Measuring the Financial Cycle in South Africa

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ERSA working paper 736

March 2018

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

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November 23, 2017

Abstract

We measure the financial cycle in South Africa using three different methodologies, consider its main characteristics and examine its relationships with the business cycle and a measure of financial stress. We identify the financial cycle using credit, house prices and equity prices as indicators, and estimate it using traditional turning-point analysis, frequency-based filters and an unobserved components model-based approach. We find evidence of a financial cycle in South Africa that has a longer duration and a larger amplitude than the traditional business cycle, and that periods where financial conditions are stressed are associated with peaks in the financial cycle. Developments in measures of credit and house prices are important indicators of the financial cycle, although the case for including equity prices in the measures is less certain.

JEL Classification: E44, E61, G21.

Keywords: Financial cycle, business cycle, spectral analysis, band-pass filters, turning points, unobserved components, credit, house prices

*The views expressed are those of the authors and do not necessarily represent those of the South African Reserve Bank, the University of the Witwatersrand, or the University of Cape Town.

1 Introduction

This paper sets out to measure the financial cycle in South Africa. Financial cycles provide a broad perspective on the evolution of risks to financial stability, and therefore provide a useful monitoring tool for policymakers who are required to set macroprudential policies. A robust measure of the financial cycle is currently particularly important for South African policymakers, given the renewed emphasis on the financial stability regulatory and supervisory framework provided by the Financial Sector Regulation Act, which was signed into law in September 2017.

Understanding financial cycles is viewed as critical for informing the use of countercyclical macroprudential policy,[1] but there is no consensus regarding the definition of financial cycles nor on the methodology that should be employed to measure them. Despite a large and growing international literature,[2] we are also not aware of published research that assesses the options available for measuring the South African financial cycle.

To fill this gap, we propose identifying the main characteristics of the financial cycle in South Africa using three different approaches. First, we apply traditional turning point analysis to identify the financial cycle by detecting peaks and troughs in the individual component variables that make up the cycle. Second, we employ a frequency domain approach that uses band-pass filters to isolate the cycles that correspond to medium-term frequency intervals. Third, we use a multivariate model-based approach to extract cycles using unobserved components time series models. We then provide a comparison of the results of the three approaches, and compare the estimates of the financial cycle with those of the business cycle to determine whether the cycles are distinct from one another. We begin, however, by defining financial cycles and selecting a set of financial variables that can potentially capture the main characteristics of the South African financial cycle.

[1] An important question for policymakers is whether macroprudential policy should be aimed at controlling the 'financial cycle' or not. See Borio (2014a, 32-33) and Constâncio (2014) for differing views on this issue.

[2] Claessens and Kose (2017) provide a recent review of studies that examine the features of business and financial cycles, and the linkages between them, for the credit, equity and housing markets.

2 Definitions, data sources and transformations

A working definition describes the financial cycle as reflecting self-reinforcing feedbacks within the financial system and between the financial system and the real economy (Borio, 2014b). Approaches to measuring financial cycles have therefore focused on the co-movement of a broad set of financial variables (BIS, 2015). However, given macroprudential policy's focus on systemic risks and the challenges of measuring risk perceptions, it is not clear which set of financial variables or indicators best captures the financial cycle.

The indicators that have been found to give the most parsimonious description of the financial cycle are credit and property prices (Drehmann *et al*, 2012 and Borio, 2014b). Credit aggregates (which can be used as a proxy for leverage) are often the sole focus (Aikman *et al*, 2015), and together with property prices (a measure of collateral available) are jointly important for the financial cycle because of mutually-reinforcing feedback effects. Strong growth in credit extension, specifically mortgage credit, often results in higher property prices. In turn, higher house prices boost collateral values and the amount of credit the private sector can obtain. Such interactions have historically been associated with the most serious bouts of financial instability (BIS, 2014; Jordá, Schularick & Taylor, 2014).

In addition to credit and housing market developments, a number of other variables have been proposed in the literature as proxies for the financial cycle. Equity prices (see for example Claessens *et al*, 2010 and Granville and Hussain, 2017), bond prices (Schüler *et al*, 2015), interest rates, non-performing loans, volatilities, risk premia and the credit-to-GDP ratio (Borio, 2014b) have all been used.[3]

We opt for a parsimonious specification that includes credit, property prices and equity prices in this initial analysis of the South African financial cycle, although it is accepted that further research into this issue is warranted. The case for including credit and property prices as components of the financial cycle is generally well supported in the literature, although that for equity prices is perhaps less certain. For example, Drehmann *et al* (2012)

[3] Even larger data sets are possible. Menden and Proãno (2016), e.g., propose constructing financial cycle measures for the US based on a data set of 7 macroeconomic and 25 financial variables. They use a dynamic factor model to estimate three synthetic financial cycle components, which they find explain most of the variation in their data.

argue that equity prices can be a distraction, while Claessens *et al* (2010) find that credit and equity cycles are most synchronised across countries.

We analyse the behaviour of the three variables over the period 1966 - 2016 using quarterly data,[4] providing sufficiently long data samples to extract medium-term cycles. Credit data were sourced from the SARB, equity data from the JSE and house price data from ABSA.[5] In line with Drehmann *et al* (2012), the three data series are in logs and deflated by the headline CPI. Where necessary to facilitate comparability, the levels of the series were normalised by their respective values in 1985Q1. Real GDP data used to estimate the business cycle were sourced from the South African Reserve Bank (SARB) (series KBP6006D).

The transformations applied to the data have implications for the types of cycles considered in the study, as is well known in the business cycle literature.[6] 'Classical' cycles consider the data in (log) levels, while 'growth' or 'deviation' cycles focus on fluctuations around a trend and 'growth rate' cycles refer to fluctuations in the growth rate of the variable.[7]

3 Approaches to measurement

There are three main approaches to measuring the financial cycle in the literature:[8]

3.1 Traditional turning-point analysis

Following Burns and Mitchell (1946), traditional turning-point analysis defines the cycle as a pattern in the level of economic activity. In the financial

[4]South African data for these variables are generally available from the mid-1960s on a quarterly basis. A notable exception is the annual series on South African equities, bonds and cash that dates back to 1900 (see, e.g. Firer and Staunton (2002) and the references cited therein).

[5]House price data are smoothed by Absa in an attempt to exclude the distorting effect of seasonal factors and outliers. Note that the value for house prices in December 2016 was estimated.

[6]In the South African case, for example, see Du Plessis (2006) and Bosch and Ruch (2013).

