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DO AUSTRALIAN INVESTMENT AND SAVINGS BEHAVE PROCYCLICALLY?

Arusha Cooray* and Bruce Felmingham**

Abstract: This study uses spectral analysis to examine the behaviour of Australian savings and investment and their synchronisation with the business cycle over the period September 1959 to December 2005. The results reveal that the major cyclical components of savings and investment cohere strongly. Further, savings coheres strongly with the business cycle suggesting that Australian savings is procyclical. Investment also exhibits a procyclical pattern although the evidence of this is weaker.

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JEL Codes: E21, E22, E32

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1 The Significance of the Saving Investment Relationship

The interrelationship between investment and savings is a widely studied issue but much less work has been completed on the cyclical characteristics of the data and their synchronisation with the business cycle. Our objective here is to fill this gap for Australian data by first examining the cyclical behaviour of Australian savings and investment and to determine if the major harmonic components of Australian savings (S) and investment (I) are coherent over time as economic theory suggests. Further, for policy coordination, it is important to know if cycles in investment and savings cohere with the major cyclical components of GDP (y). The preferred technique for identification of cycles in individual series is spectral analysis described in section 3 below. This technique is better suited to the analysis of cycles in an individual series in comparison with other techniques because it allows researchers to model non linearity directly and to identify more than one major cyclic (harmonic) component of each series. Once the major components of I, S and y are identified the study is extended to answer questions about the coherence of investment and savings and the correspondence of each of these with y using cross spectral analysis.

Spectral analysis has been used in the work of Owens and Sarte (2005) to investigate how diffusion indices capture business cycles; Selover, Jensen and Kroll (2005, 2003) to examine the regional and industrial synchronisation of business cycles in the US; A'Hearn and Woitek (2001) to examine the structure of the business cycle; Bennet and Barth (1990) money and the business cycle and Sichel (1989) on the asymmetry of business cycles.

In summary, the three goals of this study are as follows: to determine if the individual series for S and I on Australian data display cyclical patterns; to assess the strength of correlation between major cycles in I and S and to test for any pro or countercyclical patterns against the variation of *y* as a benchmark. The data are described in the following section of the paper. The methodology is explained in section 3 while the results of the spectral and cross spectral analysis are discussed in section 4. Finally, conclusions are summarised in a closing section.

2 Data

All data are quarterly, seasonally adjusted and run from 1959:3 to 2005:4. The Australian Bureau of Statistics is the sole data source[1]. Gross investment is constructed by adding to gross capital expenditure in the Australian National Accounts the value of investment in inventories. Further, gross savings is assembled by adding the aggregate measures net national savings and depreciation (capital used up in production). Real GDP (*y*) is the chain volume measure recorded in the Australian National Accounts.

3 Methodology

To test for the cyclical behaviour of each individual series a univariate spectral analysis is applied to each of the series S, I and *y*. A bi-variate (cross-spectral) analysis is applied then to the relationship between I and S, I and *y* and S and y. The I-S study will indicate if Australian savings and investment are linked thus indicating if the major cyclical components of each series are correlated, while the analysis of I-*y* and S-*y* will indicate if I and S are correlated with the business cycle.

[1] All three series for real GDP, gross investment and gross savings are constructed from ABS 5406.0: Australian National Accounts.

3.1 Spectral Analysis

Spectral methods are applicable only to time series which are covariance stationary which holds if the mean of the series is constant through time and if the autocovariance function is determined by periodic time intervals but not by historical time. In order to achieve the desired covariance stationary property the three series are filtered using the Hodrick and Prescott (1997) filter. Baxter and King (1999) in their analysis of band pass filters note that the Hodrick Prescott filter has several desirable properties: first, no phase shift is introduced; second it has trend removal characteristics; it contains multi-differencing properties; penalises variation in the growth component of the series and approximates the Baxter and King preferred band pass filter. The Hodrick Prescott filter provides a close approximation to Baxter and King's filter when quarterly data is used which is the case in this study. The filtered series is then used to determine the cyclical behaviour of the individual series.

