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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Measuring financial cycles with a model-based filter: Empirical evidence for the United States and the euro area*

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Abstract

The financial cycle captures systematic patterns in the financial system and is closely related to the concept of procyclicality of systemic risk. This paper investigates the characteristics of financial cycles using a multivariate model-based filter. We extract cycles using an unobserved components time series model and applying state space methods. We estimate financial cycles for the United States, Germany, France, Italy, Spain and the Netherlands, using data from 1970 to 2014. For these countries, we find that the individual financial variables we examine have medium-term cycles which share a few common statistical properties. We therefore refer to these cycles as 'similar'. We find that overall financial cycles are longer than business cycles and have a higher amplitude. Moreover, such behaviour varies over time and across countries. Our results suggest that estimates of the financial cycle can be a useful monitoring tool for policymakers as they may provide a broad indication about when risks to financial stability increase, remain stable, or decrease.

Keywords: unobserved component models, state space method, maximum likelihood, bandpass filter, short and medium term cycles.
JEL classifications: C22, C32, E30, E50, E51, G01.

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1 Introduction

This paper provides a new approach to measuring financial cycles, and examines their main properties in the United States and the euro area[1]. The concept of financial cycles captures systematic patterns in the financial system that can have important macroeconomic consequences, and is closely related to the concept of procyclicality of the financial system (see e.g. Borio et al. (2001), Brunnermeier et al. (2009), and Adrian and Shin (2010)). The financial cycle can be defined as self-reinforcing interactions between attitudes towards risk and financing constraints, which translate into booms followed by busts (e.g. Borio (2014)). The idea of financial cycles can be traced back to the writings of Fisher (1933), Kindleberger (1978), Minsky (1986) and Minsky (1992).

The financial cycle plays an important role in the current policy debate on how to increase the resilience of the financial system. Since the global financial crisis, policymakers have increasingly re-oriented prudential policies towards a macroprudential perspective in an effort to address the procyclicality of the financial system. The underlying idea is to build up buffers during upswings in the financial cycle – booms in which imbalances build up – in order to be able to draw them down during busts in which these imbalances unwind. The countercyclical capital buffer in Basel III can be seen as an example of a policy instrument that responds to the properties of the financial cycle, see Drehmann et al. (2011).

This re-orientation creates a need of accurately measuring the financial cycle. In recent years, increasing research efforts have been made to respond to this need. Several methods to measure the financial cycle have been proposed, which have helped gain a better understanding of some key properties of the financial cycle. These methods include frequency-based or 'non-parametric' bandpass filters, and variations on the classic turning-point analysis algorithm of Burns and Mitchell (1946). This line of research has arguably identified a financial cycle that is best characterized by the co-movement of medium-term cycles in credit, the credit-to-GDP ratio, and house prices. Peaks in this cycle tend to coincide with the onset of financial crises.

In spite of these efforts, we are still far from thoroughly understanding the properties of financial cycles comparable to our knowledge of the features of business cycles. This paper contributes to reducing this gap by applying the Kalman filter to a multivariate unobserved components time series model. In its most basic form, it decomposes a series into a long-term trend and a short- or medium-term cycle. In a multivariate setting it can subsequently be investigated whether the cycles of individual series have the same frequency and degree of dependence on the past, in which case they are called 'similar' cycles.

This approach allows for diagnostic testing of the accuracy of the estimated trend and cycle. Moreover, as opposed to non-parametric filters, it requires no prior assumptions on the length of the cycle, which, given the exploratory stage of this research agenda, is particularly convenient.

We apply our multivariate model-based filter to financial variables in the United States, Germany, France, Italy, Spain and the Netherlands between 1970 and 2013. We analyze the cyclical behavior of individual financial variables and attempt to identify the financial cycle in terms of the behavior of a combination of variables. We also explore the time variation

[1]We thank René Bierdrager (DNB) for research assistance.

in the characteristics of the financial cycle, which is important given the structural changes in the financial landscape over the past three decades. We find three main results. First, model-based filters allow to identify the cyclical behavior in house prices, credit and the credit-to-GDP ratio. Second, we find evidence of substantial variation in the period and amplitude of these cycles both over time and across countries. In particular, the amplitude and duration of the financial cycles in the United States has increased since the mid-eighties, consistent with the findings of Drehmann et al. (2012). We also find that in many cases financial cycles are 'similar', as they have the same persistence, cycle length, spectrum and cross-autocovariance funtion.

The remainder of this paper is organized as follows. Section 2 gives a brief overview of the relevant literature on this topic. Section 3 discusses the modeling approach and Section 4 describes the data. Section 5 discusses the results for the United States and the five largest economies in the euro area. Section 6 concludes.

2 Review of the Literature

The literature on measuring the financial cycle is still in its infancy, but has its roots in a rich literature on systematic boom-bust patterns in the financial system that interact with the macroeconomy. Early work includes the writings of Fisher (1933), Minsky (1986),Minsky (1992) and Kindleberger (1978). In more recent times, two literature strands are relevant.

The first consists of empirical work on early warning indicators of financial stress (see e.g. the surveys in Kaminsky et al. (1998), Demirgüç-Kunt and Detragiache (2005) and Chamon and Crowe (2012)). In the words of Shin (2013), this work is typically eclectic – in the sense that it combines a variety of financial, real, institutional and political factors – and pragmatic, i.e. it focuses is on goodness of fit rather than on providing theoretical explanations of empirical facts. Only few attempts have been made at providing conceptual underpinnings of early warning models (e.g. Shin (2013)).

The second related literature strand has documented how the dynamics of credit and asset markets are linked to financial distress or macroeconomic activity (e.g. Borio and Lowe (2002), Detken and Smets (2004), Goodhart and Hofmann (2008), Gerdesmeier et al. (2010), Agnello and Schuknecht (2011); Alessi and Detken (2011), Edge and Meisenzahl (2011), Schularick and Taylor (2012) and Taylor (2015)). Underlying this work is a view of financial instability as an endogenous phenomenon that follows cyclical patterns. Excessively strong growth in credit and asset prices reflects the build-up of financial imbalances that can potentially unwind in a disruptive fashion with large negative macroeconomic consequences.

Until now, only few papers have tried to measure the financial cycle and investigate its statistical properties. These papers rely mainly on three approaches: turning point analysis, frequency-based filters and unobserved component time series models.

The first approach, turning point analysis, goes back to a long tradition of identifying business cycles by dating their peaks and troughs, started by Burns and Mitchell (1946). This is still used, most notably by the NBER and the Euro Area Business Cycle Dating Committees. Claessens et al. (2011) and Claessens et al. (2012) are among the first to employ this method to identify financial cycles for a large number of countries. They characterize financial cycles in terms of peaks and troughs in three individual variables, namely credit, property prices and equity prices. They find that, compared to the business cycle, cycles in these series tend to be more stretched out in time and more ample. They also present evidence that credit and house price cycles – but not equity price cycles – are highly synchronized. Moreover, they document that financial cycles and business cycles are closely linked.

The second approach uses statistical, frequency-based filters to identify the financial cycle. The most well-known filters of this class are the Hodrick-Prescott filter and the bandpass filters of Baxter and King (1999) and Christiano and Fitzgerald (2003). Such filters require the user to pre-specify the range of cycle frequencies, which is why such filters are also referred to as non-parametric filters. Aikman et al. (2015) use the bandpass filter of Christiano and Fitzgerald to analyze the link between the credit cycle and the business cycle. The authors estimate spectral densities of real and financial variables – real GDP growth, real bank loan growth, real bank asset growth and real money aggregates – for a large set of countries and over a long time period (1880-2008). The resulting spectral densities justify setting a medium-term frequency range to extract financial cycles. Their evidence points to the existence of a credit cycle with similar characteristics to that documented by turning point analyses. They also show that credit booms tend to be followed by banking crises.

A few papers apply both approaches, in an attempt to reach more robust conclusions. For example, Igan et al. (2009) use the bandpass filter of Corbae and Ouliaris (2006) to filtered the data, and then feed the results into a generalized dynamic factor model. Thereafter, they use the turning point analysis to identify the duration and amplitude of cycles in house prices, credit and real activity. Their results reveal that real and financial cycles have attained more common characteristics over time, which they attribute to growing financial integration.

