REAL AND FINANCIAL CYCLES IN THE GREEK ECONOMY*

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1 INTRODUCTION

This paper presents estimates of short- and medium-term frequency cycles for a number of key variables of the Greek economy and explores their characteristics. Eight time series are considered: real GDP; real total credit to the private non-financial sector and its household and corporate lending components; an index of residential property prices; an equity price index; nominal long-term interest rates; and the interest rate term spread. The aim is to systematically study Greek real and financial cycles at both frequencies and to examine whether they exhibit the stylised facts identified in the relevant academic literature for other countries. The interaction between the business (or real) cycle and the financial cycle is also explored, against the backdrop of the insights gained from the recent financial crisis.

The most related research is by Tsouma (2014), who dates the Greek business cycle using both turning point analysis and Markov switching. However, like most of the literature, she focuses exclusively on conventional business cycle frequencies and does not consider the interplay between real and financial cycles. Michaelides et al. (2013) consider EU and US influences on the Greek business cycle using both a Hodrick-Prescott filter and a bandpass filter, but their work is subject to the same limitations. Finally, Karfakis (2013) considers the relationship between credit and business cycles in Greece using Granger causality analysis of Hodrick-Prescott filtered series, but focuses on a single decade and on short-term business cycle frequencies. Our work goes beyond existing research, as medium frequency cyclical fluctuations have not to date been extracted for the Greek economy, nor has the interplay between real and financial cyclical fluctuations at longer frequencies yet been studied.

According to the literature, variables associated with real economic activity such as GDP are thought to exhibit a cyclical behaviour of a short periodicity, known as a business cycle (see for example Baxter and King 1996). Conversely, financial variables such as credit tend to exhibit longer cycles, known as financial cycles (see Drehmann et al. 2012 and Claessens et al. 2012). We estimate both short and medium frequency cycles for all eight data series under consideration. Moreover, we attempt to gauge which periodicity is most dominant for each time series, by estimating what we call an "overall cycle". Five alternative techniques are used: turning point analysis; bandpass filters; the Hodrick-Prescott (HP) filter; univariate structural time series models (STSMs); and multivariate STSMs. The extracted cycles are compared by series, methodology and frequency, and their main features and co-movement properties are discussed. Particular emphasis is placed on the relationship between financial variables and GDP.

Finally, as these empirical estimates are an extension and update of the work undertaken by the authors as part of the Team on Real and Financial Cycles of the Working Group on Econometric Modelling of the European System of Central Banks (ESCB), part of which was published in Rünstler et al. (2018), the results presented here for Greece are also set against the corresponding findings reported by Rünstler et al. (2018) for other European economies.

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We find that medium frequency fluctuations dominate over business cycle frequency fluctuations for all variables, including GDP. The average duration of the medium frequency cycle in GDP is found to be between 32 and 55 quarters, depending on the methodology, i.e. much longer than conventional business cycle frequencies, while those of the three credit variables are almost twice as long, confirming that financial cycles are generally much longer than real ones. Finally, we find that the medium frequency cyclical components are found to be highly correlated and that their lead-lag behaviour is in line with economic intuition.

The remainder of the article is structured as follows: Section 2 presents the data. Section 3 reports the findings obtained from the non-structural approaches, i.e. the turning point analysis and the bandpass filter at different frequencies. It also discusses the corresponding results obtained using the Hodrick-Prescott filter. Section 4 presents the univariate and multivariate structural time series model estimates of the variables' cyclical components. Finally, Section 5 concludes.

2 THE DATA

We consider eight time series in the analysis: real GDP; real total credit to the private non-financial sector; real credit to households; real credit to non-financial corporations (NFCs); real residential property prices; an equity price index; a nominal long-term interest rate; and the interest rate term spread. Data are quarterly and cover a maximum time span of 1970Q1-2017Q4. The nominal long-term interest rate is the yield on 10-year government bonds. The spread is defined as the difference between the long-term interest rate and the 3-month short-term interest rate. GDP, credit variables and residential property prices have been deflated with the GDP deflator. All series with the exception of the long-term interest rate and the spread are in logs. Details about the data are provided in Table A1 in the Appendix.

3 NON-STRUCTURAL APPROACHES

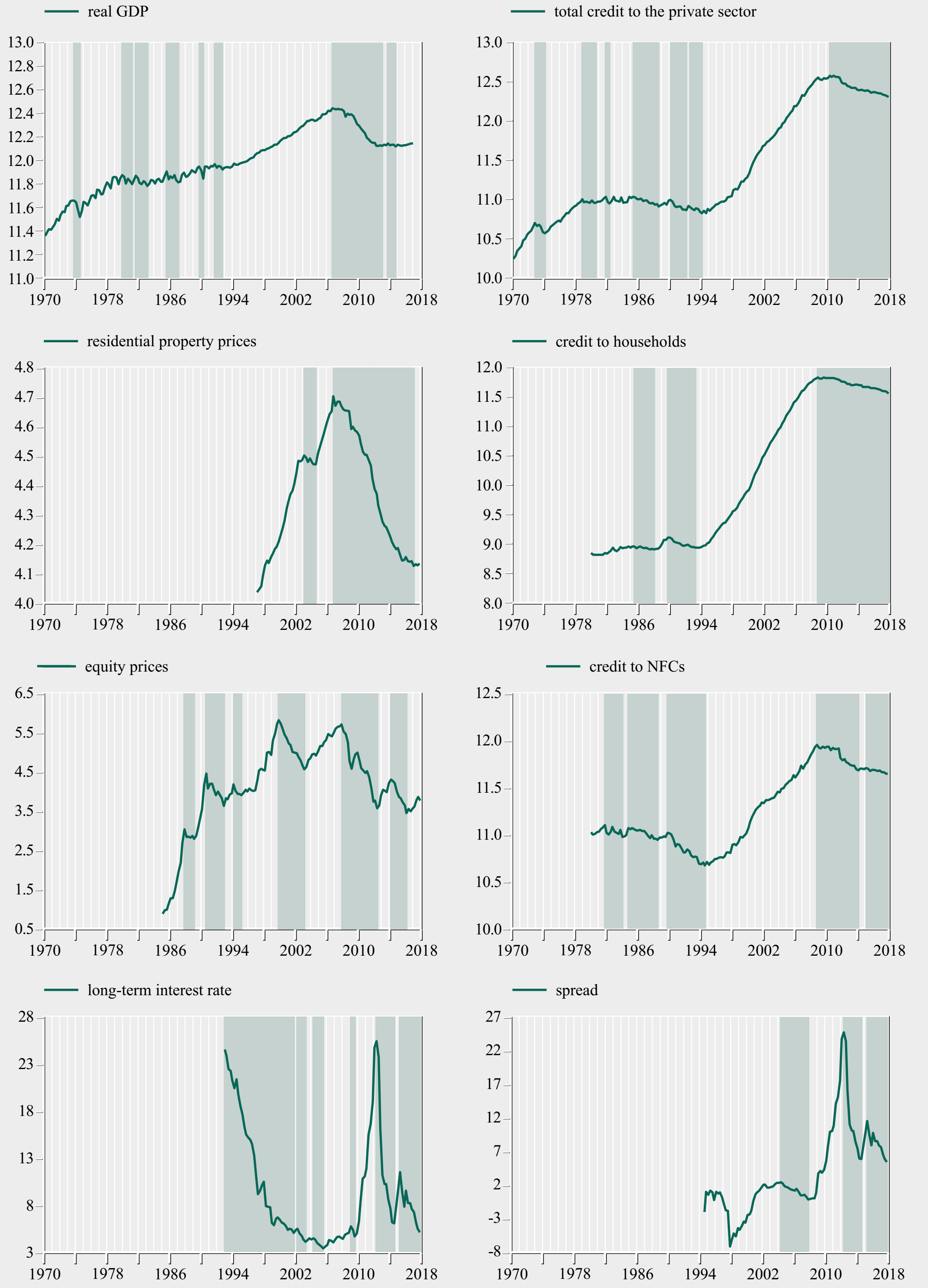
3.1 TURNING POINT ANALYSIS

Turning point analysis was originally introduced by Burns and Mitchell (1946) as a means of dating the business cycle and was subsequently modified by Bry and Boschan (1971) and Harding and Pagan (2002). It identifies cyclical peaks and troughs in a series via a two-step procedure: first, the local maxima and minima of the series are identified; subsequently they are filtered through a censoring rule, to guarantee a minimum cycle length, a minimum phase length, that peaks and troughs alternate and that a trough (peak) is lower (higher) than the preceding peak (trough).

