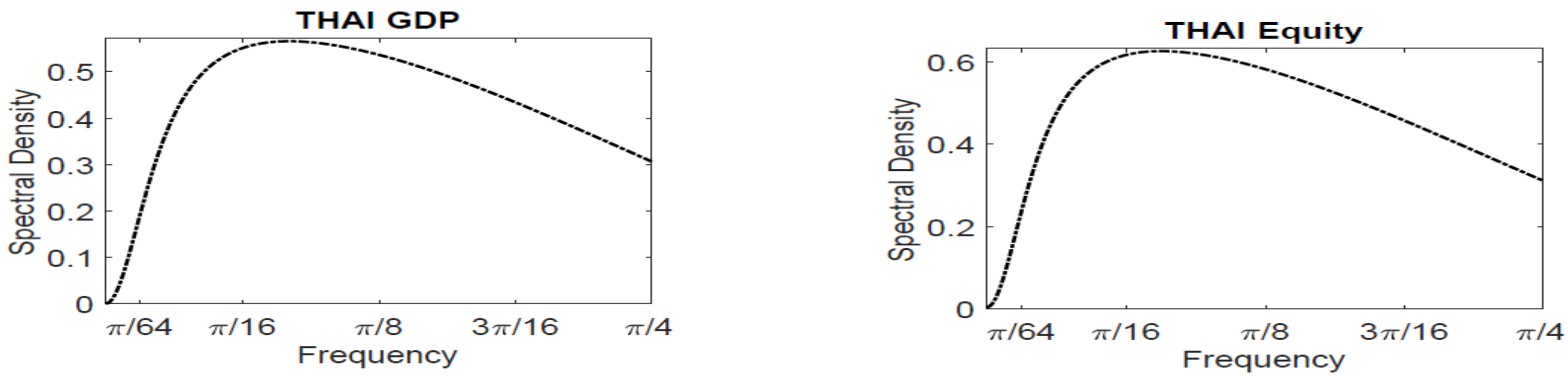
Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

Figure 7: Spectral Densities for Philippines



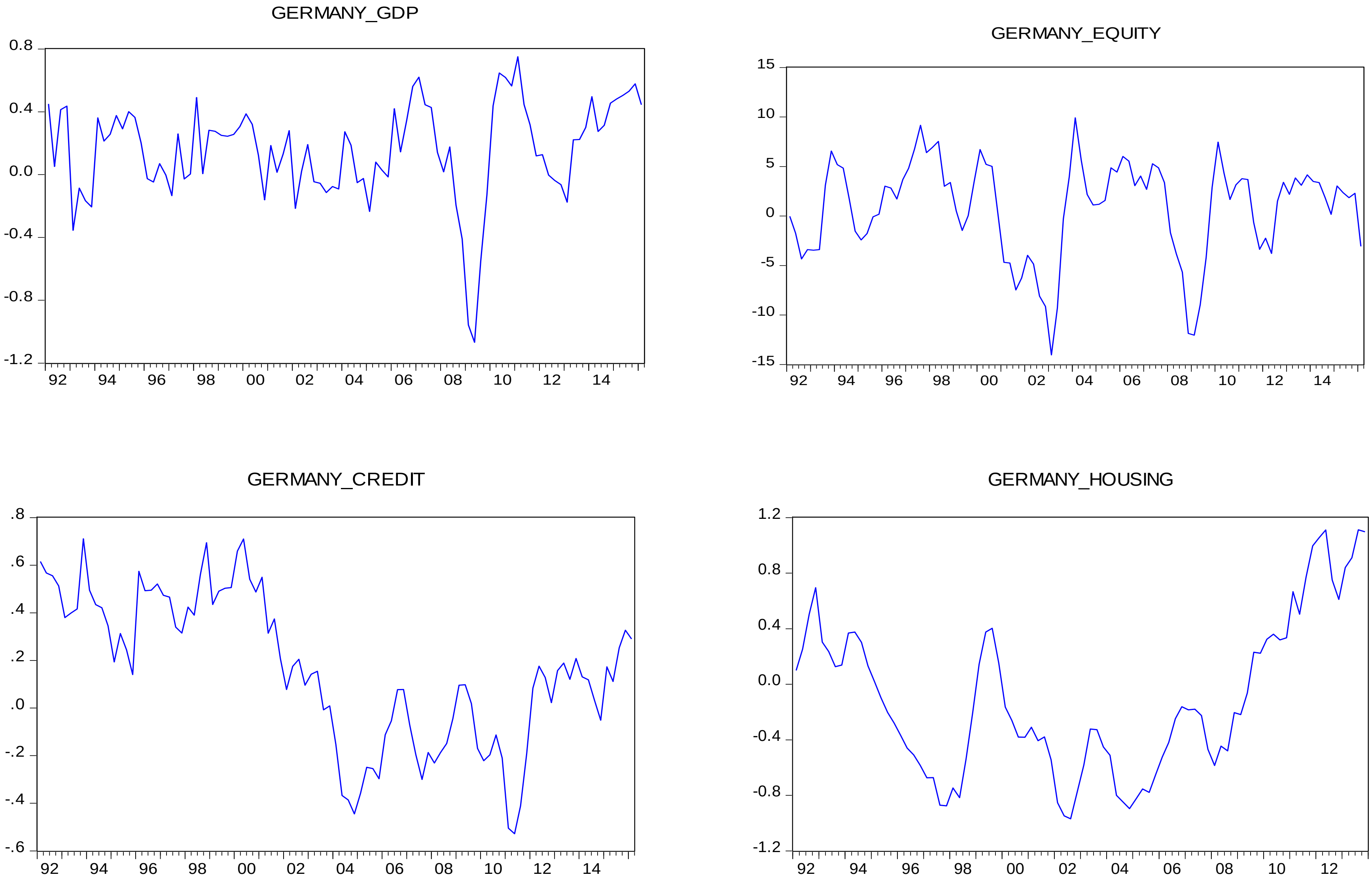
Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