In an influential paper, Drehmann et al. (2012) combine turning-point analysis and the bandpass filter by Christiano and Fitzgerald (2003). They apply both methods to five financial variables – credit, the credit-to-GDP ratio, property prices, equity prices and an aggregate asset price index, which combines property and equity prices – to a set of industrial countries over the period 1960-2011. Drehmann et al. (2012) distinguish short-term cycles, which like business cycles last between 1 to 8 years, and medium-term cycles, which last between 8 and 30 years. They thus identify the financial cycle as a medium-term phenomenon with peaks tending to occur at the onset of financial crises, which have substantial macroeconomic effects.

A third approach applies the Kalman filter to unobserved components time series models to extract cycles (see Harvey (1989) and Durbin and Koopman (2012) for an overview). This approach has been applied extensively to business cycle analysis (see e.g. Valle e Azevedo et al. (2006), Koopman and Azevedo (2008) and Creal et al. (2010)). Koopman and Lucas (2005) are among the few who provide an application to financial variables. They extract cycles from credit spreads, business failure rates, and real GDP in the Unites States and find evidence of comparable medium-term cycles.

Compared to the non-parametric bandpass filters applied in most other research on this topic, model-based filters have a number of advantages. First, rather than imposing ad-hoc parameters on the Kalman filter, these parameters are model driven, in particular they are derived from estimating an unobserved component model with a maximum likelihood method. Second, since the filter is based on a model, researchers have the possibility to use diagnostics to estimate the fit and validity of this model and hence the accuracy of their estimates. Third, whereas non-parametric filters and turning point methods require predetermined frequencies to extract cycles, model-based filters estimate the cycle frequency. This feature is especially convenient for the purpose of this research, since there is no broad consensus yet on characteristics of financial cycles. Fourth, the Kalman filter can handle non-normal data with ease, which is particularly useful for modeling financial data, which notoriously have fat tails.

The literature on measuring financial cycles has highlighted three important methodological issues. First, the jury is still out on what method is most reliable. Empirical studies such as Igan et al. (2009), Drehmann et al. (2012), Hiebert et al. (2014) and Schüler et al. (2015) in fact rely on both turning-point analysis and frequency-based filters.

Second, there is no consensus in the literature on which financial variables to include in the analysis. Ideally, one would like to extract empirical regularities from long time series for a large set of financial variables collected across a large set of countries. In practice, however, data limitations constrain both the length of the time series, the geographic coverage and the number of financial variables. Some studies concentrate on credit on the grounds that it captures the essence of boom-bust cycles in the financial sector (e.g. Dell'Ariccia et al. (2012), Jordà et al. (2014), Aikman et al. (2015), Taylor (2015)). Credit has also be seen as a measure of financial flows that is conceptually comparable to the use of flows of goods and services in the analysis of business cycles (Hiebert et al. (2014)). Among types of credit, total credit has recently been shown as being particularly relevant for economies such as the United States, where the bulk of credit to the private non-financial sector is not supplied by banks, see Dembiermont et al. (2013). A variable commonly used in policy analysis is the credit-to-GDP ratio. The deviation of this variable from its long-term trend, called "credit-to-GDP gap" has been found to be a good early warning indicator for banking crisis, e.g. Borio and Lowe (2002). It has also recently been introduced in the regulatory framework under Basel III, see Edge and Meisenzahl (2011) and Drehmann and Tsatsaronis (2014).

More often, researchers have looked at measures of credit and asset prices, most notably real estate prices (see for example Claessens et al. (2011) and Claessens et al. (2012)). In Drehmann et al. (2012), credit aggregates (and in particular the credit-to-GDP ratio) are used as a proxy for leverage, while property prices are used as a measure of available collateral. Recent research also highlighted the usefulness of the debt-to-service ratio, see Drehmann and Juselius (2012). Other financial variables that capture the attitude towards risk and stress in the financial sector, e.g. credit spreads, risk premia and default rates, are seen as providing useful complementary information (BIS, 2014).

Third, there is no consensus on how to combine multiple variables into one single measure of financial cycle, as illustrated in the debate on date-then-average and average-then-date approaches in the business cycle literature in Stock and Watson (2014). Three alternative approaches have been used. The first consists of estimating cycles of individual financial variables and then taking averages, see Drehmann et al. (2012) and Schüler et al. (2015). A second approach is used by Hiebert et al. (2014) extracts cycle measures from individual time series and then aggregates these estimated cycles using principal component analysis. A third approach is used by Koopman and Lucas (2005), who construct a multivariate model of different financial variables and then test formally whether the individual cycles are similar to each other.

3 Modeling Approach

In our empirical analysis, we proceed in two steps. First we follow Koopman and Lucas (2005) and apply the Kalman filter to extract cycles from a set of financial time series for the United States and five euro area countries. Second, we formally test whether these cycles share a few important statistical properties, in an effort to establish common characteristics. If we find evidence of some common characteristics in financial cycles, we refer to these as 'similar' cycles.

3.1 Unobserved Components Time Series Models

Suppose the number of time series under scrutiny is equal to p. Let y_t denote a vector that contains the values of p time series at time t, for $t = 1,...,n$. Then, in its most basic form, an unobserved components model is formulated as the following trend-cycle decomposition:

$$y_{it} = \mu_{it} + \psi_{it} + \varepsilon_{it}, \qquad \varepsilon_{it} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\varepsilon,i}), \qquad i = 1, \dots, p, \tag{1}$$

where y_{it} denotes the value of the ith element of y_t at time t, μ_{it} is a long-term trend and ψ_{it} is equal to a variable representing short- to medium-term cyclical dynamics. The residuals ε_{it} are assumed to to be normally distributed and independent from ε_{js}, for $i \neq j$ and $t \neq s$. All these components are unobserved and therefore need to be estimated via the Kalman filter.

There are two crucial challenges in the decomposition of y_t. The first is to choose how smooth the trend should be, i.e. how much fluctuation in the variable is assigned to the trend as opposed to the cycle. Our approach can be illustrated by defining in a general form the m^{th}-order trend for series i as, following Harvey and Trimbur (2003),

$$\begin{aligned} \mu^{(m)}_{i,t+1} &= \mu^{(m)}_{it} + \mu^{(m-1)}_{it}, \\ \mu^{(m-1)}_{i,t+1} &= \mu^{(m-1)}_{it} + \mu^{(m-2)}_{it}, \\ &\vdots \\ \mu^{(1)}_{i,t+1} &= \mu^{(1)}_{it} + \zeta_{it}, \qquad \zeta_{it} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}), \end{aligned} \tag{2}$$

meaning that $\Delta^m \mu^{(m)}_{i,t+1} = \zeta_{it}$.

The smoothness of the trend depends on the differencing order m. In the frequency domain a higher value for m implies that the low-pass gain function will have a sharper cutoff. As m increases, the resulting trend therefore becomes smoother. If $m = 0$, it is assumed that y_t is already stationary. If $m = 1$, y_t has a random walk process as the trend. If $m = 2$, y_t is specified as an integrated random walk,

$$\begin{aligned} \mu_{i,t+1} &= \mu_{it} + \beta_{it}, \\ \beta_{i,t+1} &= \beta_{it} + \zeta_{it}, \qquad \zeta_{it} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}). \end{aligned} \tag{3}$$

For most macro economic time series the maximum order for m is set to 2, see for example Valle e Azevedo et al. (2006). This specification has also used for financial variables, for example by Koopman and Lucas (2005) who model GDP, business failure rates and credit spreads in a multivariate setting.

The second crucial challenge is to specify an appropriate stochastic process for the cycle ψ_{it}. We follow the standard approach by Harvey (1989) and model the cycle as an autoregressive process of order 2, of which the polynomial autoregressive coefficients have complex roots. Accordingly, ψ_{it} is specified as a trigonometric process, given by

$$\begin{pmatrix} \psi_{i,t+1} \\ \psi^*_{i,t+1} \end{pmatrix} = \phi_i \begin{bmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{bmatrix} \begin{pmatrix} \psi_{it} \\ \psi^*_{it} \end{pmatrix} + \begin{pmatrix} \omega_{it} \\ \omega^*_{it} \end{pmatrix}, \quad \begin{pmatrix} \omega_{it} \\ \omega^*_{it} \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2_{\omega,i}), \quad (4)$$

with frequency λ_i measured in radians, $0 \leq \lambda_i \leq \pi$, for $i = 1,...,p$. The period of the stochastic cycle ψ_{it} is given by $2\pi/\lambda_i$. ϕ_i is the persistence parameter or 'damping factor', which we restrict to be $0 < \phi_i < 1$. This restriction on ϕ_i ensures that the cycle ψ_{it} is modeled as a stationary stochastic process. The disturbances $(\omega_{it}, \omega^*_{it})'$ are assumed to be serially and mutually uncorrelated and normally distributed with mean zero and common variance $\sigma^2_{\omega,i}$.