As in Harding and Pagan (2002) and Drehmann et al. (2012), we employ two alternative parameterisations, designed to capture short and medium frequency fluctuations. For the short frequency fluctuations we define local maxima (minima) at time t as points where the value of the series is the highest (lowest) within the five-quarter window centered at t. Such points are defined as peaks (troughs) of the cycle if they fulfil two conditions, namely that each cycle has a minimum length of five quarters and each phase (expansion or contraction) is at least two quarters long. To capture cycles that are longer than what is commonly considered a business cycle frequency, we modify the algorithm to set the minimum cycle length at eight years (32 quarters) and determine local maxima and minima over an eight-quarter window. Thus, we obtain a subset of the peaks and troughs obtained with the short frequency parameterisation.

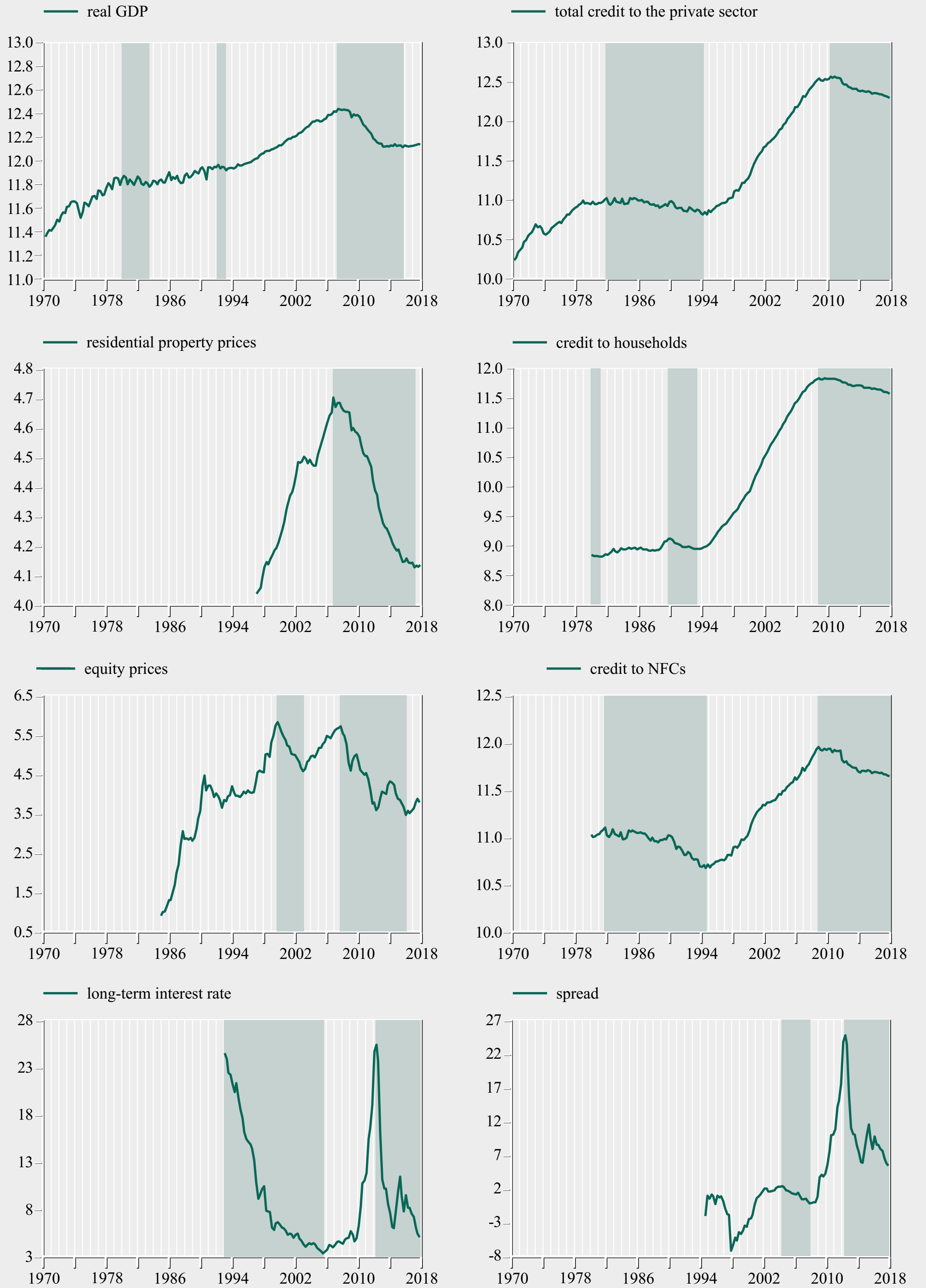
Charts 1 and 2 present the results of the turning point analysis for short-term and medium-term frequencies, respectively. In both charts, the eight data series themselves are plotted for the maximum sample available in each case. The results of the turning point analysis are presented as shaded areas. Areas in green denote downturns, while those in grey denote upswings. The peak of a cycle is the last data-

Chart 1 Turning point analysis - Short-term frequencies (1970Q1-2017Q4)



Source: Authors' own econometric estimations.

Chart 2 Turning point analysis - Medium-term frequencies (1970Q1-2017Q4)



Source: Authors' own econometric estimations.

Table 1 Turning point analysis: Duration of short-term and medium-term cycles

	Short-term cycles			Medium-term cycles		
	Expansion	Contraction	Cycle	Expansion	Contraction	Cycle
	Number of quarters			Number of quarters		
GDP	15.9	7	23.2	46	16.7	54.5
Residential property prices	9	23.5	15	40	41	-
Total credit	18	7	25	65	49	114
Credit to households	34.5	12	46.5	48.5	14	76
Credit to NFCs	17.25	16	33.25	57	51	108
Equity prices	11.2	9.5	21	19	23	32
Long-term interest rate	6.8	5	13	27	51	78
Spread	10.5	11.5	22	18	14	32

Note: The duration of a full cycle is measured from peak to peak.

point in grey and the trough is the last datapoint in green. Throughout the paper we define a full cycle as a peak-to-peak fluctuation.

The top left graph of Chart 1 presents GDP. Upturns therein denote periods of economic expansion and downturns denote recessions. A number of short-lived downturns are identified at short-term frequencies in the first half of the sample, followed by a far more protracted one during the recent crisis period. More specifically, the analysis points out six short-lived recession episodes that took place until the mid-90s and a more lengthy recession that started at the beginning of 2007 and coincided with the global financial crisis. Regarding the findings at medium-term frequencies, Chart 2 shows that the algorithm captures main peaks and troughs in GDP by eliminating short-lived fluctuations. In particular, it identifies a period of expansion during the early '80s that is followed by a stagnation period until the mid-90s, and a period of strong recovery from the mid-90s until the beginning of 2007. As regards recent developments in GDP, the results indicate a large drop in GDP since 2007 that reached its trough at the end of 2015. These results are in line with the established narrative of how the Greek economy evolved over the period under study. They closely match those documented in Tsouma (2014), who dates the Greek economic cycle, and Gogos et al. (2014), who identify a big decline in GDP during the early '80s and until the mid-90s and a strong expansion since the mid-90s.

As Charts 1 and 2 illustrate, a number of the upswings and downturns in GDP are also mirrored in the graphs for the financial variables. Notably, the beginning of the latest major property price downturn roughly coincides with the beginning of the recent recession. However, the corresponding turning point comes somewhat later for credit variables. In general, the turning point associated with the recent financial crisis is naturally identified in all panels. It is worth noting that at short-term frequencies the peak and trough dates for total credit closely match those for GDP. At medium-term frequencies, the results reveal a drop in total credit and credit to NFCs during the '80s, followed by a large expansion in all credit variables, as well as in property prices since the mid-90s. While equity prices fluctuate a lot at short-term frequencies, their cyclical fluctuations are more protracted at medium-term frequencies. The interest rate and the spread display a similar behaviour over the sample period. Both expanded during the recent sovereign debt crisis and reached their peak in 2012.

Table 1 presents the average duration of the short- and medium-term cycles identified by the turning point analysis of the data, as well as the respective average duration of contractions and expansions. The average duration of the short-term cycles in GDP is 23.2 quarters, close to the corresponding short frequency cycles identified for total credit, equity prices and the spread. However, overall the credit variables have substantially longer cycles than GDP, ranging from 25 to 46.5 quarters. For the vast majority of variables, expansions are longer than contractions during the period in question.

Turning to the medium-term cycles, the average duration of GDP cycles is 54.5 quarters, fairly long for a real variable, but substantially shorter than the corresponding metric for the three credit variables. For GDP and the credit variables, expansions remain much longer than contractions. It is notable that the characteristics of the medium frequency cycles detected for GDP and loans to households are very similar. On the other hand, the medium frequency fluctuations of equity prices are relatively short, just 32 quarters, as are those of the spread.