Figure 8: Spectral Densities for Thailand



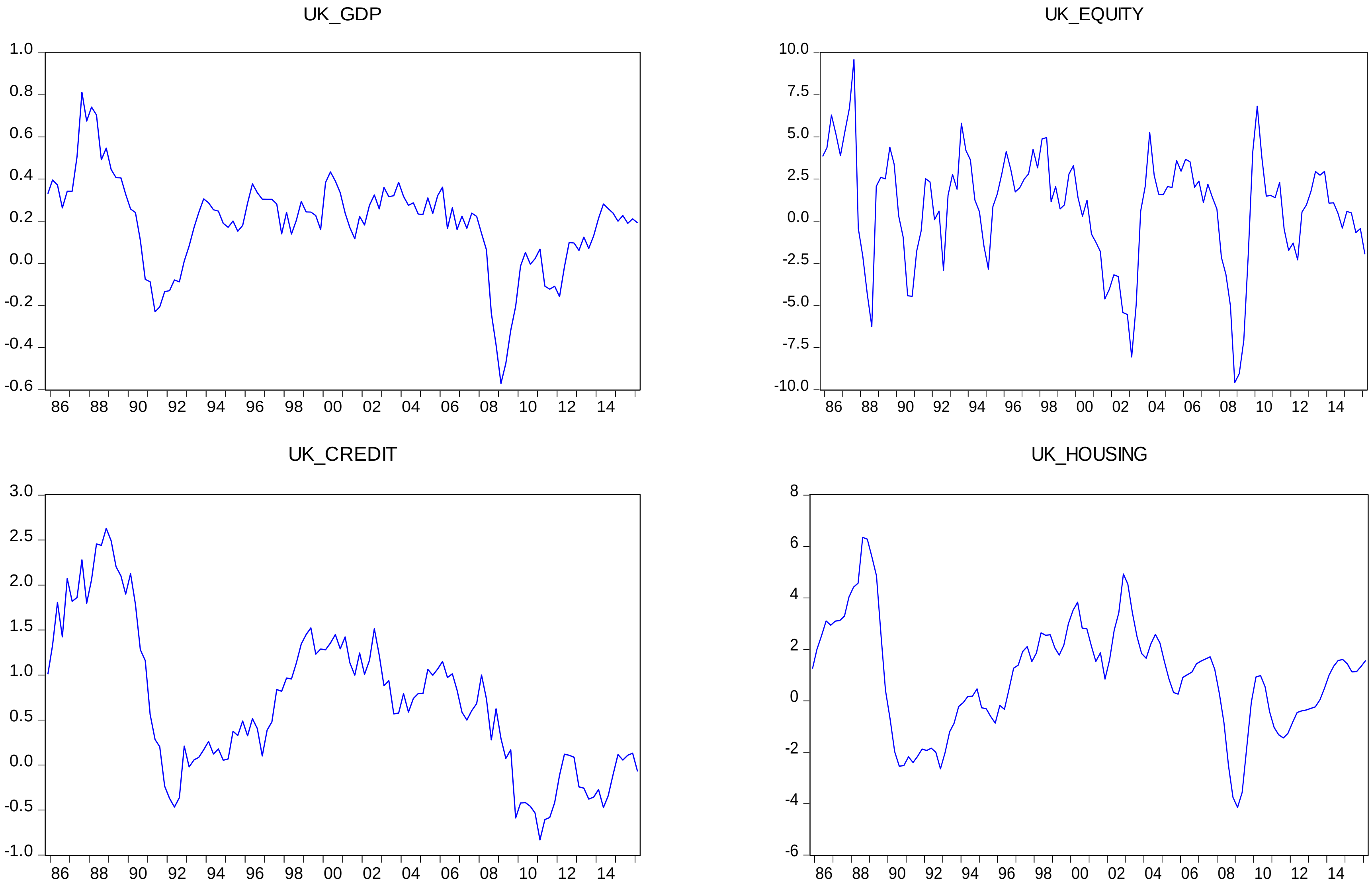
Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

Figure 9: Real GDP, Equity, Credit and House Prices – Germany



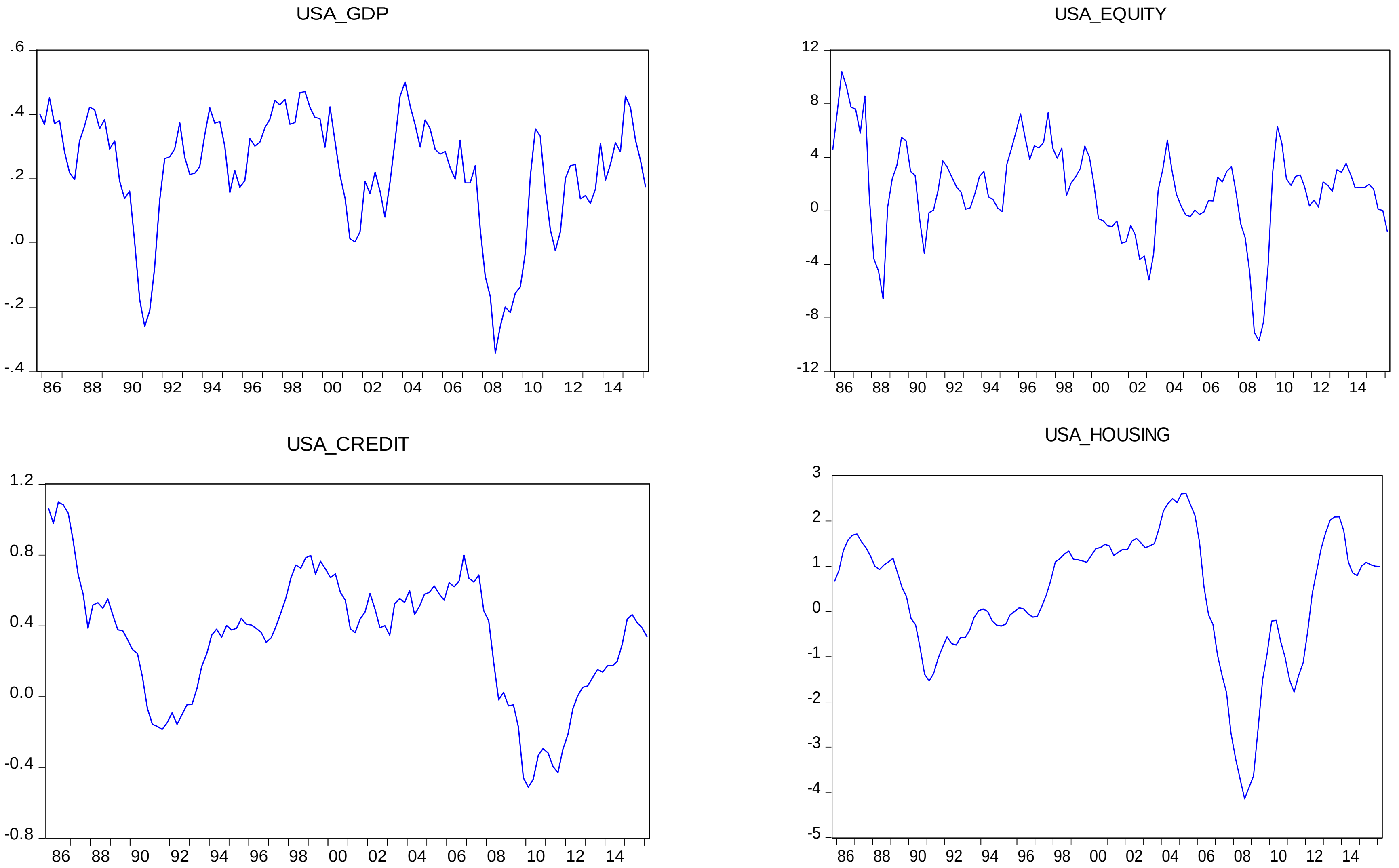
Note: All series are annual growth rates.