3.2 Modeling Similar Cycles

The cycles in a panel of time series are termed *similar* if the frequency λ_i and persistence parameter ϕ_i of each individual cycle are restricted to take the same values λ and ϕ, respectively, such that

$$\begin{pmatrix} \boldsymbol{\psi}_{t+1} \\ \boldsymbol{\psi}^*_{t+1} \end{pmatrix} = \phi \begin{bmatrix} \cos(\lambda) I_p & \sin(\lambda) I_p \\ -\sin(\lambda) I_p & \cos(\lambda) I_p \end{bmatrix} \begin{pmatrix} \boldsymbol{\psi}_t \\ \boldsymbol{\psi}^*_t \end{pmatrix} + \begin{pmatrix} \boldsymbol{\omega}_t \\ \boldsymbol{\omega}^*_t \end{pmatrix}, \quad (5)$$
$$\begin{pmatrix} \boldsymbol{\omega}_t \\ \boldsymbol{\omega}^*_t \end{pmatrix} \overset{i.i.d.}{\sim} \mathcal{N}(0, I_2 \otimes \boldsymbol{\Sigma}_\omega)$$

where I_p denotes an identity matrix of order p and $\boldsymbol{\Sigma}_\omega$ is a diagonal $p \times p$ matrix. The $p\times1$ vector $\boldsymbol{\psi}_t$ is equal to $(\psi_{1t}, ..., \psi_{pt})'$ and $\boldsymbol{\psi}^*_t = (\psi^*_{1t}, ..., \psi^*_{pt})'$. We use the likelihood ratio test to check whether λ_i's and ϕ_i's are equal to λ and ϕ, respectively.

Note that if there is evidence of similar cycles, the extracted cycles in our panel have three important common characteristics, namely the cycle frequency, spectrum and (cross)-autocovariance function, and the degree of persistence, see Harvey and Koopman (1997). We use the standard likelihood ratio test to check whether λ_i's and ϕ_i's are equal to λ and ϕ respectively.

3.3 Estimation in state-space form

To estimate equations (1)-(5), we put them into the state space form

$$y_t = Z_t \alpha_t + \varepsilon_t, \quad (6)$$
$$\alpha_{t+1} = T_t \alpha_t + \eta_t, \quad (7)$$

where equation (6) is referred to as the *observation equation*, while equation (7) is called the *state equation* or the *updating equation*. The state vector α_t contains the unobserved trend and cycle. The system matrices Z_t and T_t contain the parameters from equations

(1) to (5). The state disturbance vector η_t contains the disturbances of the trend and cycle equations. The Kalman filter recursions are applied to obtain filtered and smoothed estimates of the unobserved components contained in α_t. Maximum Likelihood is used to estimate the unknown variances of the disturbances of the different unobserved components, as well as the persistence parameter ϕ_i and the frequency parameters λ_i. For details of this estimation method, see Schweppe (1965), Harvey (1989), and Durbin and Koopman (2012)[2].

4 Data

To allow for comparisons between our results and the literature, we use credit, the credit-to-GDP ratio and house prices to capture the financial cycle. We estimate our model with both total credit and bank credit[3]. These variables are taken from the BIS macroeconomic database, and are deflated by the CPI. All variables except the credit-to-GDP ratio's are expressed in logarithms. Our method can however be easily applied to other variables used in recent research, such as leverage and the debt service burden, see Juselius and Drehmann (2015).

We carry out our analysis for the United States, and the five largest economies of the euro area, namely Germany, France, Italy, Spain and the Netherlands. Our sample period for all countries except Italy is from 1970(1) to 2014(4), and is dictated by the availability of the data on house prices that have recently been provided on the BIS website. The sample period for Italy starts only from 1974(1) due to the availability of the credit data. For multivariate estimation, data points at the start of a series that were unavailable for all series were excluded.

5 Empirical Results

We find several interesting results. First, there is evidence of medium term financial cycles in the United States and the euro area. In particular, the majority of estimated financial cycles have lengths between 8 and 25 years, see Table 5.1. These lengths are significantly longer than the typical length of the business cycle (between 6 and 8 years) as documented in the literature.

Second, most of the financial cycles also have a larger amplitude compared to the business cycle, as indicated by the range of the medium term fluctuations shown in Figures 5.1 and Figures 5.2. More detailed results on the trend-cycle decompositions for different countries are presented in Appendices A and B. The amplitude of the financial cycles ranges between 10% and 20%, while the typical business cycle amplitude found in the literature is around 5%, see Zarnowitz and Ozyildirim (2002).

Third, we find evidence of significant heterogeneity across countries. In particular, we find marked differences between Germany and the Netherlands on the one hand, and France, Italy and Spain on the other. Whereas the former has financial cycles of around 10 years,

[2]Computations are done by the library of state-space functions in SsfPack 3.0 developed by Koopman et al. (2008) for OxMetrics 8 by Doornik (2013).

[3]Detailed estimates using bank credit are not reported here, and are available upon request from the authors.

the latter exhibits longer and larger financial cycles. This is consistent with the idea that the financial sector in the euro area is not very homogeneous.

Fourth, we do not only observe heterogeneity across countries, but also over time. The United States in particular has cycles which are much shorter and smaller in the pre-1985 period. This is consistent with research that documented how the financial cycle in the United States have become much longer and more ample during the great moderation, see Borio (2014).

Table 5.1: Main estimates of total credit, total credit-to-GDP ratio and house prices

	US	DE	FR	IT	ES	NL
Univariate cycles						
ϕ_{CR}	0.998	0.946	0.986	0.994	0.998	0.984
$\phi_{C/GDP}$	0.994	0.982	0.977	0.991	0.998	0.963
ϕ_{HPR}	0.996	0.973	0.996	0.993	0.993	0.987
period CR	14.56	7.78	12.13	17.53	13.08	10.27
period C/GDP	15.50	24.75	16.84	16.94	15.99	11.77
period HPR	14.41	10.11	15.08	12.35	14.51	10.41
Log-likelihood	1754.2	1755.2	1681.1	1412.1	1495.7	1479.9
AICc	-3482.5	-3484.6	-3336.3	-2798.1	-2965.6	-2934.0
BIC	-3446.1	-3448.1	-3299.8	-2763.0	-2929.2	-2897.5
Similar cycles						
ϕ	0.996	0.956	0.992	0.992	0.997	0.983
period	14.61	9.78	14.66	14.67	14.31	10.53
Log-likelihood	1753.5	1751.2	1677.4	1407.9	1494.3	1478.5
AICc	-3490.2	-3485.6	-3338.0	-2798.9	-2971.7	-2940.2
BIC	-3465.5	-3460.9	-3313.3	-2774.2	-2947.0	-2915.5
LR test	1.4	8.0	7.3	8.4	3.0	2.8
AICc	similar	similar	similar	similar	similar	similar
BIC	similar	similar	similar	similar	similar	similar
# observations	180	180	180	164	180	180

'CR' refers to total credit (real), 'C/GDP' refers to the total credit-to-GDP ratio and 'HPR' refers to house prices (real). The estimated period of the cycle is in year. 'LR' denotes the likelihood-ratio test statistic with $H_0 : \lambda_{HP} = \lambda_{CR} = \lambda_{CR/GDP}$ and $\phi_{HP} = \phi_{CR} = \phi_{CR/GDP}$. The LR-test used in this application is asymptotically χ^2-distributed with 4 degrees of freedom. Critical values of $\chi^2(4)$ are 7.78, 9.49, and 13.28 for 10%, 5% and 1% statistical significance level, respectively. 'AICc' denotes the Akaike Information Criterion with a correction for finite sample sizes. 'BIC' denotes the Bayesian Information Criterion.

