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The great moderation under the microscope: decomposition of macroeconomic cycles in US and UK aggregate demand

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Abstract

In this paper the relationship between the growth of real GDP components is explored in the frequency domain using both static and dynamic wavelet analysis. This analysis is carried out separately for the US and UK using quarterly data, and the results are found to be substantially different for the two countries. One of the key findings of this research is that the ‘great moderation’ shows up only at certain frequencies, and not in all components of real GDP. We use these results to explain why the incidence of the great moderation has been so patchy across GDP components, countries and time periods. This also explains why it has been so hard to detect periods of moderation (or other periods) reliably in the aggregate data. We argue this cannot be done without separating the GDP components into their frequency components over time. Our results show why: the predictions of traditional real business cycle theory often appear not to be upheld in the data.

Keywords: business cycles, growth cycles, discrete wavelet analysis, US real GDP, UK real GDP

JEL classification numbers: C49, E20, E32

Suuri vakauden kausi suurennuslasin alla: vain lyhyen aikavälin kasvun vaihtelut vaimentuivat Yhdysvalloissa ja Isossa-Britanniassa

Suomen Pankin keskustelualoitteita 13/2011

Patrick M. Crowley – Andrew Hughes Hallett
Rahapolitiikka- ja tutkimusosasto

Tiivistelmä

Tässä työssä tutkitaan BKT-erien riippuvuuksia eripituisten kasvujaksojen aikana. Kasvujaksot.estimoidaan taajuusalueen väreanalyysia hyödyntäen. Tutkimuksessa BKT-erien kasvun vaihteluita tarkastellaan erikseen Yhdysvaltojen ja Ison-Britannian neljännesvuosiaineistossa, ja tulokset viittaavat merkittäviin eroihin näiden maiden välillä. Suuri vakauden kausi on tulosten mukaan vaikuttanut lisäksi vain joihinkin BKT:n eriin ja vain tietyn pituisissa kasvujaksoissa. Nämä tulokset auttavat ymmärtämään, miksi suuren vakauden kausi on vaikuttanut niin vaihtelevalla tavalla BKT:n eri komponentteihin, eri maihin ja eri aikakausina.

Tulokset selittävät myös, miksi talouden vakauden (tai muitakin) jaksoja on vaikea tunnistaa luotettavasti kokonaistaloudellisista tilastohavainnoista. Työssä argumentoidaan, että tunnistaminen onnistuu vain, kun eri ajankohtien BKT-erät hajotetaan niiden kasvun vaihtelua selittäviin jaksollisiin komponentteihin. Työn tulokset osoittavat myös, miksi perinteisten reaalisten suhdannevaihtelumallien ennusteet eivät usein osu kohdalleen.

Avainsanat: suhdannevaihtelut, kasvujaksot, epäjatkuva väreanalyysi, Yhdysvaltojen BKT:n määrä, Ison-Britannian BKT:n määrä

JEL-luokittelu: C49, E20, E32

Contents

1 Introduction

The frequency domain offers economists a different perspective from time-series analysis for analysing economic data. The number of contributions in economics that use frequency domain analysis is woefully small, and yet a number of important advances have been made in frequency domain methods which have not yet filtered properly into the economics literature. This may well change given the recent downturn in the OECD economies, which has re-focused macroeconomists on the stylized facts and proximate causes of the business cycle. While frequency domain techniques are still not yet part of the standard toolbox for analysis of time series in economics, these techniques are standard in other disciplines such as engineering, acoustics, neurological sciences, physics, geology and environmental sciences. The contribution contained in this paper attempts to use some of the more recently developed frequency domain techniques to analyse fluctuations in the components of US and UK growth[1], and the interactions between the components of US or UK growth.

We begin by noting the correlations for the US between the growth rates of the main components of aggregate demand in real GDP, namely personal consumption expenditures, private investment, government expenditures (both current and capital) and export of goods and services. The data is chained real quarterly data from 1948 to 2009, and growth rates are calculated as year-over-year changes in the logged values of each component.

	C	I	G	X
C	1	0.630	-0.148	0.058
I		1	-0.212	0.079
G			1	0.010
X				1

Table 1: Correlation of US GDP Components

Using a basic Fisher correlation test for a null hypothesis of zero correlation, only the correlations between C, I and G are significant. Unsurprisingly, the highest correlation between annual changes in components of US growth components is between consumption and investment. Government expenditures appear to be negatively related to both consumption and investment as might be expected due to counter-cyclical fiscal policy. However, although neither of these correlations are not that high, both outstrip the contemporaneous correlation of exports with consumption or investment.

[1] An analysis of fluctuations in real GNP itself has already been undertaken in Crowley (2010).

We now compare these initial correlations with those for the UK in table 2. The data is from the UK National Statistics Office and is quarterly chained real quarterly data from 1955 to 2009.

	C	I	G	X
C	1	0.516	0.063	0.132
I		1	-0.067	0.252
G			1	-0.117
X				1

Table 2: Correlation of UK GDP Components

Once again not all the reported correlations are significant - those between C and I and X are, but none of the correlations with G are significant. Again, the largest correlation is between consumption and investment; but the size of the correlation is lower than for the US. This time the correlation between C and G is positive if small, indicating a weak pro-cyclical (near a-cyclical) use of government spending, whereas that between G and I is negative. The correlations between X and C and I are all positive, with quite high correlation between X and I in particular. For the UK the correlation between X and G is small, insignificant and negative.

Not only do these simple statistics show that many of these correlations are not significant, but they also ignore two important considerations: i) that lead or lag relationships may exist between components of GDP which may change our interpretation of the facts (for example: two perfectly correlated variables that are out of phase by half a cycle will show correlation of -1); and ii) that (possibly variable) cycle relationships might be significant between the constituent components of GDP, which are only weakly related at other non-business cycle lengths. Clearly simple correlation coefficients are not going to reveal the size or causal direction of these relationships, and more appropriate frequency domain tools are required to explore if any "hidden" relationships exist. Two obvious examples will make the point: a) two perfectly correlated data series out of phase will yield contemporaneous correlations close to zero or negative; contrast the correlations between C and G which should be in phase, but negative if there is any smoothing, with correlations between C and I which are likely to be out of phase but positively correlated if they are driven by a common cycle. And b) how strong should we expect those C,I correlations to be? Since C will be subject to short to business cycles, and I to business and longer investment cycles, there is likely to be some (positive) correlation – but not that strong, unless I's cycle length is a multiple of that for C.

To address these considerations we use a frequency domain technique, namely discrete wavelet analysis, to analyze the relationship between the components of GDP in both the US and UK economies.

2 Rationale and data

2.1 Rationale

The rationale for looking at cyclical interactions between the major components of output is two-fold:

i) there are obviously some interactions between the components that occur through the business cycles - notably between consumption and investment through inventories and government policies, and between consumption and exports through the international transmission of business cycles. These interactions have important policy implications; and

ii) the real business cycle literature focused on these interactions as justification for technology "shocks" driving fluctuations in the economy and hence the business cycle. A deeper understanding of the interaction between the GDP components may better inform model-building in terms of modelling the transmission of fluctuations or shocks between spending units in the macro-economy.

The latter concern is particularly relevant here. In King, Plosser, and Rebelo (1988) it was first noted that real business cycle models do not reproduce the same variability in the components of output, notably investment and consumption, and much effort has been expended in this literature to attempt to construct models that exhibit the same degree of co-movement in investment and consumption over time (see Christiano and Fitzgerald (1998) and Rebelo (2005)). One solution to this has been explored in recent research which allows for investment-specific technology shocks[2] - as noted in recent research using New Keynesian Dynamic Stochastic General Equilibrium (DSGE) models by Furlanetto and Seneca (2010), a positive consumption response can be obtained in a standard DSGE model with nominal rigidities when preferences are non-separable in consumption and hours. It suggests that both real business cycle and New Keynesian models have difficulty in

[2] These are shocks from new investment which contains new technology rather than investment that either replaces depreciated equipment or just adds to the stock of existing capital without upgrading the technology.

generating the empirically observed movements in consumption and investment, and it is here that this research might shed some light on the interaction at different frequencies between consumption and investment.

