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A spectral analysis of New Zealand output gaps using Fourier and wavelet techniques

Paul Conway* and David Frame**

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Abstract[1]

This paper uses frequency domain techniques to illustrate the properties of various measures of New Zealand's output gap. Measures of the output gap are estimated using a number of different methods: a Structural VAR model, a multivariate unobserved components model, the Hodrick-Prescott filter, a multivariate time series filter, and a linear time trend filter. Spectral densities, calculated using the Fourier transform, highlight a number of important differences in the cyclical properties of the various output gap measures. However, the Fourier transform requires time series to be (weakly) stationary. This may be an unreasonable assumption for New Zealand data given our recent economic history. Accordingly, the paper also uses time-dependant spectra, calculated using wavelet analysis, to further illustrate the cyclical characteristics of the different techniques used to estimate the output gap.

* Economics Department
Reserve Bank of New Zealand

** Centre for Global Atmospheric Modeling
University of Reading

[1] The views in this paper are those of the authors and not necessarily those of the Reserve Bank or the Centre for Global Atmospheric Modeling.

1 Introduction

In this paper we use spectral techniques to illustrate the properties of different measures of New Zealand's output gap. The 'output gap' is simply the percentage difference between real output and 'potential output'. In turn, potential output represents an economy's steady-state level of output, that is, the level of output to which actual output reverts in the absence of temporary shocks. In the framework of monetary policy, the output gap provides a measure of inflationary pressure in the economy. If the output gap is positive through time, so that actual output is greater than potential output, then inflation will begin to move upwards in response to demand pressures in key markets.[2]

Potential output measures the productive capacity of the economy and is determined by factors such as the level of technology, the abundance and quality of productive resources and the microeconomic environment. However, because it is difficult to quantify 'technology', which is inherently unobservable, it has generally proven impracticable to estimate potential output on the basis of these fundamentals. Instead, economists use a variety of techniques to infer the level of potential output from observable macroeconomic data. In essence, the problem is one of decomposing real output into a trend and cycle component. The trend is interpreted as a measure of the economy's potential output and the cycle is interpreted as a measure of the output gap.

This is not a straightforward decomposition to effect. There is little consensus in the economics literature about the most appropriate representation of the trend and cycle components of real output. Some of the earliest estimation techniques simply assumed that the trend was a deterministic function of time that could be extracted using a simple linear regression. However, the findings of Nelson and Plosser (1982) indicate that trends in economic time series are generally not deterministic and are more appropriately modelled as stochastic processes.

During the last twenty years or so economists have developed a wide variety of techniques to extract a stochastic trend from real output. These techniques use a broad range of statistical criteria and assumptions about economic structure to identify the trend. For example, simple linear filters such as the first difference filter and the well-known Hodrick and Prescott (1997) filter identify the trend in output based primarily on the statistical properties of the actual output series and have little economic content. On the other hand, Cochrane (1994) estimates potential output based on assumptions about economic structure derived from the permanent income hypothesis. Blanchard and Quah (1989) develop a structural vector autoregressive model that also estimates potential output and the output gap based on structural assumptions about the nature of economic disturbances.

All techniques for estimating potential output and the output gap are prone to potentially large uncertainties. Methods based on assumptions about economic structure approximate unknown features of the economy and are therefore subject to model uncertainty and specification errors. Quah (1992) argues that there are an

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[2] This definition is consistent with Okun (1970) who defines potential output as being "the maximum production without inflationary pressure; or, more precisely … a point of balance between more output and greater stability" (page 98).

infinite number of trend-cycle decompositions for any given time series, implying that estimates of potential output based on statistical criteria may be arbitrary from an economic perspective.

Because of the range of methods available to measure potential output and the output gap it is useful to illustrate, in some way, the properties of their respective (uncertain) estimates. Given the obvious parallels between measuring potential output and detrending output to extract a measure of the business cycle, we adopt an illustrative technique that is often used in the business cycle literature. The 'business cycle' is typically defined on the basis of the period or frequency of volatility. Accordingly, business cycle researchers often use spectral techniques to examine the frequency components of business cycle measures.[3] This is the approach that we follow in this paper.

We begin by using the Fourier transform to calculate spectral densities for various estimates of New Zealand's output gap. Spectral densities indicate the relative importance of different frequency components and thereby highlight important differences in the cyclical properties of the output gap measures. To facilitate comparison, we use a benchmark that has become increasingly popular in the business cycle literature. Since the seminal work of Burns and Mitchell (1946), economists have generally defined the business cycle as a cycle in output that is between 6 and 32 quarters in duration. Spectral densities allow us to assess the proficiency with which the various methods of estimating potential output isolate cycles of this duration from New Zealand real output data.

A potential limitation of traditional Fourier analysis is that it does not account for variation in the frequency components of a time series through time. A single disturbance at a particular time is interpreted in Fourier analysis as an event of length T, where T is the length of the time series. The maintained hypothesis is that the same frequency components exist with the same amplitudes at all points in time. That is, the time series is homogeneous through time. Given New Zealand's rather turbulent recent economic history, estimates of the output gap are unlikely to satisfy this condition.

To overcome this limitation we also use wavelet analysis to assess the spectral properties of the various estimates of the output gap *through time*. This technique allows us to decompose the output gap measures into orthogonal components extracted at different frequencies (or scales). In this way we are able to assess the relative importance of different frequency components through time and thereby illustrate further the characteristics of the various output gap measures.

In what follows, section two outlines the different methods of estimating potential output and briefly discusses the associated measures of the output gap. The Fourier transform and the results of applying this technique to the various measures of New Zealand's output gap are discussed in section three. Section four briefly outlines the limitations of traditional Fourier analysis and discusses the mechanics of the wavelet technique. The results of the wavelet analysis are also presented in this section. Finally, concluding remarks are offered in section six.

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3 See, for example, Canova (1998), Dupasquier and Guay (1997) and Woitek (1996).

2 Methods of estimating potential output and the output gap

The measures of New Zealand's output gap that we consider are estimated using the following techniques: a Structural VAR model (SVAR), a multivariate unobserved components model (UC), the Hodrick-Prescot filter (HP), a multivariate time series filter (MV), and a linear time trend filter (LT). These various techniques and associated estimates of the output gap are briefly discussed in turn.