[7]Harding (2004) terms this an 'acceleration' cycle.

[8]Other options include wavelet analysis, which attempts to simultaneously account for both the frequency and the time variations of a time series. See e.g. Verona (2016), and Ardila and Sornette (2016).

cycle literature, Claessens *et al* (2011), Drehmann *et al* (2012) and Granville and Hussain (2017) provide turning point analyses. The approach has been employed in the South African context by Du Plessis (2006) for the business cycle, and Boshoff (2005) for financial variables.

3.2 Frequency-based filters analysis

Frequency-based filters are used to extract the medium-term cyclical components of the indicators, which are then combined to provide an estimate of the financial cycle. Similar approaches have been adopted in the literature by Aikman *et al* (2015) for the credit cycle, and by Schüler *et al* (2015), Strohsal *et al* (2015) and Gonzalez *et al* (2015) for the financial cycle. The frequently cited analysis of Drehmann *et al* (2012) uses frequency-based filters, as well as turning point analysis. In the South African literature, Boshoff (2010) and Havemann (2015) have employed frequency-based filters.

3.3 Model-based approaches

Trends and cycles may be modelled as unobserved components within the framework provided by structural time series models (Harvey, 1989; Harvey and Jaeger, 1993). The statistical approach uses the state space form, with the components being obtained from the Kalman filter and smoother. Lucas and Koopman (2005), Galati *et al* (2016), Rünstler and Vlekke (2016) and Grinderslev *et al* (2017) have used unobserved components time series models (UCTSMs) to measure financial cycles.

We proceed by applying each approach to the South African data.

4 Turning-point analysis

Harding and Pagan suggest using a dating algorithm introduced by Bry and Boschan (1971), adapted for quarterly data and termed the BBQ rule:[9] The steps for this analysis are as follows (Harding and Pagan, 2016):

1. Smooth the single time series y_t to eliminate outliers, high frequency variations and other uninteresting fluctuations.

[9]Bry and Boschan (1971) used monthly data (setting $k = 5$).

2. Determine a potential set of turning points using a rule to locate the local maxima and minima. A local peak in y_t occurs at time t if $y_t > y_s$ for s in a window $t-k < s < t+k$, i.e. where $|y_s|$ is larger than $|k|$ values of $|y_t|$ (similarly, a trough is defined as $y_t < y_s$ for s in a window $t-k < s < t+k$). So, for $k = 2$:

   Peak at t if $(y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2})$
   Trough at t if $(y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2})$

3. Use some criteria, i.e. censoring rules, to ensure that peaks and troughs alternate and that the duration and the amplitude of the two phases are meaningful.

Changing the values of these parameters will result in different peak and trough dates. Given that we are interested in both short- and medium term cycles, we used two different calibrations. Following Drehmann *et al* (2012), for the shorter cycle used to extract the business cycle we specified censoring criteria for the BBQ algorithm such that the minimum duration of a phase of a cycle is 2 quarters, and that the minimum duration of a complete cycle is 5 quarters. The medium-term criteria used to extract financial cycles are that the minimum duration of the phase of a cycle is 9 quarters and the minimum duration of a complete cycle is 20 quarters.

The turning point information supplied by the BBQ algorithm can be captured by a binary random variable (S_t) that has a value of unity in expansions and zero in contractions (Harding and Pagan, 2016, 26).[10] Once the states have been constructed, we use the information in S_t to describe the characteristics of the cycle. More specifically, we produce measures of the durations of the expansions and contractions, which we use to examine the average features of phases and to compare these features across different variables (Harding and Pagan, 2016, 89-101).

An estimator which counts the number of peaks is:

$$\hat{K} = \sum_{t=1}^{T-1} (1 + S_{t+1}) S_t \tag{1}$$

since the series $(1 + S_{t+1})S_t$ equals 1 only when there is a peak at time t. Because the total time spent in expansions is $\sum_{t=1}^{T} S_t$, the average duration

[10] The convention used by Harding and Pagan (2016, 37) is that the peak is the last period of the expansion phase and the trough is the last period of the contraction phase.

of an expansion is:

$$\bar{D}^E = \hat{K}^{-1} \sum_{t=1}^{T} S_t \tag{2}$$

The average amplitude of expansions is then:

$$\hat{A}^E = \hat{K}^{-1} \sum_{t=1}^{T} S_t \Delta y_t \tag{3}$$

Harding and Pagan (2016, 97) also formulate a steepness index which is calculated as the ratio of the amplitude to the duration of a phase. The average degree of steepness over all expansion phases is:

$$STEEP = \frac{\hat{A}}{\hat{D}} = \frac{\sum_{t=1}^{T} S_t \Delta y_t}{\sum_{t=1}^{T} S_t} \tag{4}$$

This measure leads naturally to a comparison of the steepness of expansions versus contractions. Since the amplitudes of contractions have a negative sign, this is given by (Harding and Pagan, 2016, 98):

$$\begin{aligned} COMP &= \frac{\sum_{t=1}^{T} S_t \Delta y_t}{\sum_{t=1}^{T} S_t} + \frac{\sum_{t=1}^{T} (1 - S_t) \Delta y_t}{\sum_{t=1}^{T} (1 - S_t)} \\ &= \hat{p}_e^{-1} T^{-1} \sum_{t=1}^{T} S_t \Delta y_t + (1 - \hat{p}_e)^{-1} T^{-1} \sum_{t=1}^{T} (1 + S_{t+1}) \Delta y_t \end{aligned} \tag{5}$$

where $\hat{p}_e = \sum_{t=1}^{T} S_t / T$ is the proportion of time spent in expansions.The test therefore compares the average steepness of expansions and contractions, weighted by $\hat{p}_e^{-1}$ and $(1 - \hat{p}_e)^{-1}$ respectively, to assess the symmetry in Δy_t.