Figure 10: Real GDP, Equity, Credit and House Prices – UK



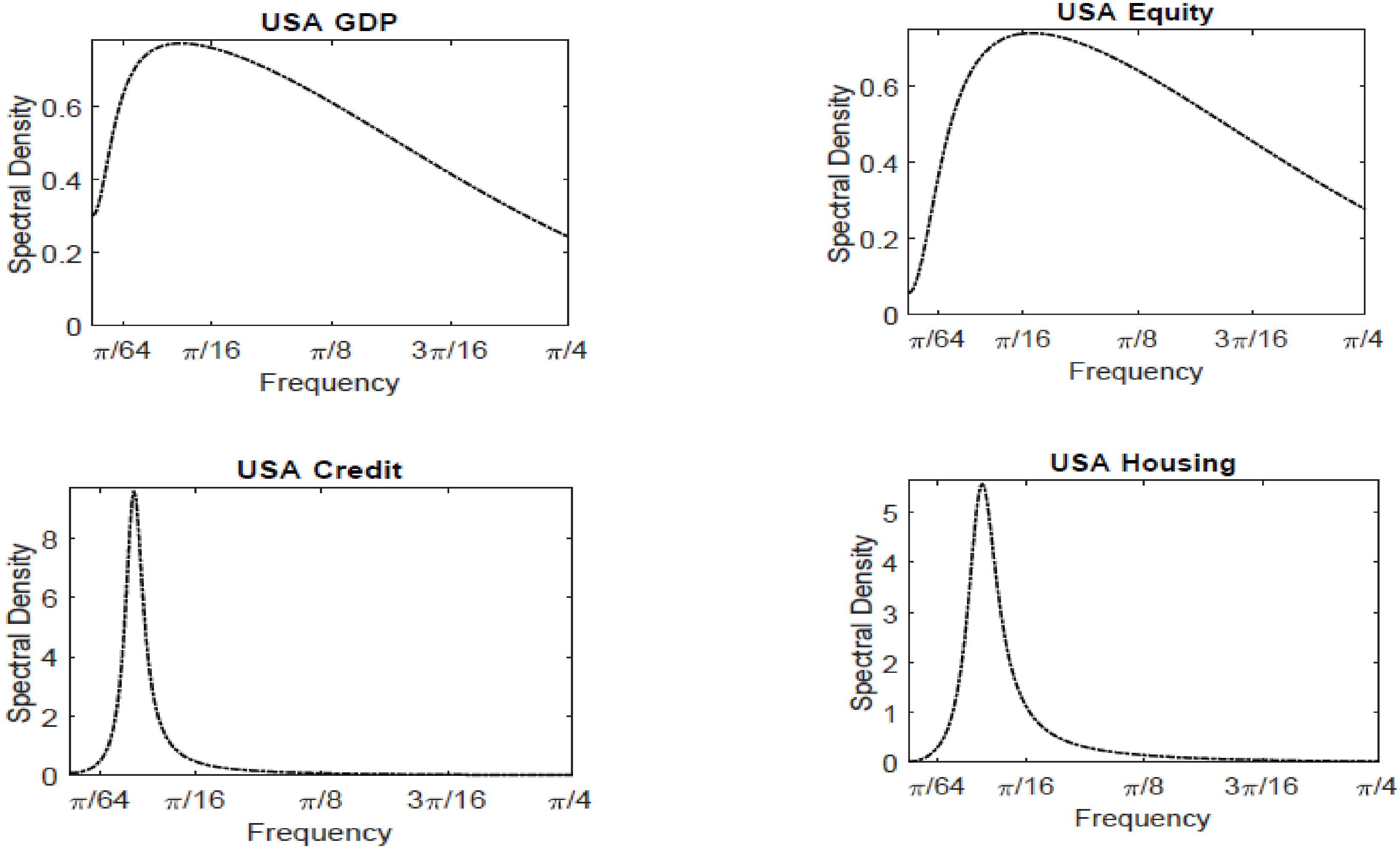
Note: All series are annual growth rates.

