Is the US No Longer the Economy of First Resort?

Changing Economic Relationships in the Asia-Pacific Region

By

Andrew Hughes Hallett[‡]

and

Christian Richter

Abstract: This paper tests the hypothesis that the economic relationships between China and her major trading partners have changed over the past 20 years with the industrialisation of China, and the emergence of Japan as a source of investment and network trade in sophisticated manufactures, and the US as a source of finance and investment assets, supplier of services and an apparently inexhaustible demand for consumer and intermediate goods. Has this changed the size and direction of spillovers in the region, and has it curtailed or eliminated American economic leadership?

We use time-varying spectral methods to decompose the links between the two leading Asian economies and the US. We find: (a) the links with the US have been weakening, while those based on China have strengthened; (b) that this is not new – it has been happening since the 1980s, but has now been reversed by the surge in trade; (c) that the links with the US have been rather complex, with the US able to shape the cycles elsewhere through her control of monetary conditions, but the China zone able to control the size of their cycles; (d) that Japan remains linked to (and dependent on) the US; and (e) there is no evidence that pegged exchange rates encourage convergence.

Keywords: Spectral Analysis, Coherence, Spillover Gains, Phase Shifts, Business Cycle Relationships

JEL Classification: C22, C29, C49, F43, O49

May 2009

‡ HUGHES HALLETT: George Mason University, University of St Andrews and CEPR; School of Public Policy, 4400 University Drive, Fairfax, VA 22030, USA, Tel: +1-703-933-9123, Email: ahughesh@gmu.edu; RICHTER: School of Economics, Kingston University, Kingston, KT1 2EE, UK, Tel: +44-(0)20-8417-2341, Email: c.richter@kingston.ac.uk.

1 Introduction

It used to be said that the US was the dominant economy in the Asia-Pacific region, and hence the locomotive, or the economy of first resort, through her consumption of final and intermediate products, trade in sophisticated manufactures, and her supply of investment capital and financial stability when exchange rates were fixed.

But the rise of China as a major supplier of cheap manufactures and intermediates, of Japan as a provider of sophisticated manufactures, partner in network trade and a source of investment, and the US as financier, supplier of services, a source of assets for investment and major deficit trading partner for the other two, may have changed all that. China and Japan may now be as important as trading partners and locomotives for the US as the other way round; and both may have significant spillovers on the US. Moreover their rapidly expanding stocks of foreign assets, acquired through the large and continuing trade imbalances in the region, gives them a certain influence over monetary conditions and financial stability.

Those developments are often hypothesised to have changed the dependency relationships between the economies in the Asia-Pacific region. That is what we wish to test for in this paper. Enhanced trade and integration effects in the region will come in three parts: increased economic convergence (coherence, correlation); increased impact (or spillovers) from developments in one economy onto another; and stronger lead/lag relationships between economies (a lead for those supplying materials, intermediate inputs or finance; and a lag for those consuming manufactures, services, or supplying investment goods), as has been shown by Chaplygin et al (2006) in a different context. We examine all three aspects here; focusing on measures of coherence, gain and phase shifts respectively. In particular, we suppose that investment, FDI and possibly network production will strengthen the correlations between long cycles; while trade in consumption goods, materials and intermediate inputs will imply strength at business cycle frequencies. We can then ask: to what extent have growth cycles become more correlated across the Pacific region? Is there evidence of convergence at the business cycle frequency? Does the US still lead in the sense of determining the movements in the other two, or has that role now passed to China? Has the rise in trans-Pacific network trade altered the lead-lag relationships between these economies?

This paper is therefore an exercise in identifying the linkages between economies of the Pacific region. We are not aware that this has been attempted before, although recent papers have tried to examine the relationships between China and her OECD neighbours.[1] However, we approach the problem by means of a time-varying spectral analysis to determine the degree of convergence at different frequencies and cycles. The inconclusive results obtained in this kind of work in the past, particularly for the Euro area, may have been the result of using correlation techniques which average the degree of contemporaneous convergence across all frequencies. That is problematic because two economies could share a trend or short term shocks, but show no coherence between their business cycles.[2] Or because they share similar cycles; but one is a supplier of inputs or capital to the other, so they are out of phase. That would imply low or possibly negative contemporaneous correlations, and give no picture of the true linkage or dependence between them.

A common feature of previous studies has been that the results are sensitive to: a) the choice of coherence measure (correlation, concordance index); b) the choice of cyclical measure (classical, deviation or growth cycles); and c) the detrending measure used (linear, Hodrick-Prescott filter, band pass etc). This sensitivity to the detrending technique is a serious difficulty highlighted in particular by Canova and Dellas (1993) and Canova (1998). The advantages of using a time-frequency approach are therefore:

i) It does not depend on any particular detrending technique, so we are free of the lack of robustness found in many recent studies.

ii) Our methods also do not have an "end-point problem" – no future information is used, implied or required as in band-pass or trend projection methods.

iii) There is no arbitrary smoothing parameter, such as in the HP algorithm, equivalent to an arbitrary band-pass selection (Artis et al., 2004).

iv) We use a coherence measure that generalises on conventional correlation and concordance measures.