3.2 BANDPASS FILTER

3.2.1 Cycles

The second approach we employ is the bandpass filter, a more sophisticated econometric methodology increasingly used for the estimation of cycles in economic variables – see for example Comin and Gertler (2006), Drehmann et al. (2012) and Aikman et al. (2015). This methodology is designed to extract cyclical components of a specific periodicity from individual time series. Following Christiano and Fitzgerald (2003) we employ the asymmetric bandpass filter assuming a unit root with a drift, to isolate short-term cycles with a duration of between 8 and 32 quarters (i.e. 2 to 8 years) and medium-term cycles with a duration of between 32 and 120 quarters (i.e. 8 to 30 years), in line with the turning point analysis.

Charts 3 and 4 plot the bandpass-filtered series obtained using the short and medium frequency specification, respectively. Turning first to Chart 3, a number of short frequency fluctuations appear in the GDP series. Credit series display a similar cyclical periodicity but seem to exhibit greater volatility. The short periodicity cycles of total credit and its subcomponents, i.e. credit to households and credit to NFCs, are highly correlated as seen in the left-hand panel of the second column of Chart 3. The same can be said for the long-term interest rate and spread fluctuations, with the recent pronounced fluctuation reflecting interest rate and monetary policy movements during the crisis. Short frequency housing price fluctuations seem relatively smaller in terms of variance.

Chart 4 presents in solid lines the filtered series obtained using the 32-120 quarter bandpass filter specification. Here, the synchronicity of the extracted medium frequency cycles is striking for the majority of variables. Real GDP and all three credit variables seem to exhibit two major cycles, which appear very highly correlated. The residential property price index is available from 1997 onwards and thus exhibits only the second hump, capturing the pre-crisis property boom and the recent protracted decline in property prices.

Table 2 presents the standard deviation of the short- and medium-term cycles identified in the bandpass-filtered series. Regarding the variability of the cyclical components, the financial variables seem to be more volatile than GDP both at short- and medium-term frequencies. In addition, for all variables, the standard deviation of the short-term cycle is, intuitively, substantially smaller than that of the corresponding medium-term cycle. The third column presents the relative standard deviation, i.e. the ratio of the two that provides an indication of the relative importance of the periodicity of the cycle in the behaviour of the series. Notably, for residential property prices and credit variables —especially loans to households, which comprise mostly mortgages— the medium-term component seems to account for much more of the variable's vari-

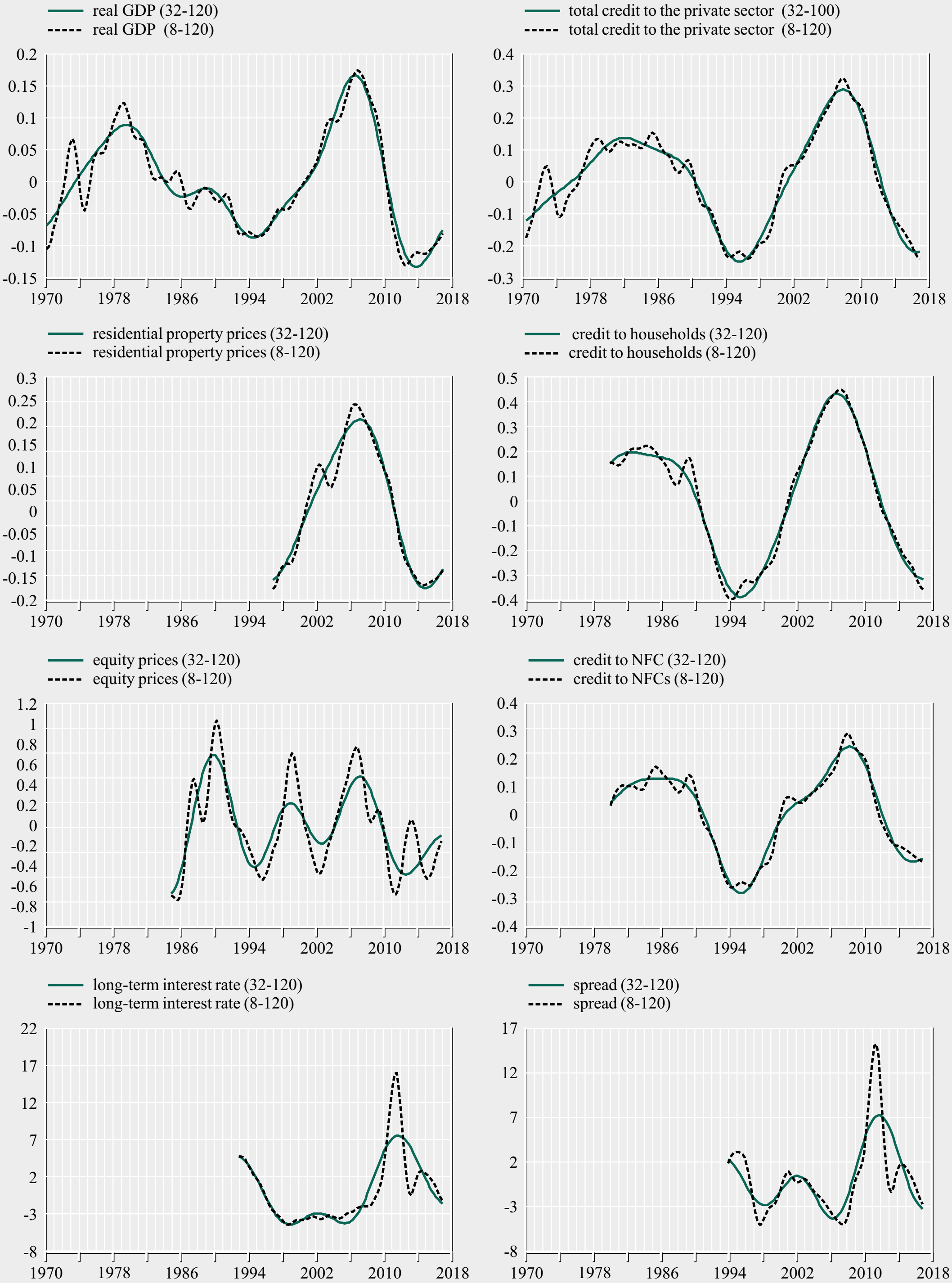
Chart 3 Bandpass filter - Short-term cycles (1970Q2-2017Q4)

Source: Authors' own econometric estimations.
Note: Short-term cycles were computed using a bandwidth of 8-32 quarters.

ation. The ratio of the standard deviation of the medium-term cyclical component to that of the short-term cyclical component is 5.783 for residential property prices and 7.656 for credit to households. The value of this metric for GDP is substantially lower, at 3.8, as credit and property prices are known to exhibit cycles that are larger than the business cycle. Nevertheless, it may be viewed as relatively high for a real variable. Conversely, the two cyclical components of the spread and the long-term interest rate have a roughly similar standard deviation.

Table 3 presents the average duration of the short and medium frequency cycles, as well as the respective average duration of contractions and expansions. As before, cycle lengths are

Chart 4 Bandpass filter - Medium-term and overall cycles (1970Q2-2017Q4)



Source: Authors' own econometric estimations.
Note: Medium-term and overall cycles were computed using a bandwidth of 32-120 and 8-120 quarters, respectively.

