Borradores de ECONOMÍA

Núm. 843
2014

Credit and Business Cycles: An Empirical Analysis in the Frequency Domain

Por: Juan Sebastián Amador,
Celina Gaitán-Maldonado,
José E. Gómez-González,
Mauricio Villamizar-Villegas,
Héctor Manuel Zárate

BANCO DE LA REPÚBLICA COLOMBIA
Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia - Bogotá - Colombia

Credit and Business Cycles:
An Empirical Analysis in the Frequency Domain

Juan Sebastián Amador Celina Gaitán-Maldonado José E. Gómez-González
Mauricio Villamizar-Villegas Héctor Manuel Zárate [1]

Abstract

The history of economic recessions has shown that every deep downturn has been accompanied by disruptions in the financial sector. Paradoxically, up until the financial world crisis of 2007-2009, little attention was given to macroeconomic and financial interdependence. And, in spite of a renewed interest on the matter, significant effort is still warranted in order to attain a comprehensive understanding of the causal links between the financial sector and the rest of the economy. In this paper we study the relationship between financial and real business cycles for a sample of thirty-three countries in the frequency domain. Specifically, we characterize the interdependence of credit and output cycles and conduct Granger-type causality tests in the frequency domain. We also perform cluster analysis to analyze groups of countries with similar cyclical dynamics. Our main findings indicate that: (i) on average, credit cycles are larger and longer-lasting than output cycles, (ii) the likelihood of cycle interdependence is highest when considering medium-term frequencies (we find that that Granger causality runs in both directions), and (iii) emerging markets tend to have cycles of shorter duration but are more profound than those exhibited in developed economies.

JEL Classification: E32, E44, C38

Key Words: Frequency domain, Granger causality, hierarchical clustering, credit and output cycle interdependence

[1] Authors are all economists at the Central Bank of Colombia (Banco de la Republica). All errors are our own. Emails: ja-madoto@banrep.gov.co, cgaitama@banrep.gov.co, jgomezgo@banrep.gov.co, mvillavi@banrep.gov.co, hzaratso@banrep.gov.co. Disclaimer: The findings, recommendations, interpretations and conclusions expressed in this paper are those of the authors and not necessarily reflect the view of the the Banco de la Republica nor its Board of Directors.

1 Introduction

The history of economic recessions has shown that every deep downturn has been accompanied by disruptions in the financial sector. In fact, severe credit contractions as well as declines in housing and financial asset prices are just some of the many outcomes that elicit the bridge between the financial sector and the rest of the economy. Paradoxically, up until the financial world crisis of 2007-2009, little attention was given to this complex link. Fortunately, the acuteness of the recent crisis has renewed interest on macroeconomic and financial interdependence. And as a result, a small but growing literature has surfaced, some of which have followed the seminal works of Fisher (1932), Keynes (1936), and Minsky (1964, 1977, and 1982).

A dominant approach within this new strand of literature has consisted of modeling financial frictions, embedded in a dynamic stochastic general equilibrium (DSGE) framework.[2] These studies purely rely on structural models to address identification issues so the validity of findings largely turns on the accuracy of the underlying assumptions. For this reason, authors such as Borio (2011) and Haldane (2012) have been advocates for the use of different modeling techniques. Regardless of the approach, some critical advances have been made, some of which include Claessens et al. (2012), Schularick and Taylor (2012), and Drehman et al. (2012). Notwithstanding, significant effort is still needed in order to attain a comprehensive understanding of the causal links between the financial sector and the macroeconomy.

In this paper we study the relationship between financial and real business cycles for thirty-three countries in the frequency domain. Our sample includes both developed and emerging market economies which allow us to make several benchmark comparisons. Also, while the literature has mainly focused on developed economies, little is known about the interdependence of cycles for emerging markets. Our paper intends to shed some light on the latter and serve as a building block for the construction of future theoretical models.

[2] See Christiano et al. (2010), Cúrdia and Woodford (2010), Meh and Moran (2010), Gertler and Kiyotaki (2010), and Hafstead and Smith (2012).

Our contributions to the literature are three-fold. First, we characterize the interdependence of credit and output cycles in the frequency domain, while sidestepping the need of assumptions regarding which frequency to select in the data. Hence, our study avoids issues that center on the differences between short and long-term analysis of cycles (see Drehman et al. 2012). Second, following the methodology presented in Breitung and Candelon (2006), we perform Granger-type causality tests in the frequency domain. By doing so, we obtain stronger results than those obtained by using cross-correlation coefficients. Finally, we perform cluster analysis to characterize groups of countries with similar cyclical dynamics.

To our knowledge, the only paper that has studied cycles in the frequency domain is Gómez-González et al. (2014). However, our investigation differs from their work in key methodological aspects as well as on a more ample country sample size (constituting a more detailed cross-country analysis). Our main findings indicate that: (i) on average, credit cycles are more volatile and longer-lasting than output cycles, bearing in mind the high country-variation that exists; (ii) the likelihood of cycle interdependence is highest when considering medium-term frequencies (Granger causality runs in both directions), which confirms the results found by Borio (2011) and Drehman et al. (2012); and (iii) emerging markets tend to have cycles of shorter duration but more profound than those exhibited in developed economies.

The remainder of the paper is organized as follows: Section 2 presents an overview of the related literature. Section 3 describes the methodology. Sections 4 and 5 present the data and results. Finally, section 6 concludes.

2 Literature Review

This section is divided in two. Section 2.1 briefly introduces Minsky's financial stability hypothesis and provides a survey of recent theoretical developments on financial and macroeconomic interdependence. Section 2.2 presents recent empirical findings that have explicitly characterized financial and output cycles.

2.1 Theoretical relationship between financial and macroeconomic variables

2.1.1 Early studies

According to Minsky's financial instability hypothesis, business cycle dynamics systematically respond to financial cycles. The latter is an endogenous result of when firms transition from a hedge finance scheme towards purely speculative (or Ponzi finance) schemes.[3]

The seed of instability is then disseminated during long periods of financial tranquility. In good times, the economy grows at a steady pace in which credit defaults are rare and risk-taking incentives are heightened. Examples include prolonged periods of loose monetary policy, often leading to the search for different yield strategies. As a result, firms and households' risk tolerance increase (bearing higher levels of debt) while private banks lower their lending standards. Higher profit expectations shift the debt structure of firms towards Ponzi finance schemes, increasing investment even further.[4] Similarly, higher income increases households' debt-to-income ratio.

In the related literature, there is strong support of this behavior in booming periods, as seen in Weinberg (1995), Asea and Blomberg (1998), Figueroa and Leukhina (2010), Amador et al. (2013), and Kaufmann and Scharler (2013).

[3] Minsky identified three different types of debt structures under which firms can be categorized: 1) hedge finance, 2) speculative finance, and 3) Ponzi finance. The first corresponds to when cash flows are sufficient for paying interest and principal debt payments. The second corresponds to paying interest payments (but not for repaying the principal). Thus, firms under this category need to issue new debt. Finally, the third correspond to when cash flows are not enough to even cover interest payments. Firms under this last category are in continuous need to refinance their debts, and are extremely vulnerable to changes in current and future short-term interest rates.

[4] Minsky argues that, under monetary tightening, speculative firms will turn into Ponzi, and the net worth of firms that were already in Ponzi positions will decrease and will have to compensate for cash flow shortfalls by selling liquid assets. If fire-sales are sufficiently large, market values may collapse, increasing the likelihood of a debt-deflationary process.

2.1.2 Recent literature

In contrast with earlier studies, the recent literature's dominant approach has consisted of modeling financial frictions; embedded in a dynamic stochastic general equilibrium (DSGE) framework. These models build on the financial accelerator model developed by Bernanke and Gertler (1989), and extended by Kiyotaki and Moore (1997), Carlstrom and Fuerst (1997) and Bernanke et al. (1999). Overall, this new strand of literature intends to emphasize the role of financial intermediaries and to characterize shocks that could potentially affect the borrowing and lending process.

There are numerous renowned examples. For instance, Cúrdia and Woodford (2010) study the desirability of modifying a standard Taylor rule by incorporating variations in credit spreads and credit quantities. Christiano et al. (2010) model financial contracts and liquidity constraints by introducing financial markets and a banking sector. Similarly, Meh and Moran (2010) include a banking sector in order to solve for information problems between banks and creditors (involving differences in the level of capital). Gertler and Kiyotaki (2010) build a hybrid model based on Gertler and Karadi (2009) and Kiyotaki and Moore (2007) to allow for financial intermediation and liquidity risk. The authors show how disruptions in intermediation can induce a crisis, which is opposite for credit market interventions (which can help mitigate a crisis). Hafstead and Smith (2012) develop a financial accelerator model in which a monopolistically competitive banking sector is introduced, and an interbank market exists. The authors find that shocks originating in the financial sector may have large macroeconomic effects and that monetary policy plays an important role in mitigating the effect of these shocks.

In sum, the recent growth in the literature has yielded important results vis-à-vis its critics. For instance, Del Negro et al. (2013), estimate a standard New Keynesian model with financial frictions that successfully predicts the crisis following the period of financial stress experienced in the late 2008. However, it is worth noting that some authors advocate for the use of different modeling techniques. For instance, Borio (2011) recalls for a reconsideration of the prevailing paradigm embedded in macroeconomics. Particularly, he dissents from a rediscovery of the monetary nature of modern economies, in which inside credit creation plays a major role. Haldane (2012) shares this call.

2.2 Recent empirical literature on the interaction between real and financial cycles

Regardless of the particular theoretical approach, the building of theoretical models warrants a better empirical understanding of the interdependence between financial and real business cycles. In this sense, some work has been conducted in the dynamic interactions among financial variables, real economic activity, monetary aggregates and asset prices. For instance, Goodhart and Hoffman (2008) use a sample of 17 industrialized economies to estimate the multi-dimensional links between money, credit, housing prices and economic activity. The authors find a strong link between housing prices (especially when they are booming) and monetary variables, predominantly after 1985. From a historical perspective, Schularick and Taylor (2012) evaluate the behavior of financial, monetary and macroeconomic indicators for a sample of 14 countries with historical data (starting in 1870). A key finding consists of an exuberant credit growth which precedes financial crises. Similar results are obtained by Alessi and Detken (2011), Borio and Drehmann (2009), and Tenjo and López (2010), who construct early warning models of financial crises.

Another strand of the literature deals with the predictive power of financial indicators on economic crises. Ng (2011), for instance, uses three alternative financial measures to evaluate the accuracy of business cycle forecasts. Similarly, Aikman et al (2011) construct a model of the banking industry in which credit cycles emerge due to the failure of banks to coordinate. The authors find evidence of financial cycles and their predictive power over banking crises. Claessens et al. (2012) measure the interdependence between business and financial cycles on short-term frequencies for a sample of 44 countries and report strong liaisons between cycles. Another example is Drehman et al (2012), who separate cycles into short and medium-term components and find that medium-term cycles are more volatile. Finally, Gómez-González et al. (2014) estimate credit and GDP cycles for 3 Latin American economies in the frequency domain. Similar to our results, the authors find that the likelihood of cycle interdependence is highest when considering medium-term frequencies.

3 Econometric Methods

In this section we present the methodology used for estimating output and credit cycles in the frequency domain and evaluate their causal links. We then describe the methodology used for grouping countries into clusters according to their credit and business cycle dynamics.

3.1 Frequency domain analysis

The frequency domain approach is implemented in three stages. First, we estimate the spectral function for each variable. This estimation allows comparing the shape of the spectral density with the "typical shape" identified in Granger (1966). Second, we use the direct filter approach to extract cycles using Fourier analysis. Finally, we estimate the co-movement between cycles by using the cross-spectral density function and its related measures of coherence.

This methodology is conducted on the entire frequency range from 0 to π. This approach allows estimating the proportion of the total variance determined by each periodic component, using spectral analysis. Therefore, we capture the components of credit and output by decomposing the original series and using approximation methods based on trigonometric functions at each frequency.

The traditional econometric methods of signal extraction are based on smoothing filters (Christiano and Fitzgerald, 2003) and modeling-based procedures. However, the components of the time series give rise to spectral structures that fall within well-defined frequency bands (isolated from each other by spectral dead spaces).[5] Thus, the frequency domain offers a

[5] See Polluck (2000).

better way of implementing signal extraction methods, and filters are used to separate time series' components.

One of the tools used in the frequency domain is the Fourier transformation of its autocovariance function $\gamma(\bullet)$. It is given by the following symmetric function:

$$f(\lambda) = \frac{1}{(2\pi)}\left[\gamma(0) + 2\sum_{\tau=1}^{\infty}\gamma(\tau)\cos(\lambda\tau)\right] \tag{1}$$

Where λ is the frequency in radians in the range $[-\pi, \pi]$. The standardized function, known as the spectral density, is obtained by normalizing equation (1) by using $\gamma(0)$. A cycle is defined as a unit period of a sine or cosine function over a time interval of length 2π.

It is important to note that the spectrum and the covariances are equivalent. However, some features of the time series, such as its serial correlation, are easier to grasp using autocovariances. Others, such as the unobserved components, are easier to analyze using the whole spectrum.

Values of λ near zero correspond to long-term cycles, while values of λ near π correspond to short-term cycles. The peaks observed in the spectrum indicate those periodicities which contribute the most to the variability of the series. Additionally, confidence intervals for the spectrum can be obtained from the fact that $f(\lambda)$ follows a χ^2 distribution with ν degrees of freedom where $\nu = \frac{3n^{1/2}}{2}$, and n stands for the sample size.

The direct filter approach (DFA) emphasizes on filter errors rather than on the one-step ahead forecasting error. Furthermore, the DFA uses an algorithm based on an optimization criterion which consists of minimizing the mean square error of the filter.

Given a stochastic process $\{Y_t\}$, the real time signal extraction is concerned with the estimation of $\hat{Y}_t$ and $\bar{Y}_t$ such that $E\left(\bar{Y}_t - \hat{Y}_t\right)^2$ is minimized. In this context, $\bar{Y}_t$ is the result of applying a symmetric filter to the original series, while $\hat{Y}_t$ is the result of applying an asymmetric filter.

The result of this minimization is the following transfer function which can be used as a filter. One particular application which we use in this study is the filter proposed by Christiano and Fitzgerald (2003):

$$\Gamma(\lambda) = \begin{cases} 1, & if \quad 0 \leq |\lambda| \leq \pi b_p \\ \frac{\pi b_p - |\lambda|}{\pi b_s - \pi b_p} & if \quad \pi b_p < |\lambda| \leq \pi b_s \\ 0 & \quad \pi b_s < |\lambda| \leq \pi \end{cases} \tag{2}$$

Where b_p determines the width of the pass band and b_s determines the width of the stop band (see Wildi, 2008).

The cross-spectral correlation function measures the correlation between two series indexed by the frequency. The square of the value of this correlation function at every frequency λ is defined as its coherence. This statistic is the analogous of the square of the correlation coefficient and takes on values in the interval $[0, 1]$. A value of coherence near one indicates that the two series are highly associated at the given frequency. A value near zero describes that at this frequency the series are almost independent.

In order to test for causality between GDP and Credit cycles in the frequency domain, we use the measures proposed by Geweke (1982) and Hosoya (1991) and adopted by Breitung and Candelon (2006) in a VAR system setup.

Let $Z_t = [GDP_t, CREDIT_t]$ be a two dimensional vector of time series observed for $t = 1, 2, \cdots T$, which represents the total cycle of these two variables. Thus, the VAR representation of this system can be expressed as in equation (3):

$$\Theta(L) Z_t = \epsilon_t \tag{3}$$

The moving average (MA) representation of the system is the following:

$$
\begin{aligned}
Z_t &= \Phi(L)\,\epsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \\
&= \Psi(L)\,\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \qquad (4)
\end{aligned}
$$

Where

$$
\Phi(L) = \Phi(L)^{-1} \text{ and } \Psi(L) = \Phi(L)\,G^{-1}
$$

And G is the lower matrix of Cholesky decomposition. Using this representation, the spectral density of GDP_t, for example, can be expressed as:

$$
f_{GDP}(\omega) = \frac{1}{2\pi}\left(\left(\Psi_{11}\left(e^{-i\omega}\right)\right)^2 + \left(\Psi_{12}\left(e^{-i\omega}\right)\right)^2\right) \qquad (5)
$$

From the above expression, and following Breitung and Candelon (2006), the measure of causality is defined in the following way:

$$
M_{CREDIT \longrightarrow GDP} = \log\left(1 + \frac{\left(\Psi_{12}\left(e^{-i\omega}\right)\right)^2}{\left(\Psi_{11}\left(e^{-i\omega}\right)\right)^2}\right) \qquad (6)
$$

This causality measure is zero if $\left(\Psi_{12}\left(e^{-i\omega}\right)\right)^2 = 0$, which means that the variable $CREDIT$ does not cause GDP at frequency ω. The causality of GDP to $CREDIT$ is built using a similar approach.

3.2 Cluster analysis

After obtaining both short and medium term cycles (using frequency domain techniques) we apply the multivariate analysis tool of hierarchical clustering on principal components over the duration and amplitude of each cycle per country. This method consists of applying factor analysis to the data for clustering objects –in our case, countries. The process reduces the dimension of the set of variables by constructing "factors" that retain most of the variance contained in the original set. The process is done trough a linear orthogonal transformation of the correlation matrix of the variables, so that each component captures a descending portion of the whole data variance. This pre-processing of the data allows reducing the dimension of the system, allowing a more robust clustering process.