We also look at the degree of synchronisation between different time series by considering the fraction of time the cycles are in the same phase. For two series x_t and y_t, Harding and Pagan (2002) proposed a concordance index:

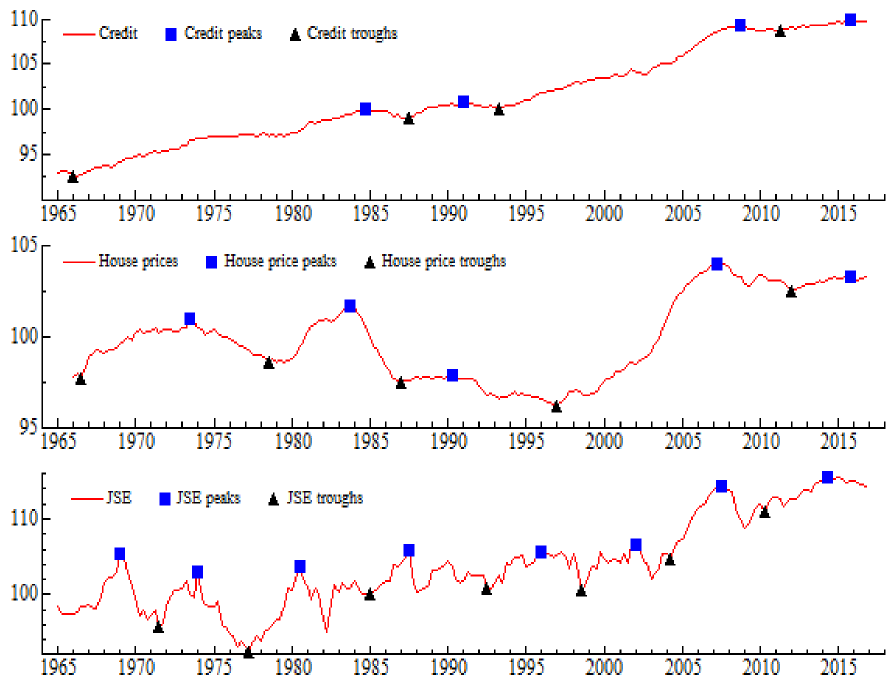
$$\hat{I} = \frac{1}{T} \left(\sum_{t=1}^{T} S_{xt} S_{yt} + \sum_{t=1}^{T} (1 - S_{xt})(1 - S_{yt}) \right) \tag{6}$$

Harding and Pagan (2016, 113-15) point out that this measure considers the proportion of time the cycles of variables are in the same phase, but not the reasons for this.

4.1 Results

Cycles are described here in terms of amplitude, steepness, and duration, as well as their synchronisation with other cycles. Figure 1 provides a graphical representation of the results (the data are in log levels, indexed so 1985Q1 = 100).

Figure 1: BBQ dating of cycles
(Log levels, 1985Q1=100)



Tables 1 and 2 show that in the short as well as medium term, credit and house price cycles have similar lengths (25 quarters or just over 6 years for the shorter cycle and around twice this for the medium-term cycle). In both cases, the average length of equity cycles is the shortest of the three variables. The equity, credit and house price time series all have similar amplitude.

Table 1: Short cycles (cycle > 5 quarters and phase > 2 quarters)

	Average duration of contraction ($\bar{D}^C$)	Average duration of expansion ($\bar{D}^E$)	Average length of full cycle	Average amplitude of contraction ($\hat{A}^C$)	Average amplitude of expansion ($\hat{A}^E$)	Steepness contraction	Steepness expansion	Concordance with credit ($\hat{I}$)
Credit	9.1	15.9	25	-11.4	2.1	-1.3	0.1	-
House Prices	16.5	8.5	25	-11.2	1.4	-0.68	0.16	0.55
Equity	7.6	7.1	14.7	-10.4	4.7	-1.4	0.65	0.51

Table 2: Medium cycles (cycle > 20 quarters and phase > 9 quarters)

	Average duration of contraction ($\bar{D}^C$)	Average duration of expansion ($\bar{D}^E$)	Average length of full cycle	Average amplitude of contraction ($\hat{A}^C$)	Average amplitude of expansion ($\hat{A}^E$)	Steepness contraction	Steepness expansion	Concordance with credit ($\hat{I}$)
Credit	15.8	34.2	50.0	-22.5	3.91	-1.42	0.11	-
House prices	21.7	20.0	41.7	-18.86	2.57	-0.87	0.13	0.73
Equity	16.0	11.8	27.8	-17.35	6.4	-1.08	0.54	0.5

The concordance index $\hat{I}$ proposed by Harding and Pagan (2006) measures the fraction of time that two series are in the same phase. The statistic is equal to 100 if two series expand and contract together, and equal to zero if the two series are always in a different cycle. When the concordance index is equal to 50 there is no systematic relationship in the dynamics of the two variables and the two series are independent. In the medium term, credit and house prices have a high concordance index (0.73) suggesting that the cycles are synchronised. The concordance index between equity and credit (0.5) indicates that the medium-term cycles for credit and equity are independent in the South African case, by this measure, supporting the contention of Drehmann *et al* (2012) that equity prices may be a distraction in analyses of the financial cycle.

5 Frequency domain analysis

We begin by using spectral methods to undertake an exploratory analysis of the component variables of the financial cycle. This analysis is intended to support the use of frequency-based filters to extract the medium-term cyclical components of these indicators, which are then combined to provide an estimate of the financial cycle. On their own, pure frequency-based filtering approaches that rely on pre-specified frequency bands run the general risk of spurious cycles[11] as well as a form of circularity in their methodology.[12]

5.1 Nonparametric estimation of the spectral density

The spectral representation of a stationary time series y_t decomposes it into a combination of cosine (or sine) waves with differing frequencies. The spectral density is a frequency domain representation of a time series that is directly related to the autocovariance time domain representation.

If y_t is a zero-mean stationary time series with autocovariance function $\gamma(\cdot)$ such that $\sum_{h=-\infty}^{h=\infty} |\gamma(h)| < \infty$, the spectral density of y_t is the function $f(\cdot)$ (see e.g. Brockwell and Davis, 2002; Hamilton, 1994)

[11]See Cogley and Nason (1995), Osborn (1995) and Hamilton (2017).

[12]As Rünstler and Vlekke (2016) argue "while Drehmann *et al* (2012) regard financial and business cycles as "different phenomena", such finding emerges from their choice of frequency bands for the extraction of GDP (8 to 32 quarters) and financial cycles (32 to 120 quarters): once the filter bands do not overlap, estimates of the two cycles are uncorrelated by construction."

$$f(\lambda) = \frac{1}{2\pi} \sum_{h=-\infty}^{h=\infty} \gamma(h) e^{-ih\lambda} \tag{7}$$

where h is a time lag, λ is the frequency $(-\infty < \lambda < \infty)$, $e^{i\lambda} = cos(\lambda) + i\ sin(\lambda)$ and $i = \sqrt{-1}$. Comprising of cosine and sine functions, $f(\cdot)$ has period 2π so we can focus on the values of $f(\cdot)$ on the interval $(-\pi, \pi)$.