Fifth, we find evidence indicating that for most countries, the cycles of total credit, the total credit-to-GDP ratio and house prices share a number of important characteristics. These are the persistence of the cycles as measured by ϕ, the cycle lengths $2\pi/\lambda$, and the spectrum and (cross)-autocovariance functions. We refer to such cycles as 'similar' cycles. For all countries in our sample, the LR tests, AICc and BIC indicate that imposing similar cycles on total credit, the total credit-to-GDP ratio and house price cycles does not result in a significantly smaller likelihood, implying that the more parsimonious similar cycles model is a good fit.

Figure 5.1: Overview univariate cycles for total credit, total credit-to-GDP ratio, and house prices

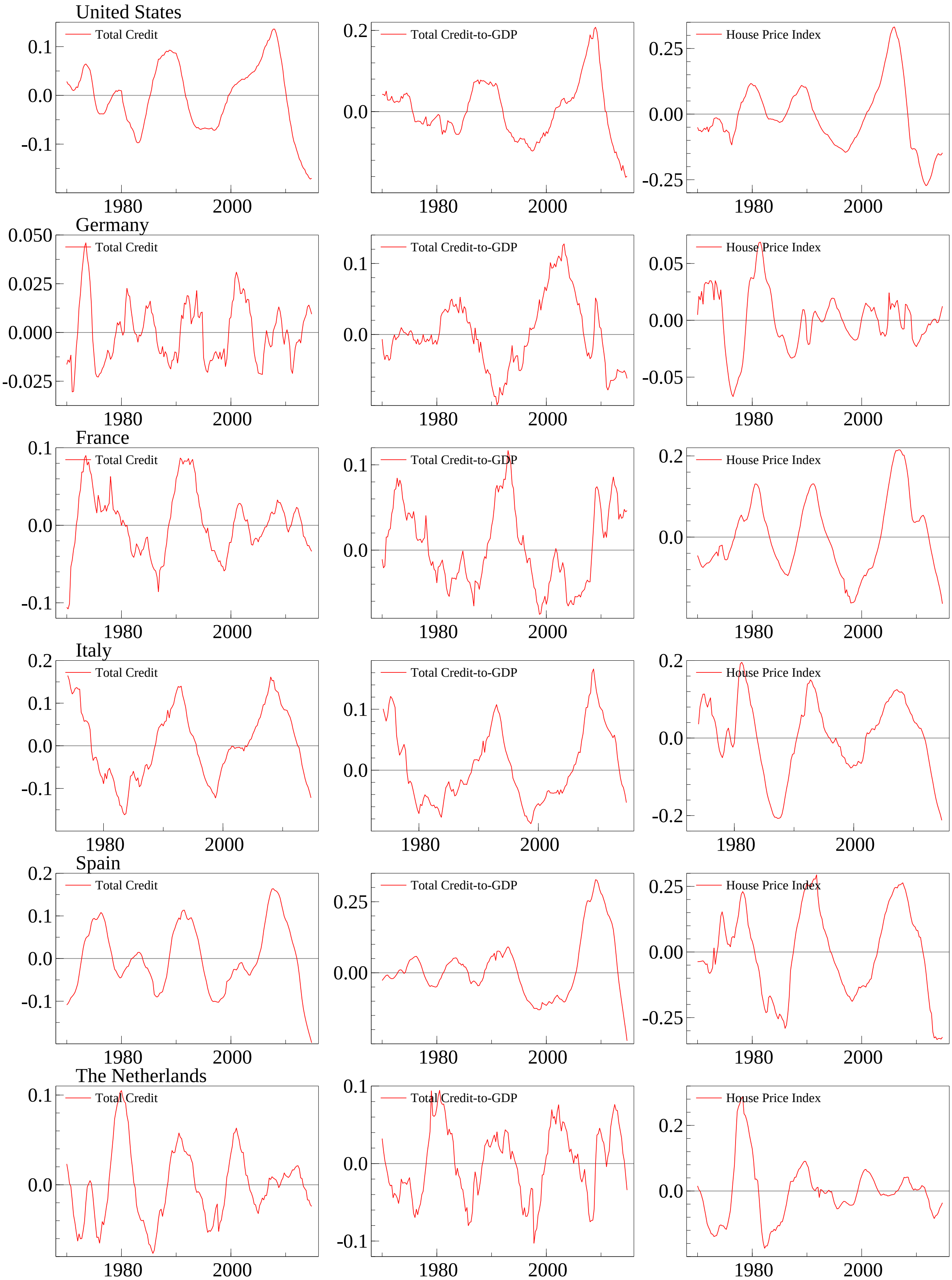
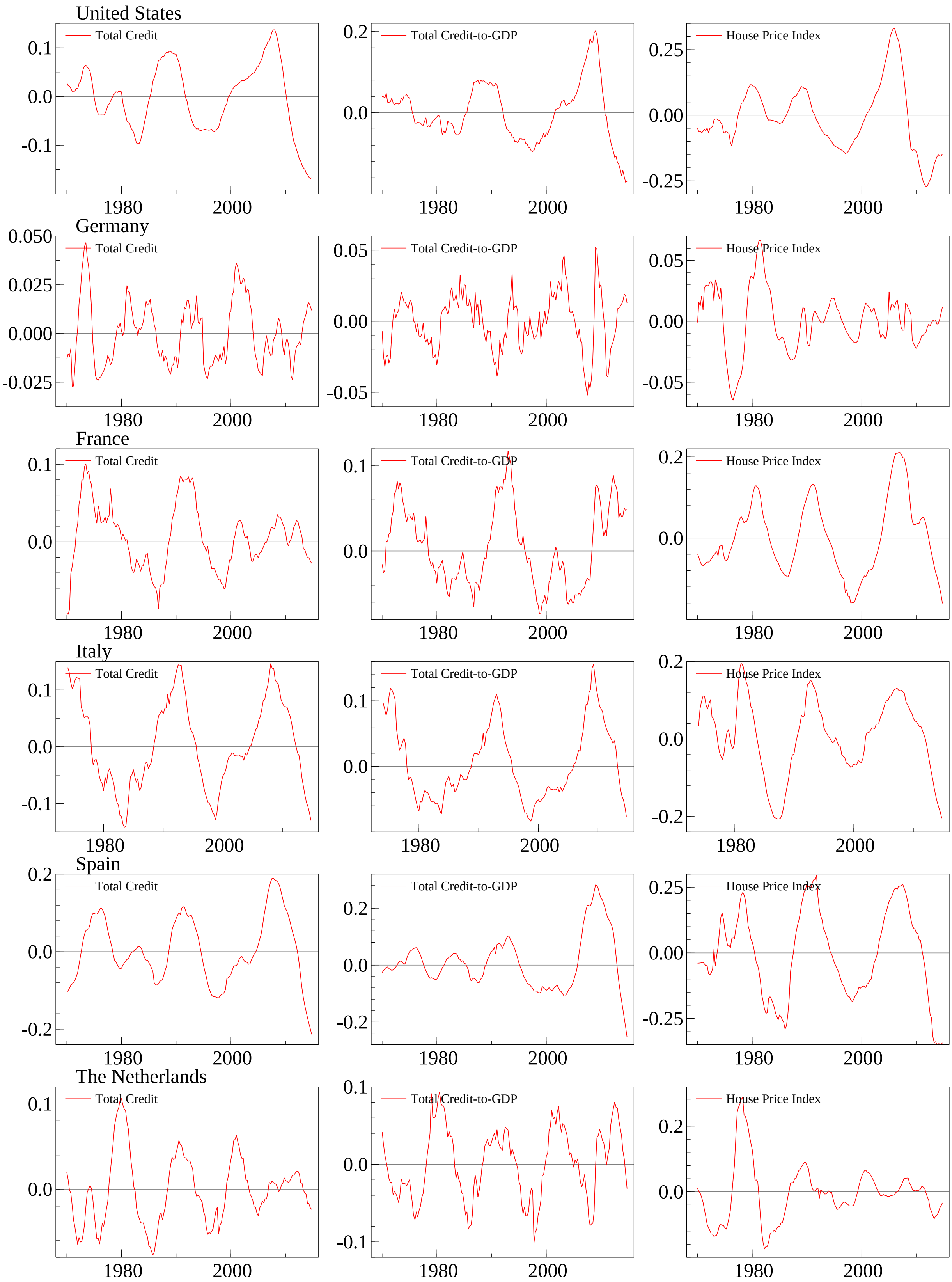


Figure 5.2: Overview similar cycles for total credit, total credit-to-GDP ratio, and house prices



Finally, we find that total credit and bank credit cycles co-move strongly in the euro area, and have comparable length and amplitude. The same is true for the ratio of these variables to GDP. By contrast, we find that in the United States, bank credit and total credit cycles are subject to different dynamics. In particular, in the United States, the trend of bank credit-to-GDP ratio is almost stationary, while total credit-to-GDP ratio exhibits an upward trend. This result is consistent with the idea that in the United States markets play an important role in financial intermediation. By contrast, in the euro area, most of credit is supplied by banks.