Figure 11: Real GDP, Equity, Credit and House Prices – US



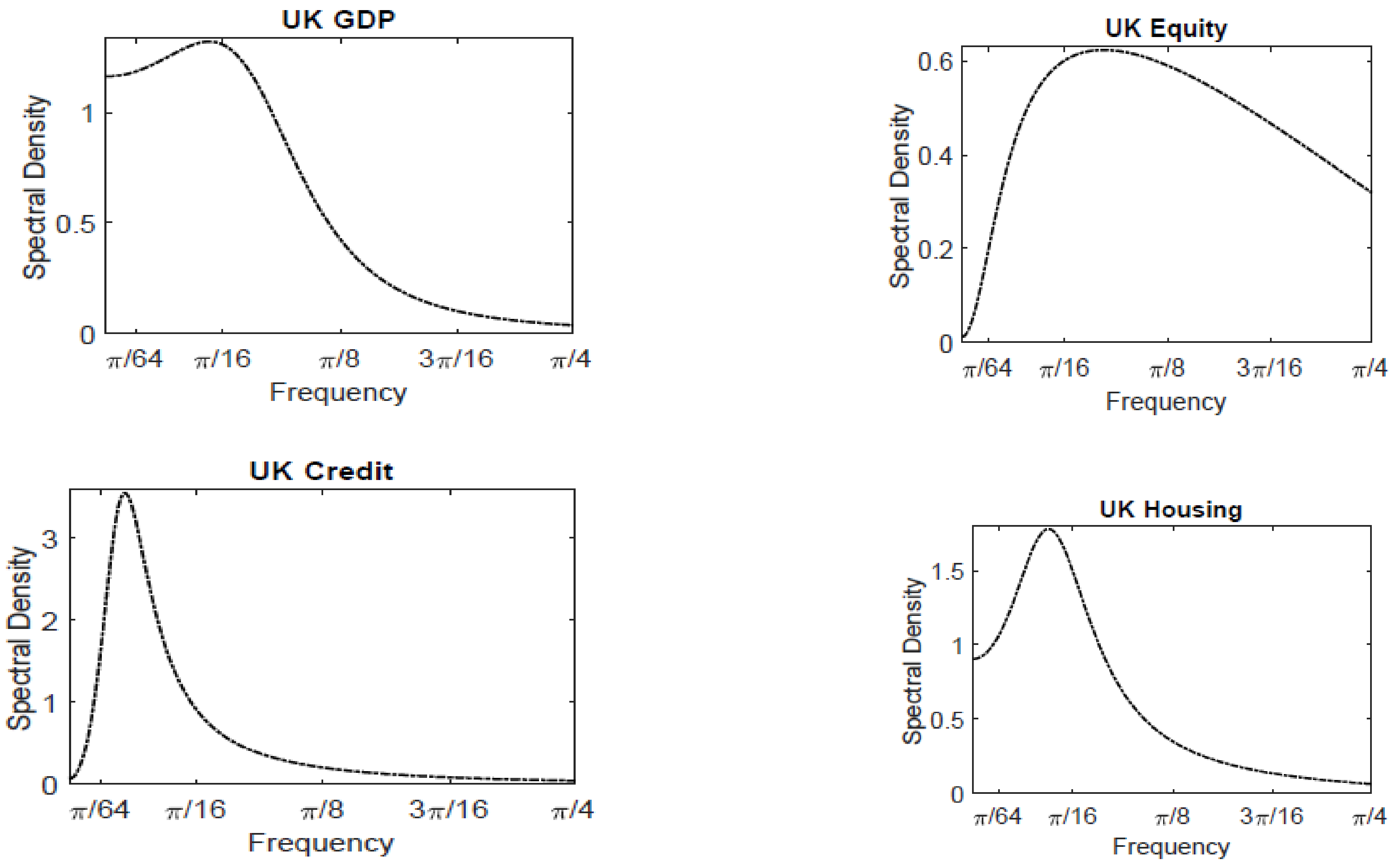
Note: All series are annual growth rates.

Figure 12: Spectral Densities for US



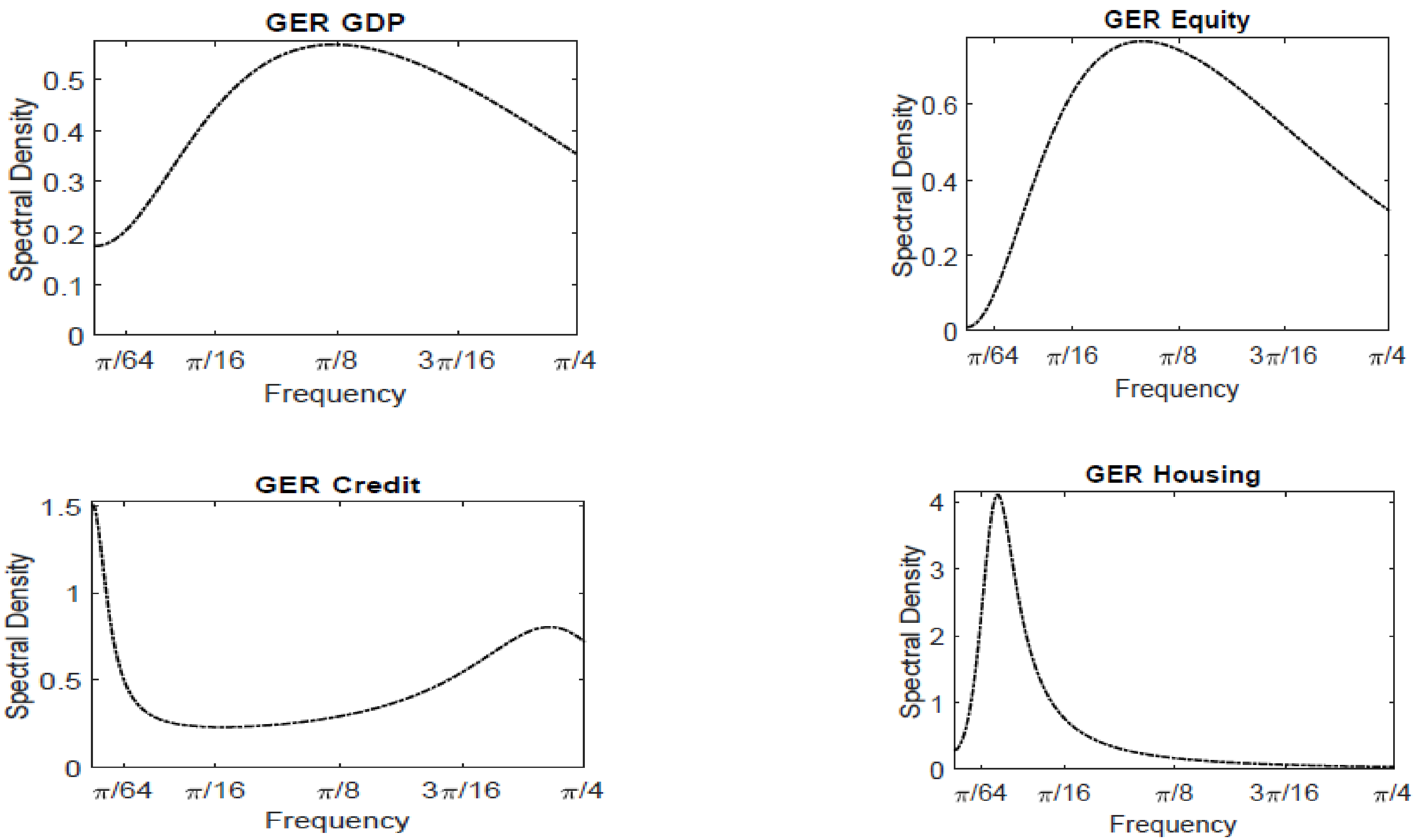
Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