The primary objective of applying this method is to define the structure of the data by placing the most similar observations into groups. The main advantage of combining these two multivariate methods into a single methodology is that clustering is more robust after de-noising the data and preserving only its signal. Cluster analysis consists of classifying objects on a set of observed characteristics so as to exhibit high homogeneity within its members but high heterogeneity between clusters. Identifying groups helps reduce the dimension of the problem.

We consider that there are interesting patterns in both business and financial cycles among countries with different levels of development and, in general, with different economic fundamentals. Those differences can be explored in more detail when characterizing "similar" economies into well-defined groups.

The nature of this multivariate technique is descriptive, hence theoretical and non-inferential. Therefore, it is not useful for performing causal analysis between variables. In our case, we use a cluster methodology after using frequency-domain statistics, mainly expecting that after characterizing business and financial cycles (i.e. uncovering the underlying structure of the data) we can group them according to similar characteristics.

In this document we use Ward's (1963) method of clustering. To exemplify this methodology consider the following example in which only one variable "x_i" is used:[6]

Suppose that x_i takes the following values for 10 individuals: $\{2, 6, 5, 6, 2, 2, 2, 0, 0, 0\}$. We are interested in defining a value function that reflects the loss in information resulting

[6] Applying Principal Component Analysis for one variable is immaterial.

from grouping two or more individuals into a single cluster. Thus, the Error Sum of Squares (ESS) function for cluster k is defined as:

$$ESS_k = \sum_{i=1}^{n_k} \left(x_i - \bar{x} \right)^2 \tag{7}$$

Where $\bar{x}$ is the average (or centroid when there is more than one variable) in cluster k and n_k is the number of elements in the same cluster. The total ESS function W, is the sum of each ESS_k for all m clusters:

$$W(m) = \sum_{j=1}^{m} \sum_{i=1}^{n_k} \left(x_{ik} - \bar{x}_k \right)^2 \tag{8}$$

If we include all observations in one single cluster, then the value of the total ESS function is $W(1) = \sum_{i=1}^{10} (x_i - 2.5)^2 = 50.5$. If instead we consider each individual as a single cluster, the total ESS function would be $W(10) = \sum_{k=1}^{10} \sum_{i=1}^{10} \left(x_{ik} - \bar{x}_k \right)^2 = 0$.

Ward's algorithm is based on the premise that the amount of information is highest when individuals are not grouped. Hence, grouping results in a loss of information which increases the value of $W(m)$. In sum, the algorithm starts assuming that every individual conforms a single cluster, so that $W(n) = 0$. Subsequently, it groups the two most similar clusters in a stepwise fashion, so that the number of clusters is reduced by one in each "step". Groups of clusters are most similar if, when joined, they produce the minimum increase in the function $W(m)$, compared to any other pair. This algorithm has high computational requirements since, for example, there are $\frac{n(n-1)}{2}$ possible pairs to compare in the first cluster merge.

After obtaining one single cluster, the number of groups that remain in the final solution from the hierarchy that was created must be decided. We use Ward's method which minimizes the intra-cluster inertia, or equivalently, the squared distance from the center of the cluster.

In our example, since there are 45 different pairs, we consider two convenient groupings: $\{2,6\}$, $\{5\}$, $\{6\}$, $\{2\}$, $\{2\}$, $\{2\}$, $\{0\}$, $\{0\}$, $\{0\}$ and $\{2,2\}$, $\{5\}$, $\{6\}$, $\{6\}$, $\{2\}$, $\{2\}$, $\{0\}$, $\{0\}$, $\{0\}$.

In the first ordering we have that $ESS_k = 0$ for $k \neq \{2,6\}$ and $ESS_{\{2,6\}} = 8$, so that $W_1(9) = 8$, where the subscript denotes that we are working with the first ordering. On the other hand, in the second ordering we have that $W_2(9) = 0$. That is, the second order virtually does not lose any information and thus preferred. In general, we can compute all of the 45 different possible orderings and find that those that merge identical individuals are the ones that produce the minimum increase in $W(9)$. The algorithm continues in this fashion until merging all observations into a single cluster. The final solution is the natural grouping: $\{0,0,0\}$, $\{2,2,2,2\}$, $\{6,6\}$, $\{5\}$, which, in fact, gives a value of $W(4) = 0$ (it also yields an intra-cluster inertia of zero).

4 Data

Our database has a quarterly frequency on credit to the private non-financial sector and real GDP for 33 economies: Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Iceland, India, Indonesia, Ireland, Italy, Japan, South Korea, Luxembourg, Mexico, New Zealand, Norway, Peru, Poland, Portugal, Russia, South Africa, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States. The private non-financial sector includes non-financial corporations, households and non-profit institutions serving households.

We use credit as an approximation to the financial cycle (given the lack of general consensus on its exact definition). However, some studies have shown that the most parsimonious definition of the financial cycle is in terms of credit and property prices.[7] Our sample includes several emerging markets for which long enough datasets on property prices are not

[7] See, for instance, Borio (2012).

available. Additionally, credit and property prices tend to co-vary rather closely in countries for which information is available. Hence, we use the credit cycle as a proxy of the unobservable financial cycle in our study, following Aikman et al. (2010), Jordá et al (2011), Schularick and Taylor (2012).

Most data on credit, adjusted for breaks, were obtained from the Bank for International Settlements (BIS).[8] For countries not included in the BIS database (namely Colombia, Chile and Peru) we collected official data from each central bank. All data were collected for the longest available period, with an average amount of credit and GDP observations of 150 and 155, respectively. Some countries have available data starting from the early 1940s and 1950s.[9] However, the last observation for all countries was 2013-Q2. Nominal GDP and Consumer Price Index (CPI) were obtained from the International Financial Statistics database of the International Monetary Fund. All data used in this study are expressed in constant prices (using the CPI of each country as deflator).

5 Empirical Results

We contribute to the knowledge of the financial cycle by studying its characteristics in the frequency domain for a large group of countries. However, for the purpose of making our results illustrative and for them to serve as a benchmark comparison with the existing literature, we first perform a characterization of cycles estimated in the time domain.

5.1 Short and medium-term cycles in the time domain

Business cycles usually span over eight years or less.[10] We follow Drehmann et al. (2012) and focus on two different cyclical patterns. First, we estimate short-term cycles with durations

[8] See Dembiermont et al. (2013) for a detailed methodology by the BIS.

[9] The exact sample size for each country is reported in Annex 1.

[10] See King, Plosser and Rebelo (1988); Rotemberg and Woodford (1991); and Christiano and Eichenbaum (1995).

ranging from 5 to 32 quarters. Second, we estimate medium-term cycles ranging from 32 to 80 quarters. As such, we are able to identify the existence of both short and medium-term GDP and credit cycles for all 33 countries. We use the Band-Pass filter presented in Christiano and Fitzgerald (2003) to isolate the component of each series that corresponds to the chosen frequency interval.

Table 1 presents the estimated duration of short and medium-term cycles for GDP and credit. On average, credit cycles are longer-lasting than output cycles, bearing in mind the high country-variation that exists. Specifically, our results show that in the short-term, credit cycles last on average 8.4 quarters, while GDP cycles last on average 8.3 quarters. In the medium-term, credit cycles last on average 40.8 quarters and GDP cycles last 38.4 quarters. Table 1B shows that output cycles for developed economies are longer (shorter) than credit cycles in the short-run (medium-run). For developing economies, credit cycles are longer than output cycles in both short and medium-terms.

In terms of cyclical phases, expansions tend to last longer than contractions in most countries both for credit and GDP (see Table 1). However, on average contractions last longer than expansions, both for output and credit. When considering developed and emerging economies separately, expansions are larger than contractions in only two particular cases: output cycles for developing economies in the medium term and credit cycles for developed economies in the medium term. For each cyclical phase, durations are longer for credit than for output. This dynamic is different for the group of developed and developing economies. Credit durations are in all cases longer than output durations for developing economies. Meanwhile, in developed economies, the latter is true only for the medium term.

Another interesting feature of the dynamics of cycles is the amplitude contractions and expansions. Our results show that both credit and output contractions are more ample than expansions. We also find that credit cycles are more volatile (two to three times more) than output cycles in both the medium and short-term. In general, developing countries exhibit higher volatile than developed countries (See Table 2).

5.2 Cluster analysis

We perform cluster analysis for cycles in the short and medium-term (for both credit and GDP) within a multivariate framework. Along each of these four categories, we consider five different variables for grouping countries. These variables comprise the duration and amplitude of expansions, contractions, and whole cycle.[11] In all cases we group countries in clusters according to the main two components of the explained variance of the series. In all four categories they explain over 90% of the total variance.

Figures 1 and 2 present results for short-term GDP cycles. While figure 1 depicts the hierarchical clustering, figure 2 depicts the corresponding factor map. Figure 1 highlights some interesting results. It shows that group 1 collects -with minor exceptions- advanced economies, such as the United States, United Kingdom, Germany, and France. Group 2 collects five emerging economies and group 3 contains both emerging and advanced economies. The factor map in Figure 2 shows that the countries in group 1 are those with longest but less ample short-term GDP cycles. Countries pertaining to group 2 are those with the amplest short-term GDP cycles. Finally, countries in group 3 are those with the shortest GDP cycles.[12]

Figures 3 and 4 depict results corresponding to medium-term GDP cycles. Figure 3 shows that the most advanced economies remain in group 1 (there is some redistribution among groups 2 and 3). Most countries in group 1 present low amplitude and short duration of medium-term GDP cycles. Two notable exceptions are Canada and the United States which exhibit low amplitude but high cycle duration (although their duration is lower than countries in group 2). Countries in group 2 exhibit long cycle duration but with a moderate amplitude. Finally, countries in group 3 are characterized for having ample medium-term GDP cycles. As expected, developed economies present less GDP volatility (amplitude) than emerging market economies both in the short and medium-term.

[11] We do not consider the amplitude of the whole cycle since it constitutes a stationary variable zero-mean. Thus, the cycle's total amplitude must be on average equal to zero.

[12] Developed economies exhibit more stability in regards to their business cycles. Meanwhile, Korea, Peru, Mexico, Turkey and Russia exhibit the highest volatility.

Figures 5 and 6 depict results corresponding to short-term credit cycles. Results show that group 1 now contains developed economies with two notable exceptions: United States and United Kingdom. These two market-based economies now belong to cluster 3. Countries in group 1 exhibit low amplitude and short duration in their short-term credit cycles. The four countries in group 2 (Indonesia, Turkey, Mexico and Poland) exhibit long and ample short-term credit cycles. Finally, countries in group 3 present cycles of long duration.

Figures 7 and 8 depict results corresponding to medium-term credit cycles. As shown in Figure 8, the factor map corresponding to medium-term credit cycles is the most disperse. As expected, the United States presents long-lasting cycles of low amplitude. The United Kingdom also exhibits cycles of low amplitude, but cycle duration is significantly shorter. Most European economies have similar medium-term credit cycles (in amplitude and duration) than those of the United Kingdom. Finally, most developing economies have more volatile medium-term credit cycles than developed countries.[13]

5.3 Characterizing cycles in the frequency domain

We also perform analyses on the frequency domain. Figure 9 shows results of computing coherence statistics between credit and GDP for all 33 countries. If coherence takes a value near unity at some frequency, then there is evidence of high correlation between credit and GDP. Results in Figure 9 show that credit and GDP cycles appear to have greater correlation at medium-term frequencies for most countries in our sample (29 out of 33). This fact highlights the importance of looking at medium-term credit cycles when designing macro-prudential policies. The only exceptions include Belgium, India, Mexico and Peru, for which the greater values of coherence occur at short-term frequencies.

Figure 10 depicts the cross-correlation between credit and GDP on the frequency domain. In all countries (except Korea), the maximum cross-correlation lies at the negative side of the domain, suggesting a positive relationship between lags in credit and output cycles. This

[13] This is probably why emerging economies (such as Brazil, Colombia, Chile, and Peru) have actively implemented macro-prudential policies since 1990.

result corroborates the findings obtained by Gómez-González et al. (2014) and Schularick and Taylor (2012). The fact that credit lags are strongly and positively associated with contemporaneous GDP constitutes an empirical support of Minsky's work, in the sense that the real economy requires financial leverage to function properly. This result is further confirmed by performing Granger-type causality tests in the frequency domain.

Figure 11 shows results of performing causality tests between credit and GDP. This procedure is based on Breitung and Candelon (2006) which allows testing for Granger-type causality between any two variables across the frequency domain. We conduct this test for the 33 countries in our sample and for the two directions of causality. Therefore, figure 11 consists of 66 graphs. The horizontal line represents the critical value at the 95% significance level. Values of the test statistic above the critical value indicate causality at a particular frequency. All data were de-trended before performing these tests.

Results show that, as expected, there is evidence of causality in both directions. Causality is stronger in medium-term frequencies. There is however, some heterogeneity among countries. For instance, there are countries such as Peru for which causality runs in only one direction. In some cases, evidence of causality is stronger in the short-run, but for most countries medium-term causality is the most evident.

Our findings shed light on salient features of macroeconomic modeling. The relationship between financial and real variables is complex, and financial factors influence economic activity beyond exogenous shocks. Overall, we illustrate that GDP and credit cycles are not perfectly synchronized. The relationship between these two cycles is stronger when lags are included. An interesting implication for monetary policy is that it is difficult to target both financial and real variables using just one instrument. Moreover, credit should not be ignored when the objective is to stabilize the economy, as credit cycles excerpt important influence over the business cycle, and vice-versa.

6 Conclusions

We study the relationship between financial and real business cycles for thirty-three countries in the frequency domain. Our sample includes both developed and emerging market economies which allow us to make several benchmark comparisons. We contribute to the literature by first, characterizing the interdependence of credit and output cycles. Second, by performing Granger-type causality tests. Finally, by performing cluster analysis to characterize groups of countries with similar cyclical dynamics.

Our findings indicate that: *i*) on average, credit cycles are more volatile and longer-lasting than output cycles, bearing in mind the high country-variation that exists, *ii*) the likelihood of cycle interdependence is highest when considering medium-term frequencies (Granger causality runs in both directions), and *iii*) Emerging markets tend to have cycles of shorter duration but exhibit a higher amplitude than developed economies. As such, monetary authorities can benefit by focusing on medium-term credit cycles when designing macro-prudential policies. Moreover, credit cycles should be carefully analyzed when trying to stabilize the economy, as they excerpt important influence over the business cycle, and vice-versa.

Our paper intends to shed some light on the interdependence of credit and GDP cycles. We believe that our findings elicit key structural differences between emerging and developed economies that can potentially serve as building blocks for the construction of future theoretical models.

7 References

- Aikman, D., A. Haldane and B. Nelson (2011) “Curbing the Credit Cycle,” March. Bank of England, Speech 463.
- Alessi, L. and C. Detken (2011): “Quasi Real Time Early Warning Indicators for Costly Asset Price Boom/Bust Cycles: A Role for Global Liquidity,” European Journal of Political Economy, 27, 520-533.
- Amador, J.S., J.E. Gómez-González and A. Murcia (2013): “Loan Growth and Bank Risk: New Evidence,” Financial Markets and Portfolio Management, 27, 365-379.
- Asea, P. and P. Blomberg (1998): “Lending Cycles,” Journal of Econometrics, 83, 89-128.
- Bernanke, B. and M. Gertler (1989): "Agency Costs, Net Worth, and Business Fluctuations," American Economic Review, 79, 14-31.
- Bernanke, B., M. Gertler and S. Gilchrist (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," In: Handbook of Macroeconomics, edited by J. B. Taylor and M. Woodford, 1341-1393.
- Borio, C. (2011): “Rediscovering the Macroeconomic Roots of Financial Stability Policy: Journey, Challenges and a Way Forward,” Annual Review of Financial Economics, 3, 87-117.
- Borio, C. (2012): “”The Financial Cycle and Macroeconomics: What have We Learnt”, BIS Working Paper 395, Bank for International Settlements.
- Borio, C. and M. Drehmann (2009): “Assessing the Risk of Banking Crises – Revisited,” BIS Quarterly Review, Bank for International Settlements.
- Breitung, J. and B. Candelon (2006): “Testing for Short- and Longrun Causality: A Frequency-Domain Approach, Journal of Econometrics, 132, 363–378.

- Carlstrom, C.T. and T.S. Fuerst (1997): "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis," American Economic Review, 87, 893-910.

- Christiano, L.J. and M. Eichenbaum (1995) "Liquidity Effects, Monetary Policy, and the Business Cycle," Journal of Money, Credit and Banking, 27, 1113-36.

- Christiano, L. and T. Fitzgerald (2003): "The Band Pass Filter", International Economic Review, 44, 435-465.

- Christiano, L., R. Motto, and M. Rostagno (2010): "Financial Factors in Economic Fluctuations," ECB Working Paper 1192, European Central Bank.

- Claessens, S., M.A. Kose, and M.E. Terrones (2012): "How do Business Cycles and Financial Cycles Interact?," Journal of International Economics, 87, 178-190.

- Cúrdia, V., and M. Woodford (2010): "Credit Spreads and Monetary Policy," Journal of Money, Credit, and Banking, 42, 3–35.

- Davidson, P. (1986): "Finance, Funding, Saving, and Investment," Journal of Post Keynesian Economics, 9, 101-110.

- Del Negro, M., S. M. P. Giannoni, and F. Schorfheide (2013): "Inflation in the Great Recession and New Keynsian Models," Staff Reports 618, Federal Reserve Bank of New York.

- Drehmann, M., C. Borio, and K. Tsatsaronis (2012): "Characterising the Financial Cycle: Don't Lose Sight of the Medium Term!," BIS Working Papers 380, Bank for International Settlements.