6 Conclusions

In this paper we applied model-based filters to extract trend and financial cycles for the United States and the euro area. Our analysis shows that credit, credit-to-GDP ratio and real house prices exhibit overall medium-term cyclical behaviour with relatively ample fluctuations. We also find that the period and amplitude of these cycles can vary over time and differ per country. In particular, in the United States we found evidence that financial cycles have increased in amplitude and duration since the mid-1980s. However, we cannot easily detect such breaks in the euro area countries in our sample.

There are several issues which we plan to explore in future research. First, given that for the countries in our sample we do find similar cycles, we plan to investigate the interactions between these cycles and develop a possible aggregation measure. Second, it would be interesting and straightforward to explore the robustness of our results to including other financial variables, such as leverage and interest payment on debt. Third, tt would be useful to apply our method to longer time series as collected for example by Jordà et al. (2014) and Knoll et al. (2014). Fourth, it would also be interesting to explore the determinants of cross-country variations of financial cycles in the euro area. Finally, our methodology can be extended to studying the synchronicity of financial and business cycle.

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A Estimated components using univariate models for total credit, total credit to GDP ratio, and house prices

Figure A.1: United States, 1970(1)-2014(4)

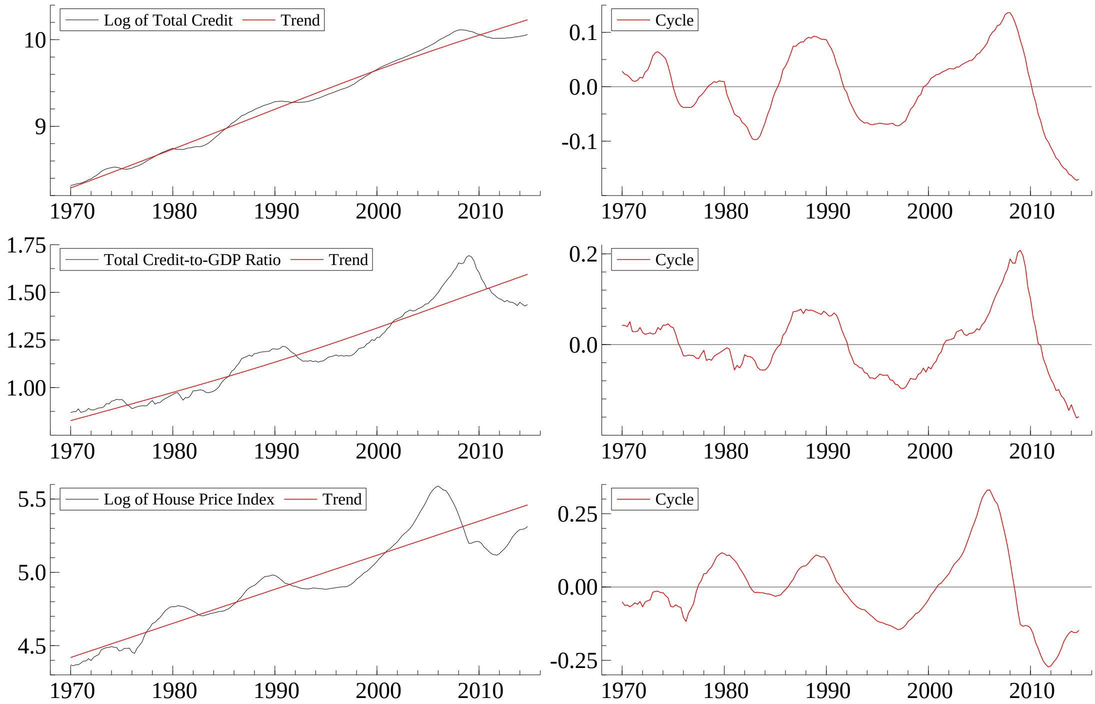


Figure A.2: Germany, 1970(1)-2014(4)

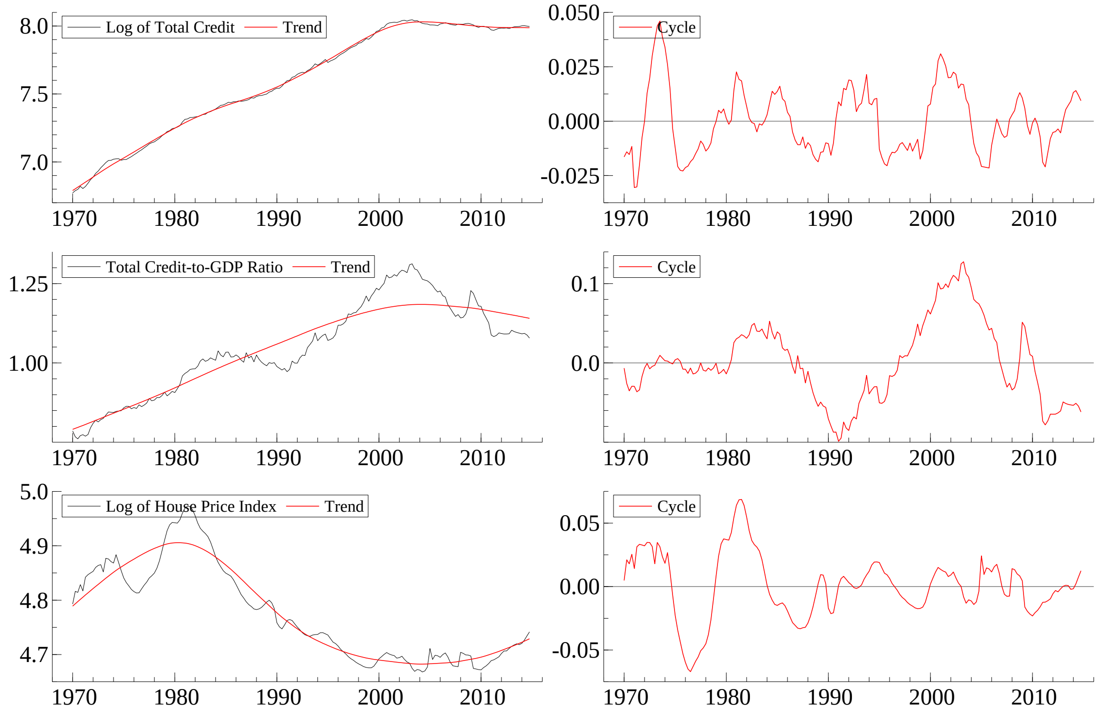


Figure A.3: France, 1970(1)-2014(4)