Table 2 Properties of the filtered series: Standard deviation of short-term and medium-term cycles – Bandpass filter

	Short-term cycles	Medium-term cycles	Relative Std.	Overall cycles
GDP	0.02	0.076	3.8	0.078
Residential property prices	0.023	0.133	5.783	0.136
Total credit	0.032	0.147	4.594	0.15
Credit to households	0.032	0.245	7.656	0.247
Credit to NFCs	0.026	0.148	5.692	0.15
Equity prices	0.229	0.342	1.493	0.43
Long-term interest rate	0.024	0.04	1.667	0.047
Spread	0.025	0.033	1.32	0.043

Notes: The standard deviation for each variable is computed for the period in which data are available. The relative standard deviation is the ratio of the standard deviation of the medium-term cyclical component to the standard deviation of the short-term cyclical component. The overall cycles are extracted from a frequency band of 8-120 quarters.

defined as the average distance between the peaks of the cycles, the latter having been obtained by applying turning point analysis to the bandpass-filtered series using the afore-mentioned parameterisations. The phases and cycles identified in the filtered series are by and large shorter than those identified in the raw data. This is especially true of short frequency credit variable expansions. Conversely, GDP, residential property prices and credit to households exhibit longer medium frequency downturns than those identified in the raw data. More specifically, short frequency cycles identified in GDP have an average duration of 13.8 quarters, compared to a duration of 23.2 quarters in the raw data. This duration is comparable to the corresponding metric for credit to NFCs, which is 14.9 quarters. Short

Table 3 Properties of the filtered series: Duration of short-term and medium-term cycles – Bandpass filter

	Short-term cycles			Medium-term cycles			Overall cycles		
	Expansion	Contraction	Cycle	Expansion	Contraction	Cycle	Expansion	Contraction	Cycle
	Number of quarters			Number of quarters			Number of quarters		
GDP	7.9	5.9	13.8	30.5	26	55	32.5	23.3	56
Residential property prices	10.5	7.25	17.5	43	32	-	41	33	-
Total credit	9.5	7.8	17.3	50	56	106	46	43	92
Credit to households	10.4	10.8	20.8	46	53	99	52	40	92
Credit to NFCs	6.67	8.25	14.9	52	34	90	55	37	92
Equity prices	9.67	8	17.5	18	19	35.5	45	20.5	67
Long-term interest rate	8	7.8	16.6	52	26	78	52	25	77
Spread	6.4	16	9.6	18.5	19	39	19	14	33

Note: The durations have been computed using turning point analysis in the filtered series. A full cycle is measured from peak to peak. The overall cycles are extracted from a frequency band of 8-120 quarters.

cycles in the remaining two credit variables, i.e. in equity prices and in residential property prices, are on average somewhat longer.

Turning to medium frequency cycles, the average duration of the medium frequency cycle in GDP is approximately half of the durations calculated for the three credit variables (55 quarters for the former and between 90 and 106 for the latter). Conversely, medium frequency cycles for equity prices are much shorter than the corresponding GDP cycles. Overall, the medium frequency cycle durations obtained from the bandpass filter are consistent with the findings of the turning point analysis.

The approach adopted above provides valuable insights. However, as discussed in Rünstler et al. (2018), the fact that the frequency bands have been chosen in advance on the basis of pre-existing perceptions of business and financial cycle frequencies implies a risk of partially truncating the cyclical dynamics or of obtaining spurious cycles (see Murray 2003). Moreover, when the frequency bands used for extracting short frequency (business) and medium frequency (financial) cycles do not overlap, as in our case, the resulting estimates of cycles will be uncorrelated by construction, rendering it impossible to explore whether business and financial cycles are independent or correlated. By contrast, to explore whether two cycles are interrelated, a methodology that allows us to extract correlated cycles is warranted. To address these concerns, we also extract an "overall cycle" using a much broader bandpass filter specification so as not to impose a constraint on the cycles extracted, namely a bandpass filter of 8-120 quarters (2-30 years).[1] This choice of bandwidth captures both business and medium-term frequencies, i.e. it is agnostic with respect to this distinction. We interpret this cycle as the dominant cyclical fluctuation driving each series and explore how the cycles detected in the various variables relate to each other.

The last columns in Tables 2 and 3 correspond to this broader bandwidth. The last column in Table 2 presents the standard deviation of the overall cycle extracted using the 8-120 quarter frequency. The overall cycle of all credit variables, i.e. their dominant cyclical fluctuation, is very close in terms of standard deviation to the medium-term cycle extracted using the 32-120 quarter frequency. This is expected on the basis of the literature, which concurs that the duration of the financial cycle is long. However, the standard deviation of the overall cycle of GDP is also very close to that of its medium-term cycle. The same is true of the cycle durations presented in the last column of Table 3. This finding contradicts the idea that GDP fluctuations are always at "business cycle" frequencies. Interestingly, in the case of Greece, real economic activity seems to exhibit more protracted cyclical fluctuations (56 quarters) than the corresponding average for other European countries reported in Rünstler et al. (2018), which is about 30 quarters (though it should be noted that they use a maximum duration of 80 quarters for their medium-term bandpass filter). The GDP cycle's standard deviation is also somewhat higher. The extracted cyclical components are plotted in Chart 4, in dashed lines, and indeed they track the corresponding medium-term cyclical components very closely.

Charts A1 and A2 in the Appendix present the bandpass-filtered series plotted against the corresponding cyclical components extracted using an HP filter. Tables A2 and A3 in the Appendix present information on the HP-filtered series derived using turning point analysis and are directly comparable to Tables 2 and 3. The only notable discrepancy between the two sets of results is the very long duration of the medium-term cycle identified in real GDP using the HP filter (114 quarters), reflecting the fact that an interim upturn is not picked up

1 As a robustness check we also extract cycles using the 8-80 quarter band, as in Rünstler et al. (2018). The findings are available from the authors upon request. The resulting cycles are qualitatively and quantitatively similar. The only exception is credit variables, which in the case of Greece appear to exhibit a medium-term cycle of more than 80 quarters. However, credit variables are key to our analysis. Moreover, our objective is to extract cyclical components without pre-imposing limits and the main advantage of the bandpass filter methodology is that it allows us to do so. Thus, we report the results extracted using the 120-quarter upper filter bound suggested by Drehmann et al. (2012) as our main results.

by the turning point analysis algorithm. This difference notwithstanding, the results are quantitatively and qualitatively very similar.

3.2.2 Co-movements

Having extracted cyclical components from the variables using a number of alternative parameterisations, we now explore how GDP cycles are related to those of other variables in Tables 4 to 6. Table 4 presents the co-movement properties of the short-term cycles extracted using the bandpass filter, i.e. the correlation of each variable's short-term cycle shifted by [-4, 4] periods, with the short-term GDP cycle in period *t*. This is a convenient way of examining which variable leads the other. The largest correlation in absolute terms determines the lead-lag property of the cycle of a given series relative to that of GDP. Numbers in bold indicate the highest correlation. In the first row, we see that the short-term cyclical component of residential property prices leads that of GDP by four quarters, while credit to households leads by one. The short frequency cycle in total credit and that in credit to NFCs lag the GDP short cycle by two quarters, while equity prices (inversely) lag by a year. Conversely, short frequency fluctuations in the long-term interest rate and the spread inversely lead those in GDP by two quarters, i.e. low interest rates today forecast future booms in the GDP business cycle. This is in line with the well-known inverted leading indicator property of real interest rates documented by King and Watson

Table 4 Co-movement properties of the filtered series: Short-term cycles – Bandpass filter

	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	**0.4787**	0.4196	0.3289	0.2196	0.1049	-0.0058	-0.1048	-0.1858	-0.2467
Total credit	0.2242	0.2715	0.3351	0.4092	0.4789	0.5232	**0.5245**	0.4709	0.3615
Credit to households	0.3999	0.4495	0.4825	**0.4956**	0.4867	0.4649	0.4089	0.3161	0.1881
Credit to NFCs	0.1508	0.2207	0.3074	0.407	0.5056	0.5808	**0.6131**	0.5879	0.502
Equity prices	0.1825	0.1503	0.1094	0.0509	-0.0313	-0.1401	-0.2676	-0.3995	**-0.5177**
Long-term interest rate	-0.5206	-0.6264	**-0.6702**	-0.6527	-0.5808	-0.4647	-0.3152	-0.1434	0.0379
Spread	-0.4995	-0.5738	**-0.5994**	-0.5767	-0.5079	-0.3954	-0.2448	-0.0665	0.126

Notes: The table presents the correlation of each variable's cycle shifted by *i*∈[–4, 4] periods with the GDP cycle in period *t*. Correlations are computed over the period 1997Q2-2017Q4. Numbers in bold indicate the highest correlation over *i*∈[-4, 4].

Table 5 Co-movement properties of the filtered series: Medium-term cycles – Bandpass filter

	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.8338	0.8734	0.907	0.9346	0.9559	0.9716	0.9808	**0.9831**	0.9782
Total credit	0.6373	0.6958	0.7491	0.797	0.8393	0.877	0.9098	0.9371	**0.9584**
Credit to households	0.7397	0.7853	0.8253	0.8596	0.8882	0.9133	0.9329	0.9465	**0.9539**
Credit to NFCs	0.5952	0.6572	0.7146	0.767	0.814	0.858	0.8973	0.9309	**0.9579**
Equity prices	0.7295	0.7582	0.7786	0.7903	**0.793**	0.7878	0.7755	0.7567	0.732
Long-term interest rate	**-0.7253**	-0.6765	-0.6206	-0.558	-0.4896	-0.4282	-0.3638	-0.2968	-0.2274
Spread	**-0.7273**	-0.6901	-0.6432	-0.5873	-0.5235	-0.4742	-0.42	-0.3613	-0.2986

Notes: The table presents the correlation of each variable's cycle shifted by *i*∈[–4, 4] periods with the GDP cycle in period *t*. Correlations are computed over the period 1997Q2-2017Q4. Numbers in bold indicate the highest correlation over *i*∈[-4, 4].