Figure 13: Spectral Densities for UK



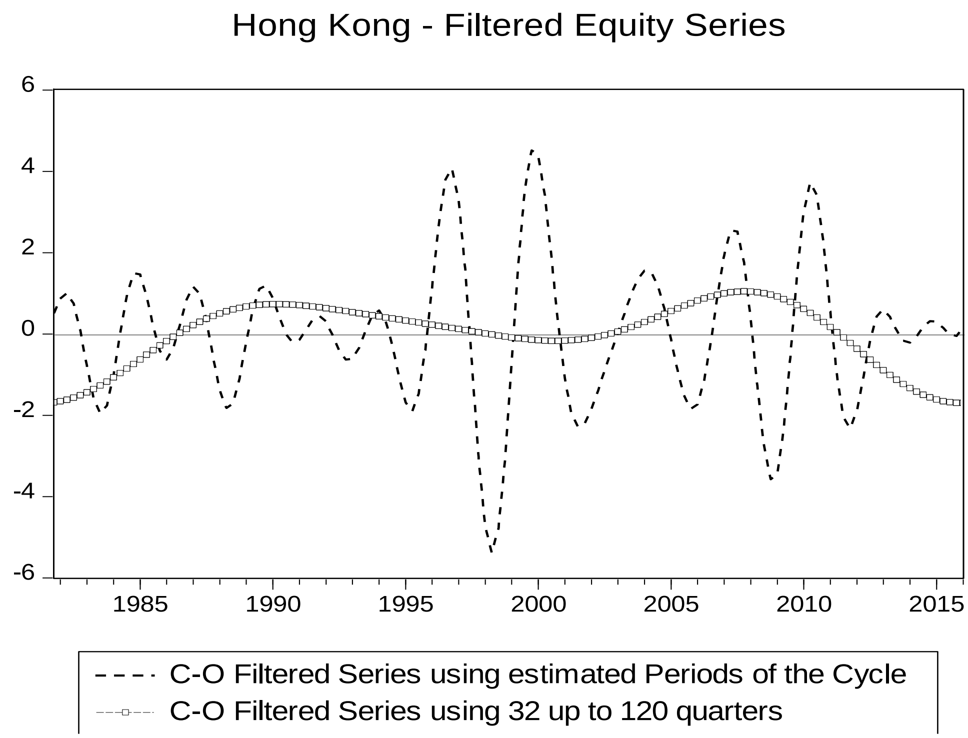
Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

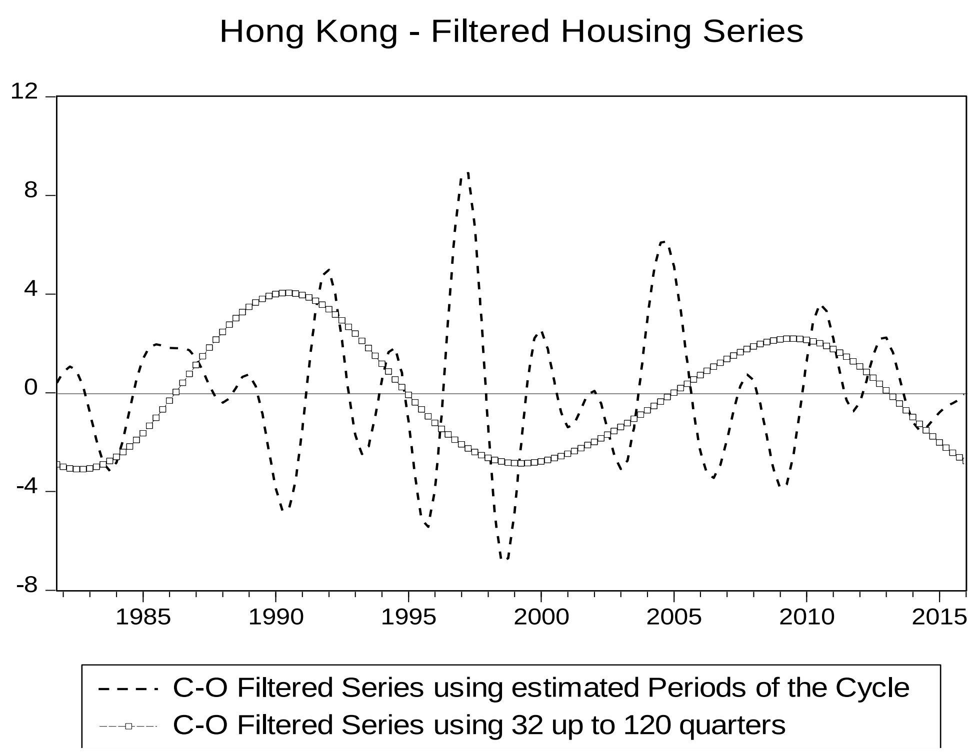
Figure 14: Spectral Densities for Germany



Note: Spectral densities from frequency zero to π/4, corresponding to a period of the cycle of infinity to 2 years. Frequency π/16 corresponds to 8 years.