The spectral density and autocovariance are Fourier transform pairs, with the latter being given by:

$$\gamma(k) = \int_{-\pi}^{\pi} e^{ik\lambda} f(\lambda) d\lambda \tag{8}$$

For y_t with autocovariance function $\gamma(\cdot)$ and spectral density $f(\cdot)$, the periodogram $I_n(\cdot)$ of the observations can be viewed as a sample analogue of $2\pi f(\cdot)$.[13] It provides information about the portions of the sample variance of y_t that can be explained by cycles of various frequencies. The periodogram $I_n(\lambda)$ is an asymptotically unbiased, but not consistent, estimator of $2\pi f(\lambda)$ (see e.g. Hamilton, 1994, p194).

The nonparametric approach to estimating the spectral density suggests averaging the periodogram estimates over a narrow frequency interval containing λ to construct a consistent estimator. Smoothing is applied here using the modified Daniell kernel.[14] The kernel determines how much weight each frequency is given. For the modified Daniell kernel the two endpoints in the averaging receive half the weight that the interior points do. Increasing m decreases the variance of the periodogram (more averaging), but introduces some bias.

[13] Due to the symmetry of the function and periodic repetition for frequencies outside the $-\frac{1}{2}$ to $+\frac{1}{2}$ range, analysis can be focused on frequencies between 0 and $+\frac{1}{2}$, as in Figure 2.

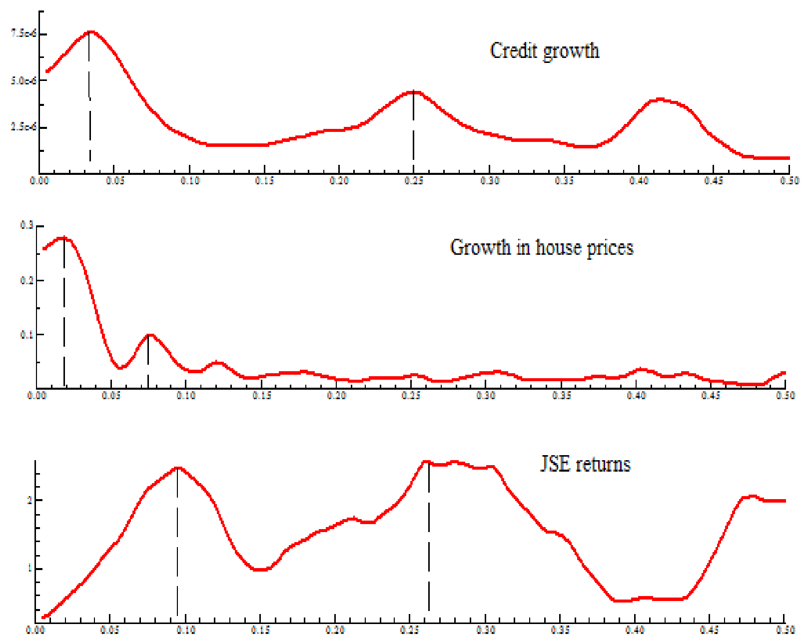
[14] The Daniell kernel with parameter m is a centered moving average of all values between $t - m$ and $t + m$ (inclusive). The smoothing formula for a Daniell kernel with $m = 2$, e.g., is

$$\hat{x}_t = \frac{x_{t-2} + x_{t-1} + x_t + x_{t+1} + x_{t+2}}{5}$$

5.2 Exploratory analysis

Figure 2 presents the periodograms of our component variables of the financial cycle:[15] credit, house prices, and equity prices. The data are constant price, demeaned log differences, over samples extending from the mid-1960s to 2016. The periodograms were smoothed using a modified Daniell kernel, which was used twice on each series. Both times, m = 2 was chosen for house prices and m=4 for credit and equity prices. A split cosine bell taper was applied to the data at the beginning and end of the series to reduce leakage.

Figure 2: Periodograms: Exploratory analysis



The periodograms of the credit, house price and equity price series each have two peaks that are of interest to us. For the credit growth series, the periodogram has a peak at a frequency of 0.032, suggesting a cycle with a duration of 30.9 quarters or around 7.5 years, and a smaller peak at 0.25 suggesting a cycle of 4 quarters. The periodogram of the growth in house prices has a peak at a frequency of 0.019, suggesting a cycle with a duration of

[15] The R function spec.pgram was used, which estimates the periodogram using a Fast Fourier Transform.

13.5 years, and a smaller peak at 0.074 suggesting a cycle of around 3.5 years. Finally, the periodogram of the JSE returns has a peak at a frequency of 0.097, suggesting a cycle with a duration of 10.3 quarters, and a smaller peak at 0.26 suggesting a cycle of almost 4 quarters. The lower frequency cycles, particularly in the credit and house price series, we interpret as tentative evidence of a medium-term cycle in the South African data.[16]

5.3 Band-pass filters

We use band-pass filters to extract the medium-term cycles in the credit, equity price and house price series, then combine these to obtain an estimate of the financial cycle. Specifically, we apply the Christiano-Fitzgerald (2003) filter to the data to isolate the cyclical component in the frequency range between 32 and 120 quarters. All data series were expressed as four-quarter changes, after having been deflated and logged.

The medium-term cycles obtained from Christiano-Fitzgerald band-pass filters for the component indicators are presented in Figure 3. These plots reveal evidence of common cyclical features - particularly in the upswings of the late 1970s and 2000s, and the downswings of the 1970s, 1980s and late 2000s.