The SVAR model, applied to New Zealand data, is outlined in detail in Claus (2000). This model is an adaptation of the Blanchard and Quah (1989) SVAR methodology. The key identifying restriction used in this model is that, in accordance with the natural rate hypothesis, demand shocks do not affect output in the long run whereas supply shocks do. The SVAR model of Claus (2000) uses additional conditioning information from the employment rate and capacity utilisation to aid in the decomposition of output into trend and cycle.

The UC model is presented in Scott (2000). This model posits that observed output can be decomposed into an unobserved trend (potential output), a trend-reverting or cyclical component (the output gap), and random noise. The key assumptions used to identify this model are that the trend component evolves subject to a local linear trend model and that the dynamics of the cyclical component are well described by an autoregressive process. The model is estimated via the Kalman filter and maximum likelihood and identifies a common cyclical component in real output, unemployment and capacity utilisation.

The HP filter is relatively well known and is often used to remove a stochastic trend from real output. The mechanics and characteristics of this filter have been extensively documented in the literature.[4] This filter calculates a measure of trend output that minimises the squared deviation of actual output from trend output subject to a trend smoothness constraint, which is weighted by the variable λ. In the context of estimating potential output, the value of λ reflects, at least implicitly, the relative importance of supply and demand shocks in the evolution of actual output. The larger the value of λ, the smoother the estimate of potential output and the larger the proportion of output variability ascribed to the output gap. We calculate two measures of the output gap using the HP filter, one with λ set at 1600 (HP1600) and one with λ set at 400 (HP400).

The MV filter is described in Conway and Hunt (1997). This technique augments the stochastic-trend estimation approach of the Hodrick-Prescott (1997) filter with information from broad macroeconomic relationships. Specifically, the MV filter incorporates additional identifying information from an Okun's Law relationship (unemployment), a capacity utilisation relationship and a Phillips curve relationship (inflation). This strategy is designed to improve the accuracy with which the filter identifies shocks to the trend and cycle component of real output.

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[4] See for example: Cogley and Nason (1995), Gregory and Smith (1995) and Harvey and Jaeger (1993).

The LT filter is one of the simplest and oldest methods of estimating potential output. This technique assumes that potential output is a deterministic process that grows at a constant rate through time. Accordingly, potential output is estimated by fitting a linear time trend and a constant to (log) actual output using least squares.

The 'output gap' is simply calculated as the percentage deviation of actual output from the measures of potential output estimated using each of the above techniques. The output gap estimates are graphed in figure one. The sample period is from 1971q1 to 1999q3.[5]

A number of empirical features are apparent from the graph. The SVAR and UC estimates of the output gap move broadly in line with each other. Furthermore, these estimates, and the LT measure of the output gap, appear to display deeper and longer cycles relative to the HP and MV filter output gap estimates. For example, according to the SVAR and UC output gap estimates, the recession in the early 1990s cost seven to eight percent of potential output, and actual output was below potential for some six years. In comparison, according to the HP and MV filter output gap estimates, this recession amounted to three to four percent of potential output and actual output was below potential for only 2 ½ to 4 years.

The output gaps estimated using the HP400 and HP1600 filters also tend to move together with the latter exhibiting cycles of slightly larger amplitude. Finally, the output gap estimated using the MV filter appears to display phase and persistence characteristics that are similar to the HP1600 output gap. However, the level of the MV output gap estimate is often different to that of the HP1600 output gap estimate.

Correlation coefficients between the various measures of the output gap are reported in table one. These statistics generally confirm the story told in the graph. Measures of the output gap obtained using the HP filters and the MV filter are highly correlated, as are the SVAR and UC output gaps.

[5] Note that the MV filter uses a survey measure of expected inflation. This series begins in the first quarter of 1983. Given this constraint, the Phillips curve component of the MV filter is estimated over the period 1983q1 to 1999q3. The estimated coefficients are then imposed on the MV filter estimate of potential output over all of the sample period.