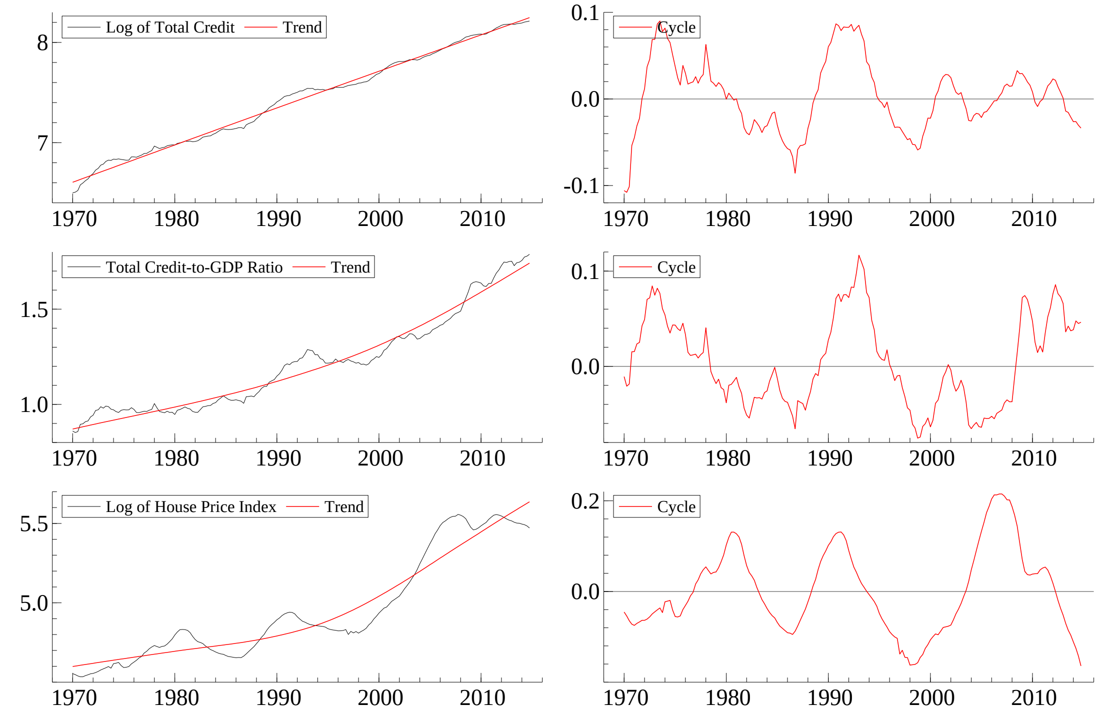


Figure A.4: Italy, 1974(1)-2014(4)

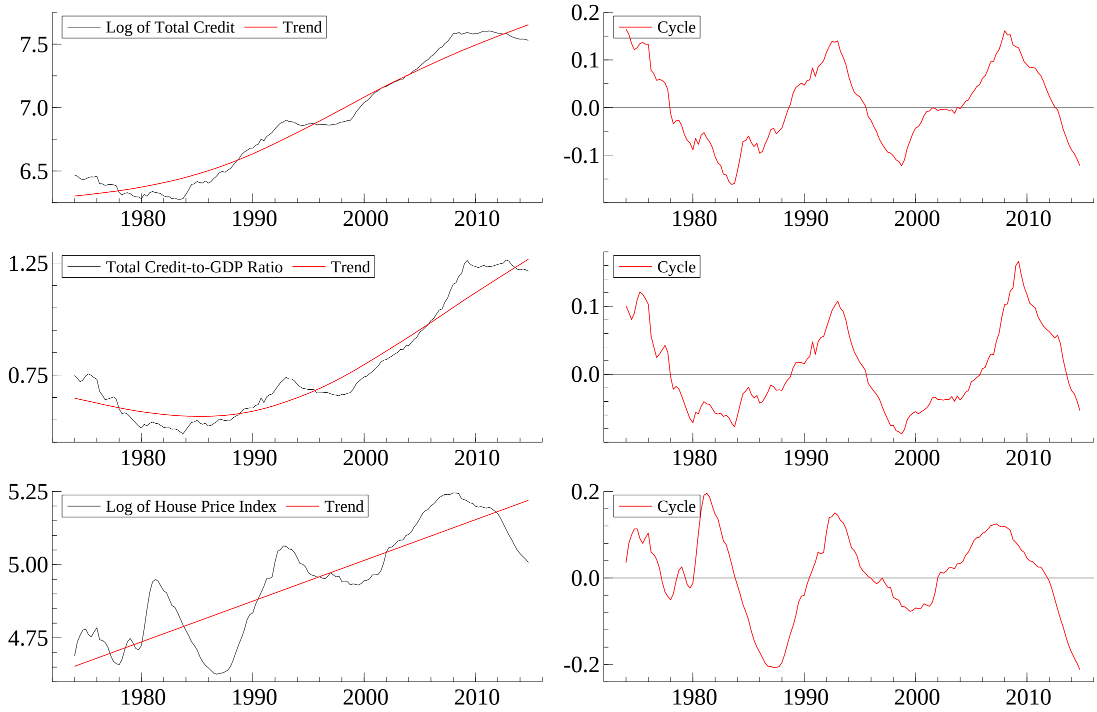


Figure A.5: Spain, 1970(1)-2014(4)

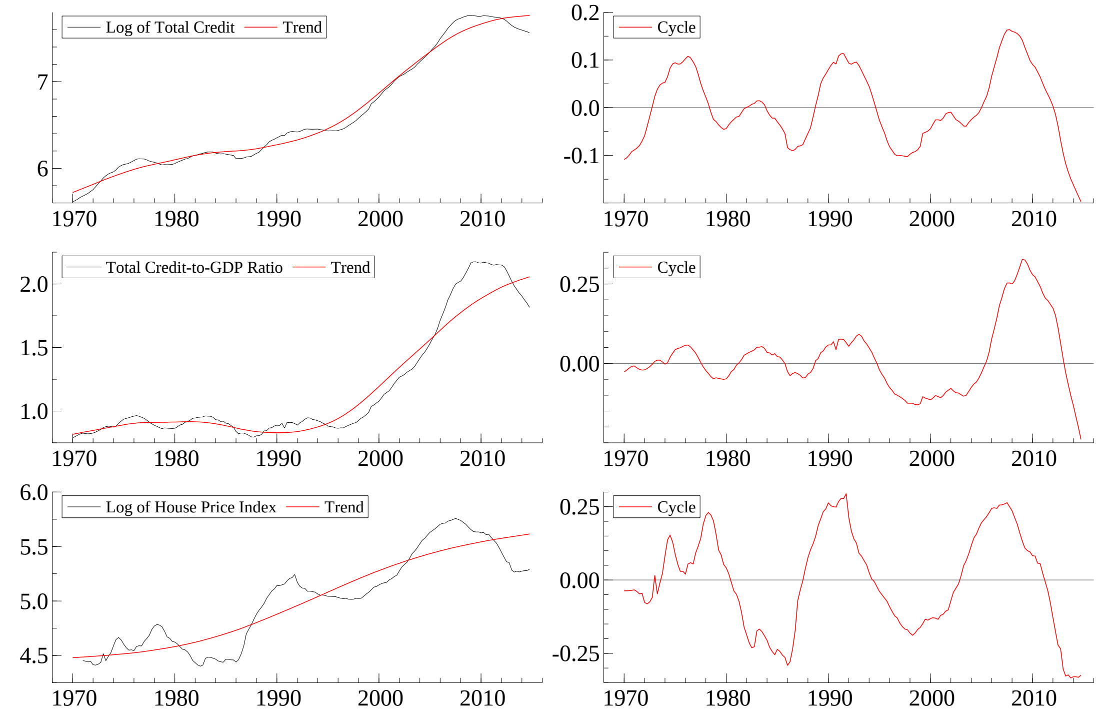
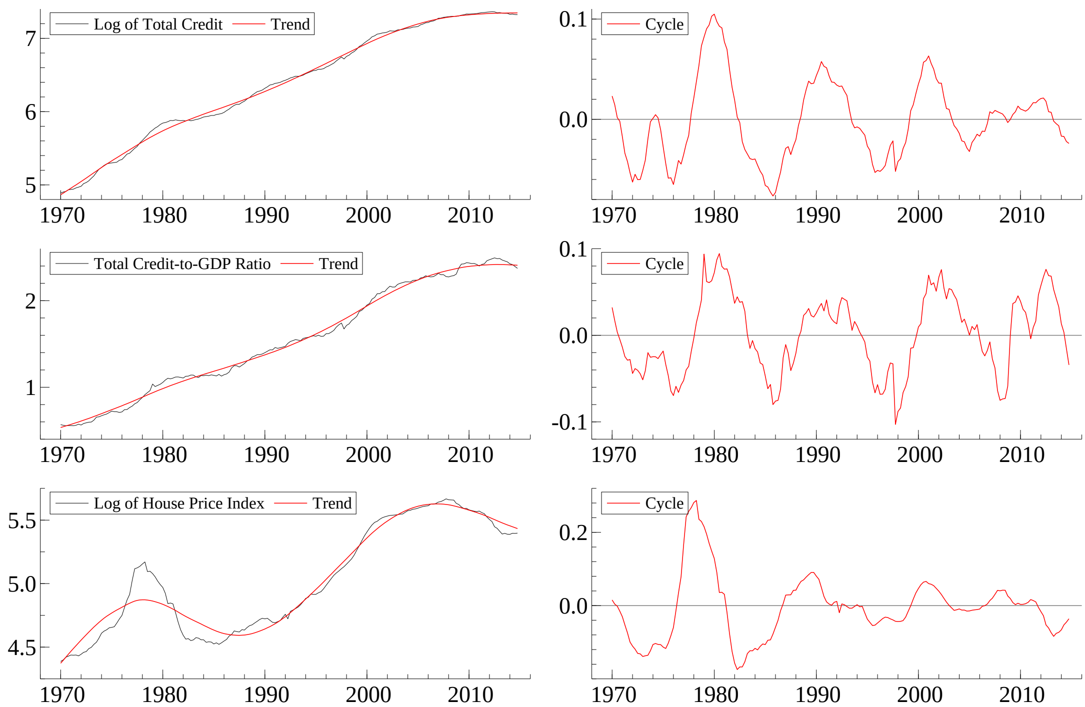