Spectral analysis establishes the cyclical behaviour of each series through time. This frequency domain methodology has many applications and is described originally by Fishman (1969), Rayner (1971) and Koopmans (1974) and more recently by Hamilton (1994). Spectral analysis decomposes a stationary, stochastic series into a set of uncorrelated cycles, each associated with a frequency (λ) or period (the inverse of the frequency) which is the time required for the series to complete a whole cycle. The variation of an individual series (x) is represented by the spectrum, which is the Fourier transform of the autocovariance function. The spectrum $\left[g_x(\lambda)\right]$ decomposes the time series into a sequence of sine and cosine waves of differing frequencies with just the right number of amplitudes to compose the whole series. It has the following definition:

$$g_x(\lambda) = (2\pi)^{-1} \int_{-\infty}^{\infty} e^{-i\lambda s} \gamma_{x(s)} ds \qquad (1)$$

where $\lambda =$ frequency, $i = (-1)^{1/2}$, $\gamma_x(s) =$ autocovariance function at lag (s) of the series in x, $e^{i\lambda} = \cos\lambda + i\sin\lambda$. The formal relationship between the spectrum and the autovariance function is defined in (1) where the integral $g_x(\lambda)$ is the area under the spectrum and is equal to the variance $\gamma(0)$. Thus the spectrum decomposes the variance into the components contributed by each frequency and in each series, cycles of differing length can be identified. In the spectral analysis of each series the objective is to identify the predominant cycles where the importance of each frequency component is assessed in terms of its power or contribution to the total variance of the series. The power density function described by Rayner [1971, p.24] estimates the percentage contribution of each cycle (frequency component) to the total variance of the series as follows:

$$P_D = \left[A^2(k) \Big/ \sum_k A^2(k) \right] .100 \qquad (2)$$

where $A^2(k)$ is the estimated variance of the kth frequency component and $\sum_k \left[A^2(k) \right]$ is the estimated variance of the whole series. The major cycle in each series is the one with the greatest power density. The variance of each frequency component is half the square of its amplitude $A^2(k)$ and the estimates of these at each frequency are provided by estimates of the spectrum for each series. This is estimated by smoothing or averaging the periodogram, which is the square of the absolute value of the Fourier transform of the autocovariance of the series at each frequency divided by the total number of observations.

3.2 Cross Spectral Analysis

The correlation of the two series is assessed in a pairwise comparison by applying the technique known as cross spectral analysis. This method analyses the joint variation of pairs of variables in the frequency domain and is equivalent to a series of individual regressions between sinusoids in two different series at the same frequency (λ). The cross spectrum is the bivariate equivalent of the spectrum in the single variable case and is defined in terms of its imaginary and real components – the quadrature spectrum $q(\lambda)$ and co-spectrum $c(\lambda)$. The cross spectrum describing the joint variation of the two series x and y at frequency (λ) is defined as follows:

$$g_{xy}(\lambda) = c(\lambda) - iq(\lambda) \qquad (3)$$

The cross spectrum is not estimated directly and its properties are summarized in two statistics associated with the quadrature and co-spectra. These statistics provide all the information required for the purpose of the study. The coherence is analogous to the correlation coefficient in the time domain and measures the strength of association of two interdependent series at particular frequencies and is formally defined as follows:

$$coh(\lambda) = \left\{ \left[c^2(\lambda) + q^2(\lambda) \right] \Big/ \left[g_x(\lambda) g_y(\lambda) \right] \right\}^{1/2}$$

$$0 \le coh(\lambda) \le 1 \qquad (4)$$

The coherence indicates the strength of association of the common harmonic components in the two series and is employed to indicate the correlation of I and S series. If the coherence of the I and S series are significant at the five percent level, according to the tests specified by Fishman [(1969), p. 138], then I and S are deemed to be correlated. If the coherence is not significant according to these tests, correlation does not occur.

