Wavelet analysis of loans in Germany *

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Abstract

ECB (2010) analyses the lead/lag relationship between changes in real GDP and real loans to households as well as real loans to non-financial corporations from 1980 to 2009. There is evidence for a lead of GDP with respect to loans to non-financial corporations. Recursive analysis of the correlation and the lead gives some indication of time variation. Busch (2011) does a similar analysis in the frequency domain for data for Germany from 1980 to 2010. She finds evidence for a lead of three quarters of real GDP. As this type of analysis has no resolution over time, structural changes cannot be identified.

This analysis uses wavelet methods (Crowley (2007), Aguiar-Conraria and Soares (2011)) for German data from 1971 to 2010. To get some idea of variation in the data, the continuous wavelet transform is calculated. The "time-varying" correlation is then analyzed using the concept of wavelet coherency. To investigate the lead/lag relationship the wavelet phase difference is calculated for various frequency bands. The results show that coherence between real GDP and loans to non-financial corporations changes over time. There is also considerable variation in phase.

Keywords Loans; Wavelet analysis

*This paper represents the author's personal opinion and does not necessarily reflect the views of the Deutsche Bundesbank. The author wishes to thank Martin Mandler and Falko Fecht for excellent discussions.

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1 Introduction

There is a renewed interest in credit growth after the outbreak of the financial crisis in 2007.[1] Before, the analysis of nominal series like money or credit was quite outdated in the conduct of monetary policy. Especially in academia the focus was on inflation targeting without any role for monetary aggregates at all (Woodford (2007)).[2] An opposing view was proposed by Goodhart (2007).

ECB (2011) argues for including credit aggregates in its monetary analysis, as credit is the main counterpart to its monetary aggregates M3. In addition, credit is an important source of external financing in euro area. On its agenda is the question, whether the reduction in credit growth is an indicator of a credit crunch or whether it is determined by a reduction in economic activity. Another aspect is the stability issue, i.e. is the relationship stable over time?

The macro analysis of the relationship between loans to the private sector and GDP is based almost entirely on time domain methods. One example is ECB (2011). There are just a few exceptions. Aikman et al. (2011) apply a bandpass filter on the series. They find that loans and GDP have cycles of different frequencies. However, they do not explicitly use frequency methods like coherency analysis. Busch (2011) analyzes loans to private households and loans to non-financial corporations in Germany for the period from 1980 to 2010 using spectral methods.[3] Spectral analysis provides information about cyclical behaviour in the time series and the identification of dominant periodicities. A disadvantage is that it assumes stationarity of the time series. Furthermore, this type of approach does not allow for instability or structural breaks.

Wavelet analysis is a modification of Fourier analysis. It allows for nonstationarity of time series. Its main focus is on the scale or frequency of cycles in the time series, whether there is coherency between these cycles, its stability over time and the stability of the lead/lag structure. Is the relationship stable over all frequencies? Are there changes in phase over frequencies (lead at short horizons, lag at long horizons or no lead or lag)?

Wavelet analysis is occasionally applied on macroeconomic time series. Its application in economics was initiated by Ramsey (1999, 2002), further explored by a series of papers by Crowley, e.g. Crowley (2005, 2006).[4] Wavelets are an easy way of incorporating time variation, presenting additional information on the importance of different frequencies and their changes over time. The continuous wavelet transform that is applied in this paper is propagated by Aguiar-Conraria and Soares (2008, 2011).

In this paper, the continuous wavelet transform is applied to real GDP growth and growth in real loans. Section 2 give some brief overview on the literature. Section 3 presents the CWT methodology and section 4 shows the results for the German data set. The approach is applied to several sectoral loans aggregates as there seems to be evidence for differing characteristics (ECB

[1] As an example see ECB (2011).
[2] Comments by Spahn (2009).
[3] A brief exposition of this analysis is presented in Deutsche Bundesbank (2011).
[4] For an overview of applications in economics and finance see Crowley (200.).

(2009, 2011), Deutsche Bundesbank (2011)). Section 5 concludes.

2 Literature on credit and business cycles

Loans are an important variable in the monetary assessment of certain central banks. They play a propagating role in transmission process, are a significant counterpart to monetary aggregates and show a strong correlation with asset price movements (information about cycles in asset prices).

2.1 Theoretical considerations

In general, there are macroeconomic models of the credit cycle on one side and models characterized by underlying microeconomic frictions on the other side (Aikman, Haldane and Nelson (2011)). The most prominent theories of the second type are the "financial accelerator" (Bernanke, Gertler and Gilchrist (1996)) and the "coordination failure" approach (Gorton and He (2008)).

The financial accelerator approach introduces financial frictions into DSGE models by assuming heterogeneous firms and credit markets characterized by asymmetric information. The implied collateral channel acts as a propagator of shocks. Changes in asset prices lead to changes in credit in a pro-cyclical manner and corresponding effects on investment demand. Hume and Sentance (2009) view this approach as "pseudo-endogenous" as it "credit and financial cycles ... can only be as pronounced as the economic cycle underlying it". This theory cannot explain excessive credit developments as were observed in a variety of countries in the last decade, but it may describe the underlying mechanism of coherency of loans to non-financial corporations and GDP.

The second approach allowing a more excessive credit supply behaviour is the so called "keeping up with the Goldmans" (Aikman, Haldane and Nelson (2011)). This model assumes a continuum of bankers maximizing their reputation in the market in the short-run. Each bank originates a risky asset. The return of this asset depends on the unobservable ability of the banker and on the state of the macroeconomy which can be good or bad. The activities of the banks cannot be observed in a direct way by the others (market) bank earnings are used as an indicator for the performance of the bankers. This model does not play a major role in this paper, as coherency of loans with GDP or short-term interest is the main focus and not coherency with banking or finance variables.

Another strand of the literature are the (macro) theories of Minsky (1982) and Kindleberger (1978). They view the credit cycle as a sequence of credit booms and credit crunches.

2.2 Empirical studies

Hofmann (2001) finds based on cointegration analysis evidence that the long-run development of credit can be explained by output, real interest rates and real property prices. The relationship between bank loans and property prices is interdependent.

ECB (2009, 2011) finds a close relation between the growth rate of real loans to NFCs and growth rate of real GDP (annual rates) for euro area data. The correlation is significantly positive, loan growth rates lag GDP growth rates with three quarters on average (statistically significant). Loans to households lead the GDP cycle by one quarter (statistically not significant). As a potential explanation for this lagging pattern in the case of loans to non-financial corporations, the ECB argues that firms first use their internal funds (cash flow improves during recovery). Later in the business cycle they turn to external financing. An alternative might be to finance themselves by issuing securities. The coincident pattern in the case of loans to households is explained by the fact that households adjust spending pattern relatively quickly. Another reason might be that household loans are better collateralized (especially those for house purchases). Rolling correlations show that correlation coefficients are relatively stable, but time lags seem to have changed.

Using the Bry-Boschan algorithm to identify turning points there are indications that there are differences in amplitudes and phases of loans and GDP. Comparing the turning points, it time lag is on average three quarters, although it varies between minus five and plus three. There are turning points in real GDP growth that are not associated with peaks and troughs in loan growth (late 90s, mid 2000s).

For euro area data authors from the ECB apply a variety of time series approaches:[5] a large BVAR (Giannone et al. (2010)), a five variable VAR model applying sign restrictions for shock identification, a DSGE model including financial frictions and a set of "financial" shocks and a panel VAR (Ciccarelli, et al. (2010)).