- Figueroa, N. and O. Leukhina (2010): "Business Cycles and Lending Standards," Unpublished Manuscript.

- Fischer, I. (1932): "Booms and Depressions: Some First Principles". Adelphi Company.

- Gertler, M. and P. Karadi (2013): "QE 1 vs. 2 vs. 3. . . : A Framework for Analyzing Large-Scale Asset Purchases as a Monetary Policy Tool," International Journal of Central Banking, 9, 5-53.

- Gertler, M. and N. Kiyotaki (2010): “"Financial Intermediation and Credit Policy in Business Cycle Analysis," Handbook of Monetary Economics, edited by B. M. Friedman and M. Woodford, 547-599.

- Geweke, J. (1982): “Measurement of Linear Dependence and Feedback Between Multiple Time Series,” Journal of the American Statistical Association, 77, 304-313.

- Gómez-González, J.E., J. Ojeda-Joya, H. Zárate and F. Tenjo-Galarza (2014): “Testing from Causality Between Credit and Real Business Cycles in the Frequency Domain: An Illustration,” Applied Economics Letters, 21, 697-701.

- Goodhart, C. and B. Hofmann (2008): “House Prices, Money, Credit and the Macroeconomy,” Oxford Review of Economic Policy, 24, 180-205.

- Granger, C.W.J (1966): “The Typical Spectral Shape of an Economic Variable”, Econometrica, 34, 150-161.

- Hafstead, M. y J. Smith (2012): “Financial Shocks, Bank Intermediation, and Monetary Policy in a DSGE Model,” Unpublished Manuscript.

- Hosoya, Y. (1991): “The Decomposition and Measurement of the Interdependence Between Second-order Stationary Processes,” Probability Theory and Related Fields, 88, 429–444.

- Jordà, O. M. Schularick and A.M. Taylor (2011): "When Credit Bites Back: Leverage, Business Cycles, and Crises," Working Paper Series 2011-27, Federal Reserve Bank of San Francisco.

- Kaufmann, S. and J. Scharler (2013): “Bank-Lending Standards, Loan Growth and the Business Cycle in the Euro Area," Working Papers 2013-34, Faculty of Economics and Statistics, University of Innsbruck.

- Keynes, J.M. (1936): The General Theory of Employment. New York, NY: Wiley and Sons.
- King, R.G., C.I. Plosser and S.T. Rebelo (1988): "Production, Growth and Business Cycles: I. The Basic Neoclassical Model", Journal of Monetary Economics, 21, 195-232.
- Kiyotaki, N. and J. Moore (1997): "Credit Cycles," Journal of Political Economy, 105, 211-248.
- Haldane, A. (2012): "What Have Economists Ever Done for Us", VoxEU.org, 1st October.
- Meh, C. and K. Moran (2010): "The role of bank capital in the propagation of shocks," Journal of Economic Dynamics and Control, 34, 555-576.
- Minsky, H. (1964): "Financial Crisis, Financial Systems, and the Performance of the Economy." In: Private Capital Markets: A Series of Research Studies Prepared for the Commission on Money and Credit, 173-380. Englewood Cliffs, N.J. Prentice-Hall.
- Minsky, H. (1977): "A Theory of Systemic Fragility," In: Financial Crises: Institutions and Markets in a Fragile Environment, edited by E. Altman and E. Sametz. New York, NY: Wiley and Sons.
- Minsky, H. (1982): Can "It" Happen Again? Essays on Instability and Finance. Armonk, NY: M.E. Sharpe Inc.
- Ng, E. (2011): "Forecasting US Recessions with Various Risk Factors and Dynamic Probit Models," Journal of Macroeconomics, 34, 112–125.
- Pollock, D. S. G. (2000): "Trend Estimation and De-trending Via Rational Square-Wave Filters," Journal of Econometrics, 99, 317-334.
- Rotemberg, J. and M. Woodford (1991): "Markups and the Business Cycle," NBER Macroeconomics Annual 1991, 6, 63 – 140.

- Schularick, M. and A.M. Taylor (2012): "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008," American Economic Review, 102, 1029-1061.
- Tenjo, F. and M. López (2010): "Early Warning Indicators for Latin America", Ensayos Sobre Política Económica, 28, 232-259.
- Weinberg, J.A. (1995): "Cycles in Lending Standards?," Economic Quarterly, Federal Reserve Bank of Richmond, 1-18.
- Wildi, M. (2008): "Real-Time Signal Extraction: Beyond Maximum Likelihood Principles". Heidelberg: Springer.

Tables

Table 1: Duration Variables for Business and Credit Cycles

	GDP Expansion		GDP Contraction		GDP Cycle		Credit Expansion		Credit Contraction		Credit Cycle	
Country	ST	MT	ST	MT	ST	MT	ST	MT	ST	MT	ST	MT
Australia	3.98	17.25	3.75	16.06	7.73	33.31	3.48	18.06	3.55	17.41	7.03	35.30
Austria	3.80	18.77	4.02	18.26	7.82	37.54	3.98	18.88	3.87	18.46	7.85	37.34
Belgium	4.06	20.97	4.06	20.29	7.91	41.08	3.48	19.54	3.67	18.93	7.15	38.22
Brazil	4.35	23.34	4.78	22.32	9.13	45.67	4.06	21.29	5.08	22.34	9.13	43.63
Canada	4.25	20.12	4.96	19.45	9.21	39.57	3.50	20.09	3.45	19.88	6.93	39.98
Chile	3.74	17.26	4.06	16.23	7.80	31.97	4.85	22.84	5.41	22.30	10.40	45.64
Colombia	3.37	17.00	4.00	17.50	7.37	34.49	4.06	18.26	5.21	23.68	9.27	41.94
Czech Republic	5.08	20.29	4.56	21.32	8.84	41.60	3.61	21.32	3.60	21.30	7.21	42.62
Denmark	4.20	19.61	4.56	19.62	8.59	39.56	3.66	25.12	3.84	21.05	7.50	46.16
Finland	4.01	17.49	3.91	17.05	7.66	34.75	3.86	16.99	3.81	18.52	7.66	35.51
France	4.70	15.99	5.43	17.65	10.08	34.50	3.38	20.81	3.30	21.98	6.68	42.27
Germany	4.15	18.26	4.94	18.09	9.09	37.54	3.62	20.04	3.81	21.10	7.54	39.31
Hungary	3.95	NA	3.38	22.30	6.59	NA	4.47	19.79	3.60	20.29	8.12	39.58
India	3.77	21.31	4.49	21.31	8.26	42.62	4.10	19.88	4.78	18.26	8.88	38.15
Indonesia	3.16	18.28	3.68	18.24	6.72	36.52	5.79	18.60	3.92	18.26	9.71	36.86
Ireland	4.40	NA	4.73	37.53	9.13	NA	4.37	20.04	4.84	19.28	9.07	38.21
Italy	4.76	19.28	5.00	19.27	9.64	38.05	4.10	18.67	4.18	18.87	8.32	37.54
Japan	3.88	17.85	3.92	18.44	7.80	36.12	4.25	19.79	4.11	19.27	8.21	39.06
Korea	3.91	18.43	3.83	17.86	7.74	35.71	4.38	26.05	3.95	24.34	8.33	52.76
Mexico	3.65	18.26	4.53	16.58	8.19	36.52	4.61	24.36	5.16	23.32	9.59	48.70
New Zealand	3.61	18.26	3.74	18.27	7.36	36.53	3.44	22.83	3.28	21.29	6.85	42.60
Norway	3.57	18.77	3.67	18.26	7.22	37.29	3.57	20.90	3.49	19.07	7.04	39.97
Peru	4.31	23.33	4.17	22.32	7.74	45.66	4.73	21.30	4.79	22.32	9.64	43.62
Poland	5.42	21.31	5.07	20.30	10.32	41.61	4.69	20.29	4.78	21.30	9.71	41.59
Portugal	4.40	18.94	4.38	18.77	8.46	37.88	4.02	17.92	3.95	18.67	7.96	37.34
Russia	4.18	22.32	4.06	22.32	8.12	NA	4.06	20.30	3.62	NA	6.93	NA
South Africa	4.02	17.26	3.98	17.24	8.00	34.29	4.46	20.80	4.81	26.04	9.29	46.67
Spain	3.74	24.35	4.56	19.54	8.17	44.64	3.91	16.99	3.67	17.51	7.66	34.50
Sweden	4.06	21.30	4.56	21.06	8.62	44.64	3.93	18.06	4.23	17.65	8.07	35.71
Switzerland	3.87	18.52	4.75	18.46	8.62	37.54	3.50	20.62	4.17	20.97	7.67	41.59
Turkey	3.63	18.77	3.59	19.78	7.18	39.58	5.07	20.29	4.47	21.31	9.54	41.61
United Kingdom	4.38	18.27	4.67	17.41	9.01	35.51	5.65	16.22	5.45	18.78	10.73	35.00
United States	4.84	19.78	4.68	20.97	9.52	40.75	6.51	23.60	5.24	21.10	11.88	45.41
Developed Countries	4.17	19.12	4.41	19.70	8.49	38.21	4.01	20.12	3.97	19.78	7.97	39.83
Developing Countries	3.96	19.86	4.15	19.70	7.95	38.89	4.58	20.67	4.63	21.77	9.18	42.54
Total Sample	4.10	19.38	4.32	19.70	8.29	38.43	4.22	20.32	4.21	20.46	8.41	40.76

Table 2: Amplitude Variables for Business and Credit Cycles (%)

	GDP Expansion		GDP Contraction		Credit Expansion		Credit Contraction	
Country	ST	MT	ST	MT	ST	MT	ST	MT
Australia	3.10	1.36	2.95	1.34	8.93	13.21	9.07	11.64
Austria	2.77	1.53	2.86	1.46	5.48	6.66	5.51	6.71
Belgium	4.65	4.27	4.43	5.37	6.35	6.15	6.64	6.93
Brazil	4.94	1.22	5.25	0.91	14.24	10.60	13.55	8.08
Canada	3.81	2.07	3.82	2.22	10.97	12.73	11.03	13.68
Chile	4.35	1.54	4.35	1.40	10.36	12.47	9.39	13.80
Colombia	2.47	2.21	2.76	2.61	8.17	11.57	8.28	12.96
Czech Republic	3.88	4.52	4.84	3.99	12.60	14.56	12.15	15.73
Denmark	3.67	2.45	3.65	2.41	4.34	8.10	4.43	8.23
Finland	3.39	3.54	3.52	3.43	5.53	6.81	5.80	6.83
France	2.44	1.35	2.46	1.34	7.86	9.05	8.25	10.82
Germany	3.73	1.79	3.67	1.67	4.04	7.43	4.00	7.65
Hungary	2.87	NA	2.86	2.08	13.94	7.47	14.31	7.85
India	2.51	2.18	2.89	1.83	12.07	6.48	11.72	5.87
Indonesia	3.69	2.47	1.85	3.20	27.31	15.69	26.70	13.43
Ireland	4.61	NA	4.69	2.00	12.34	5.53	12.44	5.72
Italy	3.09	1.45	3.26	1.40	4.86	3.01	4.79	3.88
Japan	3.73	2.74	3.78	2.84	3.29	3.91	3.42	4.49
Korea	5.44	2.44	5.53	2.60	10.51	10.54	10.71	10.06
Mexico	5.17	2.32	5.45	1.76	21.60	25.54	22.20	28.42
New Zealand	3.85	2.59	4.12	2.94	3.15	5.50	3.09	6.10
Norway	3.42	2.20	3.50	1.95	9.88	14.63	10.07	14.22
Peru	5.50	3.63	5.83	4.13	9.10	21.38	9.60	21.70
Poland	3.85	3.42	3.83	3.94	18.61	21.29	19.52	24.04
Portugal	2.37	4.50	2.71	4.14	8.83	9.07	8.85	9.56
Russia	6.94	3.56	7.05	3.31	20.45	16.26	20.43	NA
South Africa	2.88	1.88	2.85	1.96	8.91	8.17	8.81	8.18
Spain	2.14	2.47	2.22	2.66	3.75	8.48	3.67	9.09
Sweden	2.93	1.93	3.17	1.84	10.44	12.31	10.44	11.43
Switzerland	2.89	2.93	2.89	2.86	5.26	6.30	5.41	6.03
Turkey	8.23	2.99	8.31	3.52	26.12	18.63	26.01	21.17
United Kingdom	3.00	2.13	2.99	2.12	4.12	3.34	5.33	5.12
United States	3.99	2.09	4.13	2.22	2.86	4.74	3.13	4.44
Developed	3.47	2.52	3.58	2.52	6.92	8.19	7.06	8.49
Developing	4.45	2.49	4.44	2.55	15.91	14.63	15.88	15.05
Total Sample	3.83	2.51	3.89	2.53	10.19	10.53	10.26	10.75