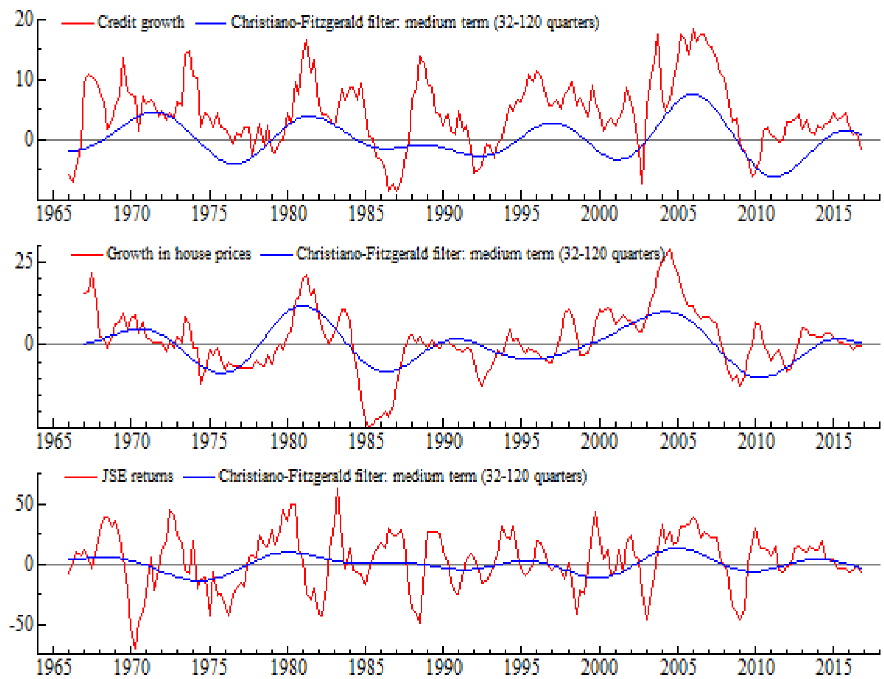
In Figure 4, we average the cycles obtained from the Christiano-Fitzgerald band-pass filters for credit, equity prices and house prices to obtain an estimate of the financial cycle (the red line). Note that since these are growth rate cycles, a decline in the financial cycle that remains positive indicates that the financial cycle in levels is still increasing but at a decreasing rate. A turning point in the financial cycle would thus be reached when the growth cycle becomes zero, as occurred most recently in 2016Q4.

An alternative way of obtaining an aggregate financial cycle from the Christiano-Fitzgerald estimates of the three variables is to use a principal components approach.[17] The first principal component is the loading vector (the rotation) that provides the linear combination of the three medium-term cycles that explains the largest proportion of the variability in the aggregate data. In the South African case the results are essentially the same as those obtained by simply averaging the three cycles. Using the normalised loadings of the first principal component for the three cycles, we

[16] To provide context here, Drehmann *et al* (2012) find the average duration of financial cycles across a number of countries to be around 16 years.

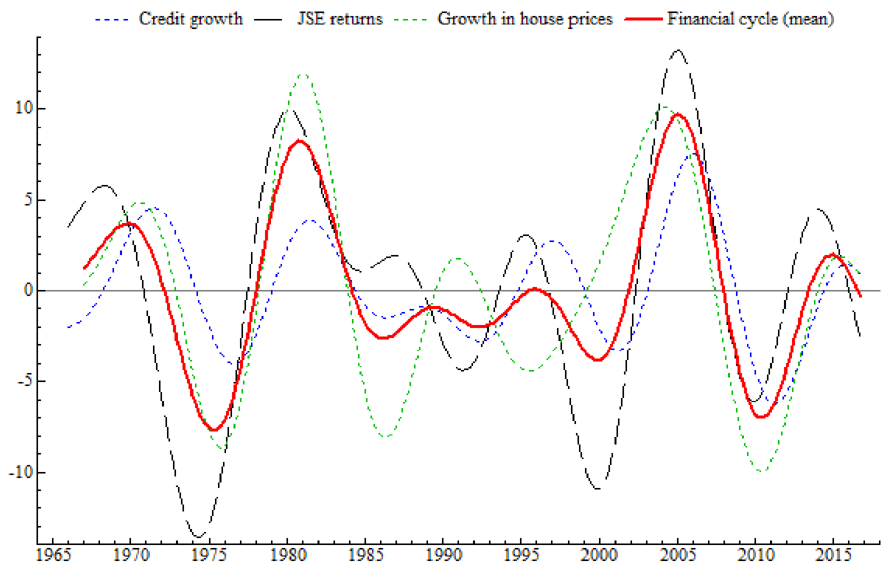
[17] See also Schüler et al (2015).

Figure 3: Financial cycles: Christiano-Fitzgerald band-pass filters (Y-o-y % changes)



find that the weights are approximately equal: Credit (0.332), House Prices (0.346) and JSE returns (0.322). This first principal component explains just over 70 per cent of the variance in the data over the sample period.

Figure 4: The financial cycle in South Africa: Frequency-based filters (Y-o-y % changes)



6 Measuring financial cycles using unobserved components time series models

Our approach here is to first extract cycles from univariate UCTSMs for the credit, house price and equity price series, and then extract the 'similar' cycles from a multivariate UCTSM consisting of the same three variables as the basis for our estimate of the financial cycle.[18]

A basic structural time series model, with a trend plus cycle plus irregular specified as unobserved components, is fitted to each variable equation i $(i = 1, \ldots, N)$:

$$y_{it} = \mu_{it} + \psi_{it} + \varepsilon_{it} \tag{9}$$

where y_{it} is the i^{th} component variable in y_t. For this component variable, μ_{it} is the trend, ψ_{it} the cyclical component, and ε_{it} the irregular ($\varepsilon_{it} \overset{iid}{\sim}$

[18]Besides the papers cited earlier that use UCTSMs to measure financial cycles, Creal *et al* (2010, 697-98) adopt a similar cycles approach to measuring the US business cycle, arguing that this is a reasonable approach to extracting a business cycle component that is common to a number of time series (assuming *a priori* that a business cycle exists).

$\mathcal{N}(0, \sigma^2_{\varepsilon,i})$), and $t = 1, ..., T$.

The smoothness of the trend component μ_{it} - which determines how fluctuations in y_{it} are apportioned between the trend and the cycle - depends on the choice of m in the m-order trend model of Harvey and Trimbur (2003). The m^{th} order stochastic trend $\mu_{i,t} = \mu^{m_i}_{i,t}$, for each component variable i and integer m, is given by

$$\begin{aligned} \mu^1_{i,t+1} &= \mu^1_{1,t} + \zeta_{i,t}, \quad \zeta_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}) \\ \mu^k_{i,t+1} &= \mu^k_{i,t} + \mu^{k-1}_{i,t}, \quad k = 2, \ldots, m_i \end{aligned} \tag{10}$$

The trend component is smoother for larger m. If $m = 0$, y_t is assumed to be stationary. For $m = 1$ the stochastic trend is a simple random walk, while for $m = 2$ the trend is an integrated random walk with a slope of $\mu_{i,t}$.[19]

$$\begin{aligned} \mu_{i,t+1} &= \mu^{i,t} + \zeta_{i,t}, \quad \zeta_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}) \\ \beta_{i,t+1} &= \beta_{i,t} + \xi_{i,t}, \quad \xi_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}) \end{aligned} \tag{11}$$