A second statistic associated with cross spectral analysis is the phase angle in radians or the time difference in quarters between peaks in each series. The phase angle $p(\lambda)$ is computed from the quad and co-spectra as follows:

$$p(\lambda) = \tan^{-1}\left[-q(\lambda)/c(\lambda)\right] \qquad (5)$$

$p(\lambda)$ assesses the fraction of a cycle by which one series leads the other. The phase in radians can be expressed as a time difference in quarters by dividing the phase by its frequency: $p(\lambda)/\lambda$.

4 Results of the Study

The results of the analysis are discussed in this section begining with the individual (univariate) spectral analysis (4.1) which is followed by discussion of the results of the cross sepctral analysis (4.2).

4.1 Spectral Analysis of Individual Time Series

The individual spectra for gross savings (S), gross investment (I), and GDP (*y*) are estimated as the Fast Fourier transform of the autocovariance function. The results of the individual spectral studies for I, S and *y* are shown on Table 1.

Table 1: Maximum Power Spectra: Australian Real GDP, Investment and Savings: 1959(3) to 2005(4)

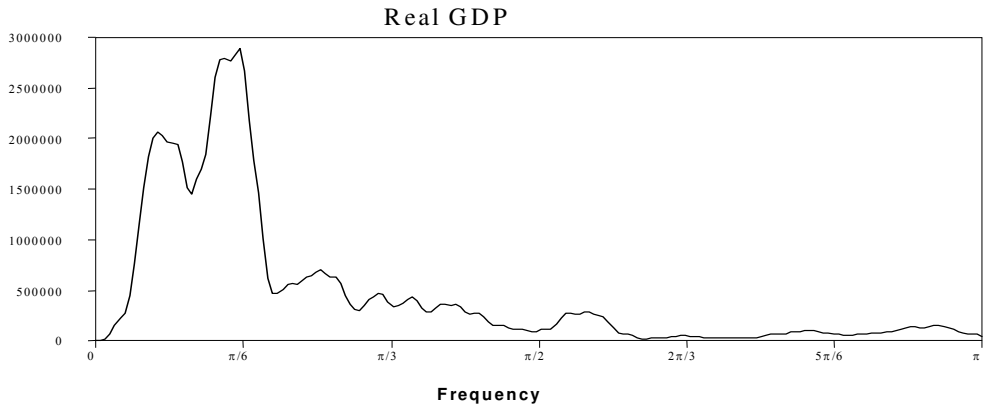
Series	***y***	**I**	**S**
Entry *(j)*	31	27	30
Frequency (radians)	0.368	0.319	0.356
Duration (Quarters)	17.067	19.687	17.650
% Variance	39.54	37.40	44.64
t statistic of sample mean	9.131	7.189	8.836
skewness	2.132	2.454	2.169
kurtosis	3.596	5.089	3.467

The first row of Table 1 show the data point (j), at which the maximum individual power spectra occur while the second row shows the frequency in radians of this maximum spectra. The percentage contribution of the maximum estimated power spectra to the variance of each series is calculated by applying the ratio in equation (4) to the estimated spectrum. The total variance of each series is the area under the power spectra on Figures 1, 2, and 3 and the percentage explained at the peak spectra is shown in the fourth row of Table 1. The diagnostics in the last few rows of Table 1 relate to the significance of the mean of the power spectra in each series; the t-ratio in each case suggests that the estimated mean of the estimated power spectra is significant in each case.

The results of this spectral estimation are interesting. The most important component of each individual series occurs at data entry points $j = 31$, 27 and 30 for *y*, I and S respectively. These points and frequencies relate to a harmonic component of around 4 to 4.75 years duration (periodicity). In the case of Australia's real GDP this harmonic component is associated with the generally agreed notion of the duration of the Australian business cycle. Some specific evidence to support this general notion is provided by Cotis and Coppel (2005) in a study of the business cycle dynamics of OECD countries. These authors find that the average duration of downswings in the Australian business cycle is 6.3 quarters and for upswings 10.7 quarters. This is very close to the estimated duration of the cycle in real GDP found in this study namely, 17.067 quarters. This leads to the conclusion that the major cycle in real GDP is the Australian business cycle.