Figures

Figure 1: Hierarchical Clustering of Short-Term GDP Cycles

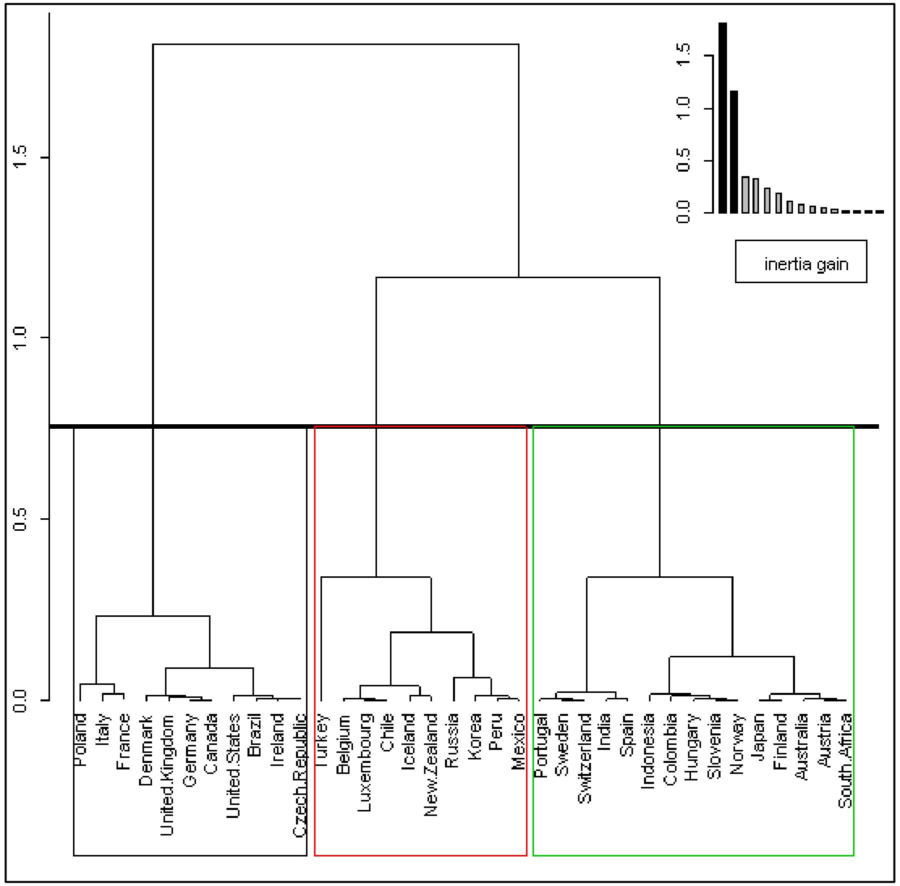


Figure 2: Factor Map of Short-Term GDP Cycles

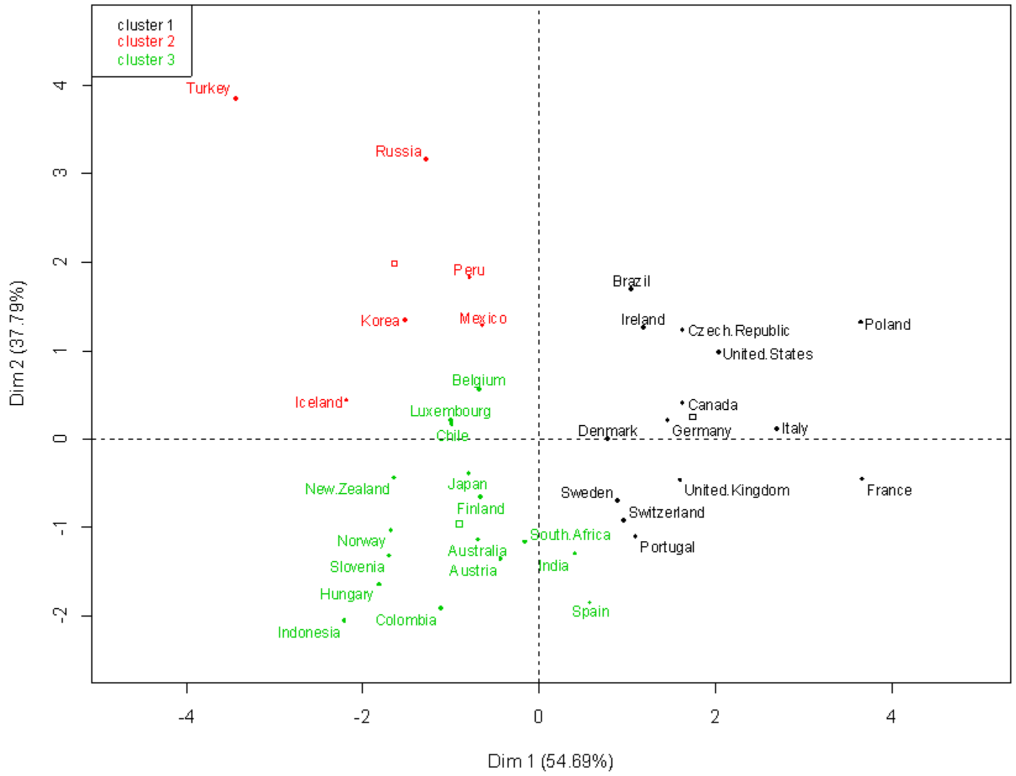


Figure 3: Hierarchical Clustering of Medium-Term GDP Cycles

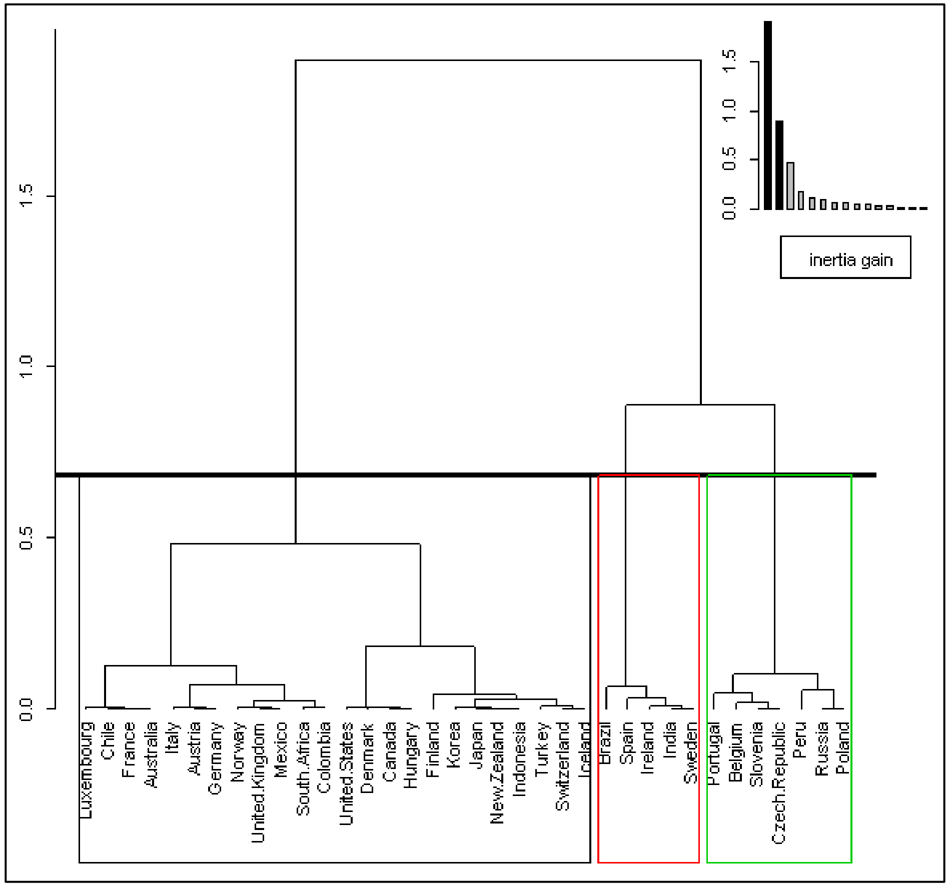


Figure 4: Factor Map of Medium-Term GDP Cycles

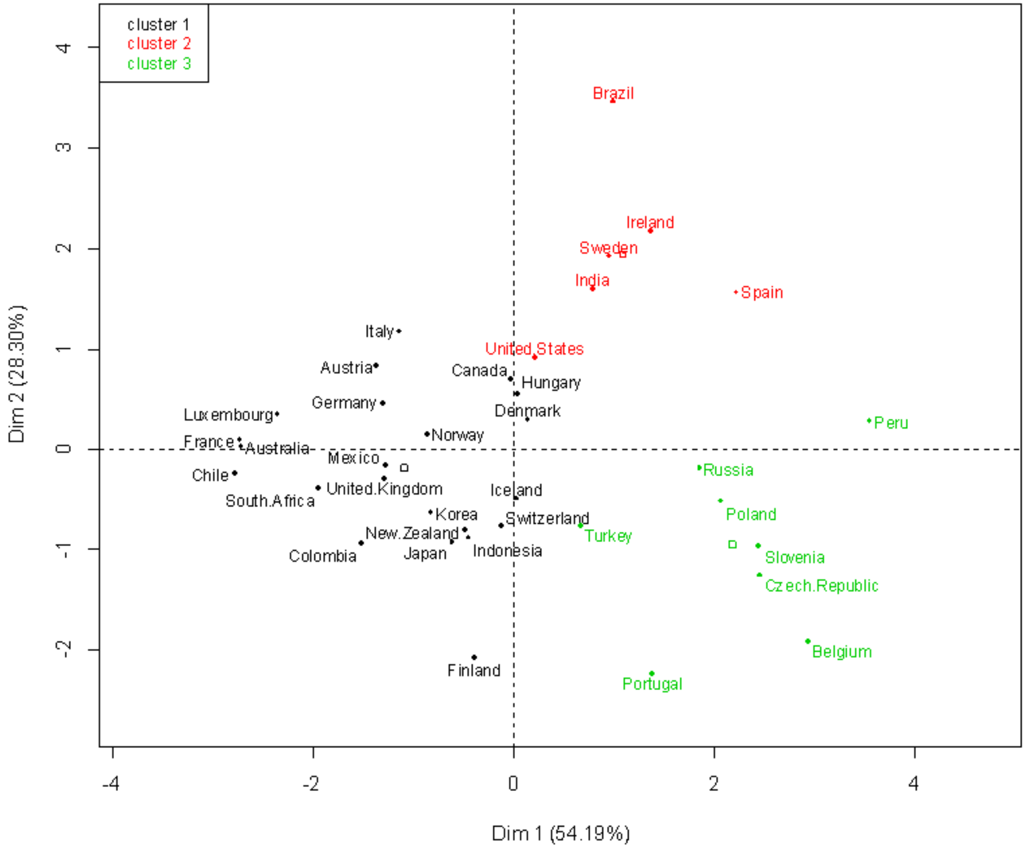


Figure 5: Hierarchical Clustering of Short-Term Credit Cycles

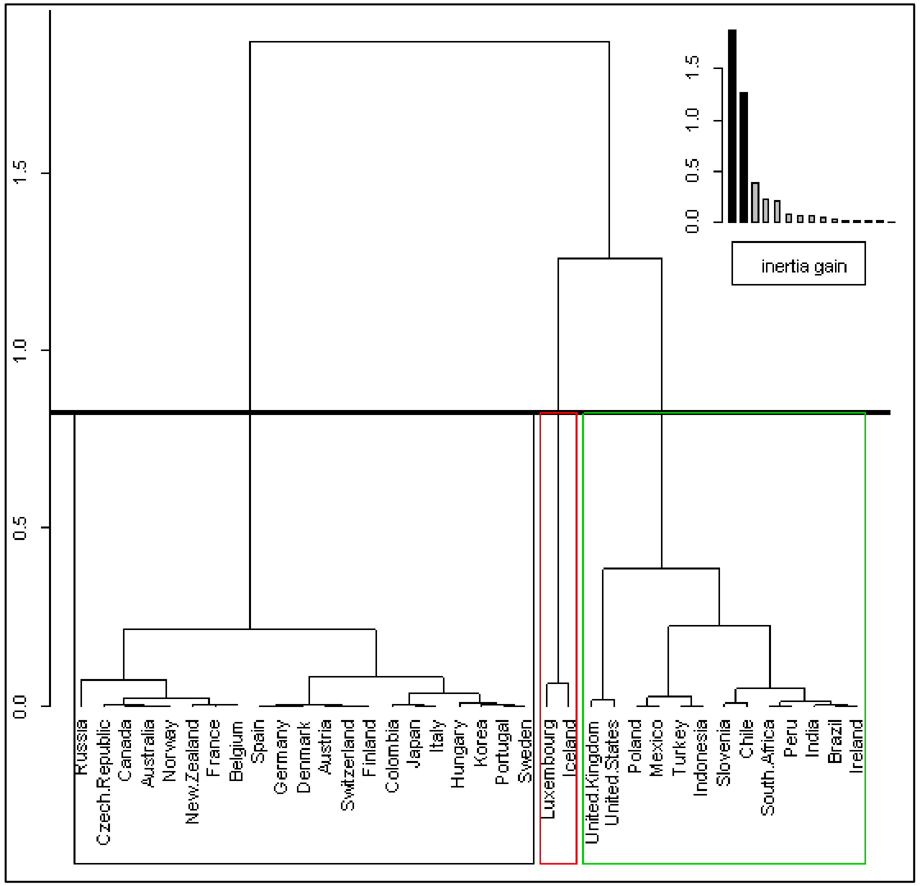