The cycle component ψ_{it} is specified as an autoregressive model with polynomial coefficients that have complex roots. Specifically, the cycle is modelled as a trigonometric process that follows (Harvey, 1989):

$$\begin{pmatrix} \psi_{i,t+1} \\ \psi^*_{i,t+1} \end{pmatrix} = \rho_i \begin{bmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{bmatrix} \begin{pmatrix} \psi_{i,t} \\ \psi^*_{i,t} \end{pmatrix} + \begin{pmatrix} \omega_{it} \\ \omega^*_{it} \end{pmatrix}, \begin{pmatrix} \omega_{it} \\ \omega^*_{it} \end{pmatrix} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\omega,i}) \tag{12}$$

where where $\psi_{i,t}$ and $\psi^*_{i,t}$ are the states ($N \times 1$ vectors, $\psi^*_{i,t}$ is an auxiliary variable), ω_t and ω^*_t are mutually uncorrelated white noise disturbances with zero means and common variance $\sigma^2_{\omega,i}$, the frequency λ_i is measured in radians ($0 \leq \lambda_i \leq \pi$) and the persistence ρ_i is the damping factor (restricted for stationarity so $0 < \rho_i < 1$). The period of ψ_{it} is $2\pi/\lambda_i$.

The trend, cycle and irregular disturbances of component variables are unrelated with those of the other variables, but the covariances between the disturbances of specific components are generally non-zero.

This approach allows the restriction of similar cycles (Harvey and Koopman, 1997) to be imposed. Similar cycles have the same frequency and

[19] Valle e Azevedo *et al* (2006) and Koopman and Lucas (2005) select a value of $m = 2$ here.

degree of dependence on the past, i.e. the same frequency and damping factor ($\rho_i = \rho$ and $\lambda_i = \lambda$). Since ρ and λ are the same in all series, the cycles have similar properties. Note that the scale of the cycle in a series depends on the variance and covariances of its disturbance, and can therefore differ despite the similarity restriction being imposed.

We place the univariate and multivariate UCTSMs in the general linear state space form, and apply the Kalman filter and related state space methods to estimate them.[20]

6.1 Results

In Table 3, we first report the parameter estimates from the univariate UCTSMs, obtained by maximum likelihood estimation. The estimates of persistence (ρ) are high and relatively similar for all three variables (0.93 for Credit, 0.99 for House prices and 0.89 for JSE returns). Furthermore, the estimates of the period (measured by $2\pi/\lambda$) are 12.7 years for Credit, 15.5 years for House prices and 9.3 years for JSE returns, longer than the typical business cycle duration and supportive of the existence of a distinct medium-term financial cycle.

Table 3: Unobserved components time series models: Parameter estimates

	Univariate			Multivariate
	Credit	House prices	JSE returns	Similar cycles
ρ_i	0.93	0.99	0.89	0.98
Period	12.66	15.50	9.28	14.74
Loglikelihood	356.16	306.08	-40.78	592.92
AIC	-3.54	-3.42	0.27	-3.66
BIC	-3.45	-3.32	0.34	-3.56
# observations	208	204	208	204

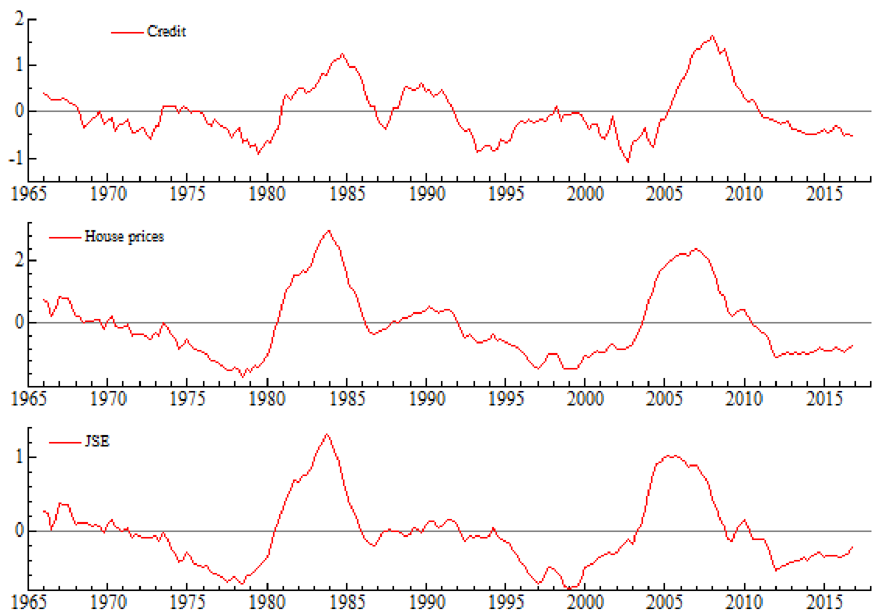
Note: The frequency of the cycle is λ (measured in radians, $0 \leq \lambda \leq \pi$) and the period is $p = 2\pi/\lambda$ (in years).

In Figure 5, based on the univariate results, we assume that the time- and frequency-domain properties of the three univariate financial cycles are similar, and estimate a joint multivariate UCTSM with the similar cycles restriction imposed. The cycles' damping factors and the frequencies are therefore

[20]Estimation was done using the STAMP 8.30 package, described in Koopman *el al* (2000).

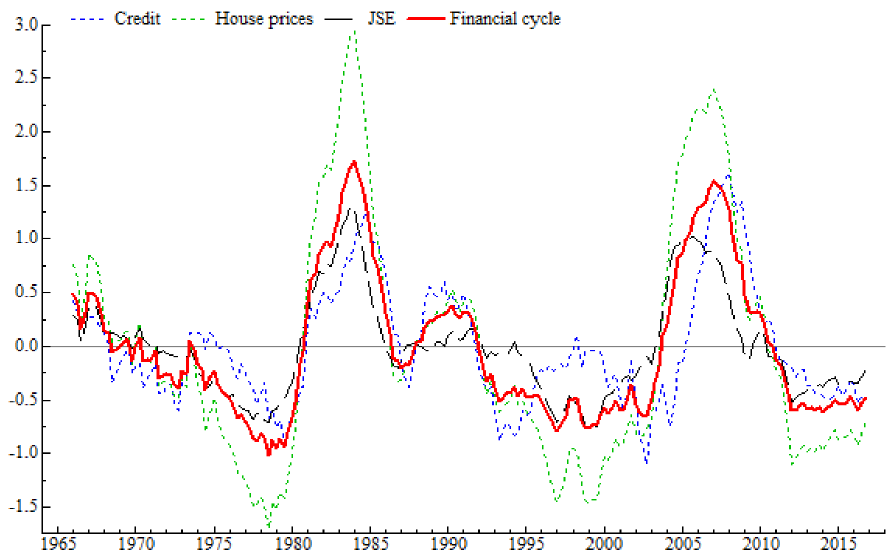
constrained to be equal for each of the variables, i.e. the parameters $\rho_i = \rho$ and $\lambda_i = \lambda$). With this restriction, the estimate of persistence is $\rho = 0.98$ and the period of the financial cycle is 14.74 years.