Figure 1: Output gap estimates

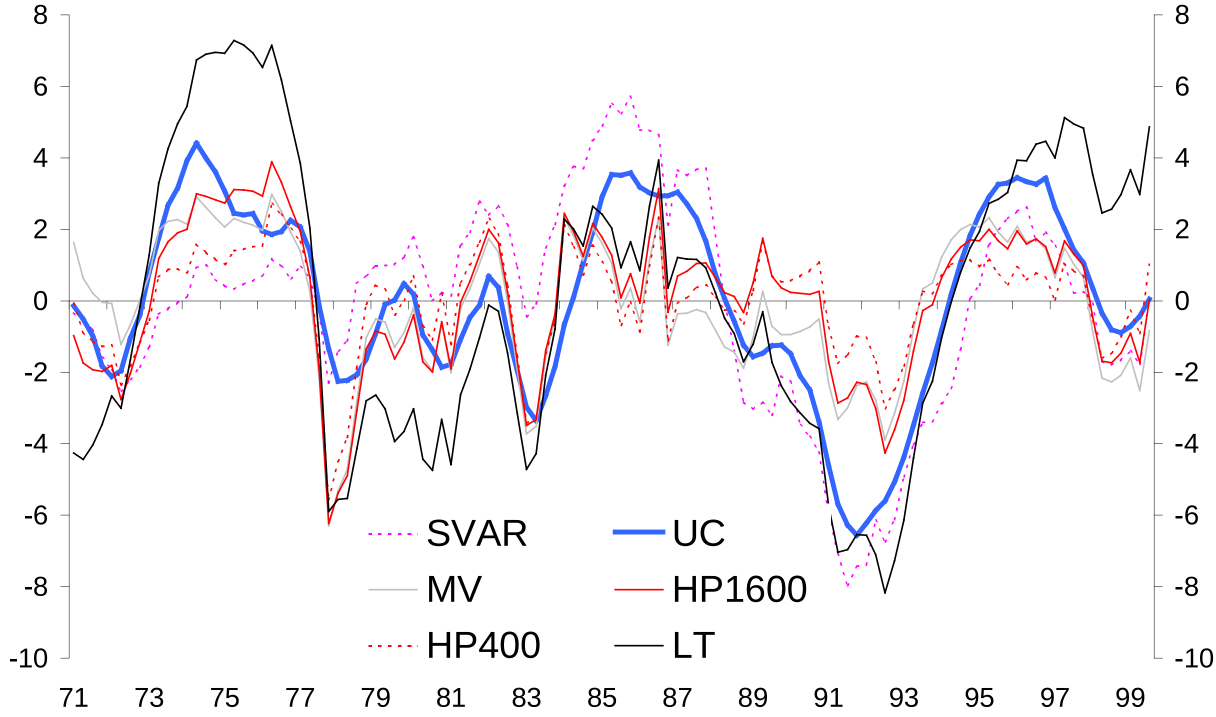

Table 1: Correlation coefficients

	SVAR	HP1600	HP400	LT	UC	MV
SVAR	1					
HP1600	0.53	1				
HP400	0.42	0.94	1			
LT	0.55	0.83	0.66	1		
UC	0.79	0.75	0.58	0.84	1	
MV	0.50	0.92	0.88	0.75	0.73	1

3 Fourier analysis

3.1 The technique

Virtually all quantitative macroeconomic information is expressed in the time-domain. That is, whatever is being measured is typically expressed as a function of time. This representation may not necessarily be the most revealing. In many cases, such as business cycle analysis, important economic information may be hidden in the frequency content of the time series. In order to access this information, transformations are employed that take a time series from the time-domain and represent it in another domain.

The Fourier transformation maps a time series from the time domain into the frequency domain. This transformation is based on the following equation:

$$F(k) = \int_{-\infty}^{\infty} f(t) e^{i2\pi kt} dt \qquad (1)$$

where *f(t)* is the original time series and *k* is frequency. In effect, this transformation looks for correlation between *f(t)* and complex exponential (sine and cosine) functions of different frequencies. If a substantial proportion of the variance in *f(t)* is due to cycles of frequency *k*, then *F(k)* will be relatively large. By calculating Fourier coefficients at different frequencies, we can expresses time series as integrals of random, uncorrelated amplitudes at various frequencies.

Spectral densities plot *F(k)* against *k* and illustrate graphically the relative importance of the different frequency components that exist in *f(t)*. The total area below the spectral density corresponds to the variance of *f(t)*, and the height at any given frequency provides a measure of the extent to which cycles of that frequency predominate. For example, if the spectral density is large for high frequencies, then the series will display a high degree of oscillatory behaviour. If the spectral density is sizeable only for very low frequencies, then the time series will evolve relatively smoothly through time.

Fourier transforms are exceptionally good at analysing (weakly) stationary time series – that is, time series whose frequency content does not change through time.[6] For example, consider the time series in figure 2a. This series is the sum of three sine functions of different frequencies. The spectral density of the time series is graphed in figure 2b. The unit of the horizontal axis is frequency measured in hertz. The unit of the vertical axis is amplitude squared, a measure of power. In this case, the spectral density identifies very clearly the three frequency components that are active in the original time series.

A potential limitation of using the Fourier transform to analyse macroeconomic data is discussed in section 4 below. However, we first present spectral densities for the estimates of New Zealand's output gap introduced above.

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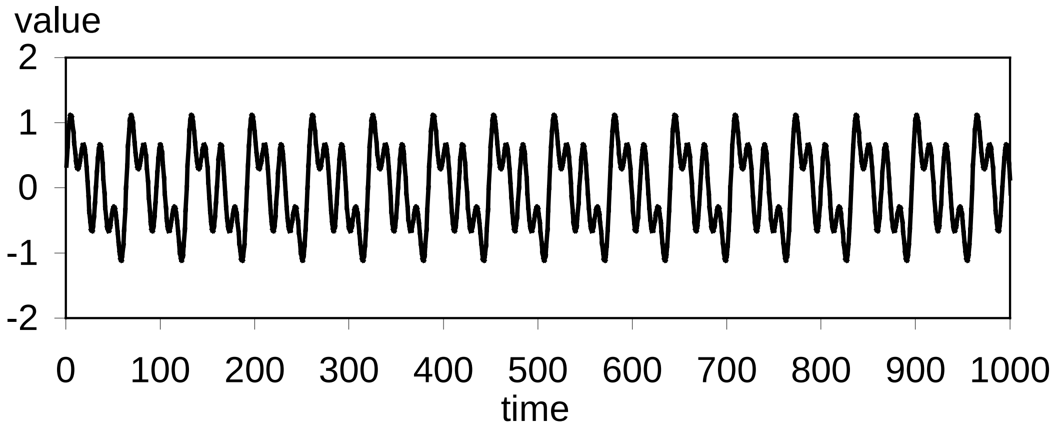
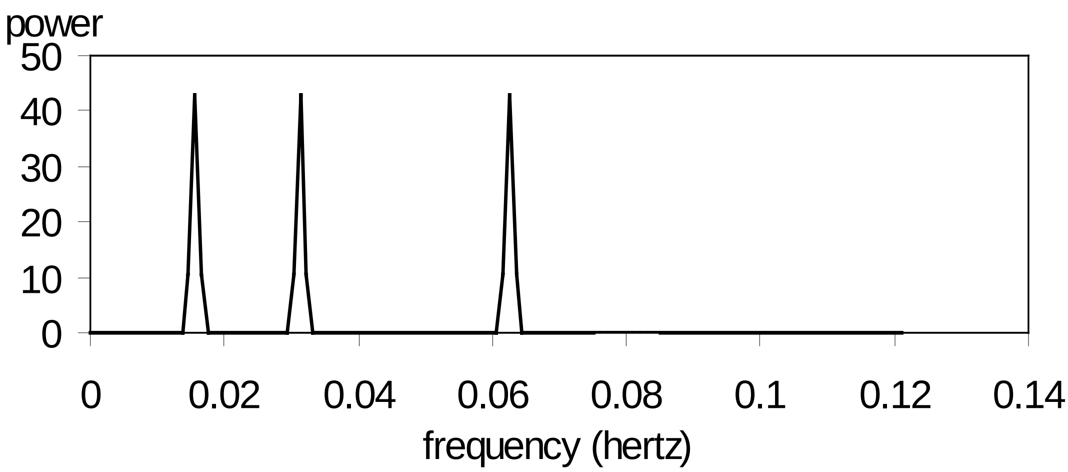
[6] This is a frequency-domain definition of a stationary time series. The (equivalent) time-domain definition of a (weakly) stationary time series is one with constant means and variances over time and covariances that depend only on the time difference between the time points in question.