There is a series of papers analyzing the impact of credit supply factors and demand effects on credit growth. Busch et al. (2010) estimate a six variable Bayesian VAR for Germany for the period from 1991 to 2009. They use sign restrictions to identify the corresponding structural shocks. This channel is not considered in analysis below as there are no consistent long series for corresponding variables. An alternative VAR is estimated using data from bank lending survey (data only from 2003Q1 onwards) to extract a factor measuring supply conditions (Deutsche Bundesbank (2011)).

Busch (2011) and Deutsche Bundesbank (2011) apply Fourier analysis to loans to non-financial corporations (LNFC), loans to private households and loans to the private sector. There is a significant long cycle in LNFC (around 8 to 10 years). No significant cycles can be identified in the other loan aggregates. The business cycle is shorter than the credit cycle with smaller amplitudes. For cycles of periods of 4 to 5 years there is a lag of 3 quarters of the credit cycle relative to the business cycle.

Aikman, Haldane and Nelson (2011) find a strong cyclical variation in real credit in their data set for 12 developed countries. They use the model by (Gor-

[5] A brief overview is given in ECB(2011).

ton and He (2008)). For these countries credit and GDP cycles have a different duration and a different amplitude. Credit cycles are statistically significantly associated with the incidence of financial stress (leverage effects).

3 Wavelet analysis

3.1 Idea

Frequency methods are an alternative to those in the time domain. They provide a different type of information (complementary) although there are direct mappings between both approaches. The spectrum of a time series can be calculated using the estimated parameters of an ARMA model. Coherency at various frequencies can be calculated by using VAR parameters (Croux et al. (2001)). Time-varying coherency can be calculated by using time-varying VAR parameters. This kind of analysis asks different questions compared to the time series type of analysis. It looks for correlations at specific frequencies. It does not analyze the propagation mechanism by means of impulse responses and it also does not try to identify shocks to the system.

Wavelet methods (spectrum, coherency) are non-parametric and therefore more robust, e.g. to specification issues and non-linearities.

The periodogram (biased estimator) can be estimated via FFT. To get a consistent estimate a windowed analysis is needed. It measures the importance (contribution) of periodic cycles of specific frequencies to the variance of the time series. These cycles are defined over infinite periods in time.

A major disadvantage is from the viewpoint of stability analysis that there is no resolution over time. There is no possibility to identify structural changes. Applying a rolling window may give some idea of the stability of the spectrum. The methodology is only applicable to stationary time series (Crowley (2009)). Granger's typical spectral shapes of integrated variables do not allow for identifying of finite cycles.

Wavelet analysis is an easy to apply nonparametric tool for the analysis of time-variation of the importance of various scales in the coherence of time series. Wavelet analysis is based on a coherent mathematical theory. Since 1990s the literature expanded rapidly especially in geophysics and oceanography. In contrast to Fourier analysis, it provides the possibility of uncovering transient relations (Aguiar-Conraria et al. (2008), p. 2864). As wavelets have only finite support ("small wave" compared with sine function which can be interpreted as a "big wave"), they are ideally suited to locally approximating variables in time or space (Crowley et al. (2006)). The multiresolution decomposition (MRD) allows for a decomposition of a time series into trend, cyclical component and noise.

The starting point is a so called mother wavelet ψ. By scaling and translation a variety of wavelets can be generated.

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)$$

where s is a scaling or dilation factor. It controls the width of the wavelet. $1/\sqrt{|s|}$ garantees the preservation of energy, i.e. $\left|\left|\psi_{\tau,s}\right|\right| = |\psi|$. τ is a translation parameter controlling the location of the wavelet.

The function ψ has to fullfil some requirements to have properties of wavelets (Percival and Walden (2002)). The integral of $\psi(u)$ is zeros.

$$\int_{-\infty}^{\infty} \psi(u)\, du = 0$$

Over time ψ has to be below and above zero. An admissibility condition is a sufficient decay.

$$\Psi(0) = \int_{-\infty}^{\infty} \psi(t)\, dt = 0$$

These properties are necessary for an "effective localization in both time and frequency" (Aguiar-Conraria and Soares (2011)).

There are various versions of the wavelet transform. The discrete time transform (DWT) gives a parsimonious representation of data: noise reduction or information compression (Bruzda (2011)). This construction generates orthogonal components. It attempts to preserve the key features of the continuous form (CWT). The major weakness is the judicious subsampling. It deals with just dyadic scales, i.e. λ has the form of 2^{j-1}, where $j = 1, 2, ...$, i.e. within a given scale 2^{j-1}, one picks times t that are separated by multiples of 2^j.

The maximal-overlap DWT removes certain deficiencies of DWT (Bruzda (2011), Crowley et al. (2006)). It gives up gives up orthogonality property and considers all time units, but only dyadic frequency bands (increased resolution at coarser scales). Therefore, it is able to handle any data size. The disadvantage is that it oversamples the data. The intuition is moving a wavelet function along a series. The size of each crystal is the same.

3.2 Continuous wavelet transform[6]

The CWT is an exploratory data analysis tool. As it is two dimensional but depending on a one dimensional signal, it contains a lot of redundancy. When moving into larger scales there is little difference in CWT between adjacent scales and there are slow variations across time at any fixed large scale.

3.2.1 Definitions

The continuous wavelet transform (CWT), $W_x(\tau, s)$, is obtained by projecting $x(t)$ onto the family $\left\{\psi_{\tau,s}\right\}$

$$\begin{aligned} W_x(\tau, s) &= \left\langle x, \psi_{\tau,s} \right\rangle \\ &= \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t-\tau}{s}\right) dt \end{aligned}$$

[6] This section draws on Aguiar-Conraria and Soares (2011).

where * denotes the complex conjugate. The CWT may also be represented in the frequency domain as

$$W_x(\tau, s) = \frac{\sqrt{|s|}}{2\pi} \int_{-\infty}^{\infty} \psi^*(s\omega) X(\omega) e^{i\omega\tau} d\omega$$

where $X(\omega)$ denotes the Fourier transform of $x(t)$, defined as

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-i\omega t} dt$$

and ω is the angular frequency.

There is a variety of different wavelet functions. In the empirical section the socalled Morlet wavelet is used.

$$\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}$$

where $\omega_0 = 6$. This specific choice for the parameter ω yields a simple relation between scales and frequencies: $f \approx \frac{1}{s}$. The Morlet wavelet is complex valued allowing for an analysis of phase differences, i.e. lead-lag structures.

The wavelet power spectrum is defined as

$$WPS_x(\tau, s) = |W_x(\tau, s)|^2$$

In the case of a complex-valued wavelet, the corresponding wavelet transform is also complex–valued. It can de decomposed into a real part, the amplitude, $|W_x(\tau, s)|$, and its imaginary part, the phase, $|W_x(\tau, s)| \; e^{i\phi_x(\tau,s)}$. The phase-angle $\phi_x(\tau, s)$ can be obtained by

$$\phi_x(\tau, s) = \mathrm{Arc}\tan\left(\frac{\Im\{W_x(\tau, s)\}}{\Re\{W_x(\tau, s)\}}\right)$$

For the calculation of phase information it is necessary to use complex wavelets.

Aguiar-Conraria and Soares (2011) use an analytical wavelet. This type is defined as one whose Fourier transform is supported on the positive real-axis only. The corresponding wavelet transform is the analytic wavelet transform.

3.2.2 Bivariate case

The cross wavelet transform is defined as

$$W^{xy} = W^x W^{y*}$$

where * denotes the complex conjugate.

The cross wavelet power spectrum is defined as

$$|W^{xy}|$$

Wavelet coherency between two time series x and y can be interpreted as local correlation and is defined as

$$R_n(s) = \frac{\left|S\left(s^{-1}W_n^{xy}(s)\right)\right|}{\sqrt{S\left(s^{-1}\left|W_n^{x}\right|\right)}\sqrt{S\left(s^{-1}\left|W_n^{y}\right|\right)}}$$

where S is a smoothing operator with respect to time and scale.