Table 6 Co-movement properties of the filtered series: Overall cycles – Bandpass filter

	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.82	0.8578	0.889	0.914	0.9329	0.9465	0.9537	**0.954**	0.9473
Total credit	0.6261	0.6842	0.7374	0.7857	0.8285	0.8664	0.8985	0.924	**0.9424**
Credit to households	0.7333	0.7771	0.8151	0.8474	0.8743	0.8967	0.9137	0.9248	**0.9296**
Credit to NFCs	0.5766	0.6381	0.6957	0.7493	0.7979	0.8419	0.8801	0.9109	**0.9335**
Equity prices	0.5487	0.567	0.5773	**0.5786**	0.5701	0.5491	0.5203	0.4853	0.4462
Long-term interest rate	**-0.6446**	-0.615	-0.5738	-0.5212	-0.4585	-0.3981	-0.3319	-0.261	-0.1865
Spread	**-0.5842**	-0.5665	-0.5359	-0.4925	-0.4374	-0.3849	-0.3275	-0.2666	-0.203

Notes: The table presents the correlation of each variable's cycle shifted by $i \in [-4, 4]$ periods with the GDP cycle in period t. Correlations are computed over the period 1997Q2-2017Q4. Numbers in bold indicate the highest correlation over $i \in [-4, 4]$.

(1996), Beaudry and Guay (1996) and Fiorito and Kollintzas (1994).

Turning to Table 5, we explore the co-movement between the medium frequency cyclical components extracted using the bandpass filter. As already observed in Chart 4, the medium frequency cyclical components are far more correlated than those at the short frequency. In addition, all variables with the exception of the long-term interest rate and the term spread are procyclical with the GDP cycle. Residential property prices and all three credit variables now appear to lag GDP. This finding is in contrast with a growing body of evidence which indicates that the medium-term financial cycle leads the business cycle and that financial cycle downturns lead on to deep recessions. It is however intuitive in the case of Greece, as the recent deep recession was prompted not by a financial crisis but by the Greek sovereign debt crisis. Thus, contrary to other countries' experience, it was indeed GDP that declined first, leading on to the subsequent downturn in credit and property prices. Equity prices are synchronous with the output cycle while, as before, the long-term interest rate and the spread inversely lead the real cycle by a full year, in line with the aforementioned intuition. The corresponding co-movements for the HP-filtered series can be found in Tables A4 and A5 in the Appendix and present broadly similar results for both frequencies.[2]

Finally, Table 6 presents the co-movement properties of the "overall" cycles which were extracted by bandpass-filtering all series with an 8-120 quarter bandwidth. This is, in a sense, the most instructive of all three tables, as we do not pre-impose a limiting common bandwidth for all series, but rather we explore the co-movement between the dominant cyclical components of our variables. Nonetheless, the co-movements reflected in Table 6 are strikingly similar to those presented in Table 5 for the medium frequency cyclical components and equally intuitive, reflecting once again the correlation between the two sets of cyclical components.[3]

4 STRUCTURAL CYCLE ESTIMATES

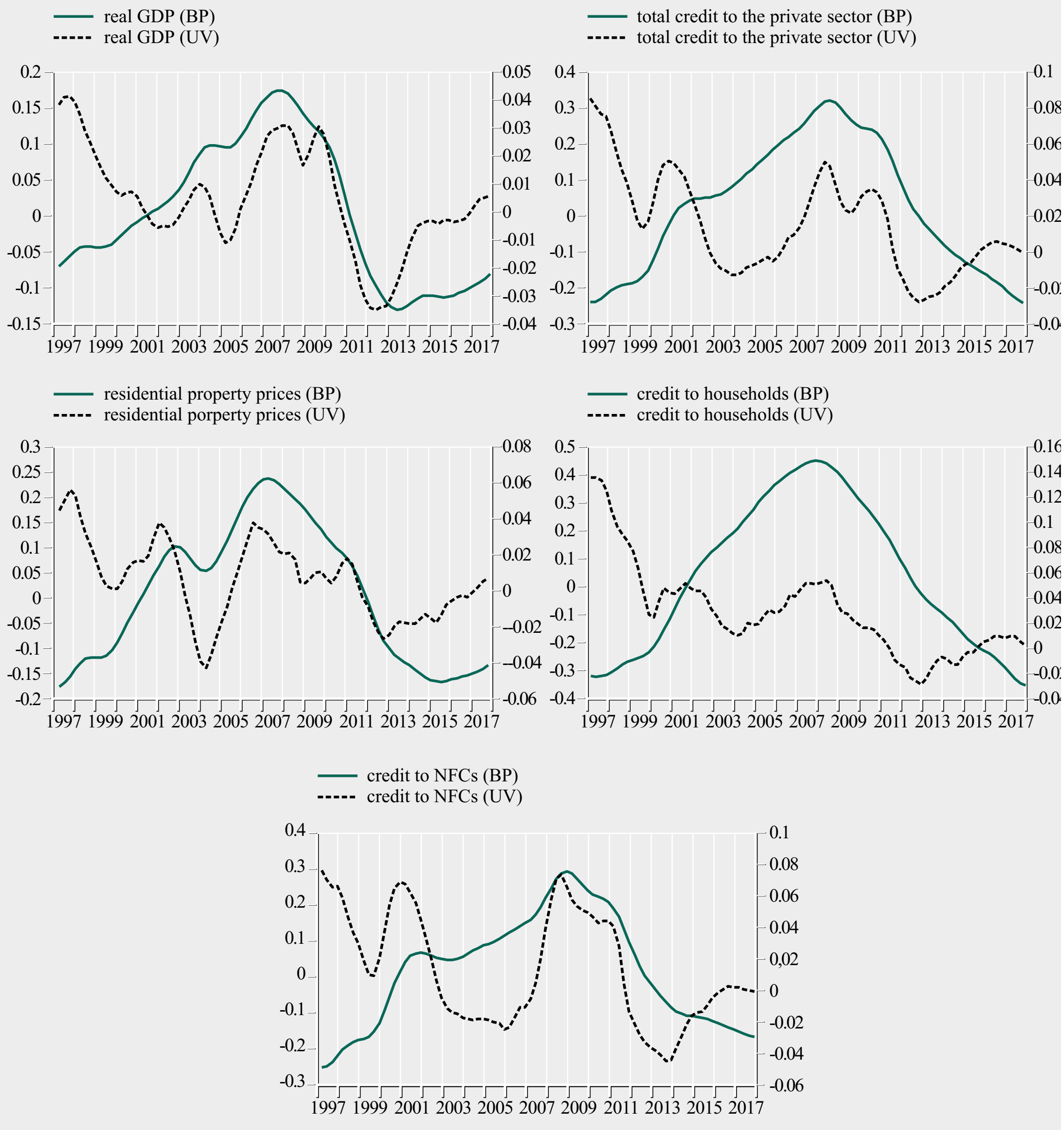
4.1 UNIVARIATE MODELS

Having employed a battery of alternative non-structural ways of extracting financial cycles, we now use a structural time series model (STSM), in both its univariate and its multi-

2 To obtain cyclical components at medium-term frequencies with the HP filter, we use a smoothing parameter equal to 400,000, as in Schüler (2018).

3 We have also calculated the co-movements between the short-term cyclical component of GDP and the medium-term cyclical components of financial variables, so as to indirectly explore the validity of the premise that medium-term financial cycles are related to the business cycle and that financial crises precede deep recessions. However, the resulting correlations were very low. The results are available from the authors upon request.

Chart 5 Univariate STSM (UV) and overall cycle (BP) (1997Q1-2017Q4)



Source: Authors' own econometric estimations
Note: Overall cycles (BP) are plotted on the left-hand scale of graphs and were computed using a bandwidth of 8-120 quarters.

variate version, to do the same. STSMs are commonly used to decompose a series or a group of series into trends and cycles, thus they are conceptually similar to the bandpass filter approach. However, with an STSM the trends and cycles are explicitly specified as parametric time series models and their parameters are directly estimated from the time series. The estimated model is thus tailored to the observed time series, ensuring a more precise characterisation of the cycle.