Figure A.6: The Netherlands, 1970(1)-2014(4)



B Estimated components using similar cycle models for total credit, total credit to GDP ratio, and house prices

Figure B.1: United States, 1970(1)-2014(4)

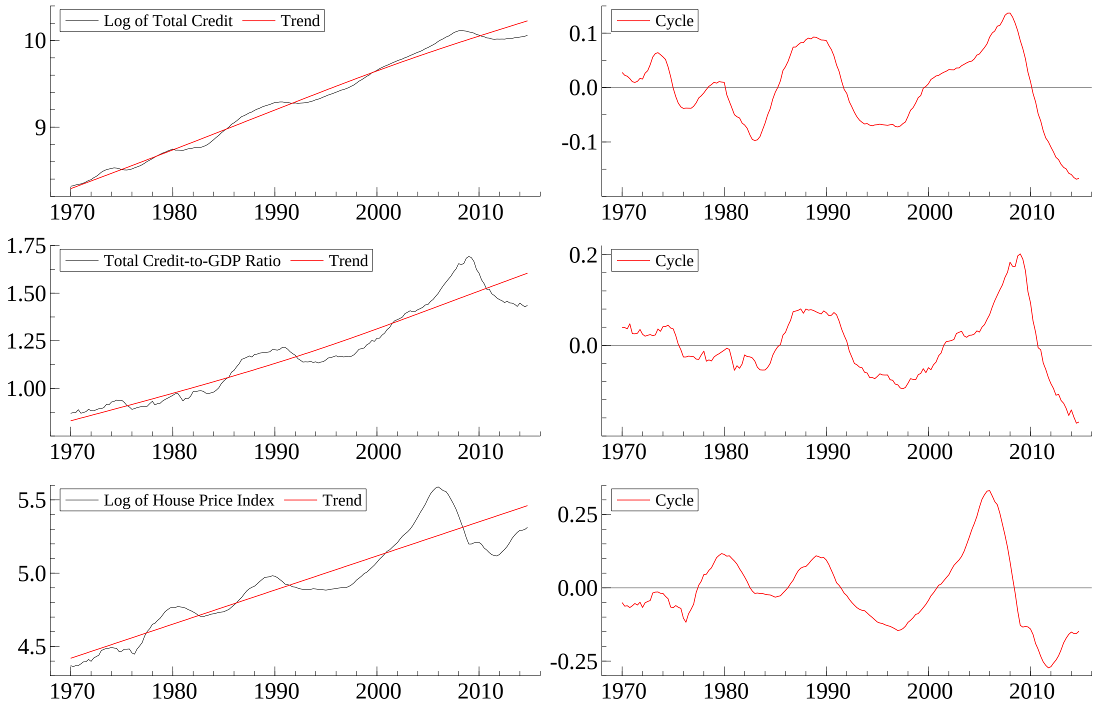


Figure B.2: Germany, 1970(1)-2014(4)

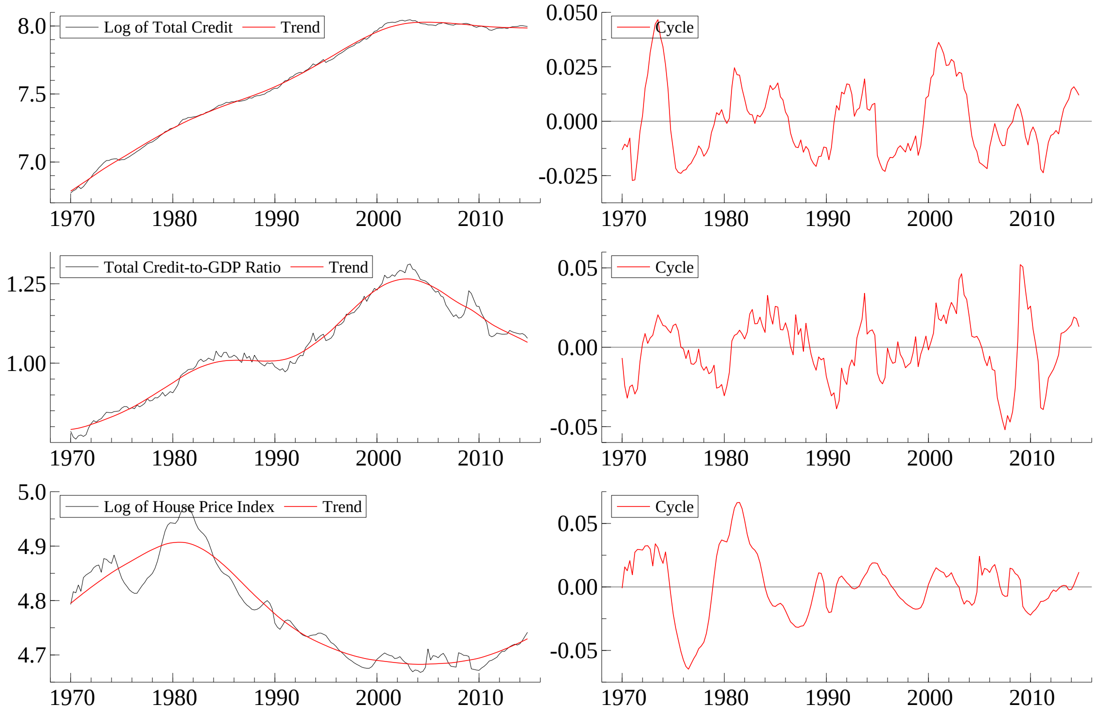


Figure B.3: France, 1970(1)-2014(4)

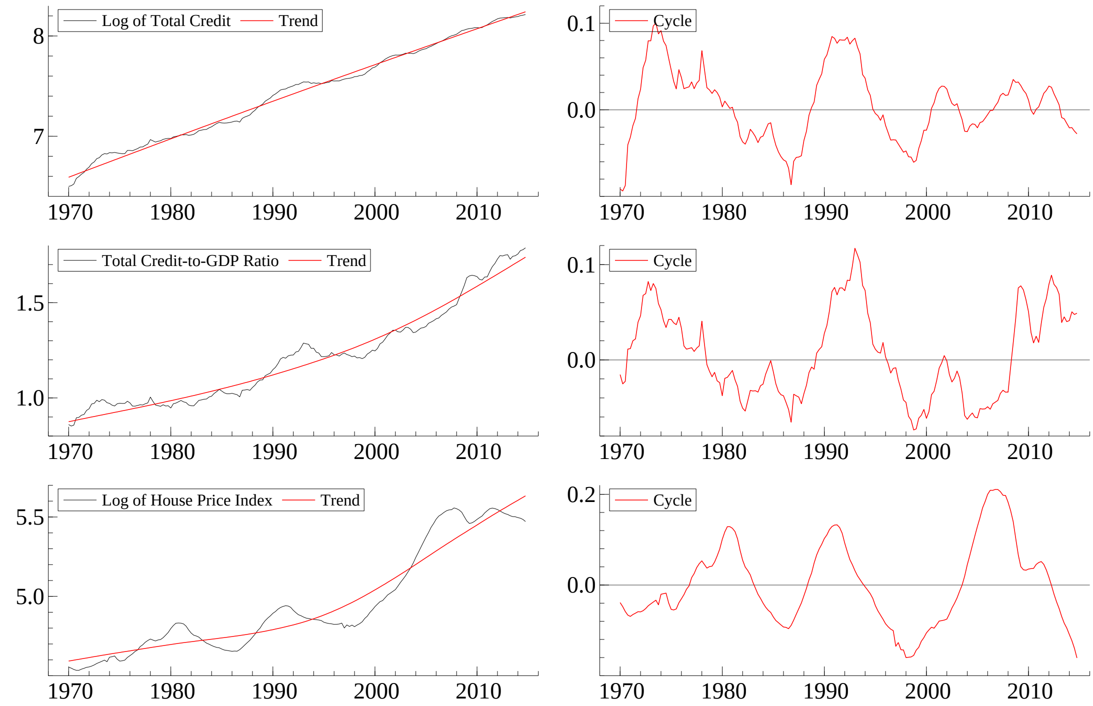


Figure B.4: Italy, 1970(1)-2014(4)