The wavelet phase difference can be computed via

$$\phi_{x,y}(s,\tau) = \tan^{-1}\left(\frac{\Im\left\{W_{xy}(\tau,s)\right\}}{\Re\left\{W_{xy}(\tau,s)\right\}}\right)$$

If $\phi_{x,y}(s,\tau) = 0$, the series x and y move together at the specified frequencies. If $\phi_{x,y}(s,\tau) \in \left(0, \frac{\pi}{2}\right)$, series y leads x. The time lag between both series can be calculated as

$$\Delta T(s,\tau) = \frac{\phi_{x,y}(s,\tau)}{2\pi f(\tau)}$$

3.2.3 Multivariate analysis

This is an extension from the bivariate to the multivariate case. In this case, the correlation of the interesting variables x and y with other variables is taken into account when calculating coherency and phase differences.

The squared multiple wavelet coherency between series x_1 and all other series x_2, ..., x_p is defined as

$$R^2_{1(23\ldots p)} = R^2_{1(q)} = 1 - \frac{L^d}{S_{11}L^d_{11}}$$

where L is the $p \times p$ matrix of all smoothed cross-wavelet spectra S_{ij}.

$$L = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1p} \\ S_{21} & S_{22} & \cdots & S_{2p} \\ \vdots & \vdots & & \vdots \\ S_{p1} & S_{p2} & \cdots & S_{pp} \end{bmatrix}$$

L^d_{ij} is the cofactor of the element (i,j) of matrix L.

$$L^d_{ij} = (-1)^{(i+j)} \det L^j_i$$

where L^j_i represents the sub-matrix obtained from L by deleting the ith row and the jth column and $L^d = \det L$.

The complex partial wavelet coherency of x_1 and x_j $(2 \leq j \leq p)$ is given by

$$\rho_{1j.q_j} = -\frac{L^d_{j1}}{\sqrt{L^d_{11}L^d_{jj}}}$$

The partial phase difference of x_1 over x_j given all other series is calculated via

$$\phi_{1j.q_j} = \arctan\left(\frac{\Im\left(\rho_{1j.q_j}\right)}{\Re\left(\rho_{1j.q_j}\right)}\right)$$

4 Empirical application[7]

4.1 Data

The development of loans to the private sector is analyzed for three different categories: loans to non-financial corporations, loans to private households (without mortgages) and mortgages. It is based on quarterly observations of quarterly growth rates for the period from 1971Q1 to 2011Q2 (#obs). The series include West German data before 1991 and German data afterwards. There is an adjustment for a break in levels due to German unificaton. The definition of the sectors is consistent with the Kreditnehmerstatistik. Data for macroeconomic variables like GDP or consumption are provided by Destatis. Data for bank variables are taken from banking statistics.

The differentiation of loans is based on the different motives for these. Loans to non-financial corporations are the most important source of external financing for corporations. Loans to households are mostly consumer loans. The focus of the analysis is on loans to non-financial corporations as these are the object of discussions about a credit crunch.

4.2 Loans to non-financial corporations

Figure 1 shows the quarterly growth rates of real loans to non-financial corporations (NFCs) and of real GDP over the sample period. During the 70s and 80s the evolution of both series was relatively close. This changed during the 90s. Figure 2 shows the corresponding annual changes in both variables. Especially during the last 20 years, the amplitude of loan growth seems to be different from that of real GDP growth.

[7] In this application the Matlab toolbox developed by Aguiar-Conraria and Soares is used.

Figure 1: Time series (quarterly growth rates)

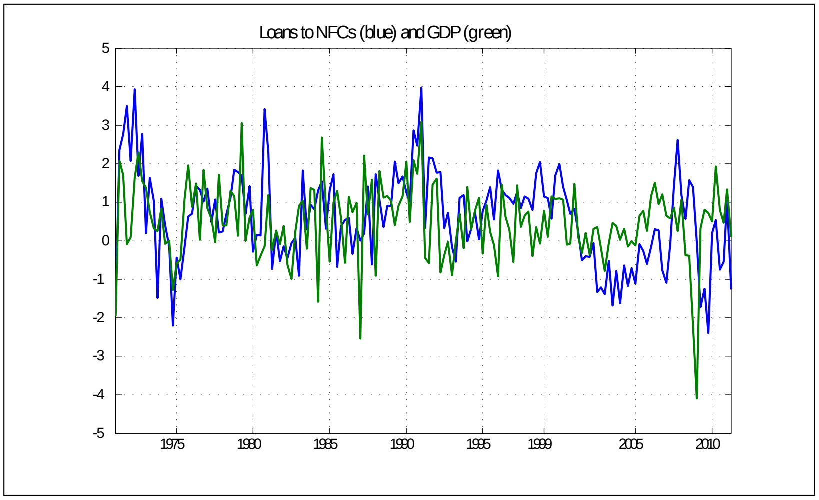
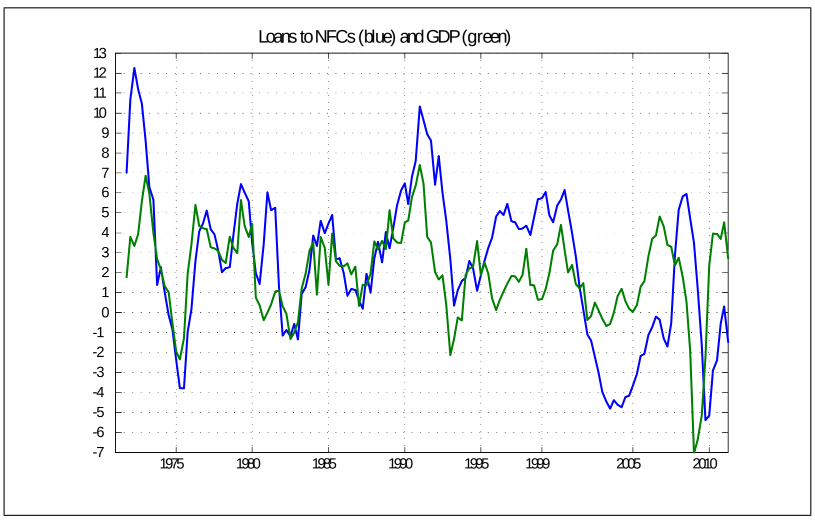


Figure 2: Annual growth rates



These series are analyzed in Busch (2011) and Deutsche Bundesbank (2011) by means of spectral methods. It allows for describing the distribution of the variance of a variable as a function of periodicity. There exists a variety of methods for estimating the spectrum. Both studies use the Fourier transform to calculate the raw periodogram of a time series. To get consistent estimates, this raw periodogram has to be smoothed by applying a filter which affects the smoothness, resolution and variance of the spectral estimate. In this paper, the spectral density is calculated by estimating an ARMA model for the series and generating the theoretical spectrum using the respective ARMA parameters.