2.2 Data

The data used is quarterly chain-weighted quarterly real GDP data and it's major components. The US data was sourced from the Bureau of Economic Analysis for 1947Q1 to 2009Q2 (giving 246 datapoints), and the data was tranformed by logging the source data and then taking annual differences. The UK data was sourced from the National Statistics Office for 1954Q1 to 2009Q2 (giving 214 datapoints) and is transformed in the same manner. Figure 1 plots the data for the US while figure 2 does the same for the UK[3].

It should be noted that in the recent downturn government spending is still rising, while all the other components of aggregate demand have clearly been falling.

2.3 Discrete wavelet analysis

Discrete wavelet analysis uses wavelet filters to extract cycles at different frequencies from the data under consideration. It uses a given discrete function which is passed through the series and "convolved"[4] with the data to yield a coefficient, otherwise known as a "crystal". In the basic approach (the discrete wavelet transform or DWT) these crystals will be increasingly sparse for lower frequency (long) cycles if the wavelet function is applied to the series over consecutive data spans[5]. So another way of obtaining crystals corresponding to all data points in each frequency range is to pass the wavelet function down the series by data observation[6], rather than moving the whole wavelet function down series to cover a completely new data span .This is the basis of the maximal overlap discrete wavelet transform (MODWT), and is the technique used here.

[3] Note that the vertical axes are scaled differently for each component.

[4] In mathematics and, in particular, functional analysis, convolution is a mathematical operation on two functions f and g, producing a third function that is typically viewed as a modified version of one of the original functions. Convolution is similar to cross-correlation. It has applications that include statistics, computer vision, image and signal processing, electrical engineering, and differential equations.

[5] But given that we seek the same resolution of cycles at different frequencies, this is still the most efficient way to estimate the crystals.

[6] Given the previous footnote, it is obvious that by doing this, it will lead to "redundancy" as the wavelet coefficients have already been combined with most of the same datapoints.

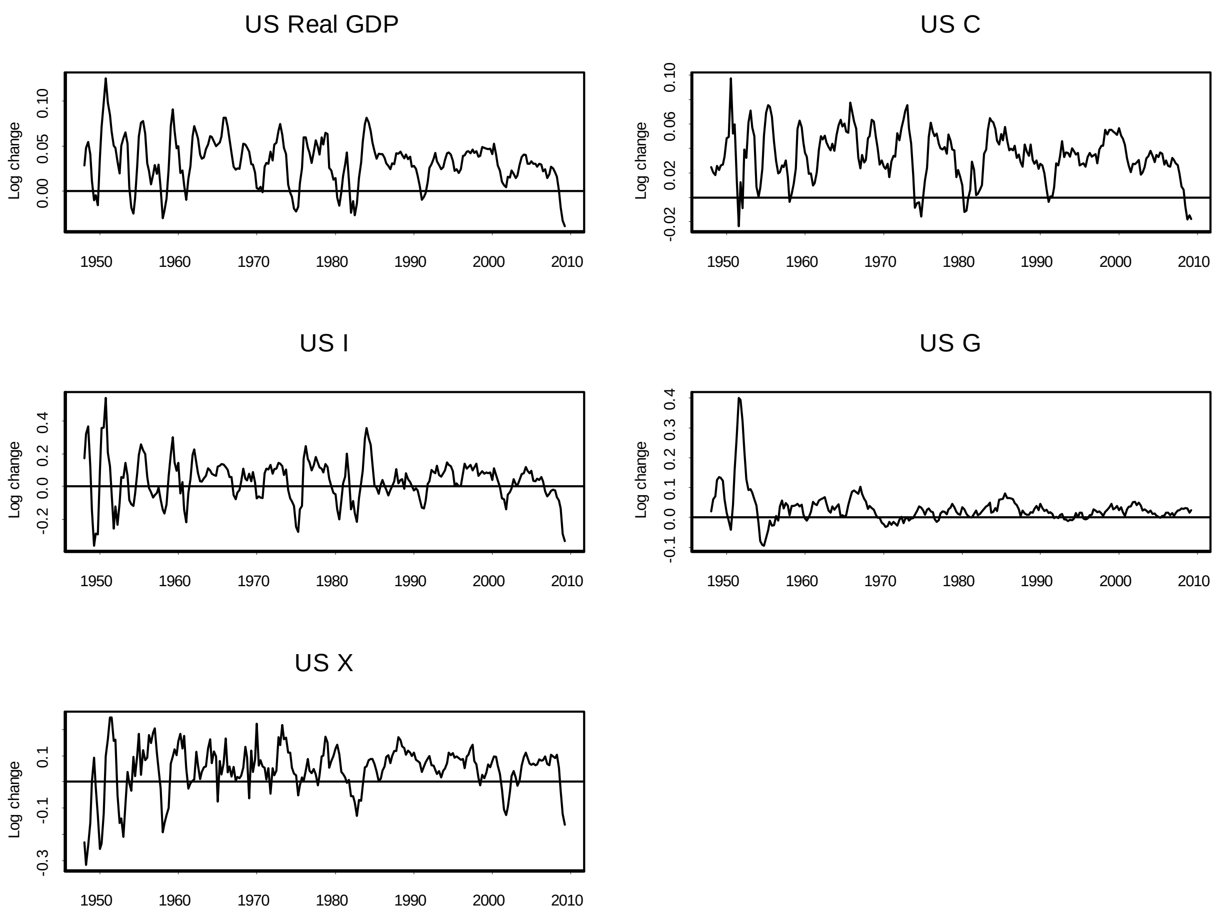

Figure 1: US GDP and components: log annual change

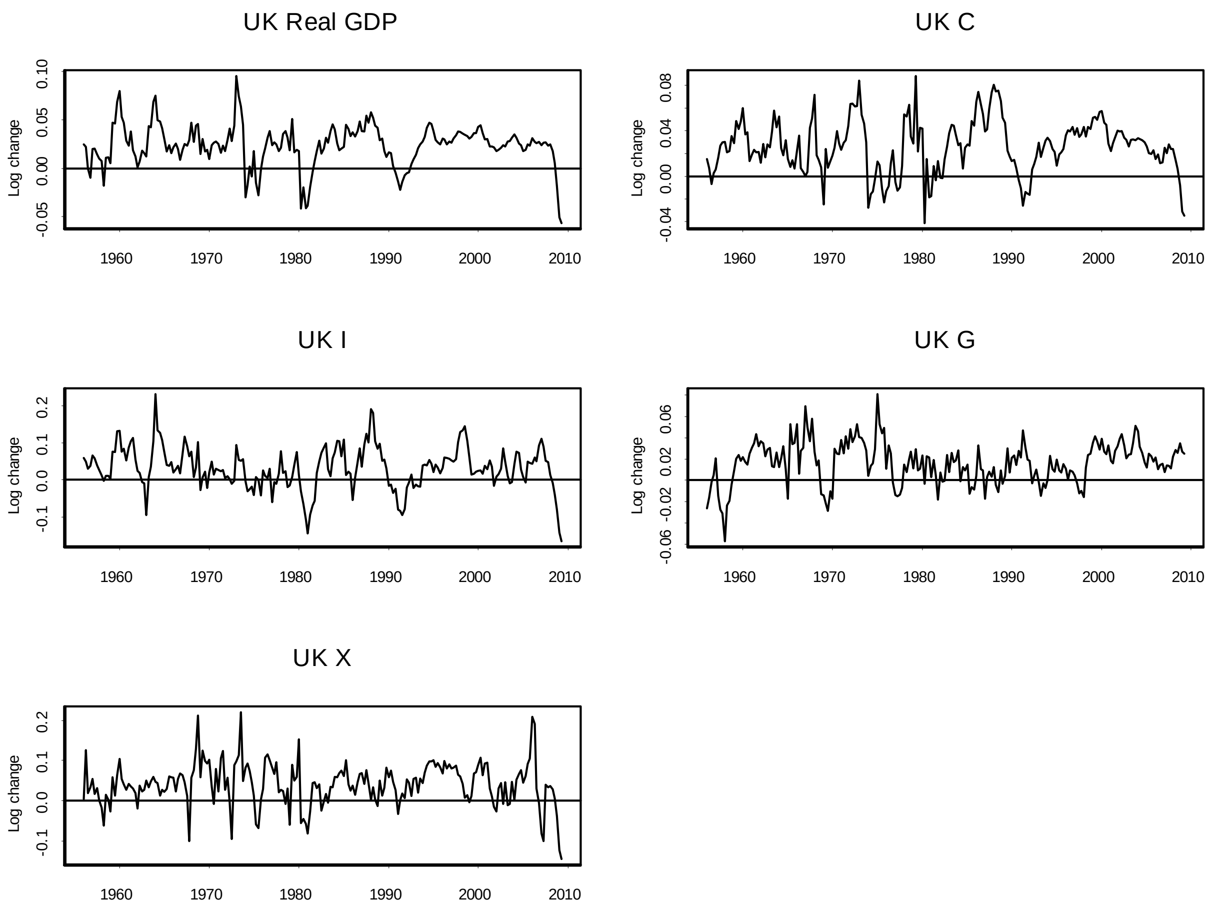

Figure 2: UK GDP and components: log annual change

In mathematical terms, consider a sequence of functions:

$$\psi(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

where s is a sequence of scales, and each scale corresponds to a particular frequency range. The term $\frac{1}{\sqrt{s}}$ ensures that the norm of the wavelet function $\psi(.)$ is equal to one. The function $\psi(.)$ is then centered at u with scale s. In the language of wavelets, the energy of $\psi(.)$ is concentrated in a neighbourhood of u with size proportional to s, so that as s increases the length of support in terms of t increases. For example, when $u = 0$, the support of $\psi(.)$ for $s = 1$ is $[d, -d]$,where $2d$ denotes the initial total width of the window, or "tap"), of the wavelet. As s is increased, the support widens to $[sd, -sd]$. Dilation (i.e. changing the scale) is particularly useful in the time domain, as the choice of scale indicates the "stretching" used to represent any given variable or signal. A broad support wavelet yields information on variable or signal variations on a large scale (zooming out), whereas a small support wavelet yields information on signal variations on a small scale (zooming in). As projections are all orthogonal: wavelets at a given scale are not affected by features of a signal at scales that require narrower support. Lastly, if a wavelet is shifted on the time line, this is referred to as translation or phase shift of u. Any series $x(t)$ can then be built up as a sequence of projections onto two different sets of wavelet functions, one used to capture trend movements and cycles beyond the scale limit (band pass range) limit chosen by the researcher (the "father" wavelet) and another used to capture deviations from trend for cycles at different frequencies (the "mother" wavelets). Wavelet functions are therefore indexed by both j, the scale, and k, the number of translations of the wavelet, where k is often assumed to be dyadic[7]. As shown in Bruce and Gao (1996), the wavelet coefficients can be approximated by the integrals for father and mother wavelets as:

$$s_{J,k} \approx \int x(t)\phi_{J,k}(t)dt \tag{2}$$

$$d_{j,k} \approx \int x(t)\psi_{j,k}(t)dt \tag{3}$$

respectively, where $j = 1, 2, ...J$ such that J is the maximum scale sustainable with the data to hand, then a multiresolution representation of the signal $x(t)$ is can be given by:

$$x(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + ... + \sum_k d_{1,k}\psi_{1,k}(t) \tag{4}$$

[7] A dyadic series has length 2^n where n is an integer.

where the basis functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ are assumed to be orthogonal, that is:

$$\begin{array}{c} \int \phi_{J,k}(t)\phi_{J,k'}(t) = \delta_{k,k'} \\ \int \psi_{J,k}(t)\phi_{J,k'}(t) = 0 \\ \int \psi_{J,k}(t)\psi_{J',k'}(t) = \delta_{k,k'}\delta_{j,j'} \end{array} \tag{5}$$

where $\delta_{i,j} = 1$ if $i = j$ and $\delta_{i,j} = 1$ if $i \neq j$. The multiresolution decomposition (MRD) of the variable or signal $x(t)$ is then defined by the set of "crystals" or coefficients:

$$\{s_J, d_J, d_{J-1}, ...d_1\} \tag{6}$$

The interpretation of the MRD using the DWT is of interest as it relates to the frequency at which activity in the time series occurs[8]. For example with a quarterly time series table 3 shows the frequencies captured by each scale crystal:

Scale crystals	Quarterly frequency resolution
d1	2-4=6m-1yr
d2	4-8=1-2yrs
d3	8-16=2-4yrs
d4	16-32=4-8ys
d5	32-64=8-16yrs
d6	64-128=16-32yrs
d7	etc

Table 3: Frequency interpretation of MRD scale levels

Note that as quarterly data is used in the present study, to capture the conventional business cycle length scale, crystals need to be obtained for 5 scales. This requires at least 64 observations. But to properly resolve at the longest frequency it would help to have 128 observations, and as we have at least 214 observations for all 8 series this is easily accomplished. Hence we can use 6 crystals here even though resolution for the d6 crystal is not high. It should be noted that if conventional business cycles are usually assumed to range from 12 quarters (3 years) to 32 quarters (8 years), then crystal d4 together with the d3 crystal should contain the business cycle.

The variance decomposition for all series considered in this paper is calculated using:

[8] One of the issues with spectral time-frequency analysis is the Heisenberg uncertainty principle, which states that the more certainty that is attached to the measurement of one dimension (- frequency, for example), the less certainty can be attached to the other dimension (- here the time location).

$$E_j^d = \frac{1}{E^d} \sum_{k=1}^{\frac{n}{2^j}} d_{j,k}^2 \tag{7}$$

where $E^d = \sum_j E_j^d$.represents the energy or variance in the detail crystals E_j^d.

Although extremely popular due to its intuitive approach, the DWT suffers from two drawbacks: dyadic length requirements for the series to be transformed and the fact that the DWT is non-shift invariant (- so if datapoints from the beginning of the series are put aside, the lower frequencies will yield different crystals with completely different values). In order to address these two drawbacks, the maximal-overlap DWT (MODWT)[9] was originally introduced by Shensa (1992) and a phase-corrected version was added and found superior to other methods of frequency decomposition[10] by Walden and Cristan (1998). The MODWT gives up the orthogonality property of the DWT to gain other features, given in Percival and Mofjeld (1997), such as the ability to handle any sample size regardless of whether the series is dyadic or not, increased resolution at coarser scales as the MODWT oversamples the data, translation-invariance, and more asymptotically efficient wavelet variance estimator than the DWT.

Both Gençay, Selçuk, and Whicher (2001) and Percival and Walden (2000) give a thorough and accessible description of the MODWT using matrix algebra. Crowley (2007) also provides an "intuitive" introduction to wavelets, written specifically for economists, and references the (limited) contributions made by economists using discrete wavelet analysis[11]. The first real usage of wavelet analysis in economics was by James Ramsey (Ramsey and Lampart (1997)), and the first application of wavelets to economic growth (in the form of industrial production) was by Gallegati and Gallegati (2007) and in the form of GDP in a working paper by Crowley and Lee (2005) and then more recently in a published article by Yogo (2008).

[9] As Percival and Walden (2000) note, the MODWT is also commonly referred to by various other names in the wavelet literature such as non-decimated DWT, time-invariant DWT, undecimated DWT, translation-invariant DWT and stationary DWT. The term "maximal overlap" comes from its relationship with the literature on the Allan variance (the variation of time-keeping by atomic clocks) - see Greenhall (1991).

[10] The MODWT was found superior to both the cosine packet transform and the short-time Fourier transform.

[11] These can also be accessed online at:
http://faculty.tamucc.edu/pcrowley/Research/frequency_domain_economics.html

3 MODWT - US data

In this section and the next we review the output from the MODWT for both US and UK real GDP and their aggregate demand components. The plots for the US in figure 3 show the phase-adjusted crystals for each of the frequency bands contained in the detail crystals d1 to d6, plus the smoothed trend residual from the series (often referred to as the "smooth"), d6, which is obtained after extracting the fluctuations corresponding to the detail crystals. The most obvious observation is that the "great moderation" clearly appears in the data from 1983 through to around 2007; but most noticeably in the d1, d2 and d3 crystals (i.e. for cycles between 6 months and 4 years periodicity), and less obviously in the 4-8 year cycle (d4 crystal) and not at all in the 8-16 year cycle (d5 crystal). There also appears to be the possibility of a longer 30-year cycle in the data, which appears here in s6, the smooth[12]. These are observations that could not be made using a traditional time series analysis approach: the "great moderation" for all its appeal at the time, was not a systematic or permanent phenomenon.