Figure 2: Periodic time series and spectral density

a) Time series



b) Spectral density



3.2 Fourier results

Estimated spectral densities for the various output gap measures are displayed in figure 3. These are calculated using Welch's method of averaging the periodogram to obtain an unbiased and consistent estimate. The shaded areas in the graphs denote business cycle frequencies – that is, frequencies that correspond to cycles with periods between 6 and 32 quarters.[7] To aid comparison, the spectral densities have all been normalised so that the area under the curve is equal to one.

The spectral densities presented in figure 3 imply that the SVAR, UC and LT methods of estimating potential output result in output gap measures that contain very predominant low frequency components. The LT and UC output gap estimates have distinctive peaks in their spectral densities at a frequency of 0.026 hertz, corresponding to a period of around 38 quarters. The spectral density for the SVAR output gap estimate has a predominant peak at a frequency of 0.017 hertz, corresponding to a period of around 58 quarters. For the SVAR, this peak is clearly outside the maximum period for 'typical' business cycle variability. For the UC and

7 The period of a cycle (the length of the cycle in quarters) is equal to the inverse of the frequency.

LT output gap measures, the peak is borderline. The spectral densities for the HP1600, HP400 and MV output gap measures imply that very low frequency components play a much less prominent role than in the SVAR, UC and LT output gap measures.

At higher frequencies the spectral densities for the SVAR, UC and LT measures of the output gap have a small secondary hump between 0.112 and 0.078 hertz (corresponding to cycles with periods between 9 and 13 quarters). However, in both cases this feature is swamped by the predominant low frequency components and does not account for a large proportion of the variance in the output gap measures. The MV and HP output gap estimates also have humps in spectral mass between 0.112 and 0.078 hertz. These humps account for a much larger proportion of the total variance than they do for the SVAR, UC and LT output gap measures.

Table 2 reports the percentage of spectral mass lying within the range of business cycle frequencies for the various output gap estimates. On this metric the HP filters are the most proficient at isolating cycles in New Zealand real output at business cycle frequencies.[8] The MV filter is also relatively proficient, followed by the UC, LT and SVAR models respectively.

[8] The larger proportion of spectral mass in the range of business cycle frequencies for the output gap calculated using the HP400 filter tentatively suggests that this filter is more proficient at isolating cycles of business cycle duration than the HP1600 filter. If one wants to use the HP filter to measure New Zealand's business cycle, a value of lambda less than 1600 may be appropriate. Razzak and Dennis (1995) reach a similar conclusion using a different framework. This result is tentative because of uncertainty about the appropriateness of the Burns and Mitchell business cycle definition. Also, the difference between the filters in this regard is small and may be within the margin of error.