Figure 3: Spectral density of real GDP

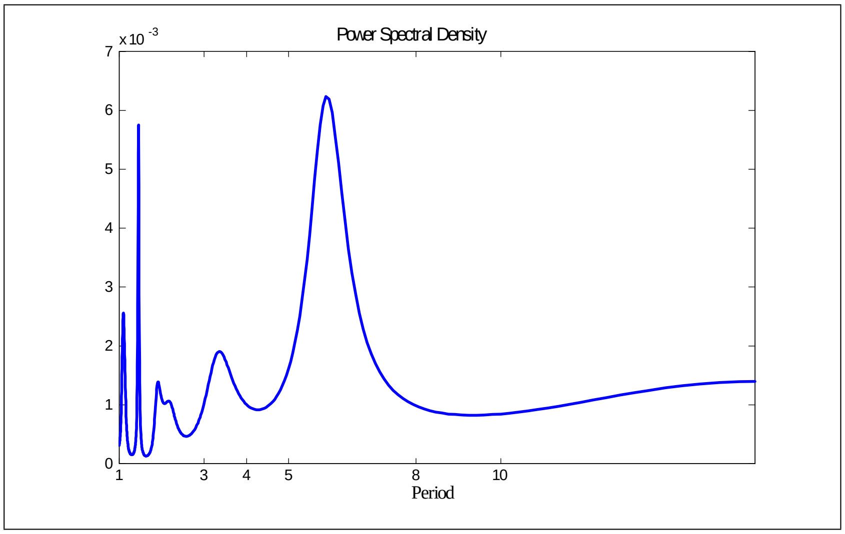
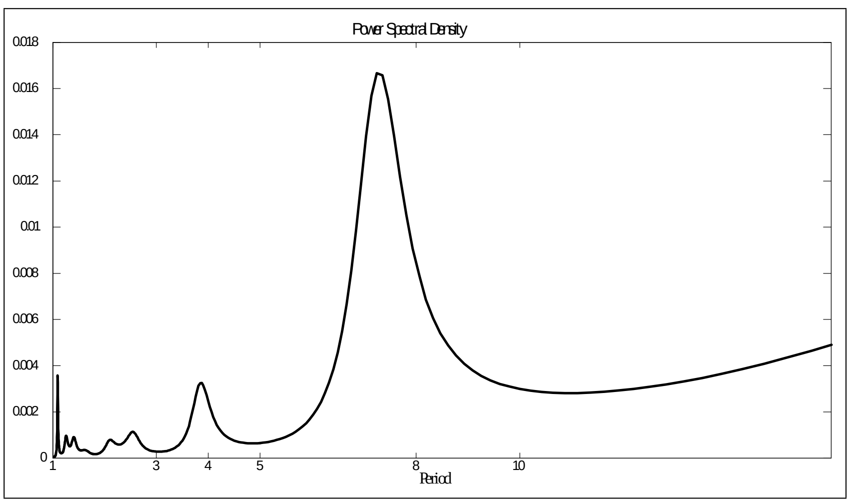


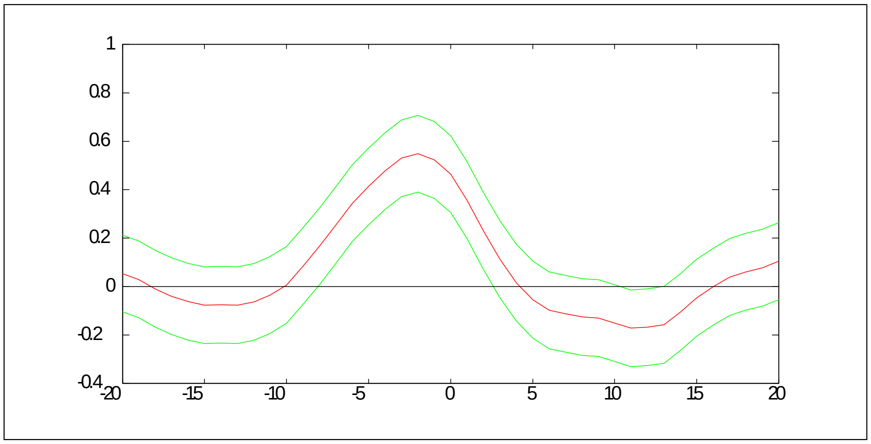
Figure 4: Spectral density of real loans to NFCs



The estimates indicate the existence of cycles in the series. For real GDP, the dominant cycle (biggest amplitude) has a period of around 6 years. It differs from that of real loans having a period of around 8 years. Both series have also shorter cycles. The spectral density of real loans to NFCs is in general higher than that of real GDP.

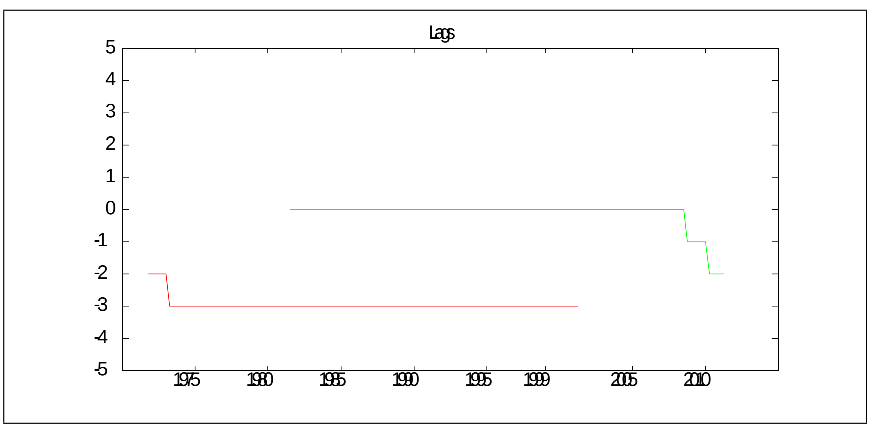
To analyze the lead-lag relationship time series methods like cross correlation are often applied (e.g., ECB (2011)). Using the full sample of data this approach indicates that real loans are lagging real GDP by 2 quarters. For this lag there is a maximum of the cross correlation values.

Figure 5: Cross correlation (full sample)



This type of analysis assumes that there are no structural breaks in the time series and in the relationship between these series. A simple exercise shows that this is not the case.

Figure 6: Cross correlation, optimal lag (recursive)



To get an idea, whether this relationship is stable over time, cross correlations and its corresponding maximum value are calculated for different sample sizes. The green series in Figure 6 represents this maximum value for a fixed starting point (1971) and an increasing end point. The red series represents the maximum value for an increasing starting point and a fixed end point (2011). The minimum size of the sample is 40 observations.

The peaks in the spectral densities (Figure 3 and Figure 4) might also be located at different subperiods of the sample. Therefore, analysing the wavelet power spectrum may be more informative.

Figure 7: Wavelet power of quarterly change of real GDP

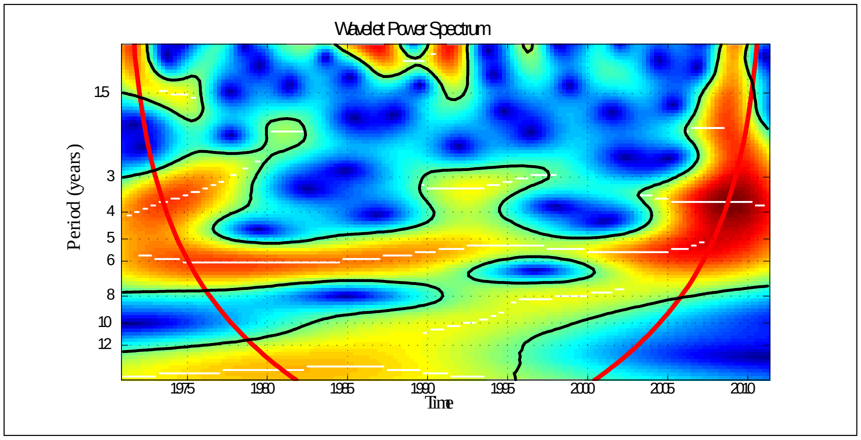
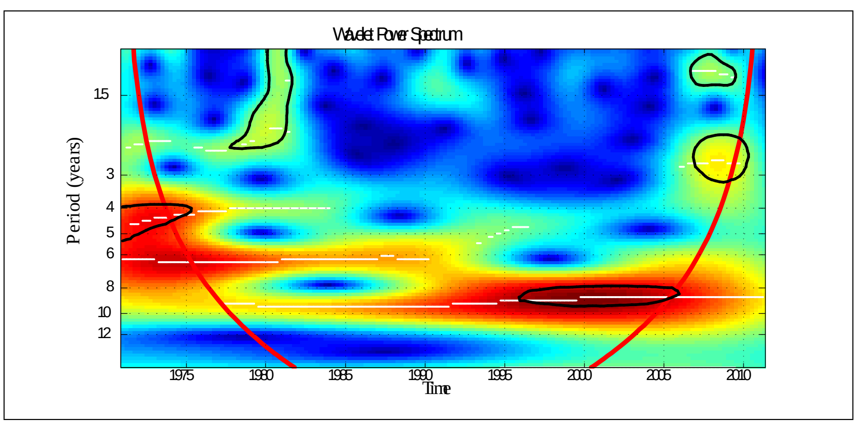