To date univariate STSMs have mostly been used for the estimation of NAIRU (non-accelerating inflation rate of unemployment) and the output gap; see for example Jarocinski and

Table 7 Univariate structural time series model – Properties of cyclical components

	Std.	Cycle length (quarters)
GDP	0.012	37.03
Residential property prices	0.017	33.34
Total credit	0.02	37.74
Credit to households	0.026	44.10
Credit to NFCs	0.024	36.69

Note: Data cover the period 1997Q1-2017Q4.

Lenza (2016), Rünstler (2002) and Gerlach and Smets (1999). A small number of papers also employ STSMs to extract cyclical components from financial variables, e.g. De Bonis and Silvestrini (2013) and Galati et al. (2016).

The cyclical components extracted from the univariate STSM are directly comparable to our previously extracted cyclical fluctuations.

However, to ensure comparability between the univariate and multivariate estimation, both have been performed on the common sample which starts in 1997, when data are first available on the residential property price index. Chart 5 plots the cycles extracted from the univariate STSM against the previously extracted "overall" cycles. With the exception of the beginning of the sample, the cycle derived from the univariate STSM tracks the bandpass-filtered cycle relatively closely. However, it is substantially less smooth, as the fact that it stems from an estimated model allows it to track the variable's dynamics more closely.

Table 7 presents the properties of the cyclical components extracted using the univariate STSM. The standard deviation of the credit variables' cyclical components is greater than that of GDP. However, with the exception of credit to households, their cycle length is comparable. The cycle length of GDP is estimated at 37.03 quarters, longer than the commonly employed business cycle frequency.

4.2 MULTIVARIATE MODELS

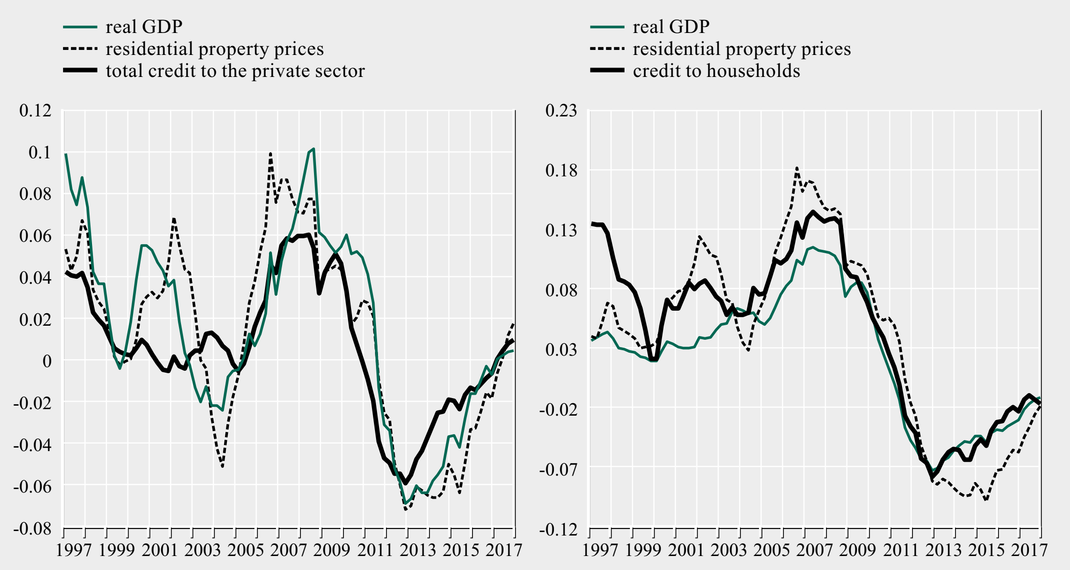
Estimating STSMs in a multivariate setup allows not only the extraction of each variable's cyclical component, but also an empirical examination of the degree of co-movement between the cyclical components of the variables included in the multivariate estimation. This approach is less common than the corresponding univariate one, but offers an advantage. The concept of an economic or financial cycle implies a degree of co-movement in the cyclical fluctuations of a number of series. A multivariate approach allows us to formally examine the concept of an economic or financial cycle by jointly modelling the cycles of several series.

We employ the multivariate STSM developed in this spirit and applied to the United States by Rünstler and Vlekke (2016) and also applied by Rünstler et al. (2018) to euro area countries.[4] This version of the multivariate STSM is specifically aimed at modelling the joint dynamics of GDP, total credit and house prices both at business cycle and at medium-term frequencies. The model provides increased flexibility in modelling the persistence of medium-term cycles and of cyclical co-movements at different frequencies. Thus it allows us to explore the extent to which real and financial cycles co-move and which cycle, if any, leads the other.

We estimate two alternative specifications. In the specification, we estimate the joint dynamics of GDP, total credit and residential property prices. In the second one, we estimate the joint dynamics of GDP, loans to households and residential property prices. Due to the relatively short length of the common sample, the models are estimated using Bayesian methods with reasonably tight priors on the cycle lengths and the smoothness of the trends.[5,6]

4 See Rünstler and Vlekke (2016) for technical details on the STSM.
5 While the sample is sufficient for a maximum likelihood estimation of the univariate models, it proved difficult to obtain convergence in the multivariate specification.
6 The Bayesian code was developed by Dimitrij Kulikov of Eesti Pank.

Chart 6 Multivariate STSM (1997Q1-2017Q4)



Source: Authors' own econometric estimations.

The two panels of Chart 6 present the cyclical components jointly estimated for each of the aforementioned two sets of variables with the multivariate model. Both panels indicate a high degree of co-movement between the series, implying the existence of a common cycle.

Table 8 presents the properties of the cyclical components extracted using the univariate STSM. The cyclical components of residential property prices, total credit and credit to households have a larger standard deviation than the cyclical component of GDP. Indeed, financial variables and property prices are known to exhibit relatively higher volatility than real output variables. The three variables' cycle lengths are however found to be roughly similar in both specifications. In the first panel of Chart 8 the estimated GDP cycle length is approximately eight years, while in

Table 8 Multivariate structural time series model – Properties of cyclical components

	Std.	Cycle length (quarters)	Variance contribution > 32 quarters	Variance contribution < 32 quarters
Version with total credit				
GDP	0.028	31.96	0.72	0.29
Residential property prices	0.049	29.91	0.69	0.31
Total credit	0.046	29.85	0.69	0.31
Version with credit to households				
GDP	0.036	37.14	0.77	0.23
Residential property prices	0.052	37.04	0.77	0.23
Credit to households	0.045	36.63	0.77	0.23

Note: Data cover the period 1997Q1-2017Q4.

Table 9 Co-movement properties of the multivariate models

Version with total credit									
	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.6648	0.7213	0.765	0.8032	**0.8363**	0.8246	0.805	0.7811	0.746
Total credit	0.5303	0.6203	0.701	0.7782	0.8514	0.8829	**0.8975**	0.8975	0.8752

Version with credit to households									
	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.8498	0.8819	0.9072	0.9273	**0.9422**	0.9403	0.9312	0.9167	0.8964
Credit to households	0.8727	0.9004	0.9213	0.9346	**0.9404**	0.9355	0.923	0.9049	0.8763

Note: The table presents the correlation of each variable's cycle shifted by $i \in [-4, 4]$ periods with the GDP cycle in period t. Correlations are computed over the period 1997Q1-2017Q4. Numbers in bold indicate the highest correlation over $i \in [-4, 4]$.

the second one it is just over nine years, confirming the importance of medium-term fluctuations not only in financial variables but also in real economic activity. These results are broadly in line with those presented in Rünstler et al. (2018) for the rest of the euro area countries, where the three cyclical components are found to be fairly highly correlated at medium-term frequencies. However, STSM cycle lengths for Greece are somewhat shorter than the corresponding euro area averages – Rünstler et al. (2018) report 10-12 years for GDP and 13-14 years for credit and house prices. Moreover, in the findings of Rünstler et al. (2018) the average estimated GDP cycle is a couple of years shorter than that estimated cycles of the financial variables, which is not the case for Greece.

The GDP cycle estimates obtained from the STSM are clearly longer than the 13.8-quarter cycle extracted from the standard business cycle bandpass filter, though much shorter than the 55-quarter cycle extracted using the medium frequency filter (see Table 3). In other words, in terms of frequency, the extracted GDP cycle seems to fall somewhere between the notion of a traditional business cycle and that of a financial cycle. The last two columns of Table 8 present the contribution of short- and medium-term frequencies to the cycle's total variance. As suggested by the results, the contribution of medium-term frequencies is substantially greater than that of short-term ones for all variables and in both specifications. The contribution of long-term frequencies appears to be larger under the estimation of credit to households, which also accounts for the longer cycles in this case.