Figure 3: Estimated spectral densities of the output gap measures

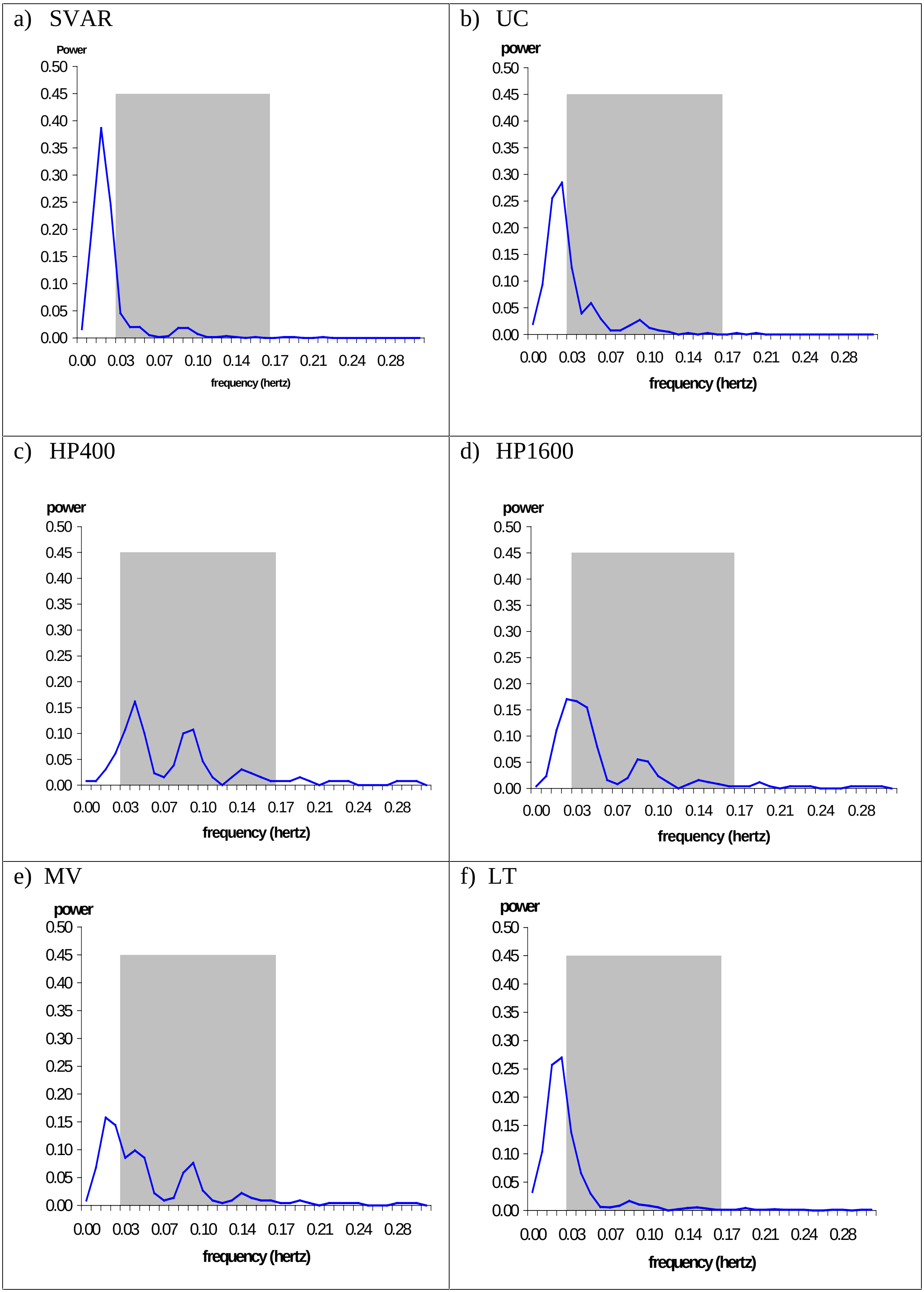


Table 2: Percentage of spectral mass within business cycle frequencies

LT	SVAR	UC	HP1600	HP400	MV
58	40	63	81	86	70

4 Wavelet analysis

4.1 The technique[9]

The Fourier transform does not cope well with time series that are not stationary. For example, figure 4a shows a time series that exhibits changing frequencies over its duration. This time series is made up of three different frequency components, each of which is active over a different interval of time. The spectral density, plotted in figure 4b, clearly identifies the three frequency components that exist in the time series.[10] However, the spectral density does not provide any information on the time localisation of the different frequency components. That is, on the basis of the spectral density, it is not possible to identify where in time each of the three frequency components are active.

In Fourier analysis, no time information is available in the spectral density and no frequency information is available in the time-domain representation of the time series. By considering the frequency-domain representation of a time series one may know which frequency components are active in the time series, but not when they were active.[11] The reverse is true in the time domain – one knows when things happened (features can be localised in the time-domain) but has no information about frequency. The maintained hypothesis underlying the Fourier transform is that all of the frequency components that are active in the time series exist with the same amplitudes at all points in time, that is, that the time series is homogenous through time.

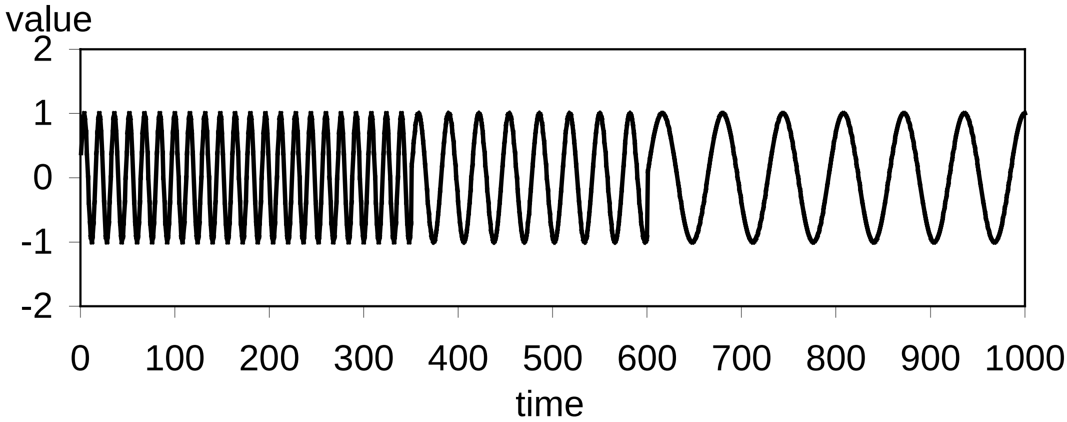
[9] This section gives only the briefest possible outline of one aspect of the wavelet technique. For a good introductory discussion see Chui (1992). A more mathematically detailed treatment is given in Daubechies (1992). Priestly (1996) links wavelet analysis with conventional time-series analysis and Ramsey (1998) reviews applications of wavelet techniques in the areas of economics and finance. Also, Robi Polikar has published a very readable series of wavelet tutorials on the Internet at http://www.public.iastate.edu/~rpolikar/WAVELETS/WTpart1.html

[10] The small ripples in the spectral density are caused by the sudden changes from one frequency to another in the time series. Also, the different power at each frequency is caused by the different duration and period of the active frequency components in the time series.

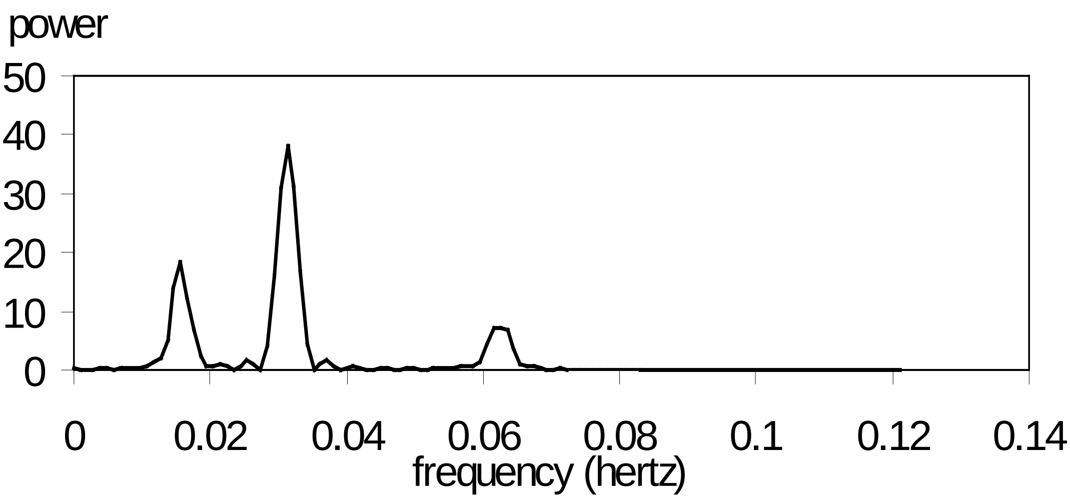
[11] Of course this limitation is not relevant for stationary series because all of the frequency components that exist in the series are active throughout its entire duration.

Figure 4: Time series of 3 different frequencies and spectral density

a) Time series



b) Spectral density



In macroeconomic applications of Fourier analysis, this potential limitation of the technique is often overlooked. However, Koopmans (1995) talks about the "scale of stationarity" of a time series and advocates splitting the time series into epochs that are smaller than this scale. Koopmans acknowledges that this solution to the problem of nonstationarity in time series may not be feasible in the case of macroeconomic data. This is particularly likely to be true for New Zealand macroeconomic data given the short sample periods of time series and the pervasiveness of economic reform.