Figure 6: Factor Map of of Short-Term Credit Cycles

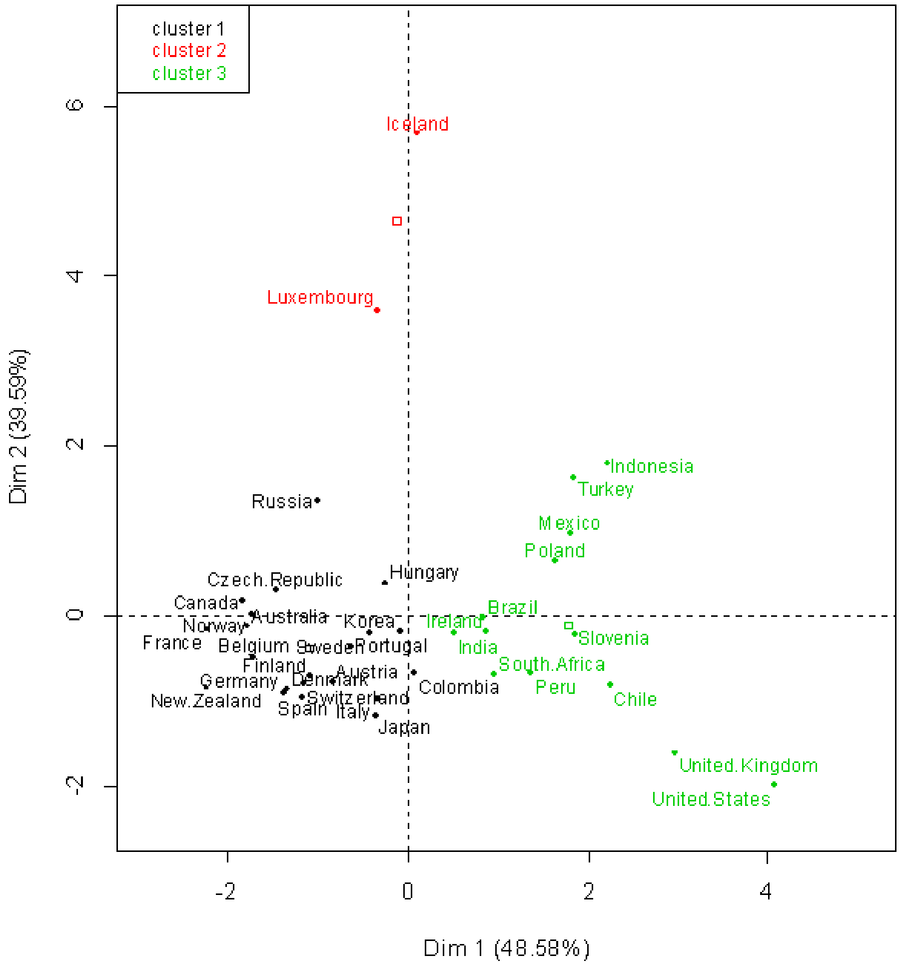


Figure 7: Hierarchical Clustering of Medium-Term Credit Cycles

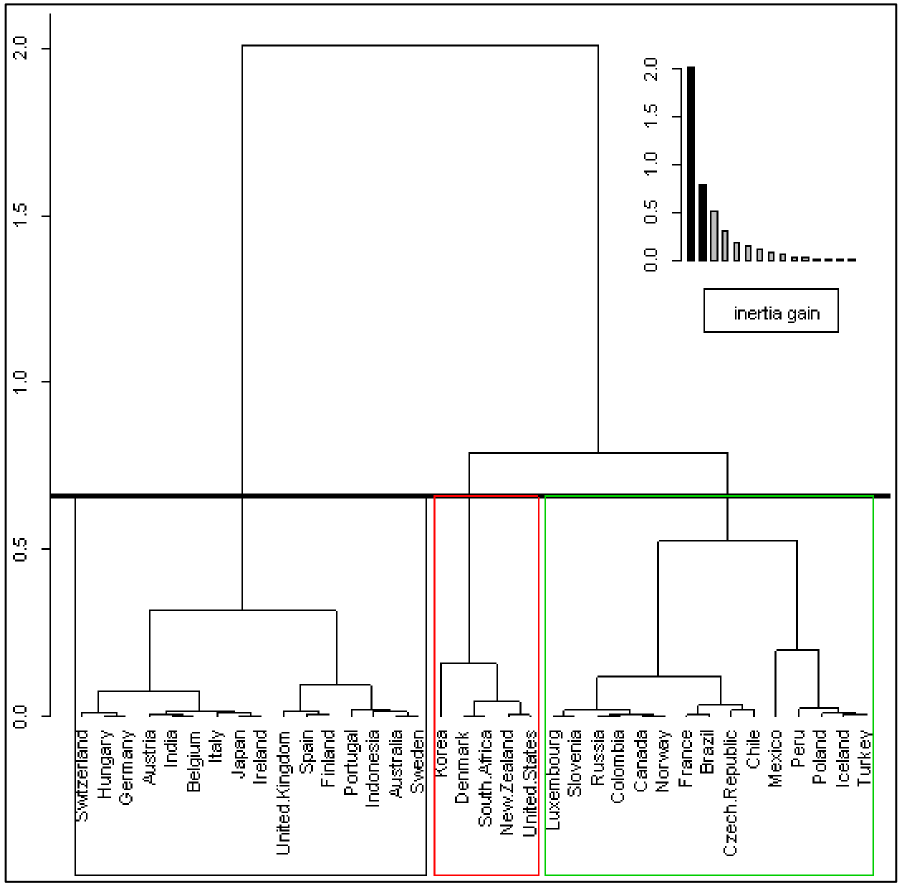


Figure 8: Factor Map of of Medium-Term Credit Cycles

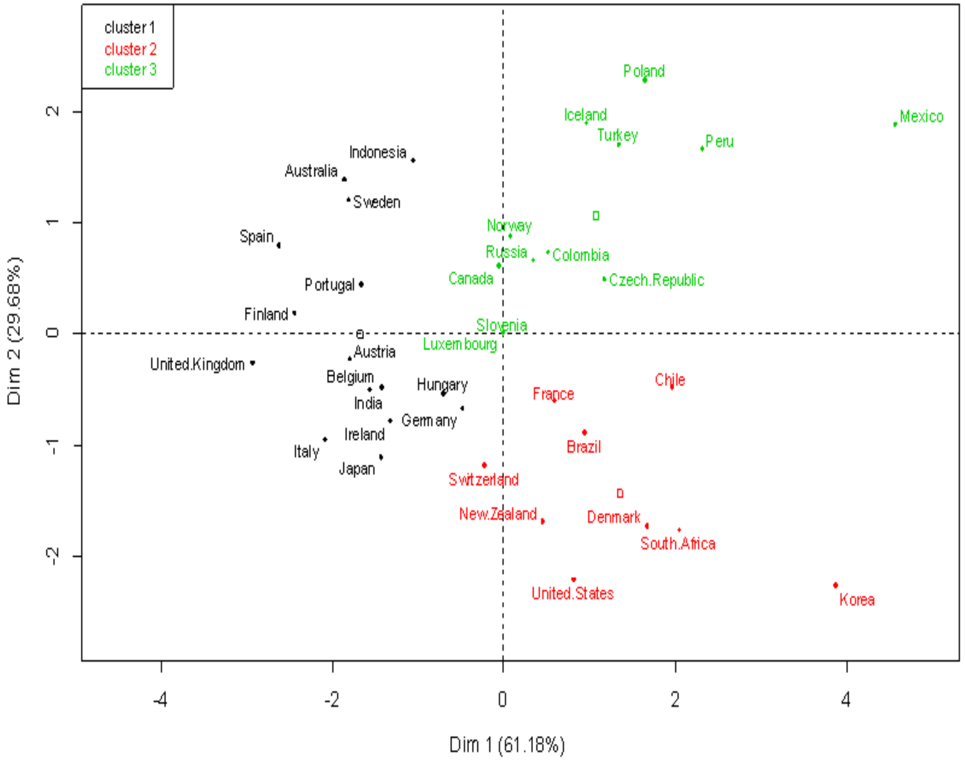
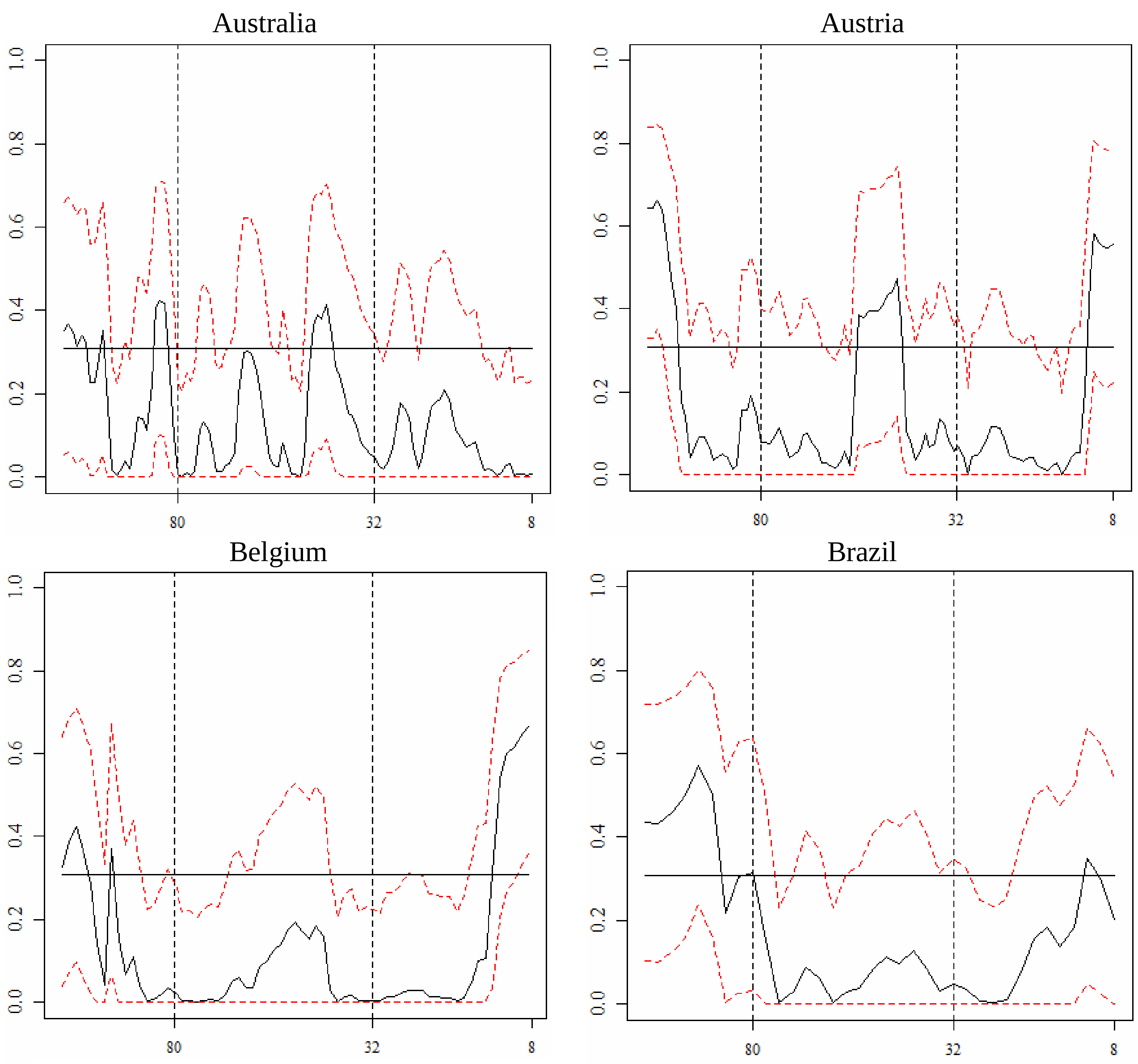
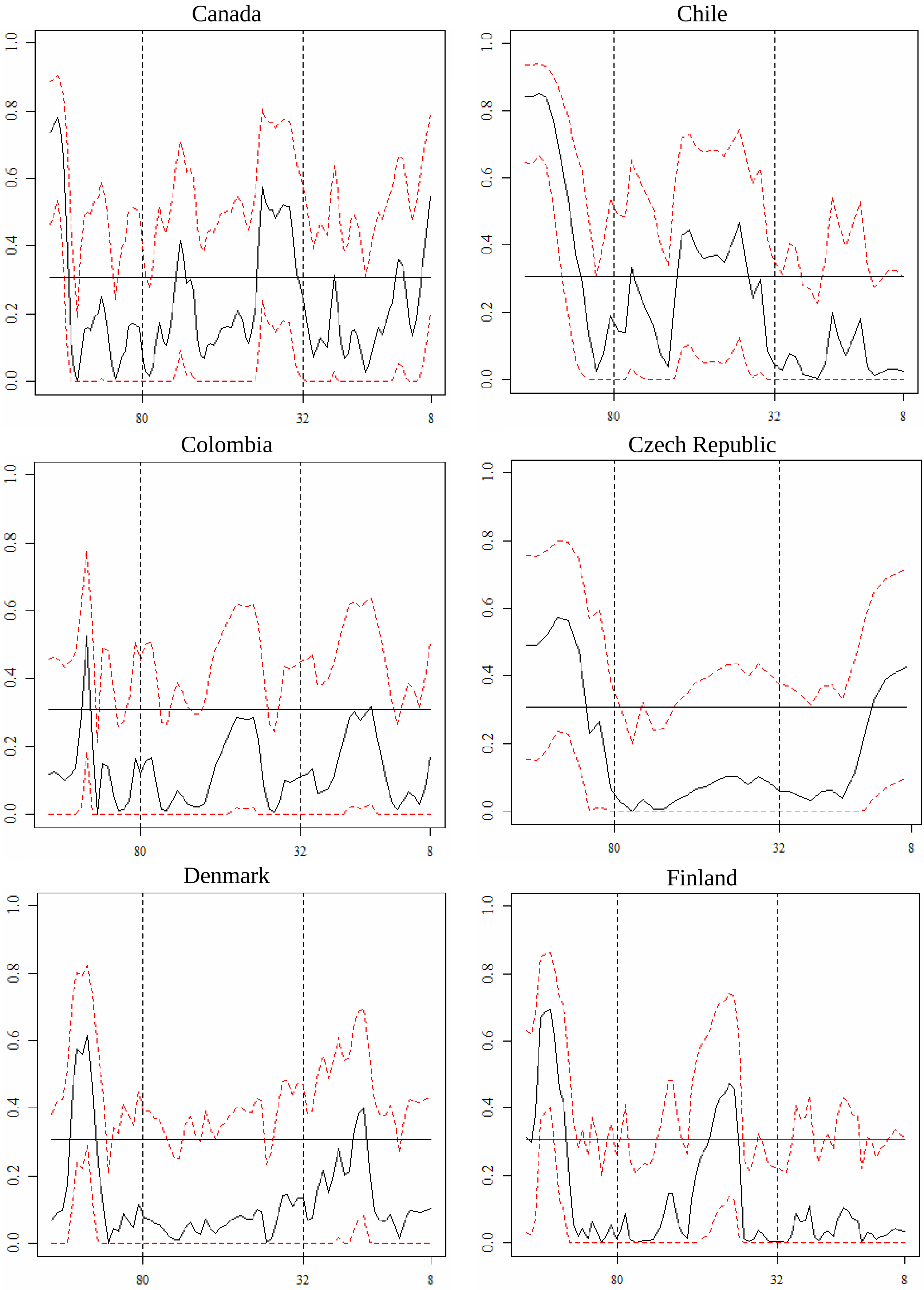


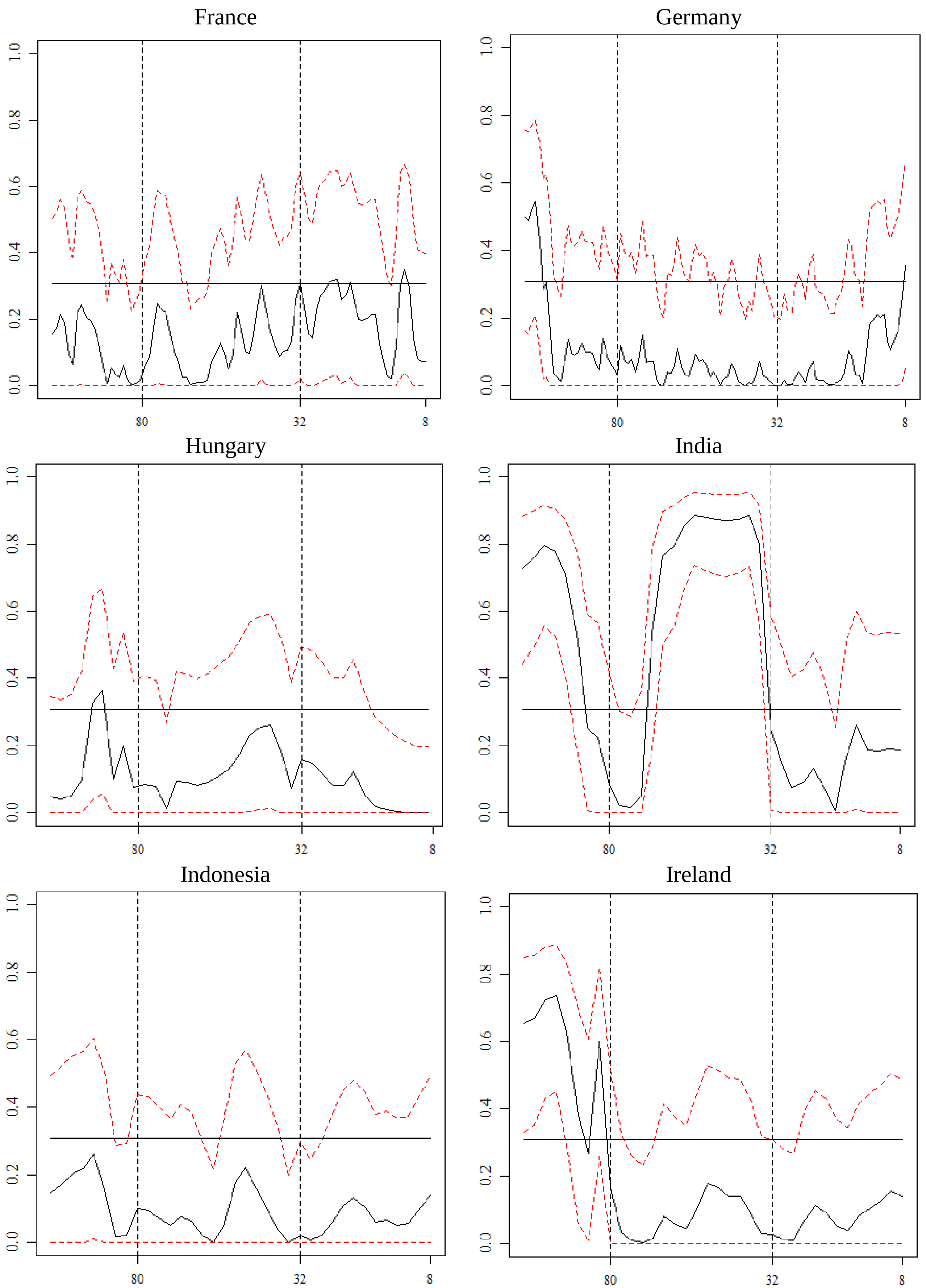
Figure 9: Coherence Statistics between GDP and Credit by Country (Frequency Domain – Horizontal axis measured in quarters)