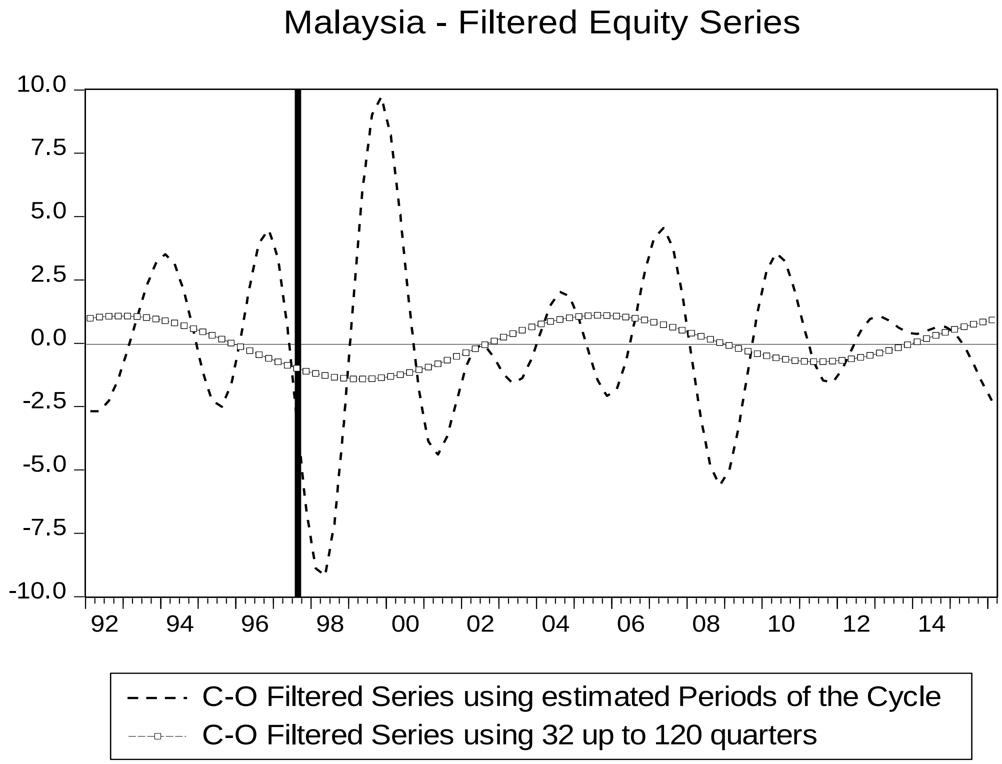
Figure 15: C-O Filtered Financial Cycles for Hong Kong

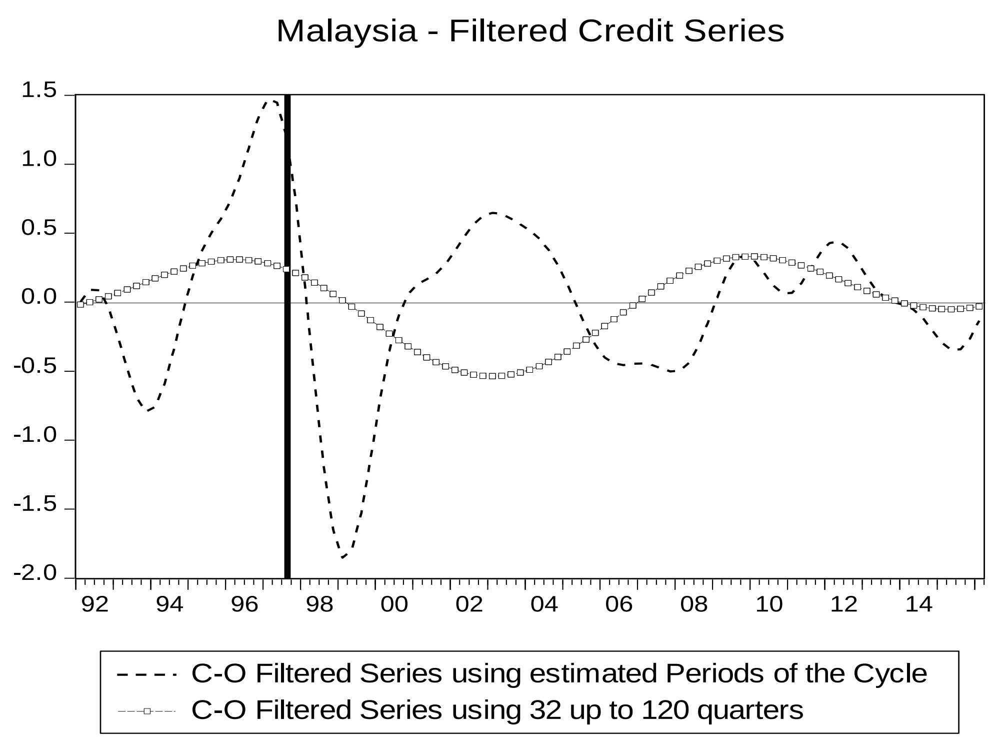




Note: C-O denotes the Corbae-Ouliaris (2006) filtered series.

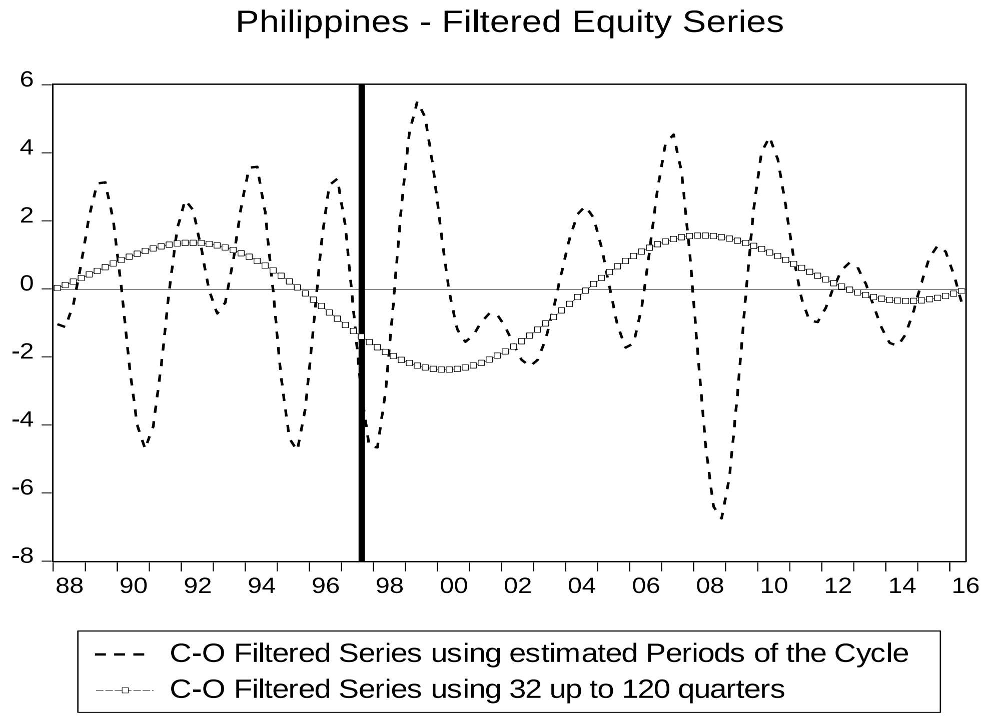
Figure 16: C-O Filtered Financial Cycles for Malaysia