Wavelet analysis offers an alternative solution to this problem.[12] The family of wavelet transforms differs from the Fourier transform in one crucial respect – wavelets are constructed over finite intervals of time, whereas the sines and cosines that underpin Fourier analysis range over ± infinity. Wavelet transforms thus have an important

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12 Although Fourier transformations are probably the most familiar method used to transform time series, there are many other possible transformations available. The Hilbert transformation, the short-time Fourier transformation, the Wigner distributions, the Radon transform and, of course, the wavelet transform are a small proportion of the potentially infinite number of available transformations.

advantage over the Fourier transform in that they can retrieve information about frequency (or scale, to be defined below) *and* time localisation from the original series.

The term 'wavelet' literally refers to a small wave: 'small' because the wavelet function is non-zero over a finite length of time (compactly supported) and 'wave' because the function oscillates. Wavelet functions are constructed on the basis of location and scale parameters, and a 'mother wavelet' function, as in equation (2).

$$\Phi_{\tau,s} = \frac{1}{\sqrt{s}}\Phi(\frac{t-\tau}{s}) \qquad (2)$$

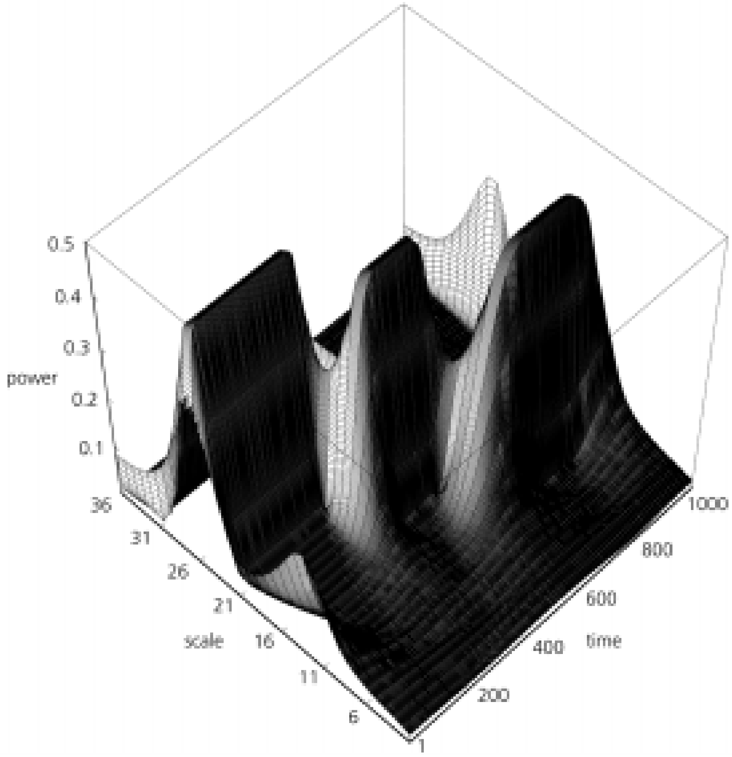
In essence, the mother wavelet, $\Phi(.)$, is a prototype function. To extract *frequency* information from the time series in question, the mother wavelet is dilated or compressed to correspond to cycles of different frequencies. The extent of compression or dilation is determined by the scale parameter, *s*. To extract *time* information from the time series the set of wavelet functions at different scales is moved through the time series from beginning to end. The position of a particular wavelet function in the time series is determined by the location parameter, τ. In this way an entire set of wavelets can be generated from a single mother wavelet function and this set can then be used to analyse the time series.

Wavelet coefficients ($C_{\tau,s}$) are given by the transformation

$$C_{\tau,s} = \int f(t)\Phi_{\tau,s}(t)dt \qquad (3)$$

If $f(t)$ has a spectral component corresponding to the current wavelet scale (s) at the location τ, then the product of $\Phi_{\tau,s}(t)$ and $f(t)$ will be relatively large. If a spectral component at scale s is not present in $f(t)$ at a given location then this product will be relatively small or zero. Wavelets constructed over short time scales will tend to isolate sharp, high frequency volatility in the time series. Because of the short time scales, this information will have good time resolution but poor scale (frequency) resolution. Relatively long-scale wavelets will tend to capture low frequency volatility and will have relatively poor time resolution but good scale (frequency) resolution.

Figure 5: Wavelet coefficients



As an example of the wavelet transform, recall the time series plotted in figure 4a above. Figure 5 graphs the wavelet coefficients of this series. This graph depicts the extent of power in the time series at each time-scale combination. Unlike the spectral density in figure 4b, the wavelet coefficients clearly identify the three different time periods over which each of the three frequency components are active.

In what follows, we use a discrete version of the wavelet transformation to analyse the various measures of New Zealand's output gap. The discrete wavelet transformation (DWT) calculates wavelet coefficients over a dyadic scale, that is, $s_j=2^j$, j=1,2,3… To illustrate the spectral properties of the various measures of the output gap, we reconstruct the original time series *at each scale* using an inverse wavelet transformation. In effect, this procedure allows us to decompose the various measures of the output gap into cyclical components at each admissible scale (or frequency). These components sum to equal the original time series.

We use the Daubechies wavelet to effect the transformations.[13] The maximum wavelet scale, which is dependent on the sample period of the data, is set at 2^6=64 quarters.

[13] There are an infinite number of possible wavelet basis functions. The simplest of these is the Haar wavelet. The Daubechies family of wavelets comprises an interesting and commonly used set – unlike earlier sets such as the Haar or Meyer sets, the Daubechies family of wavelets are continuously differentiable and have compact support.

4.2 Wavelet results

Figure 6a graphs reconstructed components for each of the output gap measures at the gravest scale available, $s_6 = 2^6 = 64$ quarters. The most obvious feature of the graph is the relatively pronounced cycle in the SVAR, LT and, to a lesser extent, the UC measures of the output gap at this scale. In contrast, virtually none of the movement in the MV and HP output gap measures is explained by volatility at this scale. Consistent with the Fourier results, this once again implies that relative to the other measures, the SVAR, LT and UC techniques impart a very low frequency component to their respective output gap estimates.