Figure 4 shows the variance decomposition by crystal over the entire data span. Clearly the strongest cycle is contained in crystal d3 (representing 2 to 4 year cycles), with d4 (representing 4 to 8 year cycles) following close behind; then d2 (1-2 years) and d5 (8 to 16 year cycles) contain roughly the same amount of energy. As noted before though, the amount of volatility in any given crystal can change over time. So during the "great moderation", crystals d4 and d5 (4 to 16 year cycles) appear to dominate fluctuations in growth, but not necessarily during other periods. Hence the great moderation in fact appears to have been a phenomenon in which volatility was shifted from short and business cycle lengths, to the longer cycles (up to 16 years in length). This would certainly explain the observation that recessions or economic slowdowns now appear to take place every 10-15 years, but the periods between are more stable than they used to be.

As might be expected, the MODWT plot in figure 5 for consumption expenditures shows relatively similar cyclical paterns to overall GDP, with a clear fall in volatility after 1983 in crystal d3 (2 to 4 year cycles) but less so for d1, d2 or d4. This is also reflected in the variance decomposition plot in figure 6 where there is now more volatility in longer cycles, relative to the shorter cycles, reflecting the success of consumption smoothing over time. As with the moderation in GDP volatility, this fall in volatility after 1983 clearly shows the smoothing power of the strict monetary controls introduced by the Volker regime at the

[12] This also appears in GNP data as shown in Crowley (2010).

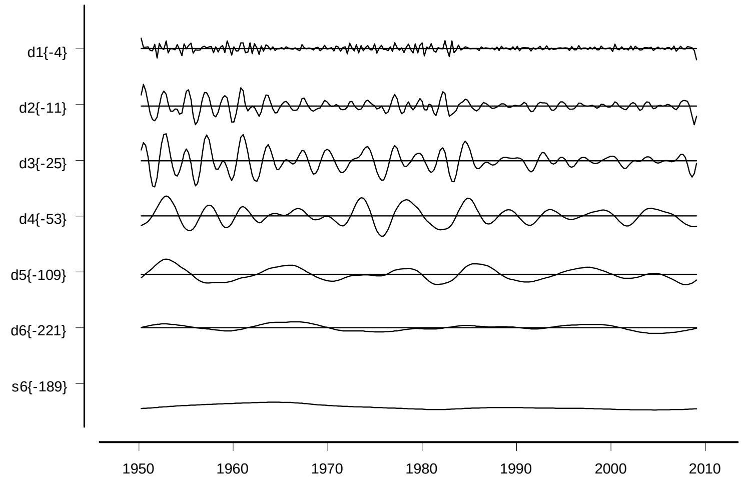

Figure 3: MODWT decomposition of log change in US GDP

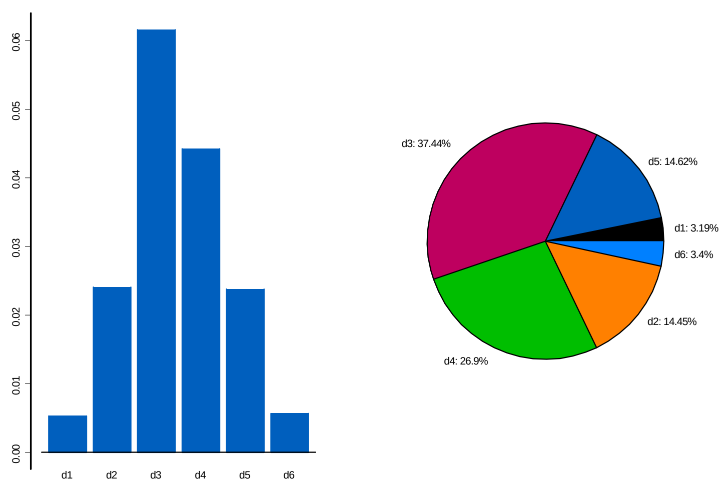

Figure 4: Variance decomposition by scale for US GDP

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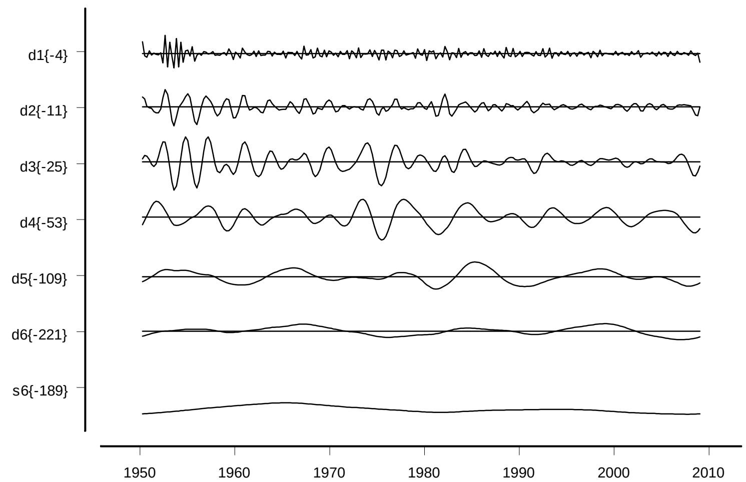

Figure 5: MODWT decomposition of log change in US consumption

Figure 7 shows the MODWT plot for US private investment, and it is clearly apparent that the "great moderation" for investment spending took place after around 1987, that is later than in consumption; and again this was mostly confined to fluctuations in d2 and d3 crystals, but does not appear in d4 and d5, and hardly at all in d1. In terms of overall energy, the variance decomposition plots in figure 8 show that most energy lies in crystal d3 (2-4 year cycles), with both d2 (1-2 year cycles) and d4 (4-8 year cycles) also containing some cyclical activity. In d2, this mostly occurred towards the beginning of the time series, whereas in d4 this appears to have been more consistent through time and likely relates to the business cycle. This finding clearly highlights the rich dynamics at play within the components of output. It shows that the great moderation started at different points within the components of GDP, and this observation would be missed if using only total GDP to measure the onset of lower volatility in output.

Government expenditures, since they contain both automatic stabilizers and for more severe recessions, discretionary spending programs should display some cyclical activity at business cycle frequencies. However figure 9 shows that apart from the very beginning of the series, there is relatively little cyclicality in this series and where there is, it clearly lies at around the business cycle in crystals d3, d4 and d5 (2 to 16 year cycles). Compared to the other components of GDP the volatility in the crystals of government spending is extremely