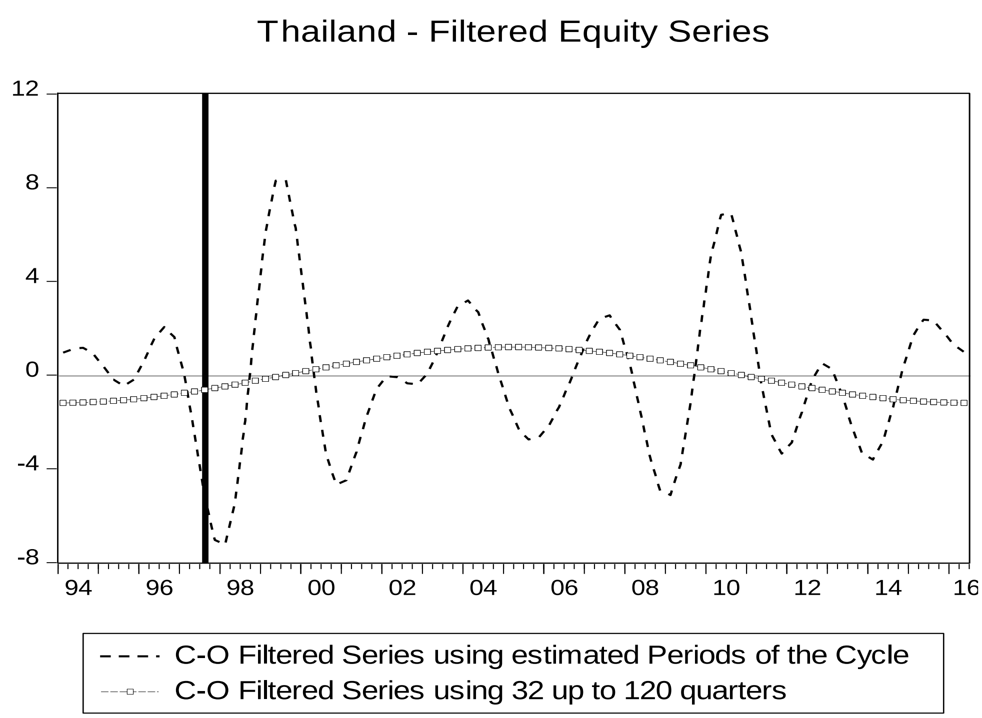
Note: C-O denotes the Corbae-Ouliaris (2006) filtered series.

Figure 17: C-O Filtered Financial Cycle for Philippines



Note: C-O denotes the Corbae-Ouliaris (2006) filtered series.

Figure 18: C-O Filtered Financial Cycle for Thailand



Note: C-O denotes the Corbae-Ouliaris (2006) filtered series.

Table 1: Estimated ARMA Models

parameters	Hong Kong			Malaysia			Philippines		Thailand	
	GDP	equity	housing	GDP	equity	credit	GDP	equity	GDP	equity
constant	0.635	0.626	0.944	0.514	0.268	0.877	0.229	0.333	0.533	0.947
	(4.53)	(4.37)	(3.13)	(13.56)	(2.46)	(11.93)	(4.30)	(1.00)	(9.50)	(1.85)
AR(1)	1.008	0.994	1.583	1.267	0.994	1.263	0.935	1.136	0.733	0.931
	(23.26)	(19.07)	(23.09)	(13.42)	(17.46)	(24.01)	(19.74)	(11.99)	(6.75)	(32.07)
AR(2)			-0.617	-0.423				-0.187	0.179	
			(-9.05)	(-4.44)				(-1.99)	(1.64)	
AR(3)						-0.317				
						(-6.07)				
AR(4)	-0.237	-0.097			-0.157		-0.202			
	(-4.37)	(-1.80)			(-2.85)		(-4.05)			
AR(5)										
MA(4)	-0.406	-1.092	-0.950	-0.891	-0.990	-0.922		-0.974	-0.994	-0.978
	(-4.16)	(-11.27)	(-41.64)	(-18.46)	(-37.62)	(-27.79)		(-62.49)	(-36.60)	(-45.78)
MA(7)	0.313			0.095						
	(3.32)			(1.956)						
MA(8)		0.166					-0.158			
		(1.77)					(-1.80)			
MA(9)							0.211			
							(2.43)			
diagnostics										
LM(8)	0.47	0.32	0.76	0.39	0.53	0.37	0.34	0.99	0.82	0.52
LM(12)	0.15	0.49	0.31	0.68	0.68	0.50	0.13	0.38	0.96	0.63

Notes: Below the parameter estimates *t*-values are given in parentheses. For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.

Table 2: Period and Variance Contribution of Cycles

		Period of the Cycle *in years* (1)	spectral mass *in percent* located… …at short to medium-term frequencies with periods (2 to 8 years) (2)	…at low frequencies with periods (8 to 32 years) (3)
Hong Kong	GDP	4.7 [4.1, 5.6]	63.5 [42.9, 81.2]	18.3 [9.5, 34.6]
	equity	4.5 [2.8, 6.2]	69.1 [60.1, 79.8]	10.3 [3.6, 15.9]
	housing	8.1 [5.6, 9.8]	66.5 [61.3, 76.8]	25.9 [14.8, 31.7]
Malaysia	GDP	3.5 [3.5, 6.0]	73.9 [61.2, 77.7]	6.2 [5.5, 16.5]
	equity	4.9 [3.4, 5.8]	76.8 [65.4, 88.8]	8.8 [1.9, 14.6]
	credit	7.8 [6.2, 9.3]	66.3 [58.4, 72.9]	27.5 [17.5, 36.7]
Philippines	GDP	4.4 [3.8, 5.4]	64.2 [38.2, 76.3]	20.0 [12.1, 36.9]
	equity	6.5 [3.9, 10.2]	63.8 [57.6, 71.8]	16.8 [7.33, 20.6]
Thailand	GDP	5.9 [4.8, 7.4]	55.4 [44.3, 60.3]	13.3 [10.0, 15.6]
	equity	6.4 [4.0, 9.3]	59.4 [56.5, 62.0]	15.3 [7.7, 18.1]

Notes: 95% bootstrap confidence intervals are given in brackets.