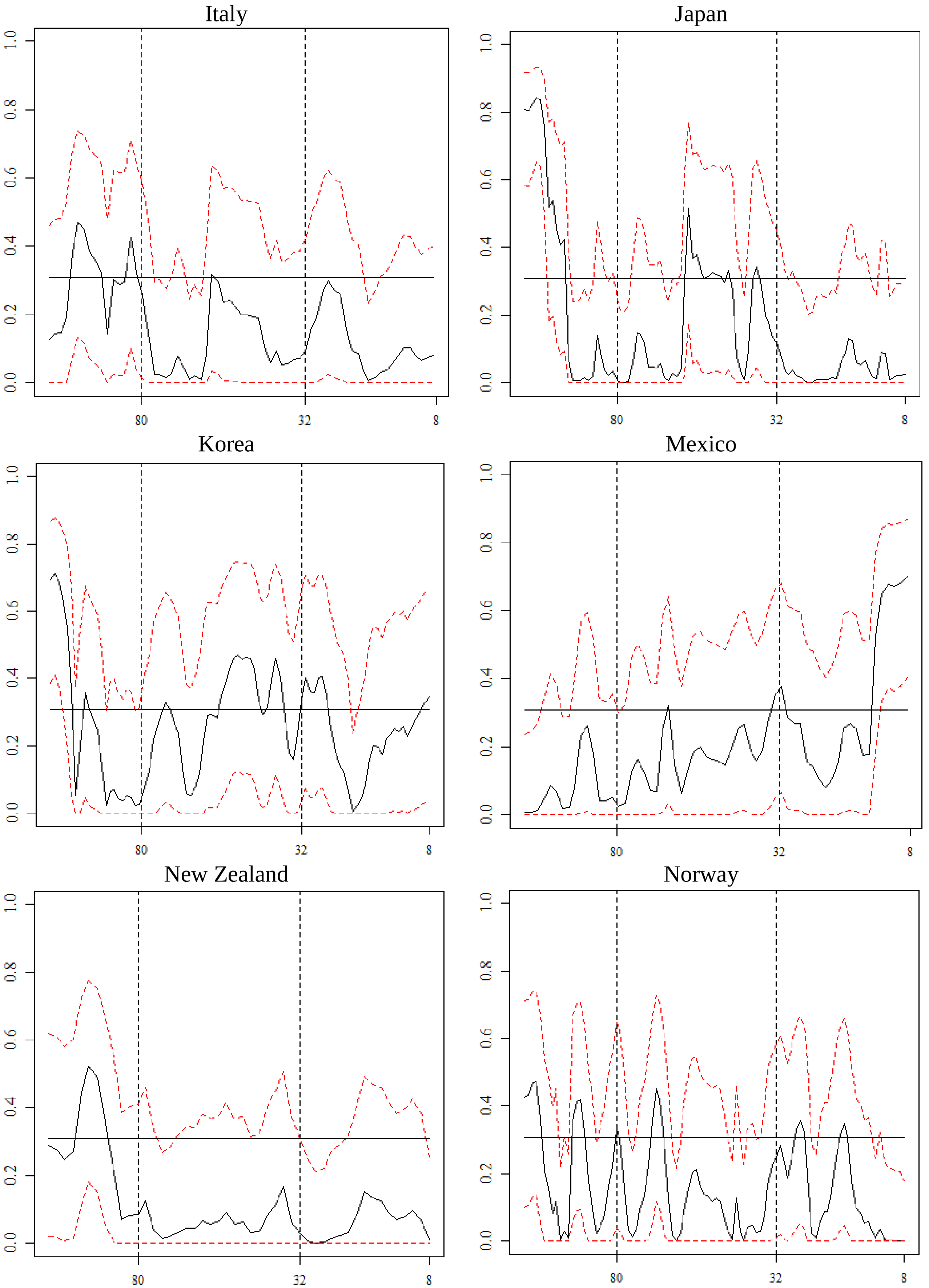
Continued from previous page



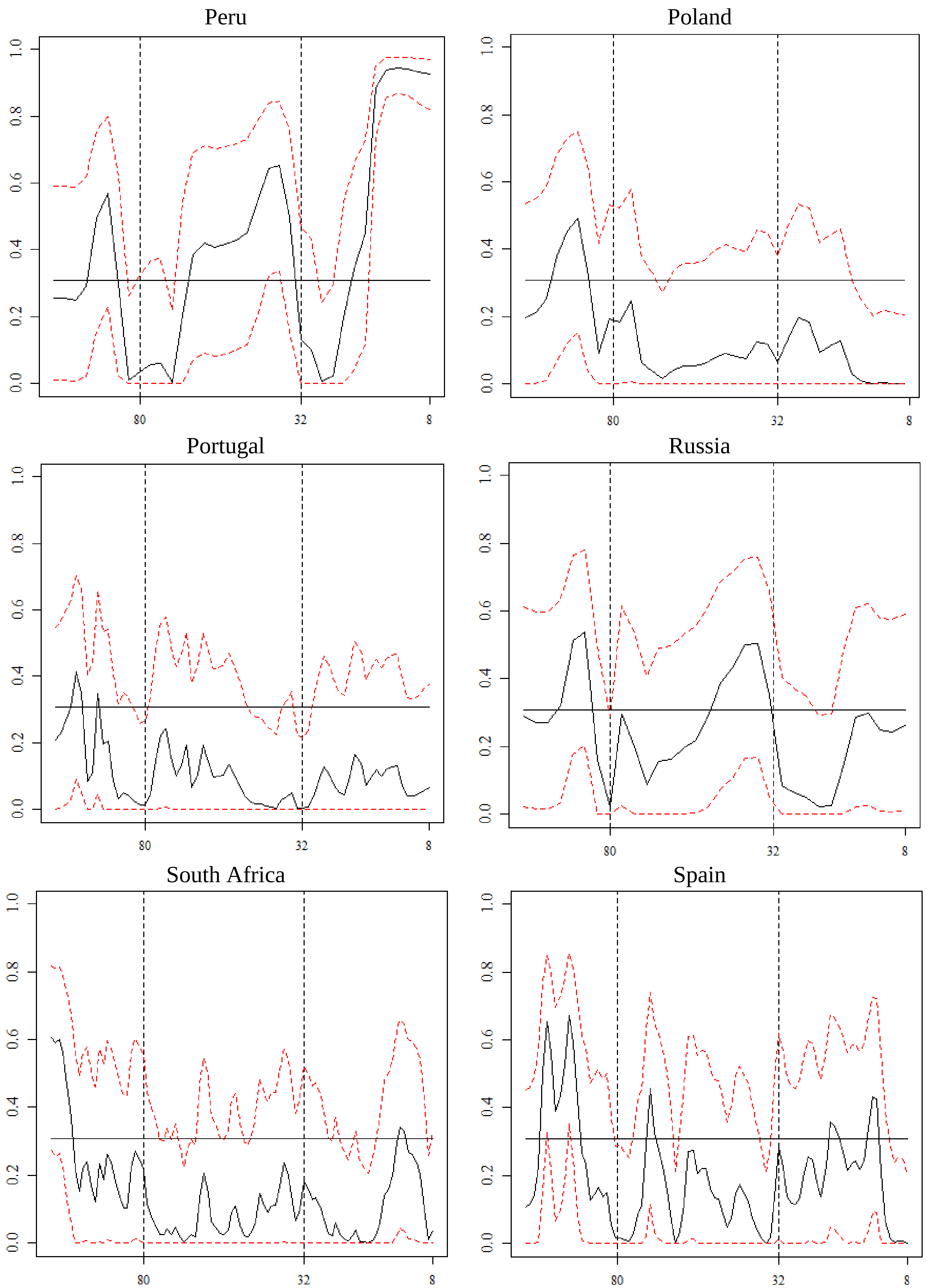
Continued from previous page



Continued from previous page



Continued from previous page



Continued from previous page

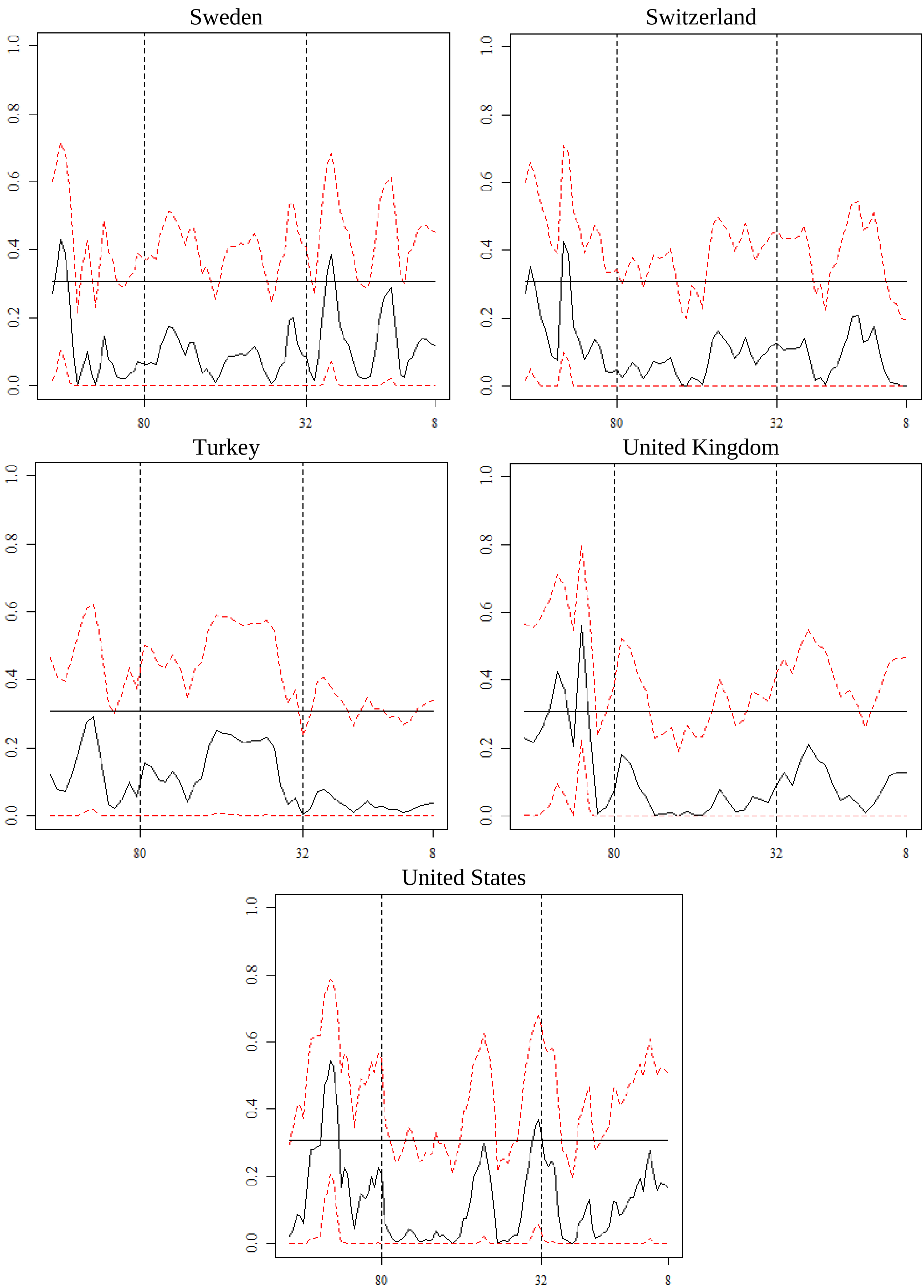
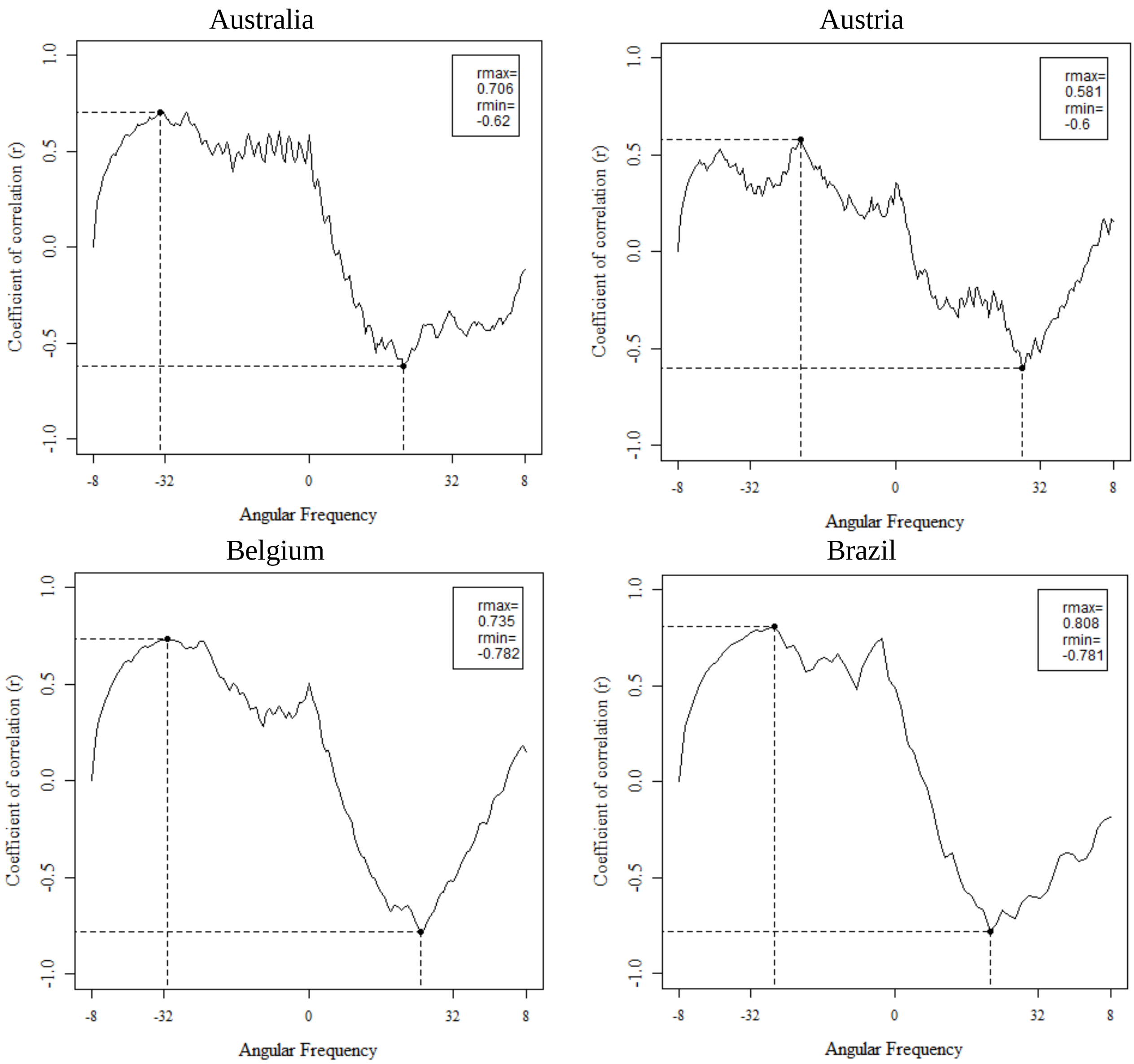
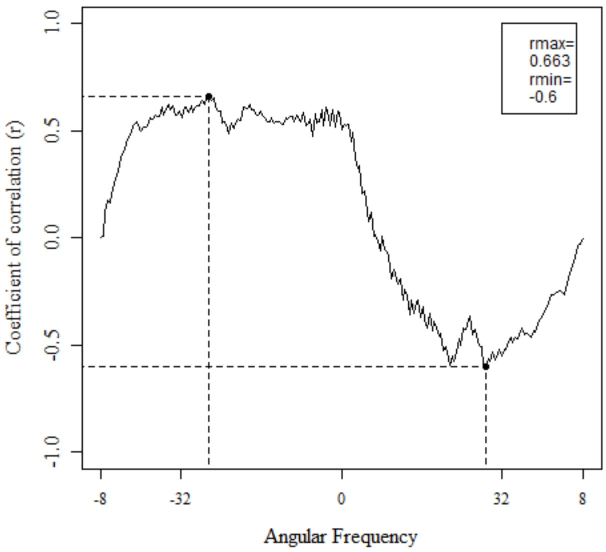


Figure 10: Cross-correlations in the frequency domain between GDP and Credit by Country