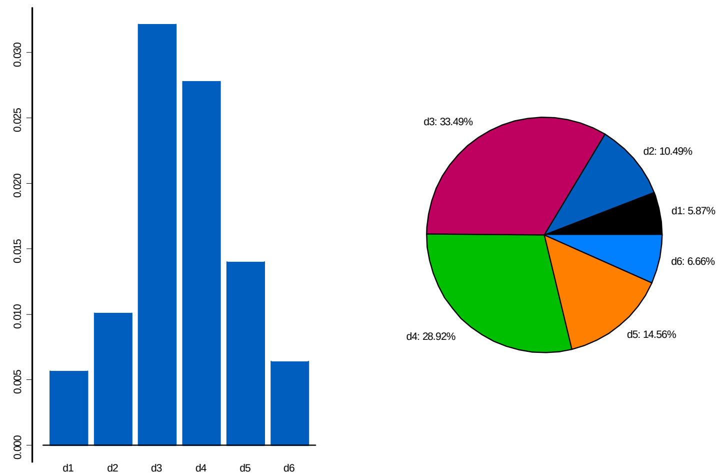

Figure 6: Variance decomposition by scale for US consumption

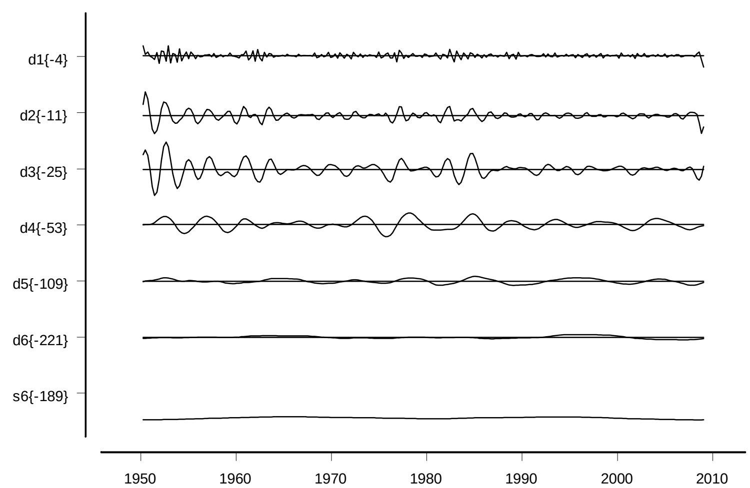

Figure 7: MODWT decomposition of log change in US private investment

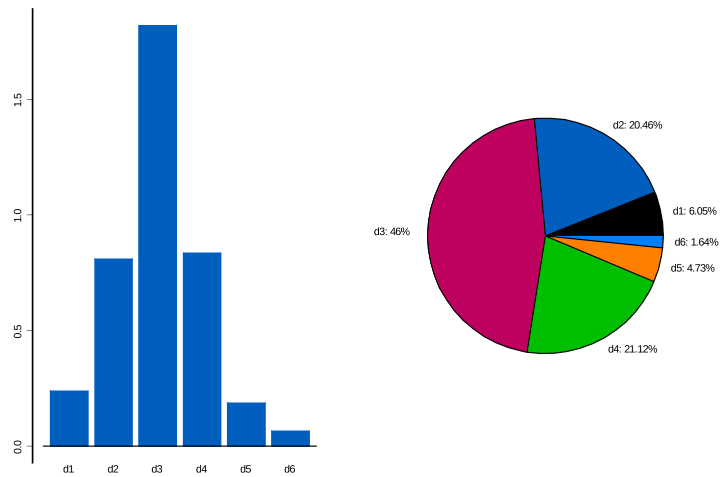

Figure 8: Variance decomposition by scale of US private investment

weak, signifying the relatively minor movements in government expenditures compared to private sector activity. Interestingly also there is virtually no energy at short term horizons (6 month to 1 year cycles), and activity in other crystals dies down to only small fluctuations after the mid-1970s, indicating that discretionary fiscal policies had largely been abandoned as an instrument of demand management at that point.

These results are also to be seen in the variance decomposition by scale which is shown in figure 10. Here crystals d4 and d5 have the highest variance. These results also help answer an old debate on whether fiscal policies have been anti-cyclical (stabilizing) or pro-cyclical (destabilizing). In the US, there is little cyclical movement in government spending at any frequency after 1960 which suggests it has largely been a-cyclical in practice. That means the US did not succeed in stabilizing her economy through fiscal policy (or possibly hasn't tried), but she hasn't made it worse either, as some claim. It is also worth noting that table 1 and the text which follows indicate that G has been a better or more effective shock absorber (stabilizer) than the export markets.

The MODWT plot shown in figure 11 for exports is rather surprising. It shows a clear reduction in volatility for crystal d1 from around the mid-1970s with a reduction in volatility in crystal d2 in roughly 1983, followed by reductions in volatility in d3 and d4 in the late 1980s. Surprisingly, volatility then picks up again for crystals d2, d3, d4 and d5 in the late 1990s and continues into the 2000s. This is not matched in the d1 crystal, which shows

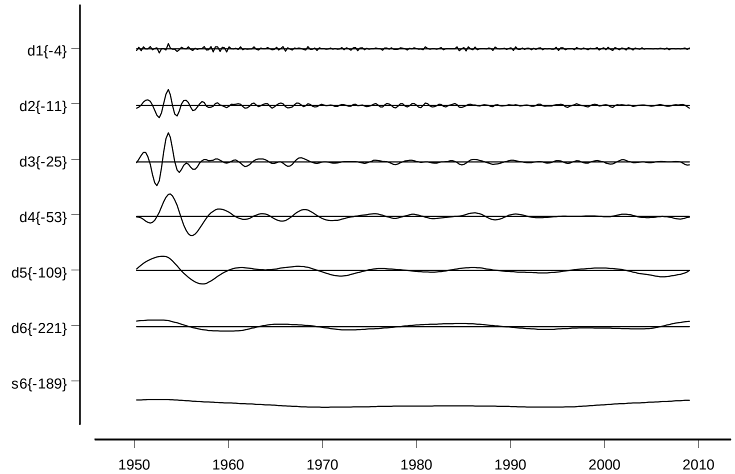

Figure 9: MODWT decomposition of log change in US G

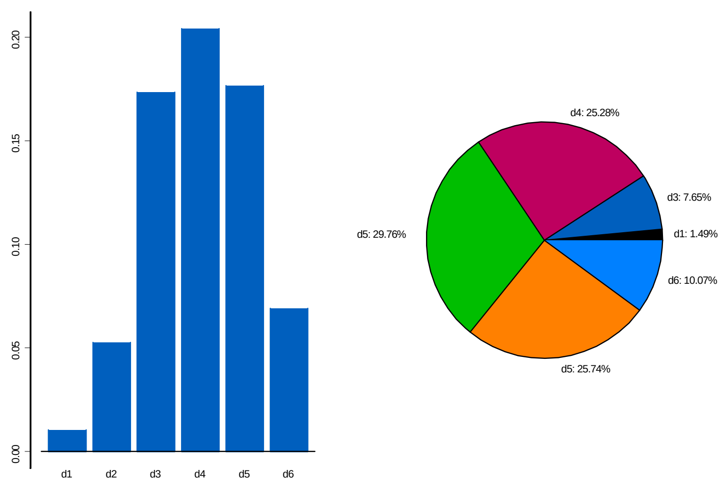

Figure 10: Variance decomposition of US log G by scale

hardly any short-term movements in exports. Figure 12 shows that most of the energy in the series resides in crystals d3 and d4, with cycle frequencies between 2 and 8 years, corresponding to the business cycle.

These last results require some explanation, but offer an interesting insight into how the US economy has operated in recent years. The fall in the volatility of X coincides with the start of the dollar's floating exchange rate regime. That fall in volatility is mostly in short cycles to start, but then spreads to the business cycles frequencies later on. That shows the more market sensitive monetary policies of the 1980s were used to stabilize the economy; but that in turn affected the exchange rate – converting it into a shock absorber and stabilizing exports at the same time. But for much of the mid-1990s and 2000s monetary policy had become more activist in pursuit of low and stable inflation, revealing the US as a *de facto* inflation targeter. The result of course was a more stable exchange rate, and hence rising export volatility as can be seen in this decomposed cyclical data (except at short cycles, a fact which shows the falling activism of monetary policy in this period).

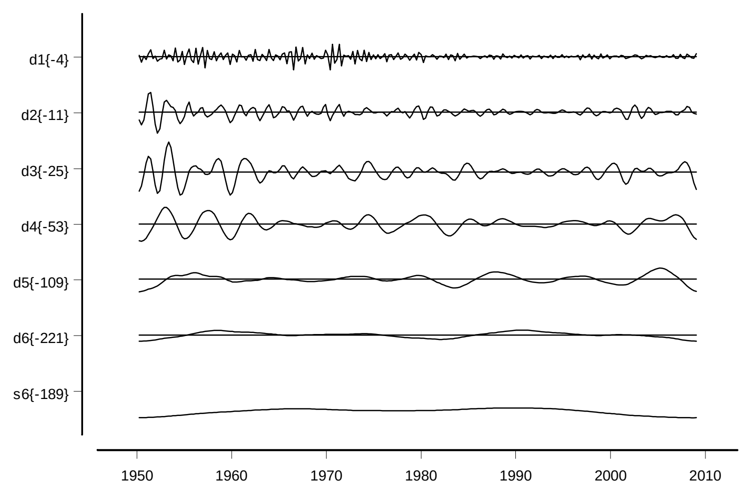

Figure 11: MODWT decomposition of log change in US X

To summarize, it is clear that the "great moderation", although discernable in GDP growth data for the US, is more apparent at various frequencies and in various components of GDP than in others. Nor does it represent some kind of long term paradigm shift. The timing and dynamics that lead to the "great moderation" do not translate directly back to the components of GDP growth. Consumption and investment appear to be the