Table 3: Period and Variance Contribution of Cycles

		Period of the Cycle *in years* (1)	spectral mass *in percent* located… …at short to medium-term frequencies with periods (2 to 8 years) (2)	…at low frequencies with periods (8 to 32 years) (3)
US	GDP	8.8 [7.9, 11.4]	59.9 [58.6, 61.8]	22.6 [19.1, 25.8]
	equity	7.5 [4.5, 9.4]	63.3 [59.7, 71.3]	19.3 [10.3, 22.0]
	credit	15.6 [16.1, 17.2]	9.6 [6.8, 12.3]	87.6 [85.4, 89.8]
	housing	12.8 [11.4, 13.9]	19.9 [14.9, 28.0]	78.6 [70.2, 83.9]
UK	GDP	9.1 [8.3, 12.1]	45.7 [32.08, 57.7]	38.3 [25.9, 41.4]
	equity	5.8 [3.5, 7.6]	60.2 [57.8, 62.0]	14.1 [5.6, 17.1]
	credit	18.5 [16.1, 19.9]	24.1 [20.4, 29.9]	66.6 [61.5, 69.2]
	housing	10.6 [7.24, 38.4]	41.8 [23.3, 69.8]	46.2 [24.4, 60.7]
Germany	GDP	4.1 [2.8, 5.7]	58.6 [53.0, 61.9]	9.9 [3.13, 14.7]
	equity	4.9 [3.1, 6.1]	71.1 [64.6, 79.6]	11.8 [3.6, 16.5]
	credit	∞ [–, –]	53.7 [–, –]	8.64 [–, –]
	housing	19.9 [9.2, 23.8]	19.8 [11.7, 60.1]	68.5 [28.8, 78.9]

Notes: 95% bootstrap confidence intervals are given in brackets. "–" means no distinct solution found in the frequency range $0 < \omega \leq \pi$.

Table 4: 1997 Asian Financial Crisis and the Peaks in the C-O Filtered Series

		C-O Filtered Series using 32 up to 128 quarters (1)	C-O Filtered Series using estimated Periods of the Cycle (2)
		Number of quarters	
Malaysia	Equity	-19	-3
	Credit	-5	-2
Philippines	Equity	-21	-3
Thailand	Equity	31	-4

Notes: (i) The numbers refer to the distance (in quarters) between the July 1997 Asian financial crisis and the nearest peak in the relevant filtered series of the respective proxies of financial cycles. Negative (positive) numbers indicate that the nearest peak precedes (follows) the crisis date.
(ii) C-O denotes the Corbae-Ouliaris (2006) filtered series.

Appendix Table 1: Estimated ARMA Model for US

parameters	GDP	Credit	Housing	Equity
constant	0.201	0.378	0.379	0.875
	(5.14)	(8.234)	(3.467)	(2.171)
AR(1)	1.314	1.408	1.875	1.232
	(15.14)	(15.506)	(20.434)	(13.882)
AR(2)	-0.339	-0.256	-1.095	-0.277
	(-3.90)	(-2.148)	(-5.656)	(3.147)
AR(3)			0.440	
			(2.267)	
AR(4)			-0.239	
			(-2.601)	
AR(5)		-0.892		
		(-16.211)		
MA(4)	-0.909	-0.892	-0.941	-0.935
	(-23.135)	(-16.211)	(-50.647)	(-40.116)
diagnostics				
LM(8)	0.82	0.18	0.29	0.98
LM(12)	0.89	0.38	0.49	0.96

Notes: Below the parameter estimates *t*-values are given in parentheses.
For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.

Appendix Table 2: Estimated ARMA Model for UK

parameters	GDP	Credit	Housing	Equity
constant	0.174	0.514	0.701	0.344
	(2.137)	(3.071)	(1.493)	(1.512)
AR(1)	1.096	1.183	1.541	0.916
	(22.745)	(44.888)	(16.613)	(25.625)
AR(2)			-0.376	
			(-2.222)	
AR(3)			-0.199	
			(-2.179)	
AR(4)	-0.543			
	(-5.415)			
AR(5)	0.356	-0.200		
	(4.112)	(-7.674)		
MA(4)		-0.957	-0.780	-0.956
		(-57.680)	(-13.089)	(-43.968)
MA(6)			0.166	
			(2.752)	
diagnostics				
LM(8)	0.19	0.52	0.39	0.96
LM(12)	0.20	0.48	0.63	0.99

Notes: Below the parameter estimates *t*-values are given in parentheses. For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.

Appendix Table 3: Estimated ARMA Model for Germany

parameters	GDP	Credit	Housing	Equity
constant	0.147	-0.075	-0.045	0.567
	(4.120)	(-0.477)	(-0.088)	(1.780)
AR(1)	0.794	1.003	1.399	1.235
	(11.482)	(18.367)	(13.324)	(12.417)
AR(2)			-0.264	-0.335
			(-1.963)	(-3.362)
AR(4)		-0.552		
		(-5.197)		
AR(5)		0.510	-0.147	
		(5.510)	(3.031)	
MA(4)	-0.661		-0.920	-0.939
	(-8.220)		(-52.343)	(-40.932)
MA(8)		-0.725		
		(-8.719)		
diagnostics				
LM(8)	0.29	0.25	0.55	0.97
LM(12)	0.20	0.21	0.24	0.93

Notes: Below the parameter estimates *t*-values are given in parentheses. For LM(*k*) tests of no autocorrelation up to order *k* the table shows *p*-values.