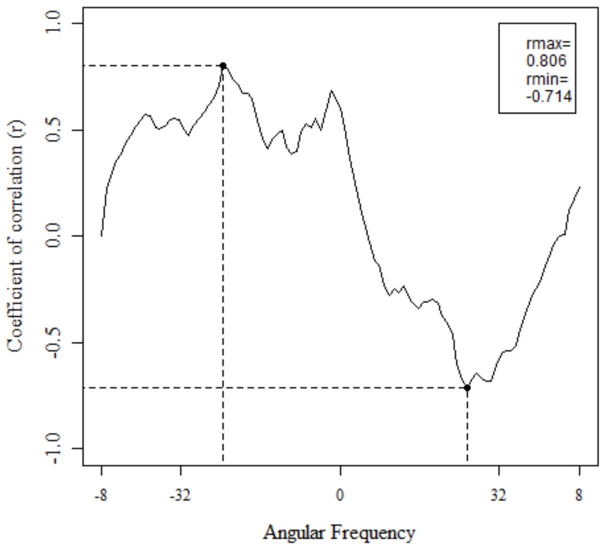


Continued from previous page

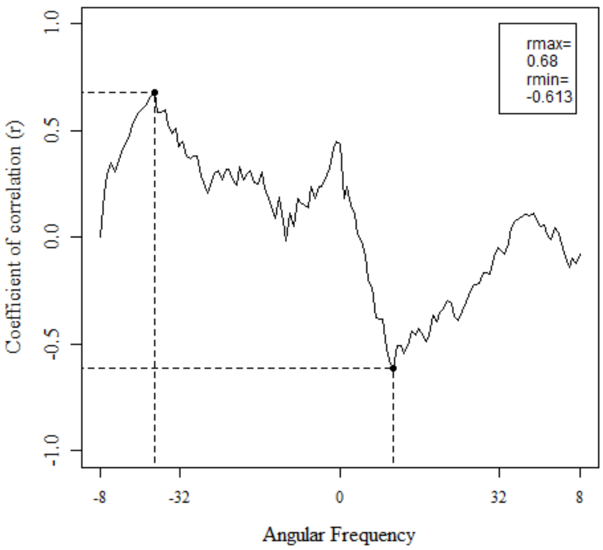
Canada



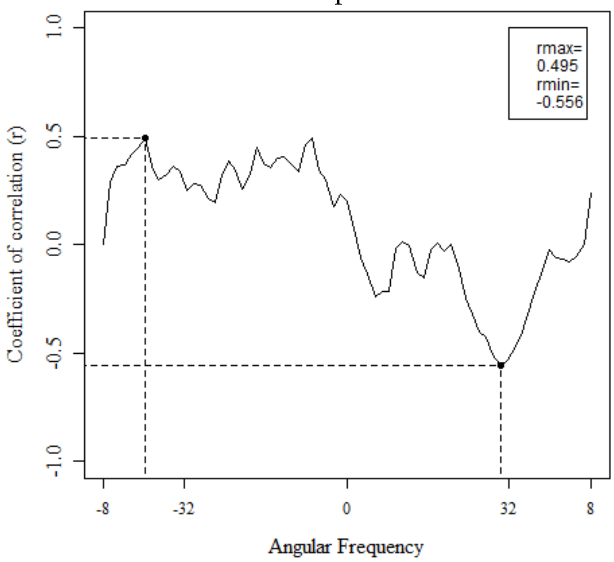
Chile



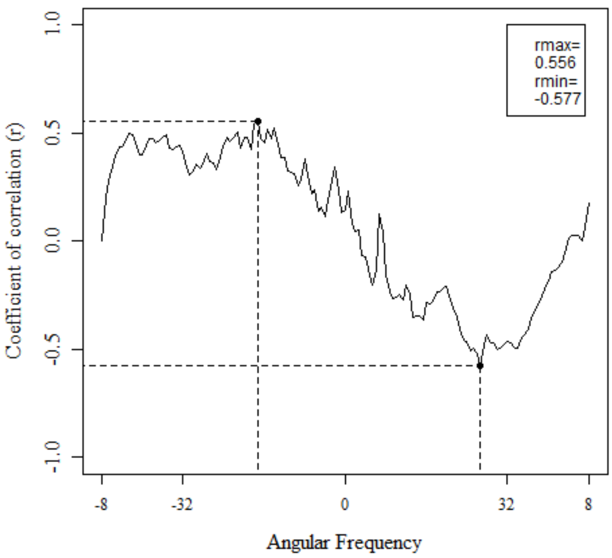
Colombia



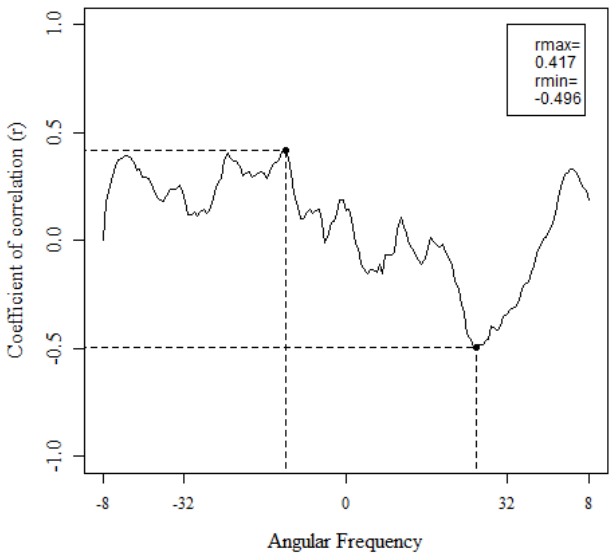
Czech Republic



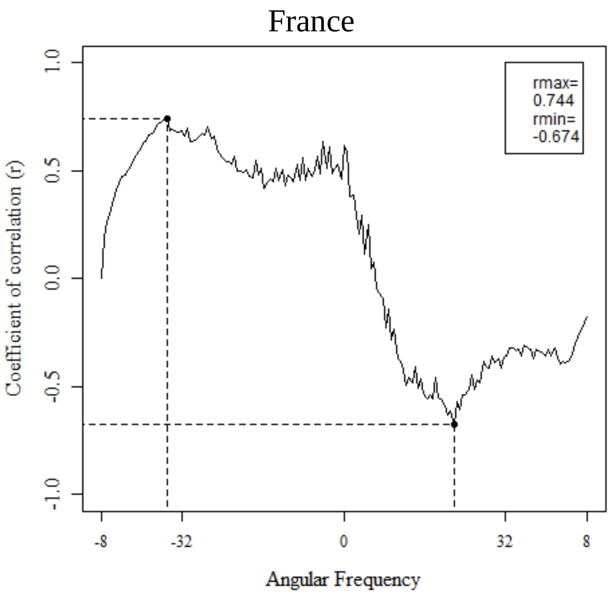
Denmark

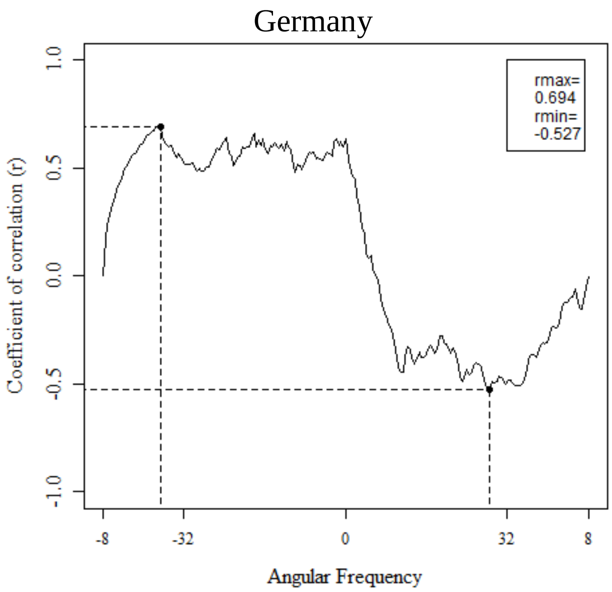


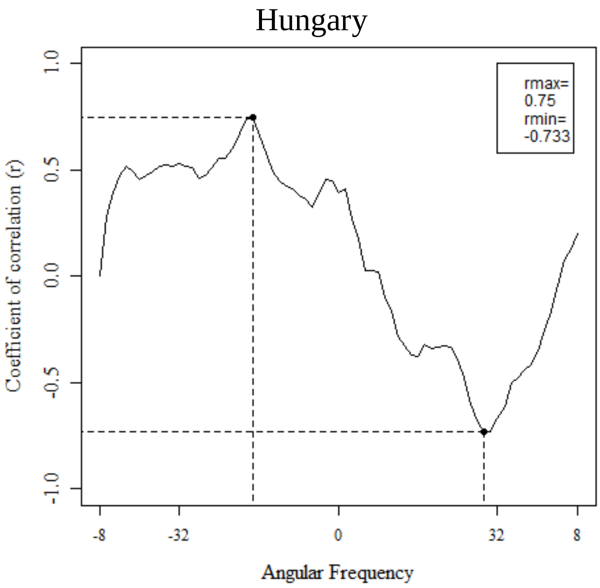
Finland

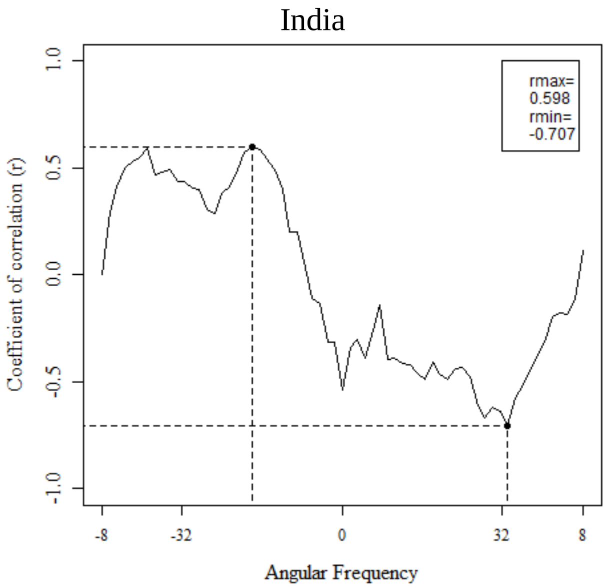


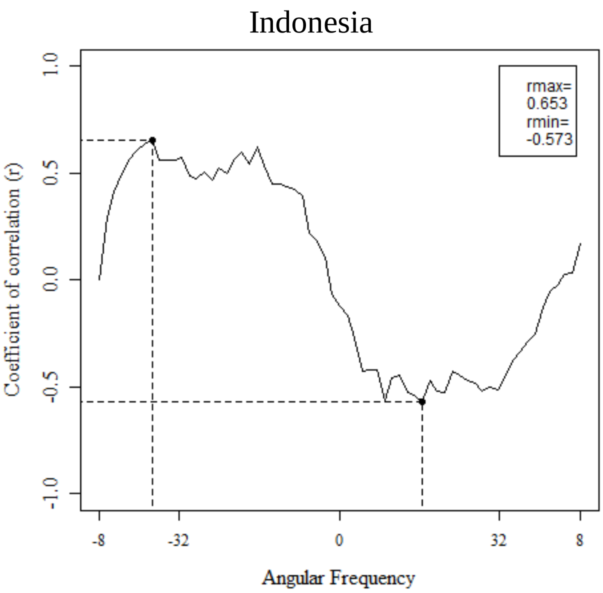
Continued from previous page





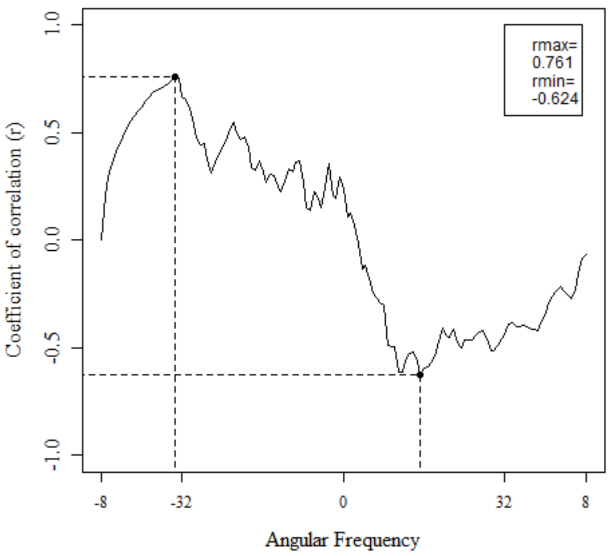




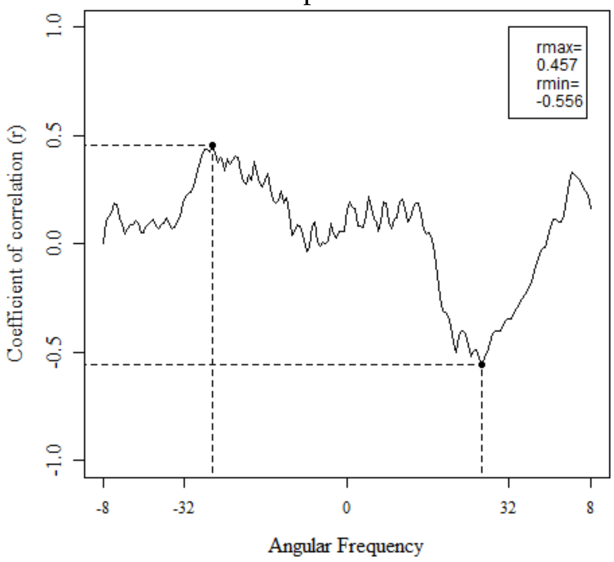


Continued from previous page

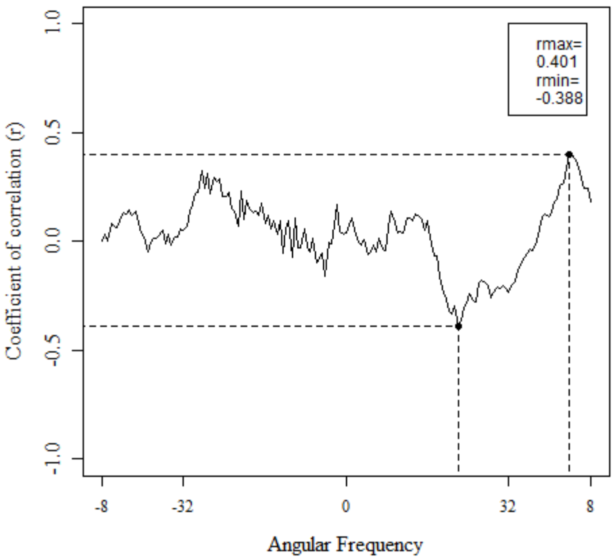
Italy



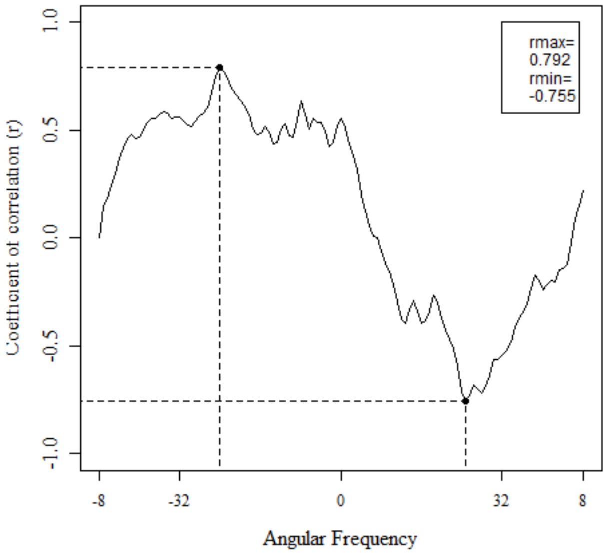
Japan



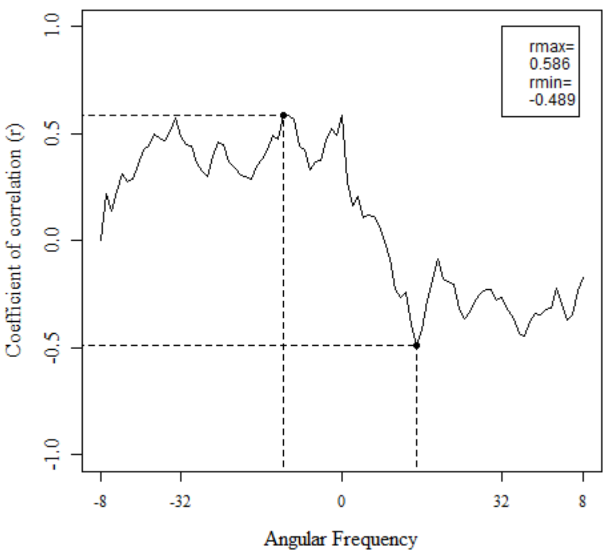
Korea



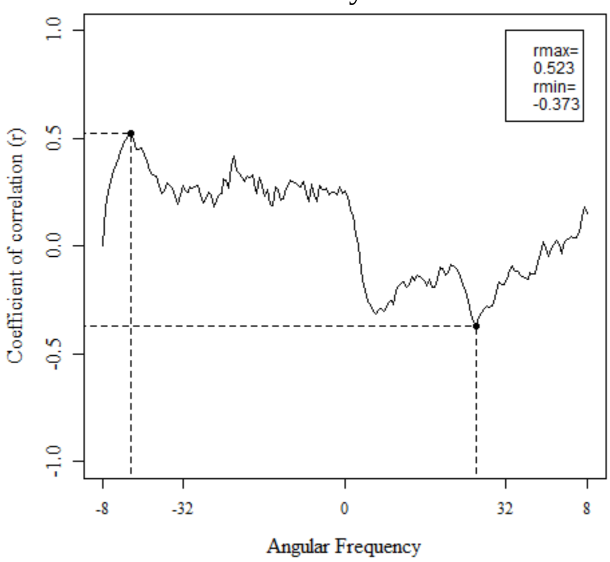
Mexico



New Zealand

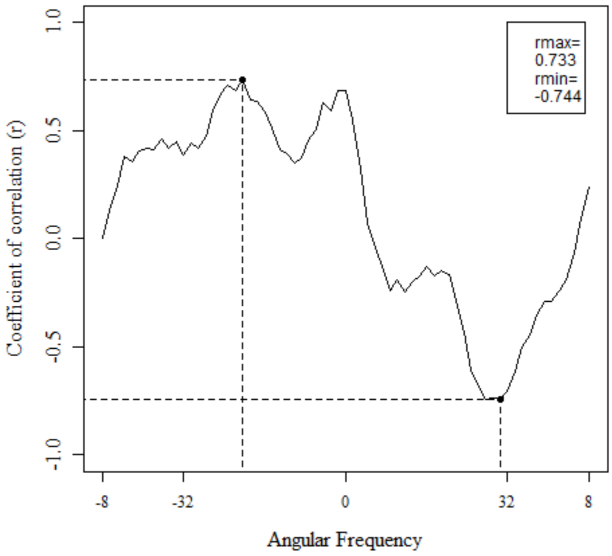


Norway

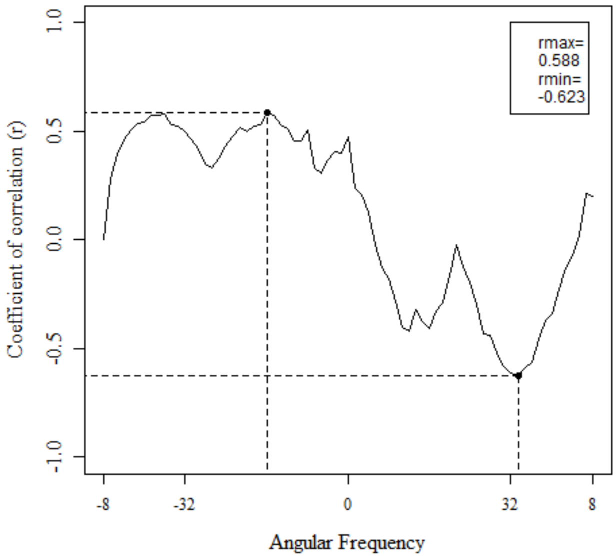