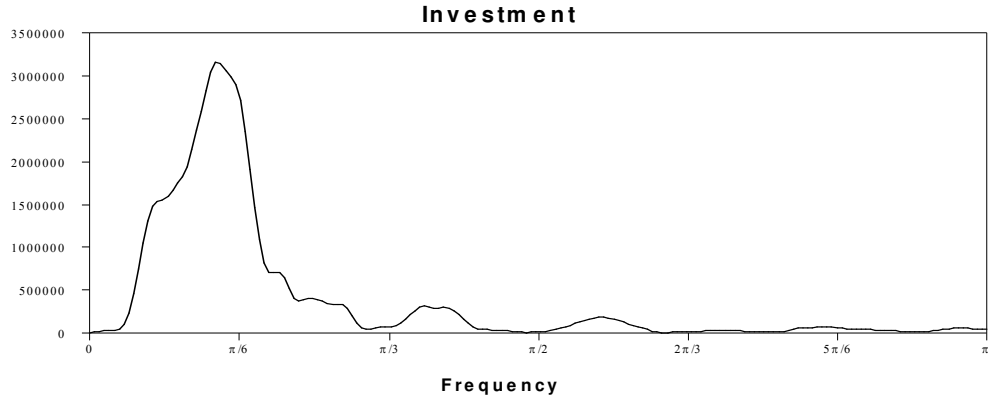
It is also of interest to note that the peak spectral estimate also occurs on a frequency component of similar duration in the case of both I and S. For I, this is data entry j=27 and for S j=30. This peak component is also evident on Figures 1, 2, and 3. These provide a graphical representation of the estimated spectra. The respective peak frequencies are 0.368 for y, 0.319 for I and .356 for S. This band of frequencies explains 39.54 percent, 37.4 percent and 44.64 percent of the total variance of y, I and S respectively. The individual series behave differently when harmonic components other than the peak ones are considered. In particular, there is clearly a longer swing of some importance occurring at a lower frequency than the business cycle on Figure 1.

Figure 1



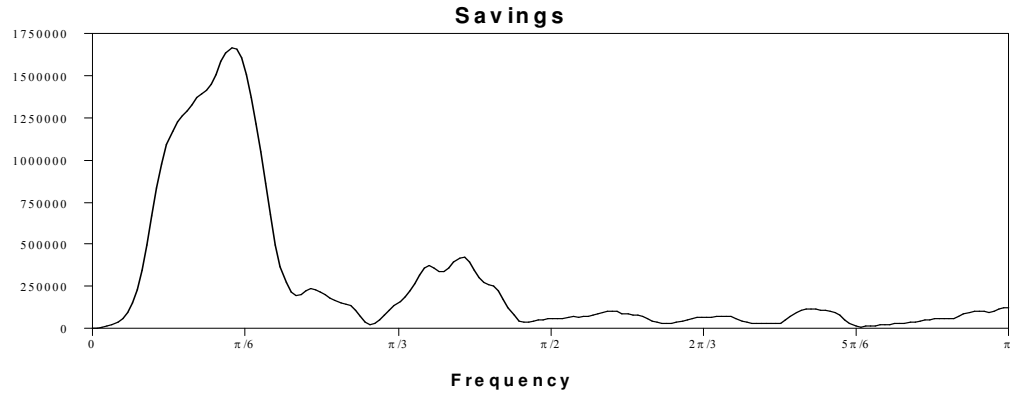
This occurs at entry $j=14$ at a low frequency of 0.159 radians consistent with a periodicity of 39.386 quarters a much longer swing of almost 10 years in duration. By way of contrast, the graph of investment (Figure 2) reveals a second peak at frequency $\pi/3.4$ with a periodicity of 10 quarters or 18 months shorter than the main component of 4 years duration.