Figure 7 shows high and statistically significant wavelet power at business cycle frequencies up to 1990. From 1990 to 2000 the volatility is lower, but increases again afterwards, although at higher frequencies (around four years). Blue represents low power and red represents high power. The areas within black lines represent significant effects at 5 percent, within the grey lines at 10 percent.

Figure 8: Wavelet power of quarterly change of real loans to NFCs

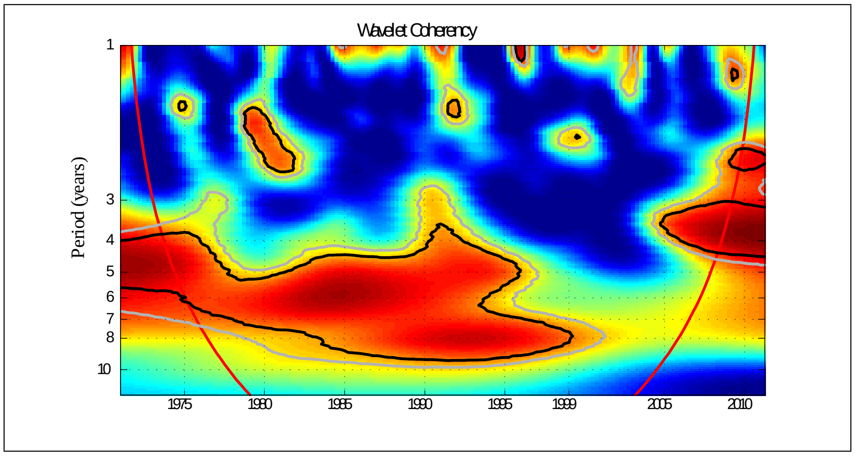


The wavelet power spectrum of real loans varies considerably over time (Figure 8). Periods of high volatility are the 70s and the subsample from 1995 to

2006. In the first case, the maximum of the spectrum (represented by white lines) is at periodicities around six years, in the second case, around nine to ten years. After 2005 there are also significant effects at higher frequencies.

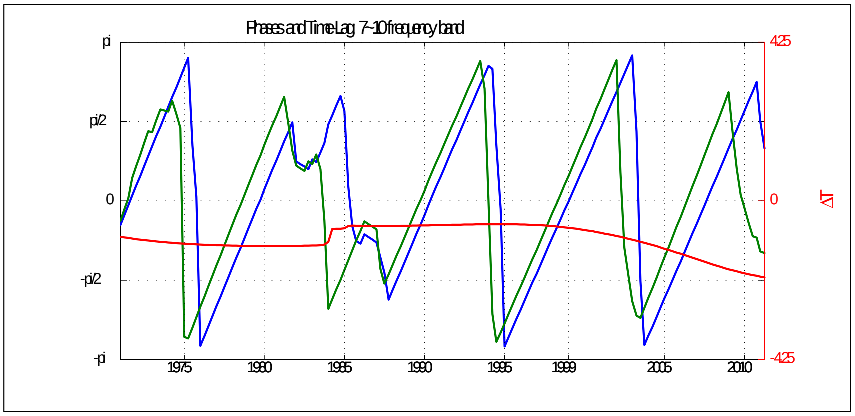
Comparing the power spectrum of both series might support the result by Aikman et al. (2010) that there are differences in the relevant periodicities of loans and GDP.

Figure 9: Wavelet coherence (loans to NFCs) and GDP



Regions outside the red lines ("cone of influence") should not be interpreted to much due to the beginning of and end of sample problem (zero padding or reflection).

Figure 10: Phase and time-lag



The results show that the coherence between real GDP and loans to non-financial corporations changes over time. In the 70s and 80s, there is a significant correlation in the frequency band of 5-8 years. Between 1997 to 2005 the coherence breaks down. For the most recent years, there is coherence for a period of 3 years. There is also considerable variation in the phase.

It might be that GDP is not the right determinant of the demand for loans. The same type of analysis is done for loans and investment shown in Figure 11. The time series of real gross investment is much more volatile than that of real GDP.

Figure 11: Loans and investment (quarterly growth rates)

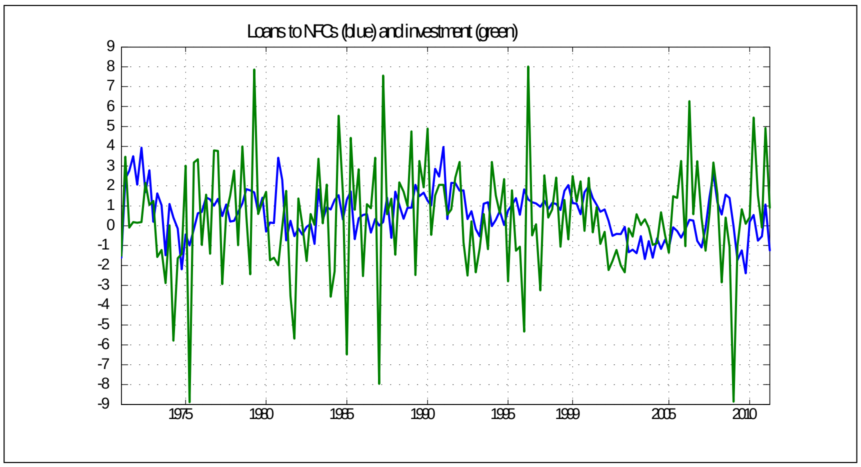
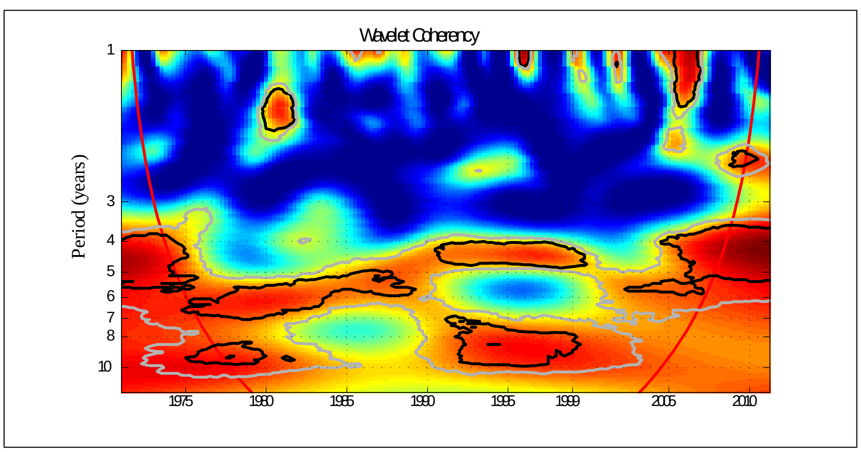
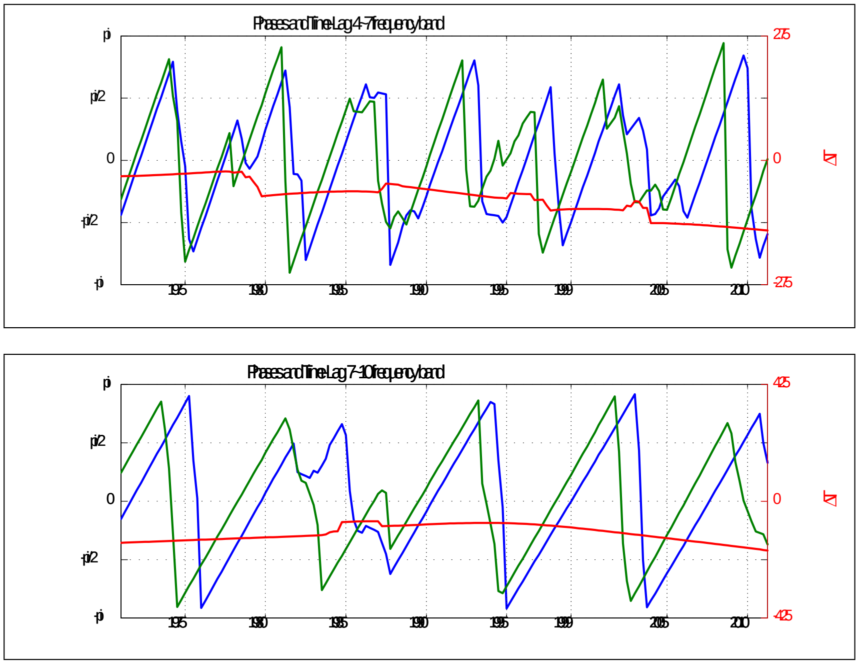