To illustrate the significance of this very low frequency cycle, figure 7 plots the SVAR and UC estimates of the output gap with the s_6 component removed. For comparative purposes the HP1600 and MV estimates of the output gap are also graphed. Without the s_6 component, the (adjusted) SVAR and UC output gaps suggest that the recession in the early 1990s troughed at around 5 percent, significantly less severe than the unadjusted SVAR and UC output gap estimates. In general, the adjusted SVAR and UC output gap estimates are more highly correlated with the HP1600 and MV output gap measures than the unadjusted measures. This implies that the very low frequency cycles in the SVAR and UC output gap measures explain a substantial proportion of the differences between these output gap measures and the HP1600 and MV filter measures.[14] During the 1980s, however, the output gap measures in figure 7 are still considerably different. This highlights the increased uncertainty associated with estimating the output gap during the period of New Zealand's economic reforms.

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[14] Note that the LT output gap estimate with the s_6 component is still significantly different from the HP1600 and MV output gap estimates.

Figure 6: Components

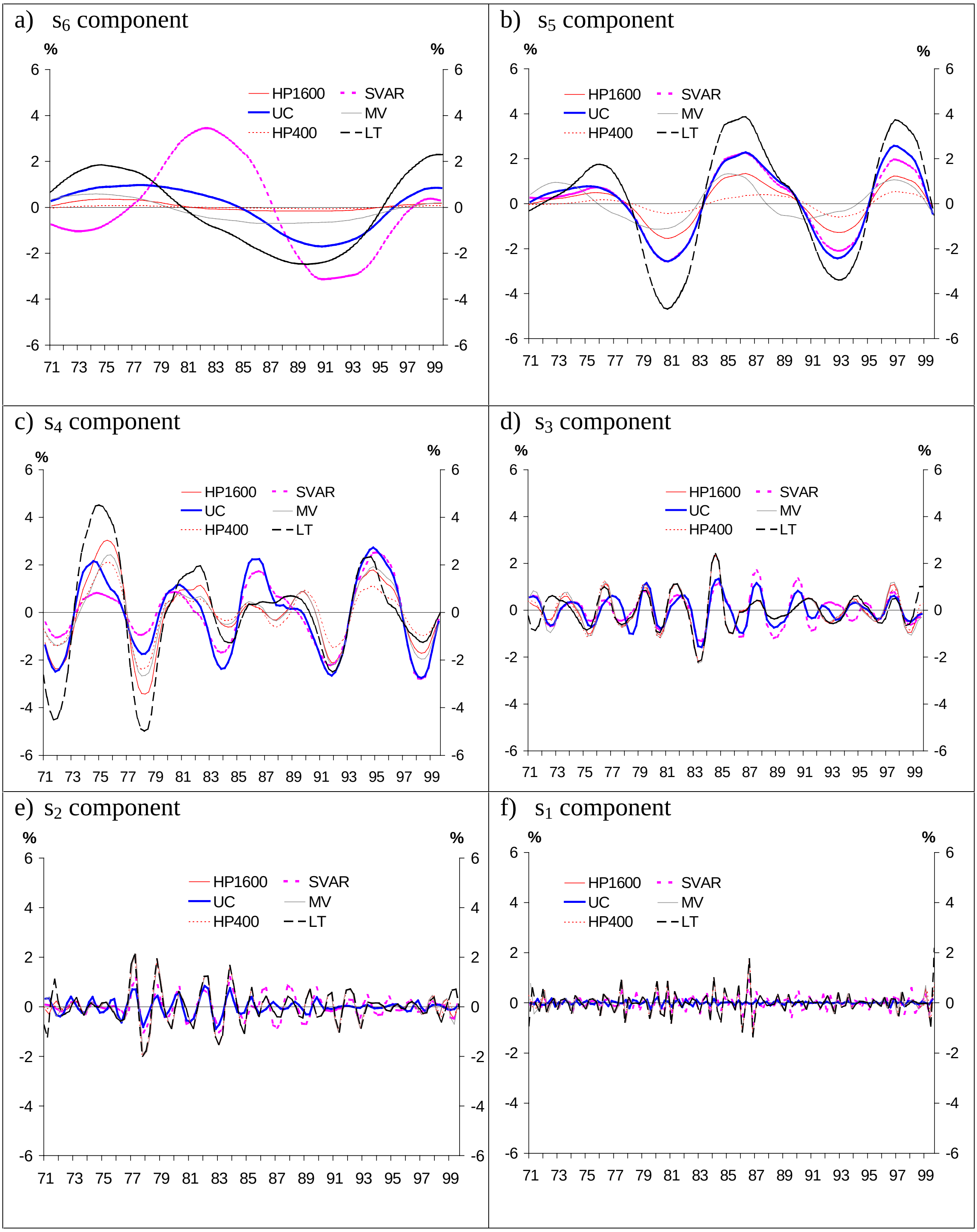
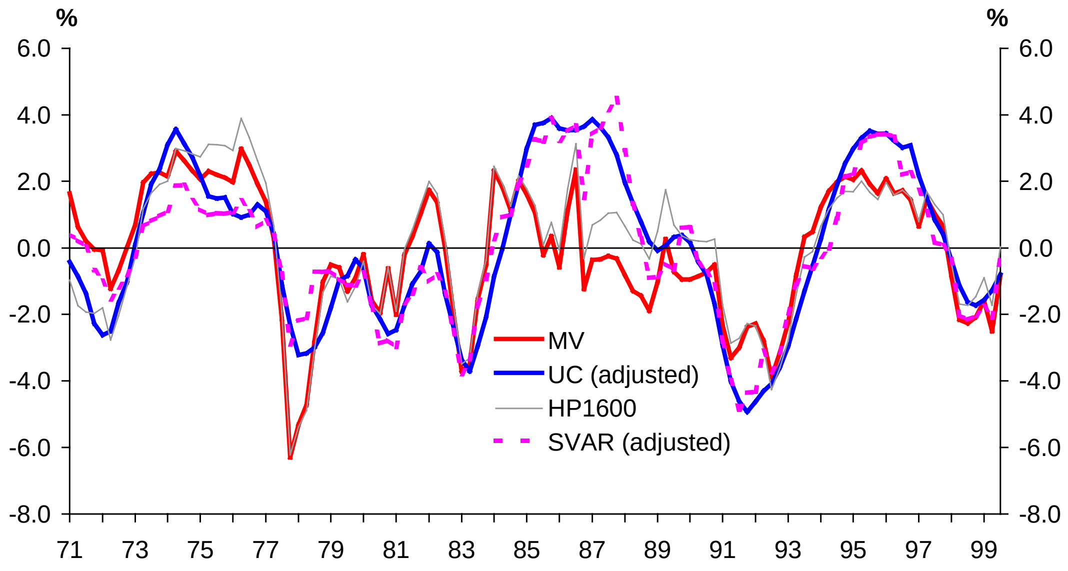