Figure 2



Savings also displays an important shorter swinging component with a frequency of 8.722 radians periodicity of 7.2 quarters. This short swing may reflect the motives of both savers and investors. In each case this second important component of the I and S series is much shorter than the conventional view of the Australian business cycle.

Figure 3



In summary, the major component of each of the three series is one which completes a full cycle in 4 to 4.75 years. A longer swinging 10 year cycle is evident in the Australian real GDP series although it does not contribute as much to its total variance GDP in comparison with the four year business cycle. The second most important contributor to the variance of Australia's S and I series is a swing of 18-21 months.

These attributes of the I and S series may reflect the motives of investors and savers who are influenced by short term as well as long term effects on their investment and savings plans.

4.2 Cross Spectral Relationships

An interesting aspect of the results from the univariate spectral analysis is that the peak frequencies in each individual case appear to occur on cycles of similar periodicity: the predominant cycle in each series has a duration of 4 to 4.75 years. This correspondence of cycles in the individual series prompts further bivariate cross spectral analysis with the purpose of determining if the predominant cycles in each series cohere. The results of this cross spectral analysis are shown on Table 2 beginning with the bivariate analysis of I and S and moving to the coherence of S with *y* and I respectively. The diagnostics shown below the maximum coherence in each bivariate study on Table 2 indicate first that the mean coherence between I and S (0.621) and I and *y* (0.630), S and *y* (0.697) are of commensurate size across all components. Table 2 has been constructed to capture the coherence between the major swings in the three variables at j = 27, 30 and 31 for I, S and *y* respectively. Thus in the analysis of cycles in S and I, the coherence between components at j = 27 (frequency 0.319 radians) the coherence is 0.754 and significant at the 5 percent level according to the tests for $c\hat{o}h = 0$ specified by Koopmans (1974, p.284). We reject this hypothesis at the given level because the relevant F=10.958. The same conclusion is drawn about the coherence of S and I at j = 28 (frequency 0.335 radians) and j = 29 (frequency 0.343 radians). The coherence between the common major cyclical episodes in I and *y* is weaker.

Table 2: Cross Spectral Analysis of S and I and *y*

I and S				
j	Coherence	F (1)	Phase (Radians)	Time Difference
27	0.754	10.958	-1.51	-0.473
28	0.757	11.002	-1.68	-0.507
29	0.758	11.231	-1.78	-0.519
Min Coh	0.013			
Max Coh	0.981			
Mean	0.621		0.082	
T ratio	33.165		4.001	
Skewness	-0.559		-0.548	
Kurtosis	-0.927		0.911	

I and *y*				
j	Coherence	F (1)	Phase (Radians)	Time Difference
27	0.550	3.608	0.034	0.107
29	0.523	3.257	0.030	0.088
31	0.498	2.767	0.022	0.155
Min Coh	0.024			
Max Coh	0.992			
Mean	0.630		-0.046	
T ratio	32.558		2.683	
Skewness	-0.577		-0.783	
Kurtosis	-0.799		3.026	

S and *y*				
j	Coherence	F (1)	Phase (Radians)	Time Difference
29	0.870	25.720	-0.160	-0.690
30	0.874	26.879	-0.162	-0.456
31	0.875	27.099	-0.156	-0.424
Min Coh	0.100			
Max Coh	0.987			
Mean	0.697		-0.108	
T ratio	-4.083		4.083	
Skewness	1.121		1.121	
Kurtosis	1.819		1.891	

(1) Koopmans (1974 p.284) test statistic for the coherence on Table 2 will exceed the $\alpha = 0.05$ critical value for Fisher's F distribution. $F_{2,2(n-1)} = (n-1)\hat{coh}^2 / (1-\hat{coh}^2)$ has the critical value 19.5 at 2, 2(n-1) degrees of freedom. The null of $coh = 0$ is rejected in each case.