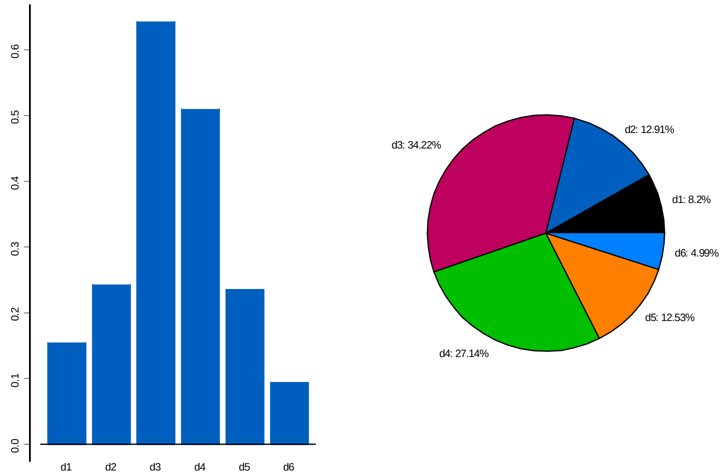

Figure 12: Variance decomposition of US log X by scale

sources for the "great moderation", with consumption volatility moderation occurring in the early 1980s and investment volatility moderation occurring in the later part of the 1980s. Changes in government expenditure and export expenditures do not appear to be major sources of the origina of lower volatility in real GDP growth. Lower volatility is not a result of government stabilisation policies therefore. Instead monetary policy, with effects on the exchange rate, must be the culprit because the residuals (s6) and short term shocks (d1) play little or no role in these moderations after the mid-1950s. These are all features that cannot be detected from aggregate data on output, or with traditional time series analysis.

4 MODWT - UK data

The same exericise is now repeated for the UK. In figure 13 we observe the same patterns for UK GDP as in US GDP, with crystals d1, d2 and d3 exhibiting lower volatility after the era of the miners and other strikes in 1984-5 and after the Thatcher policies took hold, but with d4 exhibiting slightly lower volatility and d5 and d6 hardly changing. The longer residual cycle is once again weak, and has a periodicity of approximately 35 years. Figure 14 once again shows that most of the variance resides in d3, d4 and d5 (2 to 16 year periodicities), with d4 (4 to 8 year cycles) containing most energy. However, compared with the US, the

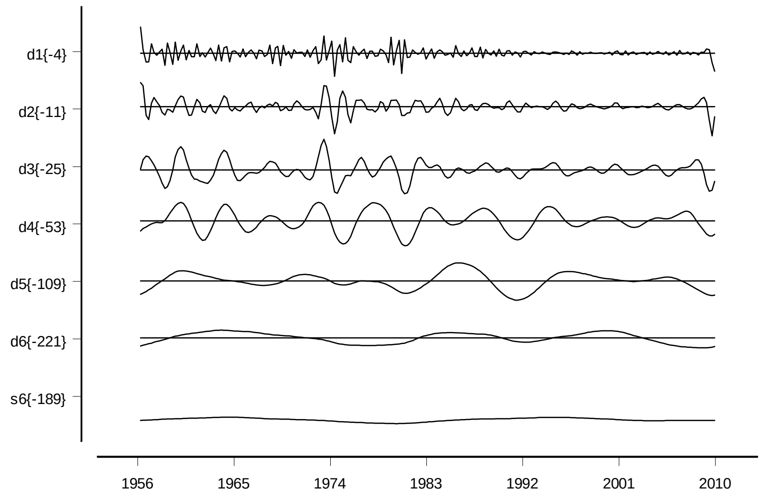

Figure 13: MODWT decomposition of log change in UK GDP growth

volatility is more evenly spread across cycles. It is also evident that d1 to d3 show the great moderation like the US, while d4 and d5 actually get *less* stable in the moderation period. This again suggests a mechanism that shifts short run instability to long term instability.

In figures 15 and 16 the MODWT and the variance decomposition by scale are shown for UK consumption growth. In figure 15 the "great moderation" is evident from 1983 in d1, but doesn't occur until roughly 1991 in d2 and d3, and not until 1995 in d4. In terms of volatility, d4 and d5 clearly have most energy and, although d4 has been less volatile until the recent downturn, d5 has not. Apparently a new cycle appears to also have emerged since the mid-1970s in the d6 crystal with roughly a 16 year periodicity. There appears to be little cyclicality beyond this frequency. Once again the volatility is spread across a wider range of frequencies compared to the US. As with the GDP data, these restults show a much richer and more complex set of dynamics than could be captured by traditional real business cycle models.

In figure 17 the change in UK private investment expenditures are decomposed using the MODWT, and here much more cyclicality is detected than with the US, with only one of the crystals, d1, exhibiting any real lowering in volatility, and then only after 1990. This is a surprising result (given that the great moderation effect is hardly evident in the data), and definitely does not match that obtained for the US. In figure 18 most of the volatility lies in crystals d3 and d4, with clearly a recent increase in volatility in d5, perhaps reflecting a