Finally, Table 9 presents the co-movements between the GDP's cyclical component and that of each of the other two variables, for the two multivariate estimations. The highest correlation coefficient appears for contemporaneous correlation ($i=0$), indicating that the cyclical fluctuations in the two variables are found to be synchronous when jointly estimated. The same is true for the cyclical component of loans to households, a variable closely linked to mortgage credit and thus to residential property prices. This link is also manifested in the fact that the correlations reported in all columns of the lower panel are higher than the corresponding ones in the top panel. In contrast, the cyclical component of total credit lags the GDP cycle by two quarters, echoing the results presented in Tables 4-6 and contradicting yet again, for the case of Greece, the stylised fact that credit leads the cycle.

5 CONCLUSIONS

We use a battery of alternative methodologies to extract and study short and medium frequency cycles from eight key Greek economic and financial variables. Overall, we find that medium frequency fluctuations dominate over business cycle frequency fluctuations for all variables, including GDP. The average duration of the medium frequency cycle in GDP is found to be between 32 and 55 quarters, depending on the methodology, i.e. much longer than conventional business cycle frequencies. The corresponding durations calculated for the three credit variables are almost twice as long, confirming that financial cycles are generally much longer than real ones. The cyclical components of the financial variables also exhibit much greater variance than those of GDP at both frequencies.

The medium frequency cyclical components are found to be highly correlated. All except those of the long-term interest rate and the term spread are procyclical with respect to the GDP cycle. Residential property prices and the three credit variables lag GDP, despite post-crisis evidence that the medium-term financial cycle leads the business cycle. This finding is however intuitive in the case of Greece, as the recent recession was prompted not by a financial crisis but by a sovereign debt crisis, thus it was indeed GDP that declined first, before credit and property prices. Equity price cycles on the other hand seem to be synchronous with the output cycle. Finally, the long-term interest rate and the spread inversely lead the real cycle by a year, i.e. low interest rates today forecast future economic booms in line with the well-established inverted leading indicator property of real interest rates.

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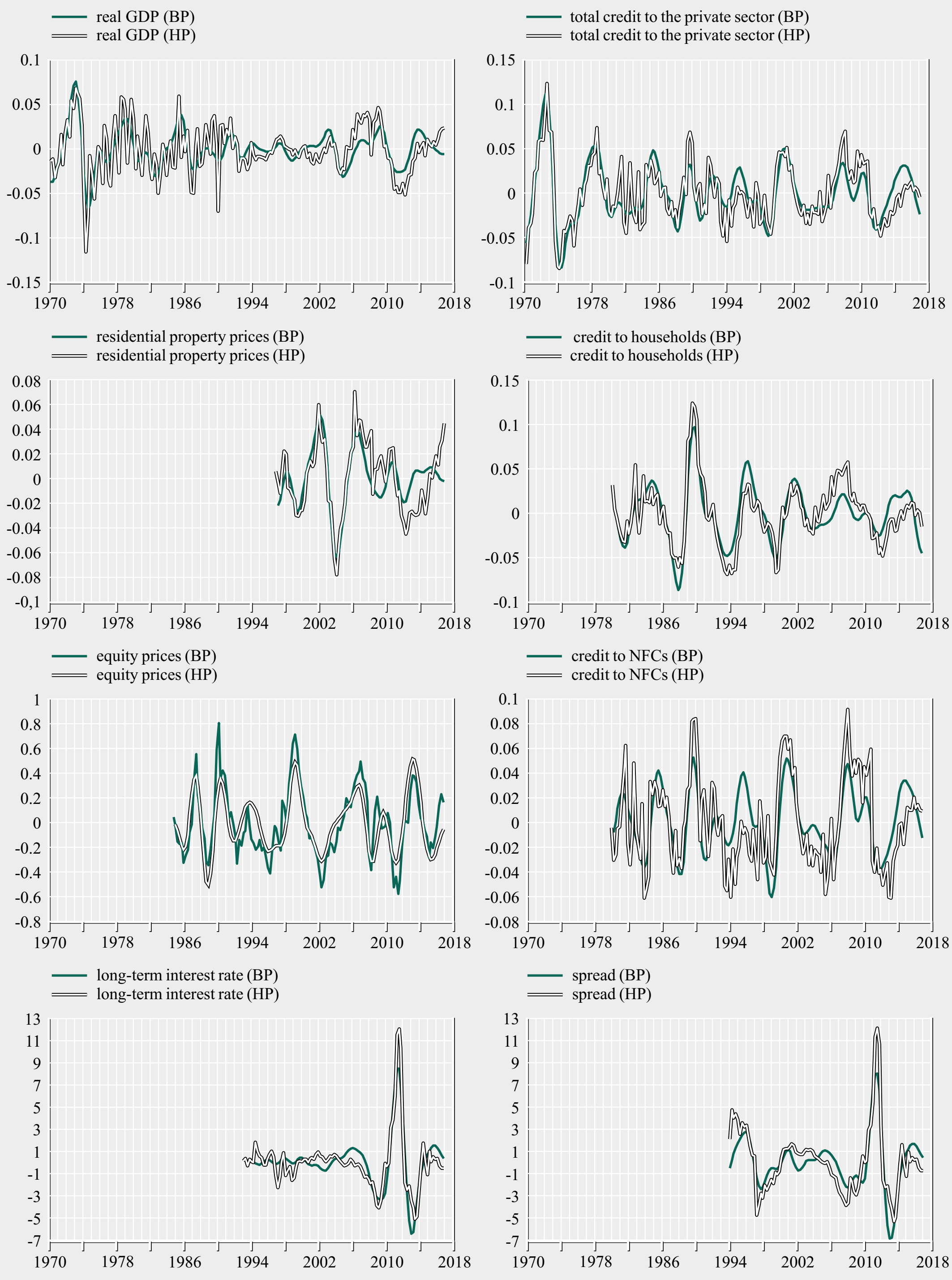
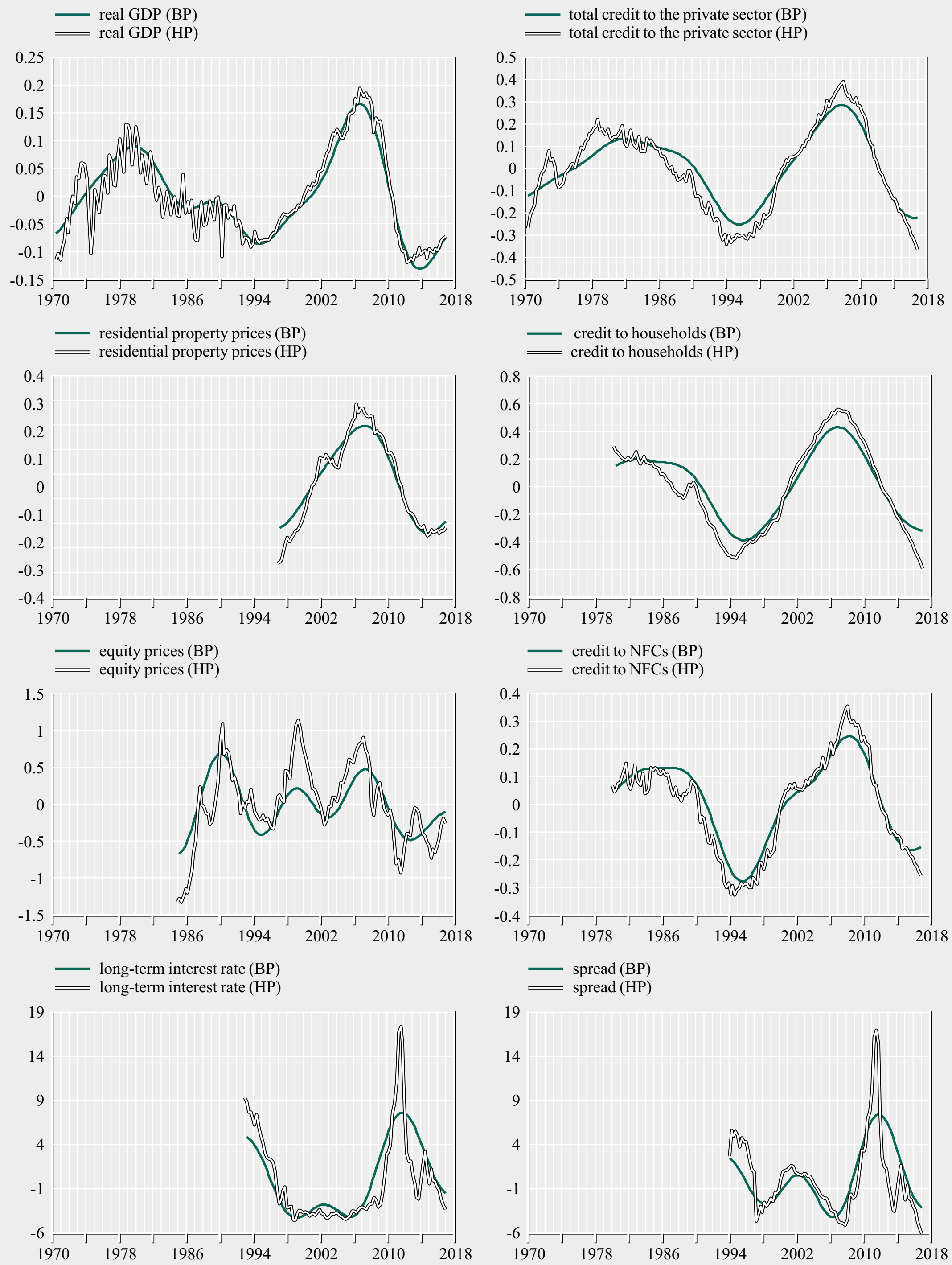
APPENDIX