Continued from previous page

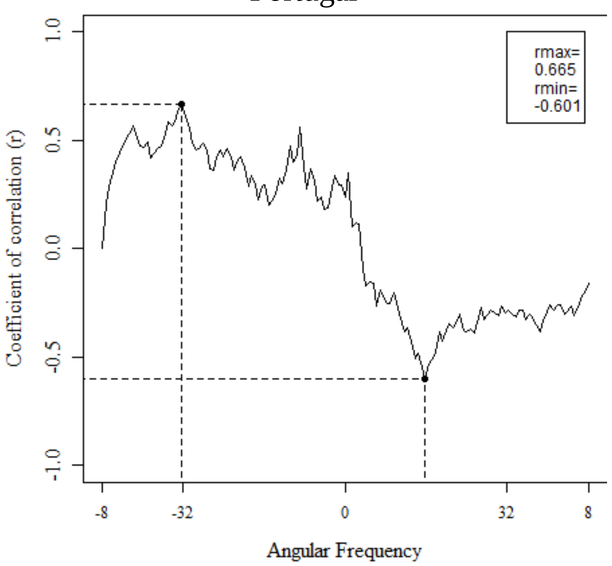
Peru



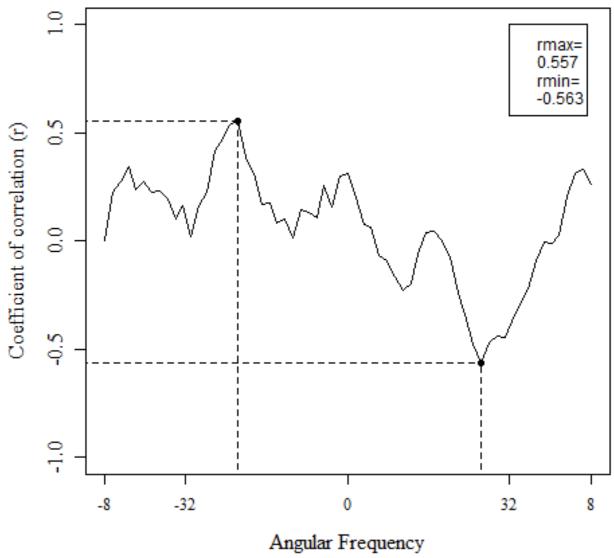
Poland



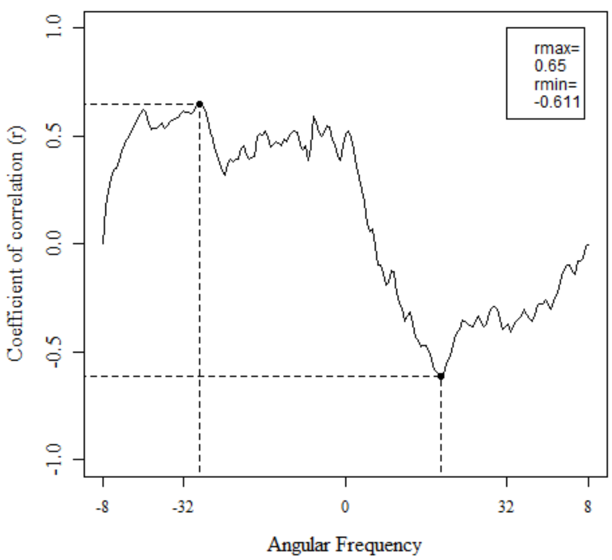
Portugal



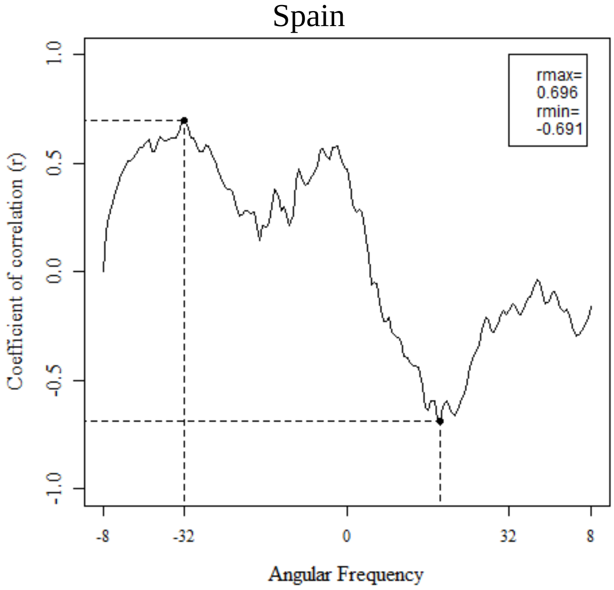
Russia



South Africa

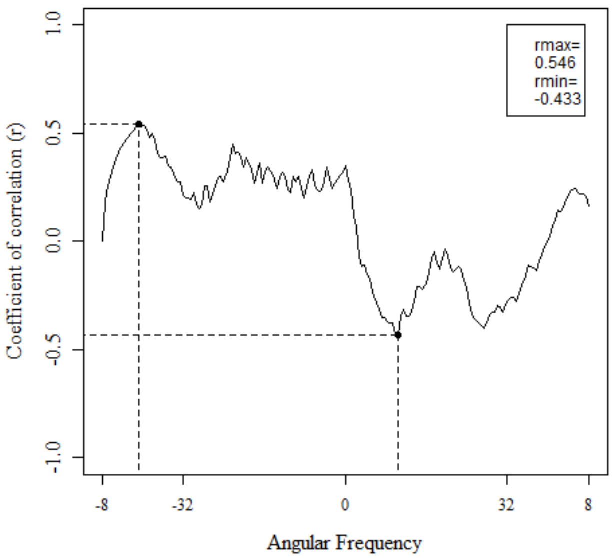


Spain

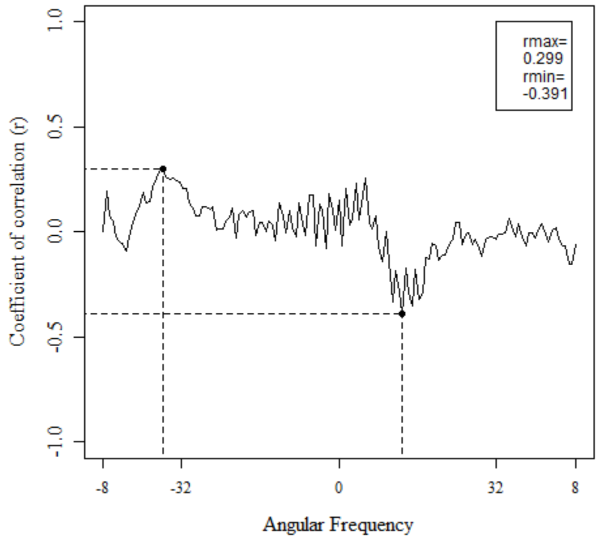


Continued from previous page

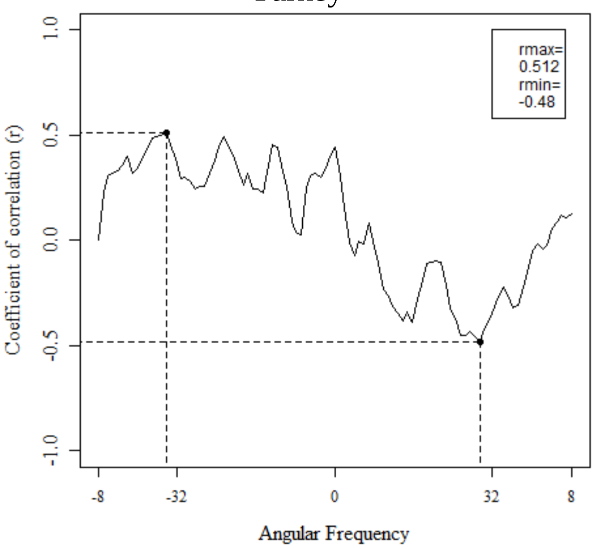
Sweden



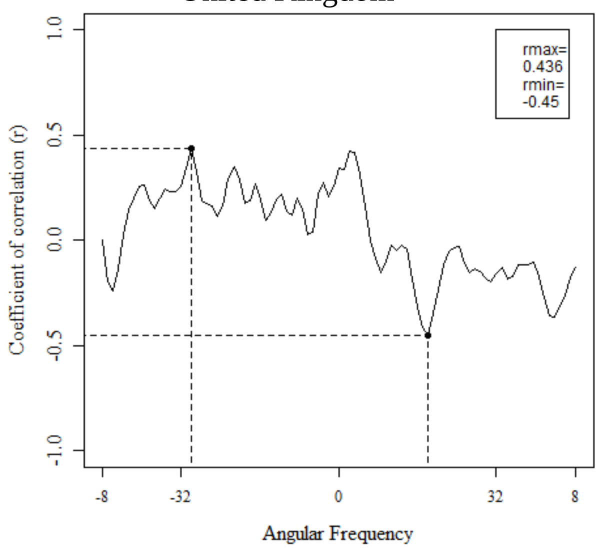
Switzerland



Turkey



United Kingdom



United States

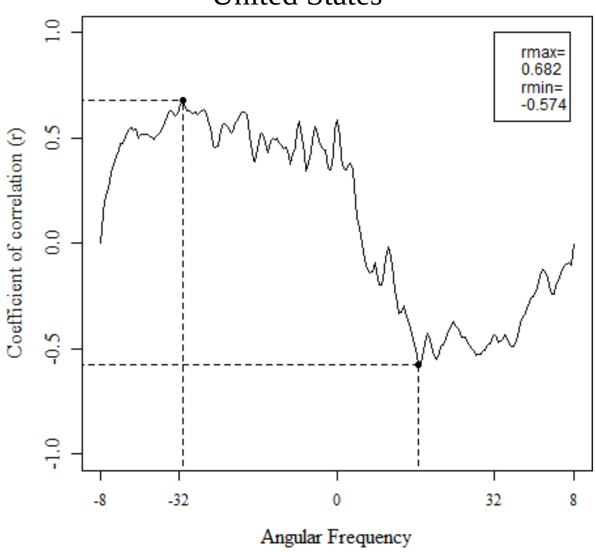
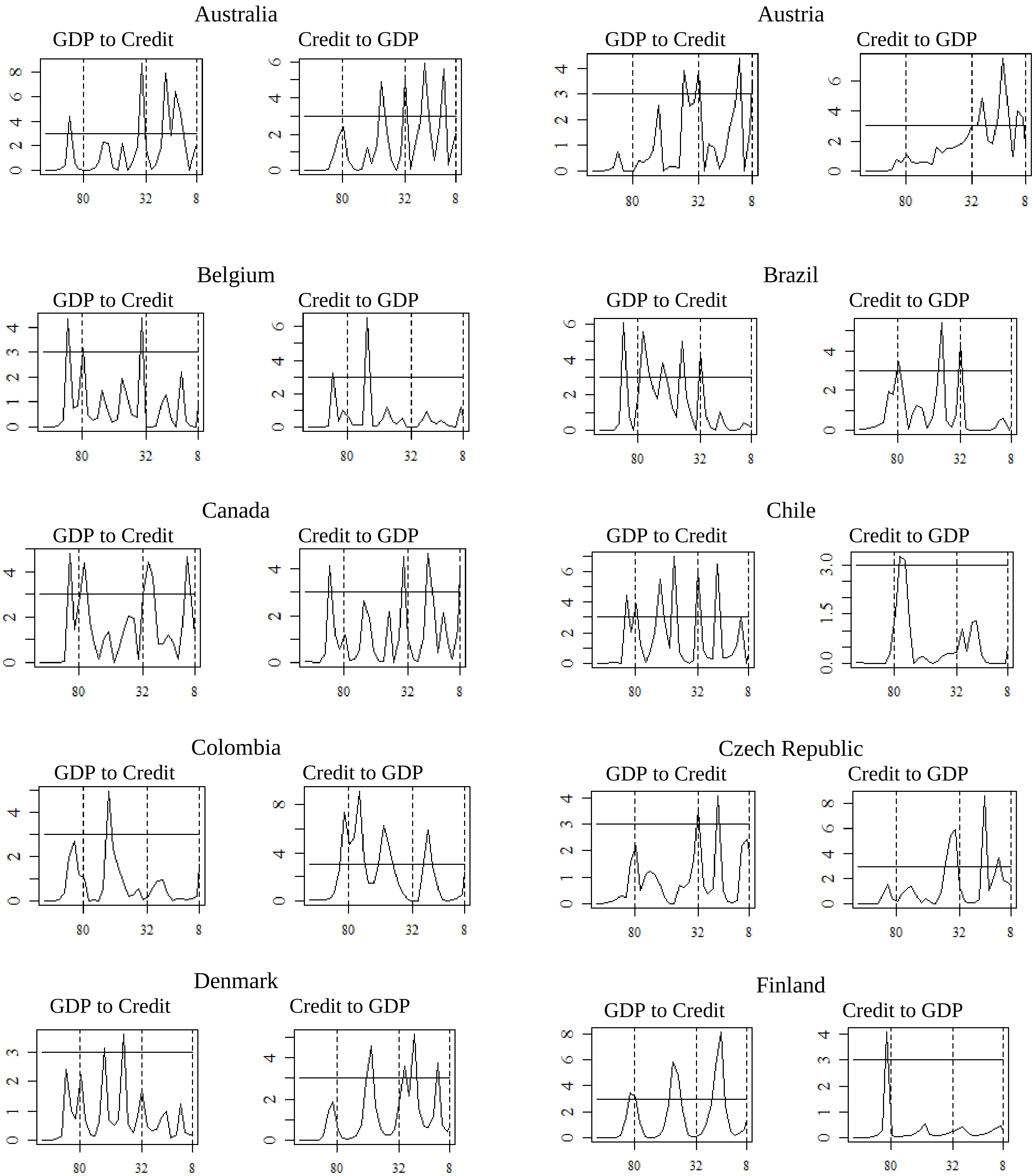
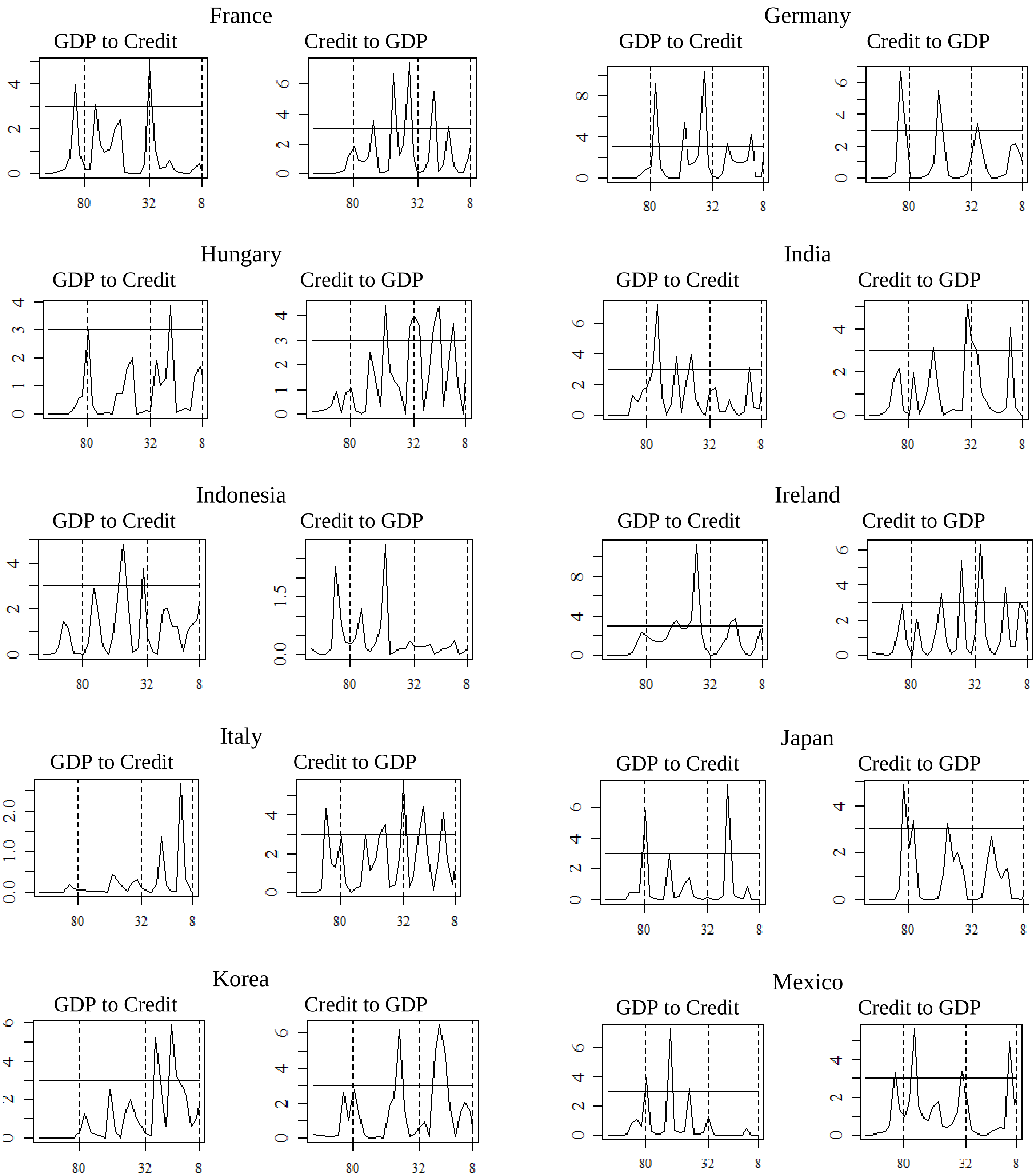


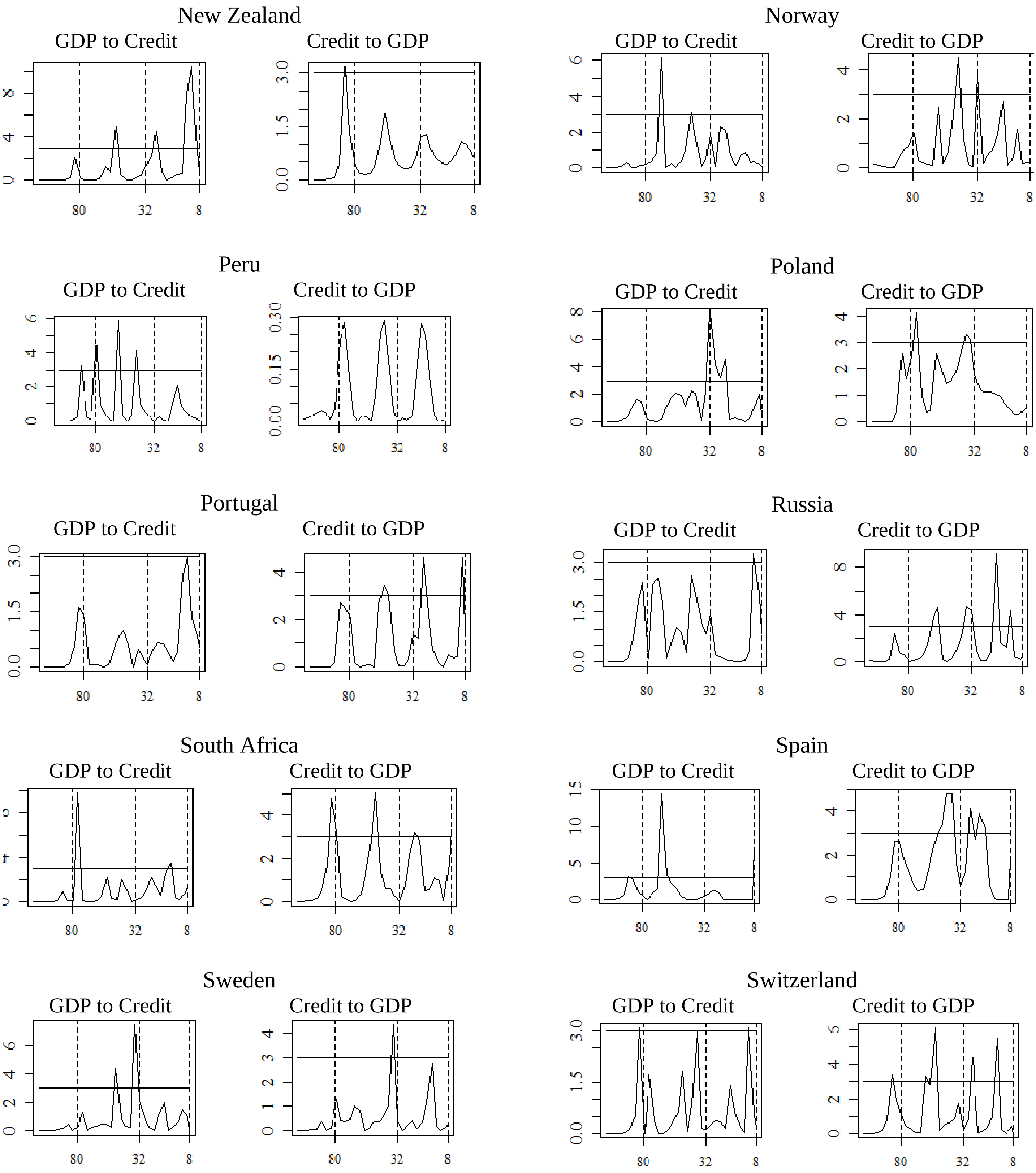
Figure 11: Causality Tests by Country in the Frequency Domain
(Quarters in the horizontal Axis)



Continued from previous page

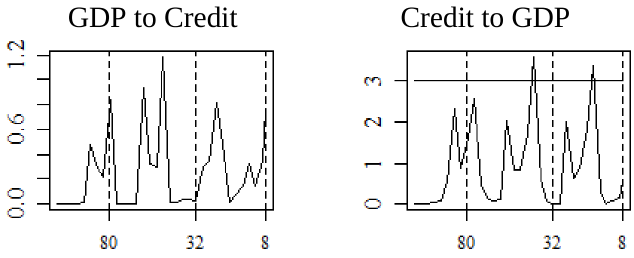


Continued from previous page

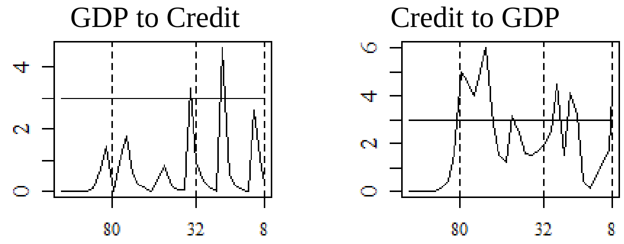


Continued from previous page

Turkey



United Kingdom



United States