The calculated F statistics in this case hover just below the 5% critical value and are only significant at the 10% value. Further, the coherence statistic is markedly lower, ranging in value from 0.498 to 0.550 at j = 27. Finally, from Table 2, the strongest coherence relates to the study of S with y. In this case the major common swing at j = 29, 30 and 31 cohere strongly so that in each case the F statistic exceeds its critical value comfortably. The value of the coherence at j = 29, 30 and 31 is 0.870, 0.874 and 0.875 respectively.

This cross spectral study indicates the presence of a medium term relationship between the I and S series of approximately four to four and three quarter years duration. This frequency component was also found to be the predominant harmonic component in the individual series and is also strongly correlated in the bivariate case. The correlation of the 4.75 years swing in gross saving and the four year swing in the I series may be explained by their association with the predominant 4.5 year swing in y. In addition we can add that the Australian gross savings series cohere strongly with the predominant 4.25-4.75 year cycle in GDP. The negative signs on each estimated time difference in the last column of Table 2 indicate that investment leads savings by 0.473 quarters at j = 27, by 0.507 quarters at j = 28 and by 0.519 at j = 29 quarters.

The outstanding finding from this cross spectral study is that Australian gross savings and gross investment cohere strongly and that gross savings are also strongly correlated with the major swing in real GDP however, the coherence between gross investment and real GDP is not as strong. The policy implications which follow from this frequency domain analysis are discussed in the concluding section.

5 Conclusions

The cyclical behaviour of I and S and confirm that both series are cyclical in nature. The most important cyclical component in each series is a swing of 4 to 4.75 years duration. A second noteworthy feature of the I series is the presence of a cyclical component of 18 months somewhat shorter than the 4 year business cycle perhaps reflecting the shorter term motives of some investors. The S series also displays a shorter swing of less than 2 years duration reflecting the short run motivation of some savers. Finally, the major component of the real GDP series is a cyclical component of 4 years consistent with the commonly accepted duration of the business cycle. This business cycle component explains 37 percent of the total variation of the real GDP series. Further, a longer swing of 10 years duration is also evident in the real GDP series. This component explains one quarter of the variation of the real GDP series.

The study of the individual I and S series is augmented by bivariate comparisons of cycles in the individual series and in this way we find the strongest coherence between the I and S series occurring on the cyclical component of 4.75 years duration. So from this outcome it can be argued that the Australian saving and investment ratios are strongly correlated in the medium term. Further the coherence between the variation of the I series and real GDP is at a maximum on a cyclical component of 4.25 about the same duration as the business cycle. However, the coherence of the peaks in gross investment and real GDP is smaller. Finally, gross savings and real GDP exhibit their strongest coherence on a cycle of 17 quarters again close to the duration of the business cycle.

The studies of Obstfeld (1986), Finn (1990), Mendoza (1991) show that the persistence of business cycle shocks is the main reason for the high correlation between savings and investment. The results derived in this study are consistent with the findings of these studies. Moreover, Mendoza (1991) finds that in the case of Canada, there is a high correlation between savings and investment with high capital mobility contrary to the findings of Feldstein and Horioka (1980). The Australian economy is very similar to that of Canada in that it is a small open economy. The high correlation between savings and investment in the Australian economy need not therefore be interpreted as evidence against capital mobility although this has not been specifically tested.

These finding are significant for policy coordination. If investment and saving ratios are coherent with the business cycle then policies motivated by the presence of internal imbalances will have a simultaneous impact on saving and investment and consequently on external balance. Thus the procyclical characteristic of saving and to a lesser extent investment greatly enhances the prospective benefits of harmonising policy strategies to achieve both internal and external balance. In conclusion, we can infer from the results of this study that Australian savings behave procyclically potentially making the effects of policy changes more predictable and effective. However, the correlation of swings in gross investment with the business cycle is not so strong suggesting that gross investment in Australia is explained by factors other than the business cycle.

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