Chart A1 Bandpass filter (BP) and Hodrick-Prescott filter (HP) - Short-term cycles (1970Q1-2017Q4)



Source: Authors' own econometric estimations.
Note: For the computation of short-term cycles using the bandpass filter, a bandwidth of 8-32 quarters was employed. For the computation of short-term cycles using a Hodrick-Prescott filter, a smoothing parameter equal to 1,600 was applied.

Chart A2 Bandpass filter (BP) and Hodrick-Prescott filter (HP) - Medium-term cycles (1970Q1-2017Q4)



Source: Authors' own econometric estimations.
Note: For the computation of medium-term cycles using the bandpass filter, a bandwidth of 32-120 quarters was employed. For the computation of medium-term cycles using a Hodrick-Prescott filter, a smoothing parameter equal to 400,000 was applied.

Table A1 Data description

	Source	Time span
Real GDP	OECD.Stats	1970Q1-2017Q4
Residential property prices	ECB Data Warehouse	1997Q2-2017Q4
Total credit to the private non-financial sector	BIS	1970Q1-2017Q4
Credit to households	BIS	1980Q1-2017Q4
Credit to NFCs	BIS	1980Q1-2017Q4
Equity price index	ECB Data Warehouse	1985Q1-2017Q4
Nominal long-term interest rate	ECB Data Warehouse	1993Q1-2017Q4
3-month nominal interest rate	OECD.Stats	1994Q3-2017Q4

Notes: Series for credit to households and credit to NFCs in the BIS database are available since 1994Q4. We backcast the series and obtain data from 1980 using information from series for total loans to households and NFCs that are available since 1980Q1 from the Bank of Greece. In particular, we assume that prior to 1994Q4, the series for credit to households and NFCs grow at the same rate as the series for loans to households and NFCs, respectively. We make the same assumption in order to obtain data for 2017Q4 for total credit, credit to households and credit to NFCs.

Table A2 Properties of the filtered series: Standard deviation of short-term and medium-term cycles – HP filter

	Short-term cycles	Medium-term cycles	Relative Std.
GDP	0.027	0.081	3
Residential property prices	0.029	0.161	5.552
Total credit	0.034	0.191	5.618
Credit to households	0.035	0.315	9
Credit to NFCs	0.036	0.174	4.833
Equity prices	0.274	0.539	1.967
Long-term interest rate	0.026	0.05	1.923
Spread	0.031	0.044	1.419

Notes: The standard deviation for each variable is computed for the period in which data are available. The relative standard deviation is the ratio of the standard deviation of the medium-term cyclical component to the standard deviation of the short-term cyclical component.

Table A3 Properties of the filtered series: Duration of short-term and medium-term cycles – HP filter

	Short-term cycles			Medium-term cycles		
	Expansion	Contraction	Cycle	Expansion	Contraction	Cycle
	Number of quarters			Number of quarters		
GDP	8.1	5.8	13.3	67	35	114
Residential property prices	9.67	8	18.5	40	35	-
Total credit	6.85	6.7	13.5	57	63	120
Credit to households	10	16	17	26.5	49	99
Credit to NFCs	6	9.6	15.6	53	53	108
Equity prices	8.14	8.86	17.5	12	37.5	37
Long-term interest rate	4.75	5.63	10.38	52	26	78
Spread	10	10	17.7	16	26	41

Notes: The durations have been computed using turning point analysis in the filtered series. A full cycle is measured from peak to peak.

Table A4 Co-movement properties of the filtered series: Short-term cycles – HP filter

	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.3749	0.3941	0.4103	0.4074	**0.4753**	0.4147	0.3643	0.3498	0.3046
Total credit	0.101	0.1678	0.2507	0.3232	0.4625	0.5255	0.5624	**0.6209**	0.5844
Credit to households	0.5375	0.5593	0.5797	0.5767	**0.6087**	0.5701	0.5087	0.4952	0.4113
Credit to NFCs	-0.0017	0.0788	0.1752	0.2735	0.427	0.4955	0.538	**0.6042**	0.5856
Equity prices	0.2815	0.3139	0.3551	**0.3914**	0.366	0.2639	0.1613	0.0624	0.0174
Long-term interest rate	-0.4758	-0.5325	**-0.5627**	-0.5455	-0.4997	-0.4155	-0.2883	-0.1579	-0.0444
Spread	-0.5231	-0.5576	**-0.5796**	-0.5774	-0.5538	-0.4768	-0.347	-0.1987	-0.074

Notes: The table presents the correlation of each variable's cycle shifted by $i \in [-4, 4]$ periods with the GDP cycle in period t. Correlations are computed over the period 1997Q2-2017Q4. Numbers in bold indicate the highest correlation over $i \in [-4, 4]$.

Table A5 Co-movement properties of the filtered series: Medium-term cycles – HP filter

	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.7486	0.7903	0.8265	0.8575	0.8867	0.907	0.9226	0.934	**0.9363**
Total credit	0.5896	0.6489	0.7035	0.7529	0.799	0.8371	0.8704	0.9	**0.9219**
Credit to households	0.7262	0.7696	0.8073	0.8393	0.8665	0.8893	0.9074	0.921	**0.9274**
Credit to NFCs	0.5623	0.6238	0.6814	0.735	0.7864	0.8281	0.864	0.8973	**0.9221**
Equity prices	0.6293	**0.6298**	0.6245	0.6119	0.588	0.5475	0.5065	0.4623	0.4192
Long-term interest rate	**-0.6398**	-0.6105	-0.5689	-0.514	-0.4496	-0.386	-0.3163	-0.2418	-0.1652
Spread	**-0.4555**	-0.4322	-0.3961	-0.3482	-0.2909	-0.2368	-0.1718	-0.1012	-0.0455

Notes: The table presents the correlation of each variable's cycle shifted by $i \in [-4, 4]$ periods with the GDP cycle in period t. Correlations are computed over the period 1997Q2-2017Q4. Numbers in bold indicate the highest correlation over $i \in [-4, 4]$.

Table A6 Co-movements between the short-term cyclical component of GDP and the medium-term cyclical components of financial variables – HP filter

	i = -4	*i* = -3	*i* = -2	*i* = -1	*i* = 0	*i* = 1	*i* = 2	*i* = 3	*i* = 4
Residential property prices	0.2267	0.2298	0.2324	0.2379	0.2632	0.2812	0.2997	0.3207	**0.3268**
Total credit	0.0943	0.1072	0.122	0.1402	0.1716	0.2185	0.2625	0.3062	**0.3286**
Credit to households	0.1682	0.1649	0.1612	0.1607	0.1677	0.1964	0.2235	0.2504	**0.2631**
Credit to NFCs	0.0646	0.0905	0.1196	0.1542	0.2055	0.2625	0.3144	0.3686	**0.3962**
Equity prices	0.3576	0.3801	0.4057	**0.4265**	0.4079	0.3575	0.3033	0.2456	0.2107
Long-term interest rate	-0.559	-0.5889	**-0.598**	-0.5747	-0.5299	-0.4521	-0.3427	-0.2276	-0.1203
Spread	-0.71	**-0.7345**	-0.7405	-0.7214	-0.6805	-0.5882	-0.4517	-0.2977	-0.1599

Notes: The table presents the correlation of each variable's cycle shifted by $i \in [-4, 4]$ periods with the GDP cycle in period t. Correlations are computed over the period 1997Q2-2017Q4. Numbers in bold indicate the highest correlation over $i \in [-4, 4]$.