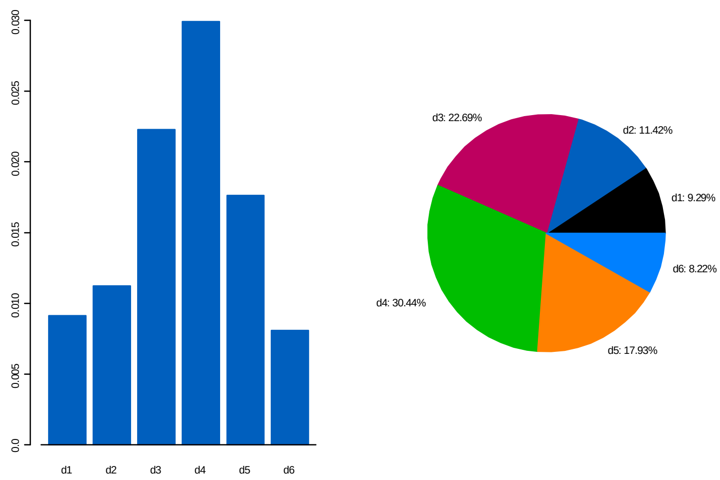

Figure 14: Variance decomposition of UK GDP by scale

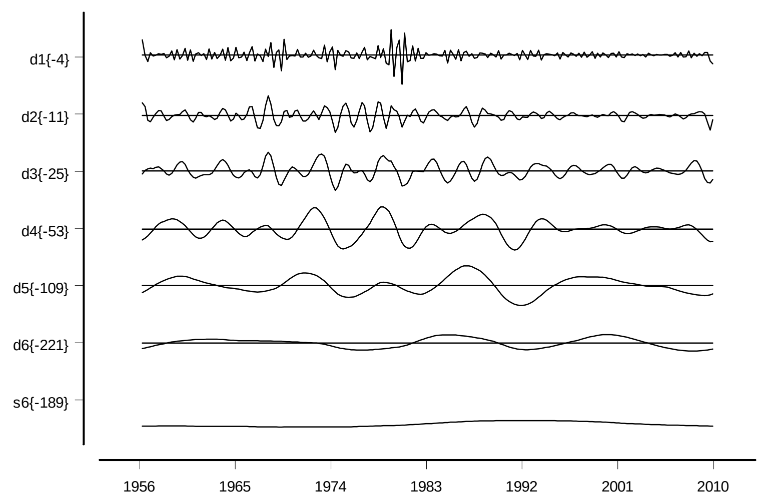

Figure 15: MODWT decomposition of log change in UK consumption

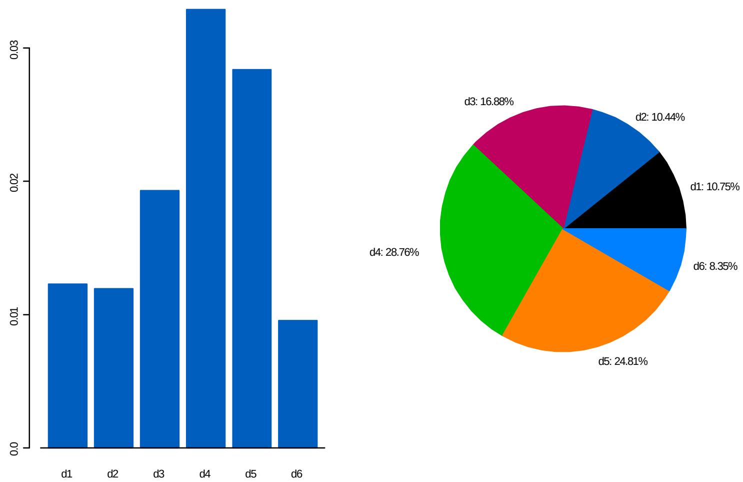

Figure 16: Variance decomposition of UK C by scale

lengthening of the business cycle. Compared with the US though there is more volatility in longer and shorter cycles. A reasonable question is, why does the UK show more volatility in investment spending than the US – especially at frequencies shorter and longer than business cycles? It will be observed from figure 17 that this higher volatility is mostly in the boom years of the mid-1980s and late 1990s, and is largely restricted to d2 to d5. In addition, because this extra volatility does not show up (proportionately) in the other components of UK GDP, nor is there any excess volatility in the residuals or short cycles while the investment itself is less well coordinated/correlated with C and G but better coordinated with UK exports, we can conclude that the extra investment volatility is due to the UK's successful record of attracting FDI in those boom periods.

With the log annual change in UK government expenditures, there is also much more volatility than with the US measure, as figure 19 shows. Here there appears to have been a dampening of volatility in d1 beginning only in the mid-1990s. And while for d2 very little change has occurred, for d3 and d4 a dampening of volatility appears to have taken place around 1982, a time when monetary policy moved away from monetarism and fiscal policy started to be more closely managed. There seem to be cycles operating at lower frequencies as well, with a very irregular cycle captured by the d5 crystal and rather strange semi-cyclical movements in the d6 crystal, which almost certainly means that the UK moderation has been achieved by policy actions not by a smoother operating economy. The implication

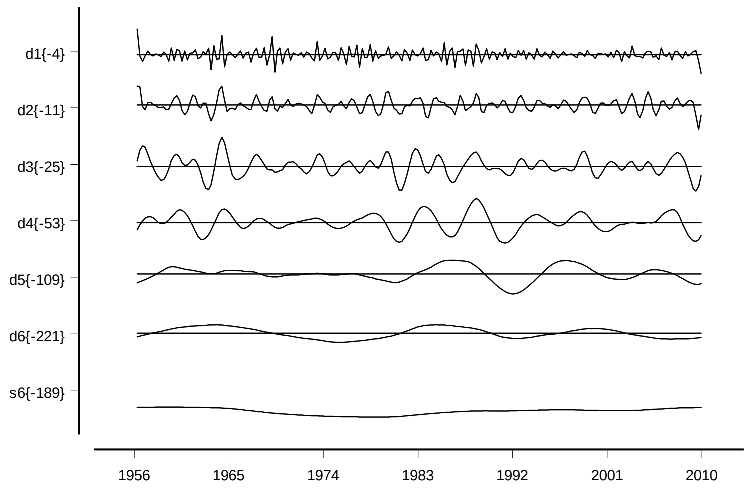

Figure 17: MODWT decomposition of log change in UK investment

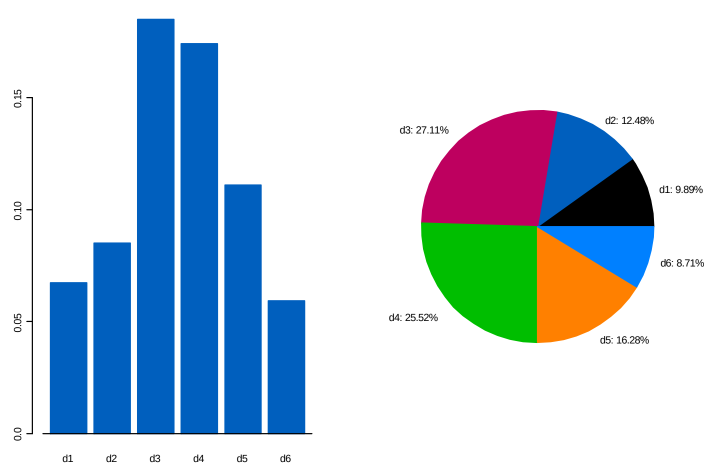

Figure 18: Variance decomposition of UK I by scale

therefore is that the better and smoother performance of the UK economy in the Thatcher and Blair years was held together by policy actions, rather than by favourable market and institutional reforms that promote smoother running markets. The contrast with the US post-1970 for any cycle is instructive Further, there are no obvious breaks in behaviour (except possibly d5 and d6 after the 1970s).

Figure 20 shows that most energy resides in the d4 crystal, but what is surprising here is that a significant amount of movement is found in d1, which contains cycles of 6 months to 1 year duration. Here the volitility is fairly evenly distributed across different cycles with noise less important than business cycles. Hence automatic stabilisers must have been at work. There is also no obvious shift in weight from short to long run, so it is difficult to see a distinction between discretionary policy vs automatic stabilizers[13].

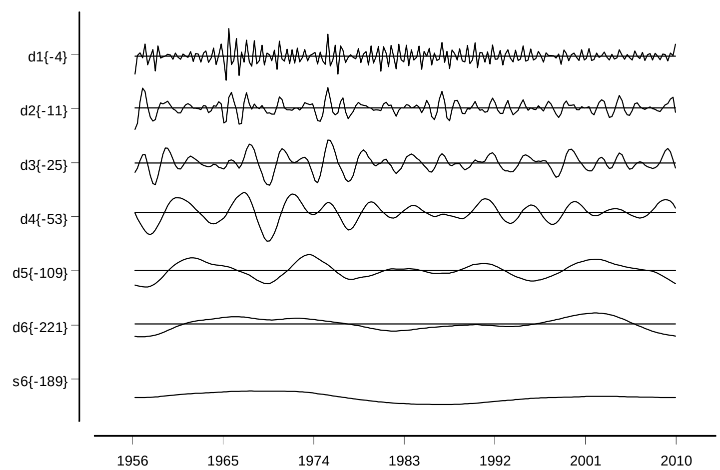

Figure 19: MODWT decomposition of log change in UK government spending

In figures 21 and 22 the MODWT decomposition of expenditures on UK exports is plotted together with the variance decomposition by scale crystal. Here, rather surprisingly, there are two episodes of high volatility in export expenditures, presumably in this instance mostly related to the fortunes of the British currency. After the (in)famous 1967 devaluation of the pound by the Wilson government, this clearly led to greater volatility in export growth, and this then continued with the collapse of the Bretton Woods system in 1973.

[13] Separating automatic from discretionary fiscal policies in a cyclical environment is not an easy matter. Bernoth, Hughes Hallett, and Lewis (2011) review different methods, and show how it can be done by combining real time and ex-post data.