Figure 12: Wavelet coherency of loans to NFCs and investment



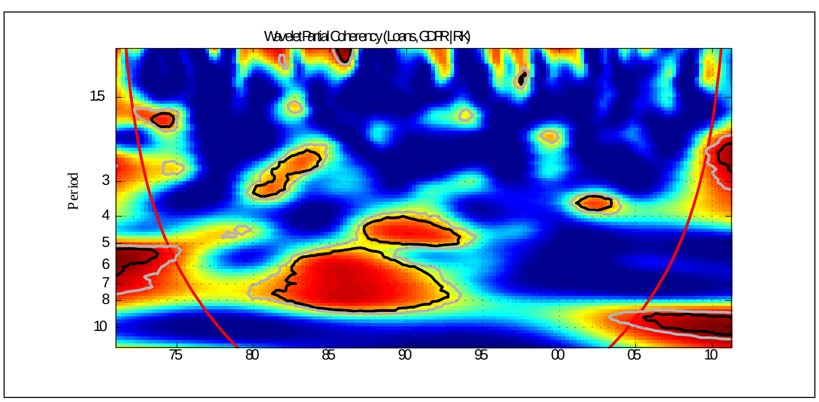
In this case, the coherency is more stable over time, although the contributions of various scales are time-varying (Figure 12). Figure 13 shows that real investment is leading relative to real loans.

Figure 13: Phase (loans to NFCs, investment)



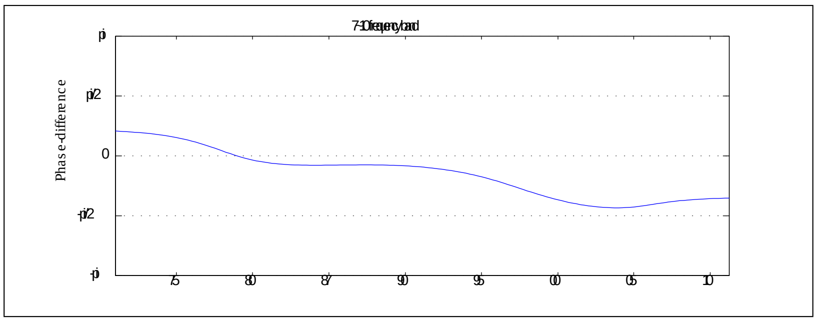
Due to the interaction with other macro variables the bivariate coherencies might be effected by these interdependencies. For the combination of loans and GDP the partial wavelet coherency conditional on the short-term interest rate (RK) is calculated (Figure 14). The short-term interest rate is included as a measure of monetary policy. A decreasing interest rate reduces the funding costs for the banking sector and also affects aggregate demand.

Figure 14: Partial wavelet coherency (LNFC, BIPR | RK)



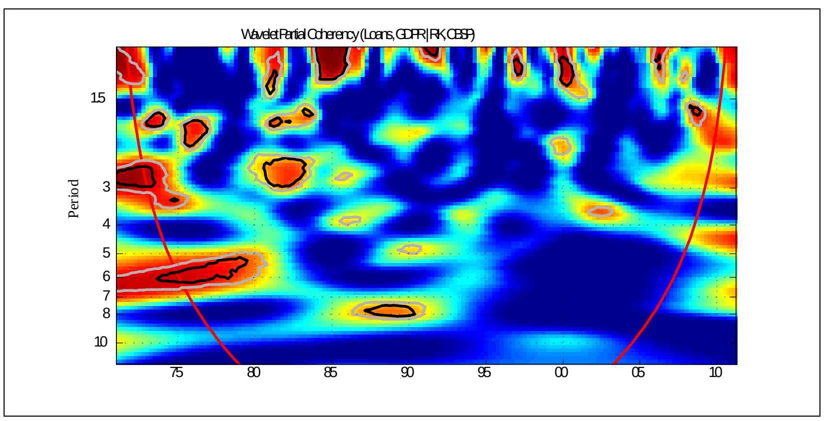
There is high coherency in the 80s and the first three years of the 90s. Between 1995 and 2005 there is no coherency at all. The high coherency at the beginning of the sample and at the end of the sample should be interpreted with caution as these subsamples are at the specific frequencies outside the cone of influence. Therefore, the lead of loans relative to GDP at the beginning of the sample should not be taken for sure. Within the cone of influence the lagging behaviour of loans doe not change.

Figure 15: Phase-difference (LNFC, BIPR | RK)



The evolution of loans might also be influenced by risk characteristics. Therefore, the corporate bond spread (CBSP) is included in the set of conditioning variables (Figure 16).

Figure 16: Partial wavelet coherency (LNFC, BIPR | RK, CBSP)



Extracting the effects of monetary policy and risk effects (spread), coherency in the 80s reduces dramatically. This implies that risk shocks are relevant.

4.3 Loans to private households

The analyses of ECB(2011) and Deutsche Bundesbank (2011) focus on the correlation of loans to private households and real GDP. The loans series excludes mortgages which are analysed separately.