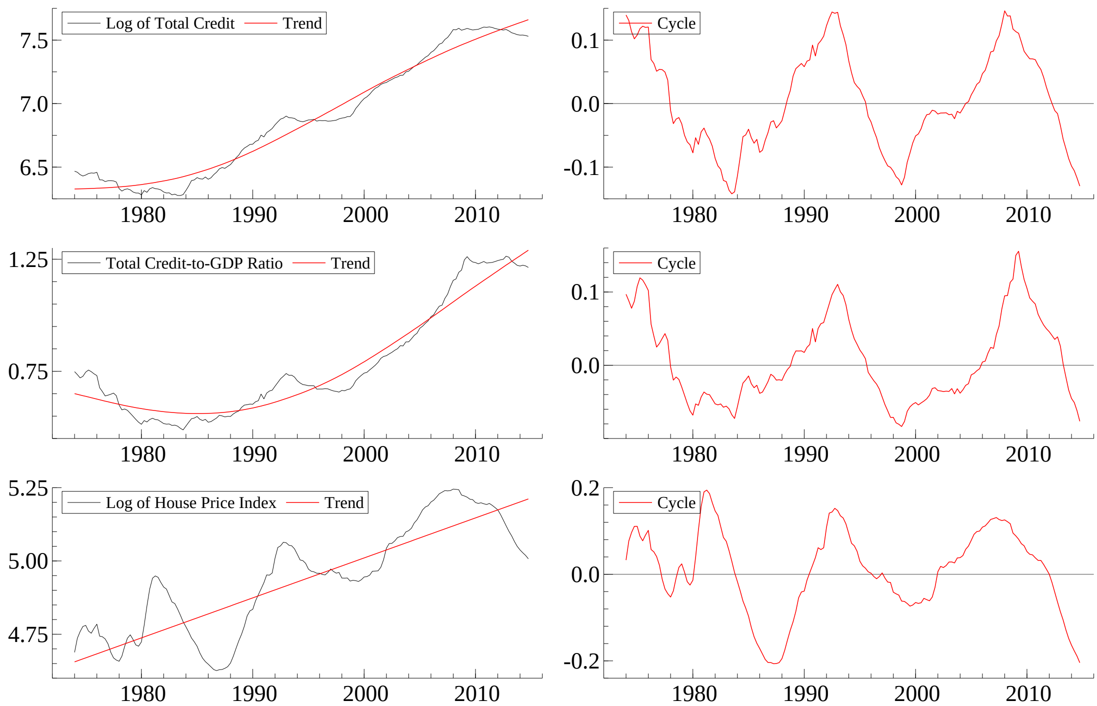


Figure B.5: Spain, 1970(1)-2014(4)

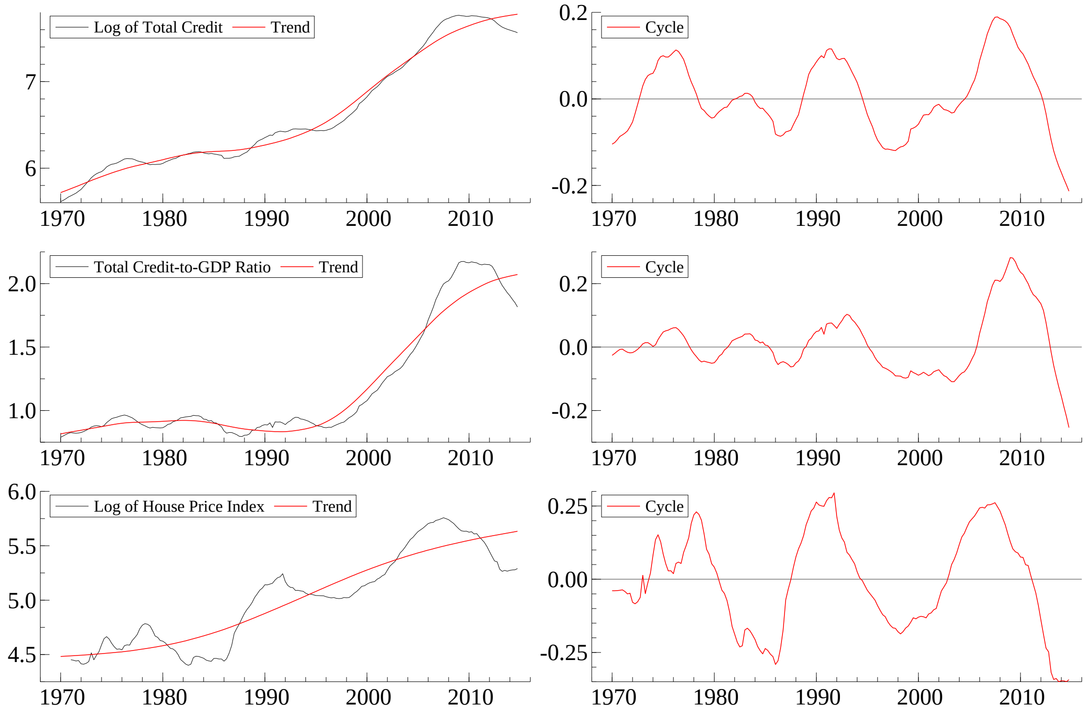
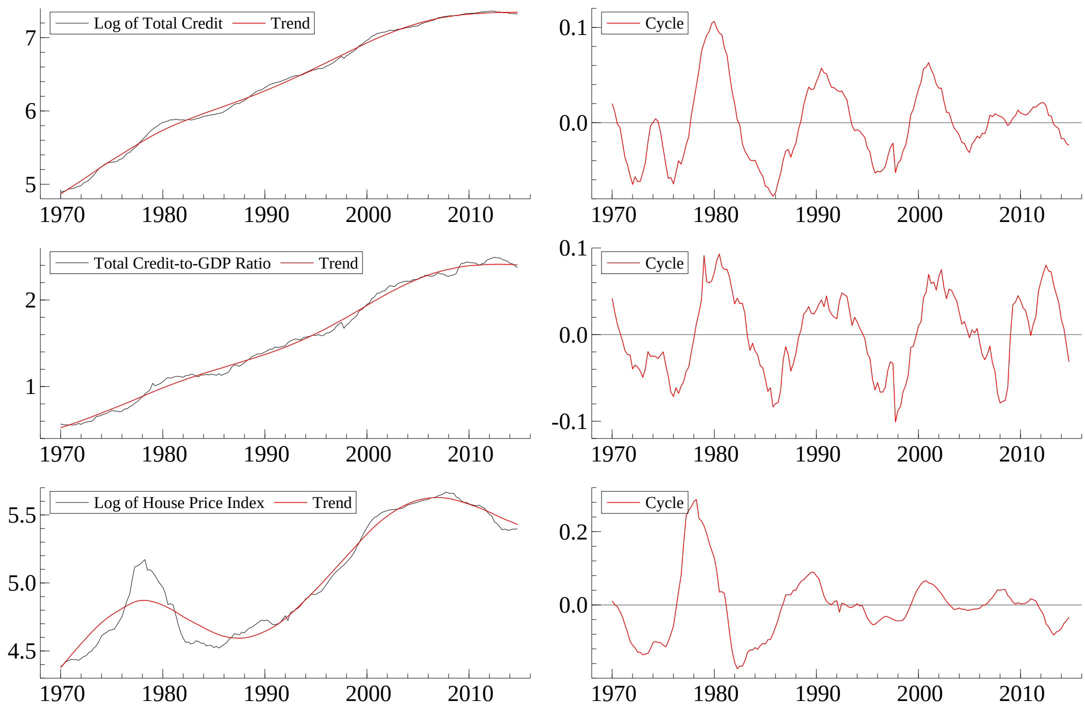


Figure B.6: The Netherlands, 1970(1)-2014(4)



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