Figure 5: Similar cycles for credit, house prices and equity prices:
Unobserved components time series models
(Log levels)



Since aggregation of similar cycles leaves the properties unchanged (Harvey and Koopman, 1997, 273), we combine the three cycles in Figure 5 in the same way as the Christiano-Fitzgerald band-pass filters to facilitate comparison. Figure 6 plots the average of the similar cycles obtained for credit, equity prices and house prices to obtain an estimate of the financial cycle (the red line).

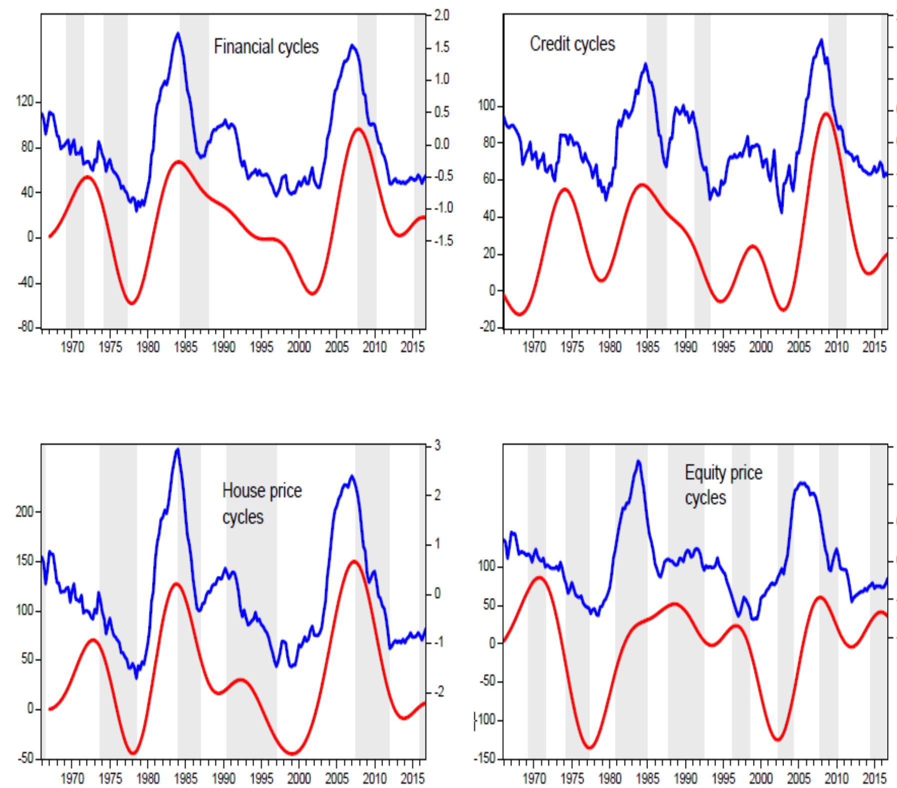
Figure 6: Financial cycles: Unobserved components time series models (Log levels)



7 Comparison of results of the different approaches to measuring the financial cycle

In Figure 7, we compare the financial and component series cycles extracted using frequency-based filter analysis to the BBQ turning-point analysis and the cycles obtained from the unobserved components models. To facilitate this comparison, the frequency-based growth cycles were converted into levels by cumulating the growth rates, similar to Drehmann *et al* (2012). The downswings obtained from the BBQ turning point analysis are shown as shaded areas.

Figure 7: Comparison of financial cycles



— Unobserved components model (right-hand axis, log levels)
— CF filter (left-hand axis: cumulated percentage changes)
Shaded areas are BBQ turning point dated downswings

The results of the three methodologies are sufficiently similar to provide some confidence in the characteristics of financial cycles in South Africa we report. The downswings obtained from the BBQ turning point analysis are generally closely aligned with the downswings in the cycles extracted from the unobserved components models (the blue lines). Our results from the frequency-based filters provide somewhat smoother cycles, but these are generally also consistent with those of the other two methodologies.

The results for the overall financial cycle (the top graph in Figure 7) are less convincing at the end of the sample than elsewhere. The BBQ reports a downswing, the frequency-based filter financial cycle has just reached an upper turning point, and the unobserved components model financial cycle is relatively flat. These results are perhaps reflecting the end-of-sample problem common in filter-based analysis of cycles, and this issue may benefit from further study. The results for the JSE equity prices, as discussed earlier, also show shorter, more frequent cycles than those of the other components, and suggest that the case for including these prices in measures of medium-term financial cycles may need to be revisited.

8 How do estimates of the financial cycle differ from the business cycle?

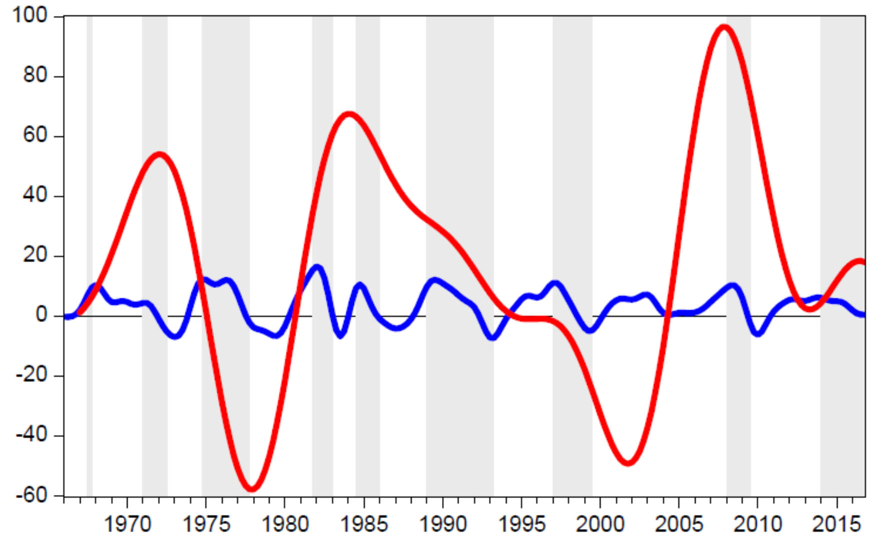
The interactions between business cycles and financial cycles play an important role in determining the characteristics of recessions and recoveries in the real economy, with recessions accompanied by financial disruptions tending to be longer and deeper (Claessens *et al*, 2012). In this section we compare estimates of the South African business cycle with our estimate of the financial cycle. We use the results of the frequency-based filters approach to provide consistent estimates of both cycles and to facilitate the comparison.