Figure 17: Loans to private households and real GDP

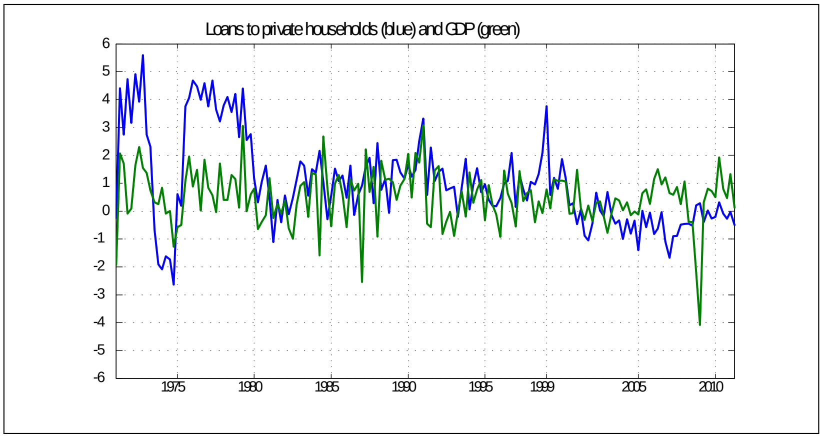
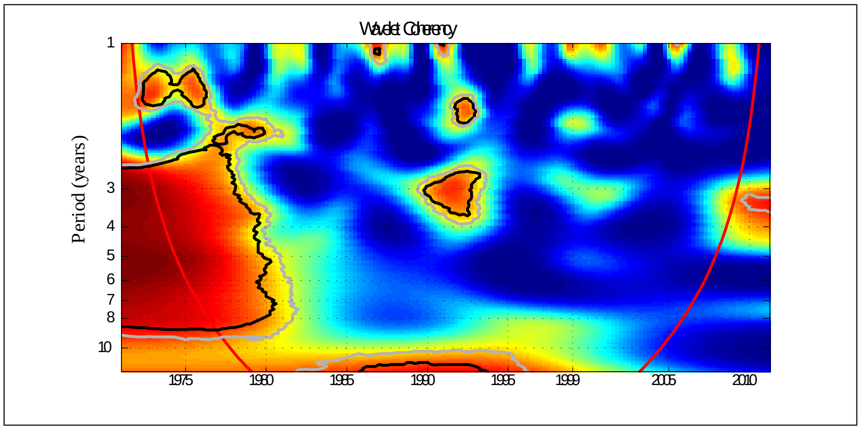


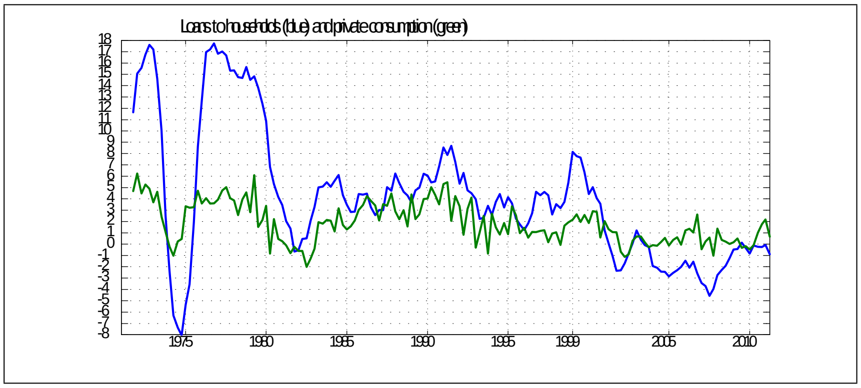
Figure 18: Wavelet coherency of loans to private households and GDP



For these series, the wavelet coherency is high only up to the 80s. Afterwards only for a short period and a high periodicity there are significant coherency effects.

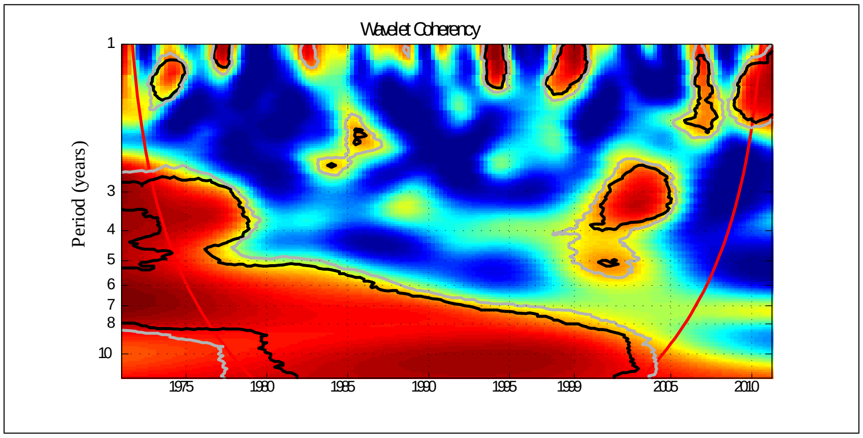
As loans to private households are mainly raised for consumption purposes it may be more reasonable to substitute GDP for private consumption.

Figure 19: Loans to private households and consumption (annual differences)



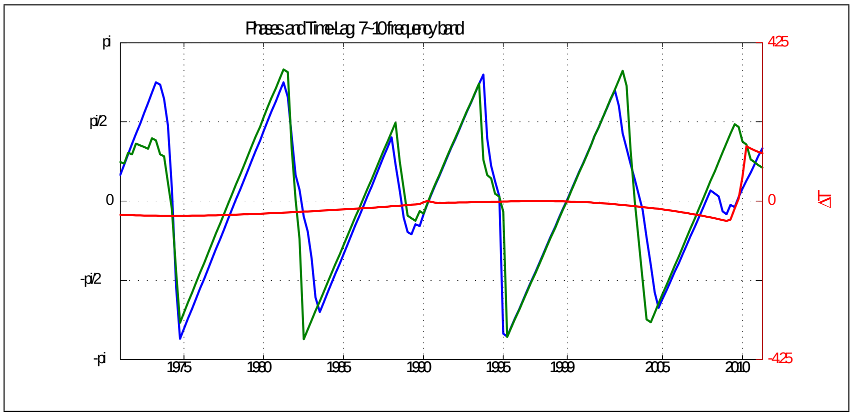
For the combination with private consumption, wavelet coherency is high for most of the sample (Figure 20). At the end of the sample, there seems to be a structural break as high coherency can only be observed for small scales. This might be explained by the increasing availability of credit to households for consumption purposes.

Figure 20: Wavelet coherency of loans to private households and consumption



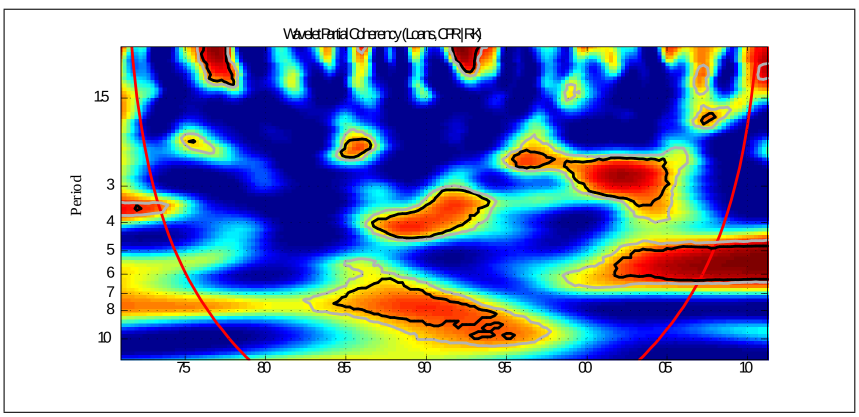
Until 1990 the phase diagram indicates a lead of real consumption, although the time lag is short. In the 90s the correlation of both variables at periodicities between 7 and 10 years was contemporaneous (Figure 21).

Figure 21: Phase (LHH, CONS)



Looking at the partial coherency of loans and consumption removing the interaction with the short-term interest rate reduces the correlation at most scales and for most of the sample period (Figure 22).

Figure 22: Partial wavelet coherency (LHH, CONS | RK)



4.4 Mortgages

For mortgages (Figure 23) the coherency with GDP differs from that of the other types of loans.