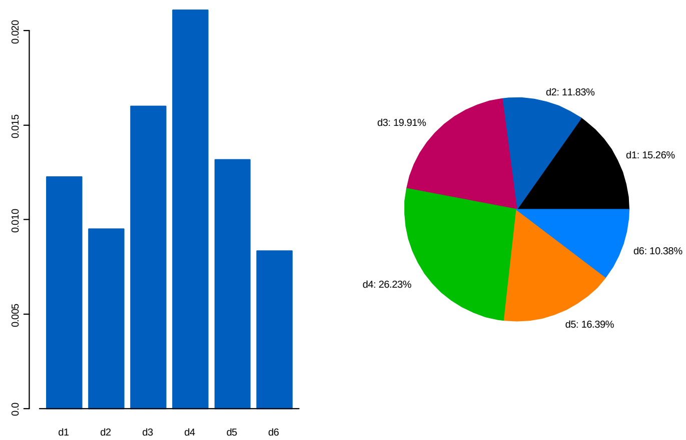

Figure 20: Variance decomposition of UK government spending by scale

Much smaller fluctuations are observed in d1 to d3 (and to a lesser extent in d4) after 1983. But by 2005 the volatility in export expenditures had clearly returned. At that point d5 appears to suggest that a regular 10 year cycle has emerged and d6 suggests a weak cycle at roughly a 27 year periodicity So what is notable here is the moderation in short-run cycles (noise) and post 1980 (up to d3), a moderation that was lost again by 2004. The explanation for this result is the same as in the US. During the 1980s the UK became a convinced floating exchange rate economy, which meant the exchange rate became the shock absorber that lowered the volatility of exports (at least in the shorter cycles). But, by the end of the 1990s she had adopted explicit inflation targets which led to smoother monetary policies and a (mostly) smoother exchange rate path – and with it higher export volatilities, once the new monetary regime had settled down. However these results also show that there is no case for saying that fixing the exchange rate stabilizes the economy, at least for the UK. Significant regime changes, like fixing the exchange rate on joining the EMS in 1990-92, or the EMS crisis which seriously unfixed them again in 1992-93, do not destabilize the economy or exports. Those events do not show up in the data.

Figure 22 shows that higher frequency cycles (with periodicity less than 4 years) dominate the variance decomposition in this case - once again, quite a different result from that obtained for the US.

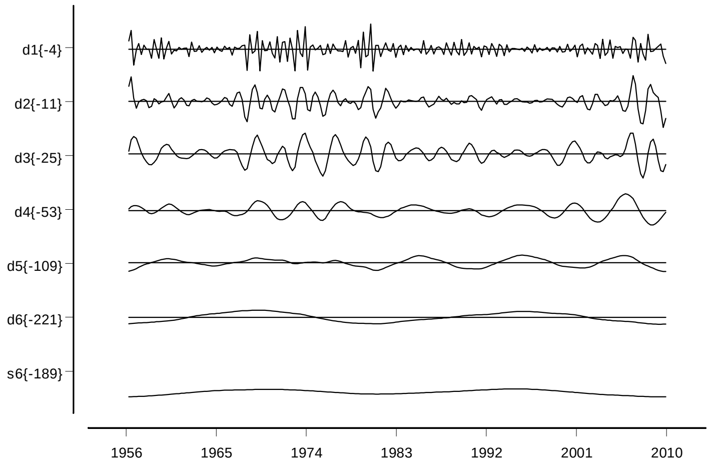

Figure 21: MODWT decomposition of log change in UK exports

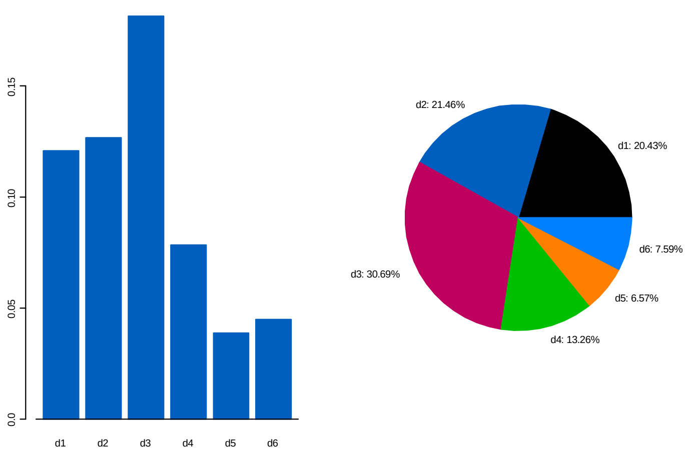

Figure 22: Variance decomposition of UK X by scale

5 Conclusions

In this paper we have used wavelet transformations to decompose the separate parts of domestic expenditures which make up real GDP for the US and the UK into their component cycles. The first finding is that decomposing the components of real GDP growth separately into different cycles reveals characteristics of the cycles in growth, and the relationships between them, that cannot be seen in an analysis of the aggregate data for real GDP alone. That is because the cycles of the various components offset each other to a degree, leading to a loss of information at the aggregate level. The second finding is that although the "great moderation" is found in most of the data, it is not consistent across different frequency cycle lengths, appearing only in cycles generally shorter than or equal to the business cycle. This is an important finding, as it demonstrates (as we now know) that the so-called "great moderation" was not as significant as economists had thought, given that the business cycle still was evident, and that longer cycles did not abate in strength at all. The "great moderation" in fact appears to have been more a case of shifting short term volatility to long cycle volatility, than moderating volatility as such. This means that changes in volatility, like the "great moderation", will be very difficult to detect with any certainty without a full frequency decomposition of the components of GDP.

In terms of the comparison between the US and the UK, the volatility in components at the specified frequency ranges in discrete wavelet analysis is markedly different. The analysis shows that there is much more volatility in GDP components at very short and longer frequencies for the UK than there is in the US. This is particularly the case for government expenditures, where activist fiscal policies have clearly had a much greater impact than in the US. There has also been a tendency for volatility to have been shifted from shorter cycles to longer cycles, more in the UK than the US. This we put down to the changes in monetary regimes, and hence exchange rate arrangements, which focussed first on stabilisation and then on explicit or implicit inflation targeting. Fiscal policies, by contrast, have largely been acylical or ineffective for stabilisation in the US; but pro-cyclical and destabilising in the UK.

References

Bernoth, K., A. Hughes Hallett, and J. Lewis (2011). The cyclicality of of automatic and discretionary fiscal policy: What can real time data tell us? pp. Under review.

Bruce, A. and H.-Y. Gao (1996). *Applied Wavelet Analysis with S-PLUS*. New York, NY, USA: Springer-Verlag.

Christiano, L. and T. Fitzgerald (1998). The business cycle: It's still a puzzle. *Federal Reserve Bank of Chicago Economic Perspectives 22*, 56–83.

Crowley, P. (2007). A guide to wavelets for economists. *Journal of Economic Surveys 21*(2), 207–267.

Crowley, P. (2010). Long cycles in growth: Explorations using new frequency domain techniques with US data. Bank of Finland Discussion Paper 6/2010, Helsinki, Finland.

Crowley, P. and J. Lee (2005). Decomposing the co-movement of the business cycle: A time-frequency analysis of growth cycles in the euro area. Bank of Finland Discussion Paper 12/05, Helsinki, Finland.

Furlanetto, F. and M. Seneca (2010). Investment-specific technology shocks and consumption. Norges Bank Discussion Paper 30-2010, Oslo, Norway.

Gallegati, M. and M. Gallegati (2007). Wavelet variance analysis of output in g-7 countries. *Studies in Nonlinear Dynamics Econometrics 11*(3), 1435–1455.

Gençay, R., F. Selçuk, and B. Whicher (2001). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics*. San Diego, CA, USA: Academic Press.

Greenhall, C. (1991). Recipes for degrees of freedom of frequency stability estimators. *IEEE Transactions on Instrumentation and Measurement 40*, 994–9.

King, R., C. Plosser, and S. Rebelo (1988). Production, growth and business cycles i: The basic neoclassical model. *Journal of Monetary Economics 21*, 195–232.

Percival, D. and H. Mofjeld (1997). Analysis of subtidal coastal sea level flusctuations using wavelets. *Journal of the American Statistical Association 92*, 868–80.

Percival, D. and A. Walden (2000). *Wavelet Methods for Time Series Analysis*. Cambridge, UK: Cambridge University Press.

Ramsey, J. and C. Lampart (1997, January). The decomposition of economic relationships by time scale. 97-08.

Rebelo, S. (2005). Real business cycle models: Past, present and future. *Scandinavian Journal of Economics 107*(2), 217–238.

Shensa, M. (1992). The discrete wavelet transform: Wedding the à trous and mallat algorithms. *IEEE Trans. Signal Processing 40*, 2464–2482.

Walden, A. and C. Cristan (1998). The phase-corrected undecimated discrete wavelet packet transform and its application to interpreting the timing of events. *The Proceedings of the Royal Society of London: Mathematical, Physical, and Engineering Sciences 454*(1976), 2243–2266.

Yogo, M. (2008). Measuring business cycles: A wavelet analysis of economic time series. *Economics Letters 100*(2), 208–212.

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