Figure 7: Adjusted measures of the output gap



Components at the scale of 2^5 = 32 quarters (s_5) for the various output gaps are displayed in figure 6b. Again, the LT, and to a lesser extent, the SVAR and UC output gap estimates display more volatility in this component than do the HP1600, HP400 and MV gap estimates. In general, the s_5 components for the various output gaps are broadly in phase with peaks and troughs occurring in reasonably close proximity.

At a scale of 16 quarters (s_4, figure 6c), the cyclical components for the various output gap measures are broadly in phase prior to the early 1980s and after the early 1990s. Over the intervening period turning points in the s_4 cyclical component are substantially less similar. This phase pattern is also apparent in the s_3 component (figure 6d). Both of these observations highlight the 1980s – a decade of extensive economic reform in New Zealand – as a period of disagreement about the level of the potential output and the output gap.

Another notable feature of the s_3 component for all of the output gap measures is the generally smaller amplitude of cycles in the 1990s, relative to the rest of the sample period. This feature is also apparent from Figure 6e, which plots the s_2 components (with a scale of 4 quarters).

Finally, figure 6f displays cyclical components at the lowest admissible scale of s_1=2 quarters. This component tends to capture high frequency volatility in the output gap measures. At this scale the UC estimate of the output gap has virtually no amplitude. From figure 8 it is apparent that this occurs because the UC estimate of potential output effectively 'soaks up' high frequency volatility in actual output. The most obvious example of this is the 'GST spike' that occurred in 1986q3.[15] The UC estimate of potential output effectively matches this spike in actual output thus leaving the UC output gap measure void of high frequency volatility.

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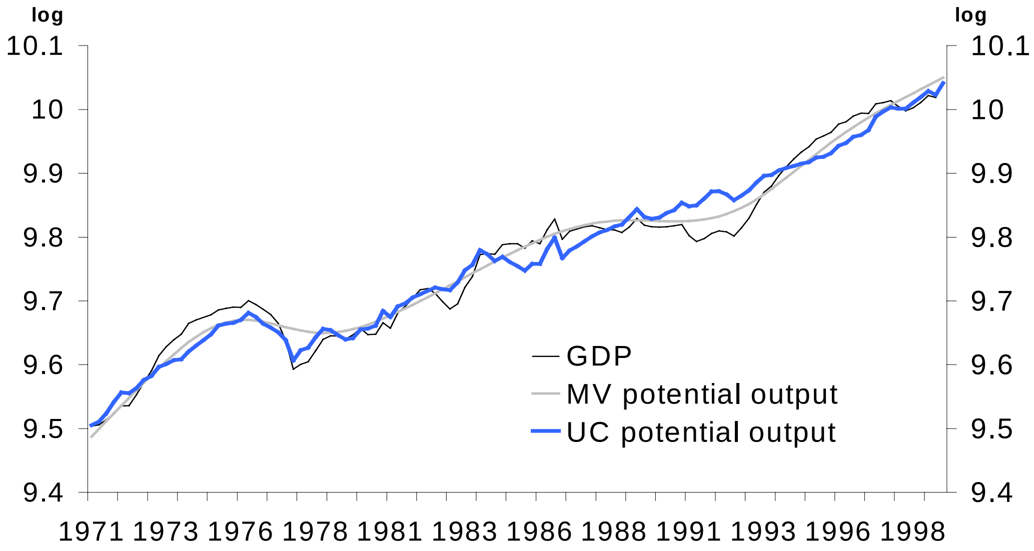
15 GST is a goods and services tax that was introduced at a rate of 10% from 1 October 1986 (subsequently increased to 12.5% in July 1989). In anticipation of the introduction of GST, demand surged in 1986q3 resulting in the GST spike in New Zealand's GDP.

Figure 8: GDP and UC and MV potential output



6 Conclusions

The frequency-domain results illustrate that substantial differences between the various output gap measures reside in their low frequency components. The SVAR, and to a lesser extent, the UC and LT methods of estimating potential output result in output gap measures that have predominant low frequency cycles in comparison to the HP1600, HP400 and MV filter output gap estimates. The obvious question that this raises is where should volatility at such low frequencies reside? Is it part of the demand cycle in the economy or does it reflect the evolution of potential output? According to conventional business cycle wisdom, this volatility is below the range of typical business cycle variability, indicating that the HP and MV filters are more proficient than the LT, SVAR and UC techniques at measuring the output gap.[16]

Despite their differences, all of the output gap measures do have common cyclical characteristics at particular frequencies. The spectral densities for all of the output gap estimates identify a common hump of spectral mass corresponding to cycles between 9 and 13 quarters duration. In addition, prior to the early 1980s and after the early 1990s, components of the various output gaps at scales of 8 and 32 quarters are broadly concordant. Over the 1980s, however, the output gap components at this scale are less similar. This suggests that the various estimation techniques have more difficulty disentangling the relative incidence of demand and supply shocks over the period of New Zealand's macroeconomic reforms. This is not surprising given the relative turmoil of economic reform and the associated structural adjustment.

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16 It is worth noting that 6 to 32 quarter benchmark is not above suspicion. It is a little arbitrary and based on the business cycle experience of the US economy. New Zealand's output gap may well display idiosyncratic characteristics given our unique economic history. From the perspective of monetary policy, the ultimate test of competing measures of the output gap is their ability to explain inflation in a Phillips curve context. The very long period cycles in the SVAR, UC and LT measures of the output gap may be legitimate if they are consistent with the historical evolution of inflation in New Zealand.

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