Figure 23: Mortgages and GDP

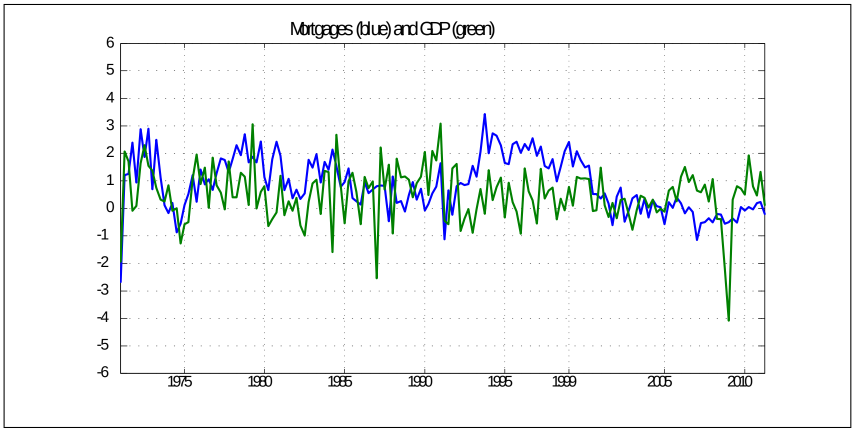
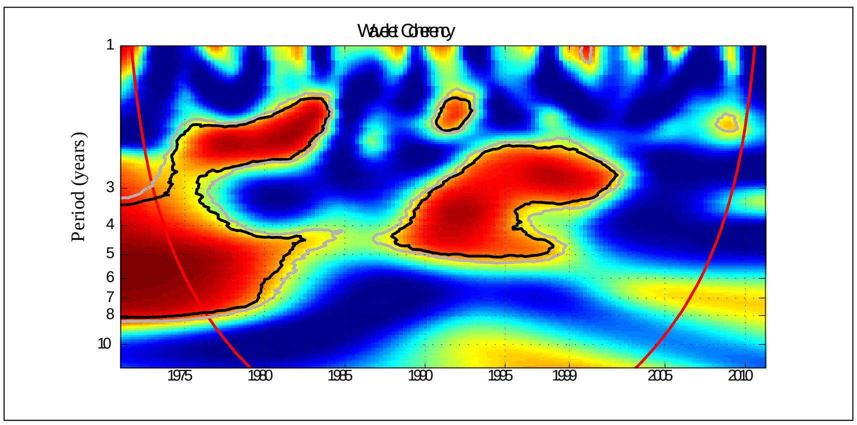
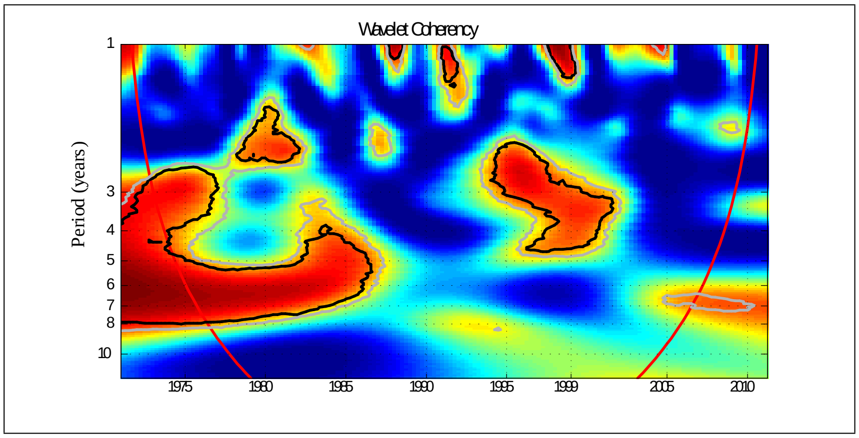


Figure 24: Wavelet coherency with real GDP



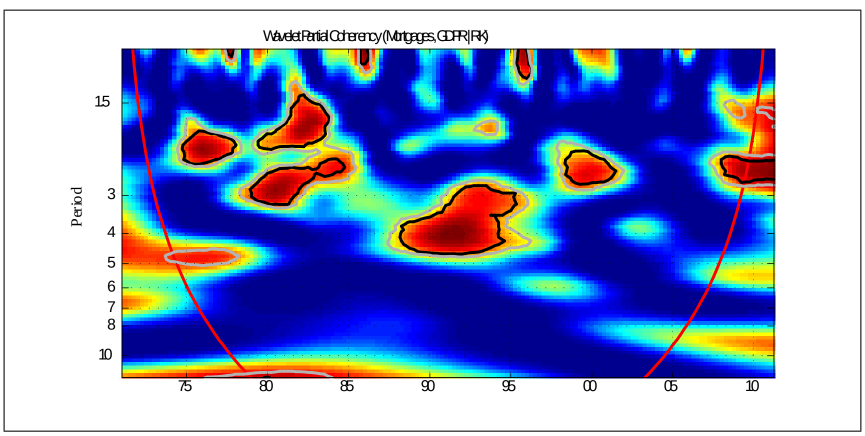
There is coherency in the 70s on the business cycle type of scales but also at smaller scales (Figure 24). In the 80s coherency is quite low. At small scales there is high correlation in the 90s but not afterwards. This might be caused by a small boom in construction of houses after German unification. The results for coherency with the short-term interest rate are quite similar (Figure 25).

Figure 25: Coherency with short-term interest rate



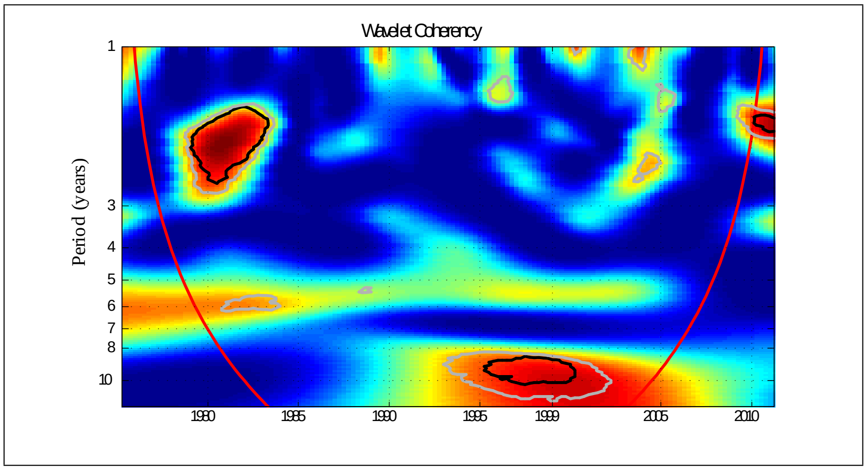
Extracting the interaction of mortgages and loans with the short-term interest rate, the partial coherency reduces to small intervalls in time and scale.

Figure 26: Partial wavelet coherency with real GDP conditional on short-term interest rate



Another possible determinant of mortgages could be the variation in house prices. Figure 27 shows that coherency in general is not high. This reflects the fact that there was no housing bubble in Germany. Economic agents did not buy houses expecting rising prices in the future, i.e. (future) house prices were no criterion for buying a house.

Figure 27: Coherency with house prices



5 Conclusion

Wavelet analysis allows for a quick look at the time-variation of comovement of time series at various frequencies. This methodology can be used to identify structural breaks in the sense of a complete break down of correlation or a shift in relevant frequency bands.

The results indicate a different structure of correlation between various components of loans and the business cycle. For loans to non-financial corporations there is a high coherency with GDP up to the 90s, whereas for loans to private households there is no coherency apart from the 70s. Coherency for loans to non-financial corporations is higher with investment and for loans to private households with private consumption. Differences in the lead-lag relationship at business cycle frequencies are also time-varying in the sense that the time-lag changes but not in the sense that the relevant variables change their roles.

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