The shaded areas showing downward phases of the business cycle in Figure 8 represent the official turning points for the South African business cycle taken from table S-151 of the SARB's Quarterly Bulletin. These shaded areas correlate closely with our estimate of the business cycle (the blue line), which is the cumulated cycle extracted from real GDP growth data using the Christiano-Fitzgerald frequency-based filter (with a duration between 5 and 32 quarters). The financial cycle (the red line) is the cycle extracted using the frequency-based filter approach in Section 5.

In line with the findings in other studies (e.g. Drehmann *et al* 2012; Borio, 2014b; Claessens *et al* 2011), we find in Figure 8 that the financial cycle has a much lower frequency than the traditional business cycle, and that the amplitude of financial cycle is larger than that of the business cycle.

The financial cycle shown in Figure 8 is closely associated with other measures of financial conditions in South Africa. Kabundi and Mbelu (2017), for example, estimate a time-varying financial conditions index (FCI) for South Africa that uses 45 monthly financial series as inputs. They use indicators from five sectors (the funding, credit, foreign exchange, real estate and eq-

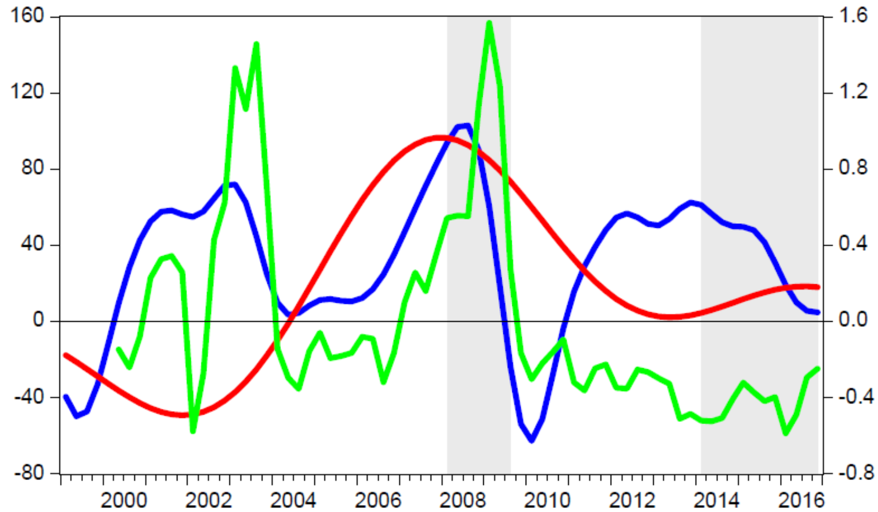
Figure 8: The financial and business cycles in SA:
Frequency-based approach



— Business cycle (cum % changes, CF filter 6-32 quarters)
— Financial cycle (cum % changes, CF filter 32-120 quarters)
Shaded areas are SARB official BC downswings

uity markets), and use different weights for different divisions within financial markets to facilitate the identification of sectors that are under stress. Figure 9 compares the FCI (converted from monthly to quarterly frequency using end-of-period observations, available from 2000) to the financial and business cycles presented in Figure 8 (the business cycle is scaled by a factor of 10 to facilitate comparison here). The FCI and the financial cycle correlate fairly closely from 2004 onwards, with the turning points in the financial cycle perhaps marginally leading those of the FCI (although there is as yet insufficient data to make this determination with any confidence). The peak in the FCI in 2003-4 is not reflected in the financial cycle estimate, although it does appear in our estimate of the business cycle.

Figure 9: Financial conditions and the financial and business cycles



— FCI (right-hand axis)
— Business cycle (cum % changes scaled by 10, CF filter 6-32 quarters)
— Financial cycle (cum % changes, CF filter 32-120 quarters)
Shaded areas are SARB official BC downswings

9 Conclusion

Financial cycles provide a broad indication of the change in risks to financial stability and therefore provide an important monitoring tool for policymakers. Allowing for the phase of a country's financial cycle is also important when implementing macroprudential policy, given that the impact of policies may differ depending on the phase of the cycle. An understanding of financial cycles is therefore a key element informing macroprudential policymaking.

We use credit, house prices and equity prices as indicators to extract the financial cycle in South Africa using three different methodologies. We report the results obtained from traditional turning-point analysis, frequency-based filters and unobserved components models, finding evidence of a financial cycle in South Africa that has a longer duration and a larger amplitude than the traditional business cycle. We also find that that periods where financial conditions are stressed are associated with peaks in the financial cycle, suggesting that the estimated financial cycle may have similar leading indicator properties to financial conditions or stress indices.

We find that developments in credit and house price variables are important component indicators that serve to capture the financial cycle in South Africa. The case for including equity prices is less clear. It may be that equity prices in South Africa are influenced by external variables such as international developments and foreign-exchange movements, and as a result may not be representative of only the domestic situation.

The finding that the financial cycle is distinct from the business cycle in South Africa differs, for example, from Leamer's (2007, 2015) finding that for the US, housing is the business cycle, and that the finance, housing and business cycles have correlated closely for several decades. In this regard, the existence of a separate South African financial cycle is more closely aligned with the findings of Borio (2014b), Claessens *et al* (2012) and Barrell *et al* (2017).

An important implication of this finding is that the coordination of monetary and macroprudential policies will be more complicated. If financial and business cycles are closely correlated, they will seldom be in different phases and policy conflicts will be rare. However, when they are not well correlated and the cycles are in different phases for extended periods of time, conflicts are more likely. The interactions between business cycles and financial cycles will also play an important role in determining the characteristics of recessions and recoveries in the real economy, with recessions accompanied by financial disruptions tending to be longer and deeper. Crucially important from a financial-stability perspective is that failure to take medium-term financial cycles into account and focusing only on the business cycle may allow vulnerabilities to build up unattended. Policymakers may contain recessions in the short run, but at the expense of larger crises down the road.

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