Any spectral approach is of course tied to a model based on a weighted sum of sine and cosine functions. However, that is not restrictive. Any periodic function may be approximated arbitrarily well over its entire range, and not just around a particular point, by its Fourier expansion (a suitably weighted sum of sine and cosine terms) – and that includes discontinuities and step functions. Hence, once we have time-varying weights, we can get almost any cyclical shape we want. For example, to get long expansions but short recessions,

[1] See Sato and Zhang (2006), Shin and Sohn (2006), Shin and Wang (2004), and Kocenda and Hanousek (1998).

the typical shape of economic cycles, we need only a regular business cycle plus a longer cycle whose weight increases above trend but decreases below trend (i.e. varies with the level of activity). This is important because many observers have focused on how the shape of economic cycles has changed over time in terms of amplitude, duration and slope (Harding and Pagan, 2001; Peersman and Smets, 2005; Stock and Watson, 2002).

The paper is structured as follows. Section 2 gives a brief introduction in our time-frequency approach, and explains how conventional time series results can be transposed to show the interrelations between different economies at different frequencies or cycle lengths. Section 3 presents the empirical results for the individual countries, and section 4 the inter-dependencies between them. Section 5 then examines the phase shifts (time shifts) between their various cycles. Finally, section 6 concludes.

2 Empirical Techniques

2.1 Estimation in the Time Domain

For countries in the Asia-Pacific region, and for the US, GDP will be expressed in US dollars over the entire sample period. We use the IMF's *International Financial Statistics* data base to ensure that price deflations, seasonal adjustment and exchange rate conversions are applied consistently to each country. Growth rates are then defined, using real GDP data, as:

$$y_t = \Delta\left(\log\left(Y_t\right)\right) = \log\left(\frac{Y_t}{Y_{t-1}}\right) \tag{2.1}$$

Next we employ a two step procedure. Evans and Karras (1996) have shown that, if business cycles are to converge, they need to follow the same AR(p) process. We therefore estimate an AR(p) process for each variable individually. That is, we estimate the data generating process for each growth rate separately. Then we estimate the bilateral links between the cycles in those growth rates. In order to allow for possible changes in the parameters, we create a time-varying model by applying a Kalman filter to the chosen AR(p) model as follows:

$$y_t = \alpha_{0,t} + \sum_{i=1}^{9} \alpha_{i,t} y_{t-i} + \varepsilon_t \tag{2.2}$$

---

[2] As shown by the results in Fidrmuc and Batorova (2008).

with $$\alpha_{i,t} = \alpha_{i,t-1} + \eta_{i,t}, \text{ for i=0...9} \tag{2.3}$$

and $\varepsilon_t, \eta_{i,t} \sim \text{i.i.d.}\left(0, \sigma^2_{\varepsilon,\eta_i}\right)$, for i=0...9.

In order to run the Kalman filter we need initial parameter values. The initial parameter values are taken from OLS estimates applied to the entire sample (Wells, 1996)[3]. Given these start values, we then estimate the parameters of (2.2) using the Kalman filter. We employ a general to specific approach to obtain the final specification for (2.2), eliminating insignificant lags using the strategy specified in the next paragraph. The maximum number of lags was determined by the Akaike Criterion (AIC), and was found to be nine in each case. Each time we ran a new regression, we used a new set of initial parameter values. Then, for each regression we applied a set of diagnostic tests, shown in the tables in the Appendix, to confirm the final specification found. The final parameter values are therefore filtered estimates, independent of their start values.

2.2 Significance tests and diagnostic tests

Using the procedure described so far implies that we get a set of parameter values for each point in time. Hence a particular parameter could be significant for all points in time; or at some periods but not others; or it might never be significant. These parameter changes are at the heart of this paper as they imply changes in the lag structure and hence changes in the spectral results. We therefore employed the following testing strategy: if a particular lag was never significant then this lag was dropped from the equation and the model estimated again. If the AIC criterion was less than before, then that lag was excluded altogether. If a parameter was significant for some periods but not others, it was kept in the equation with a parameter value of zero for those periods in which it was insignificant. This strategy minimised the AIC criterion, and leads to a parsimonious specification. Finally, we tested the residuals in each regression for auto-correlation and heteroscedasticity.

The final specification (2.2) – (2.3) was then *validated* using two different stability tests. Both tests check for the same null hypothesis (in our case a stable AR(9) specification)

---

[3] Using the entire sample implies that we neglect possible structural breaks. The initial estimates might therefore be biased. The Kalman filter however corrects for this bias since, as Wells (1996) shows, the Kalman filter will converge to the true parameter values independently of the initial values. And choosing initial values which are "close" to the true values accelerates this convergence. Hence we employ an OLS estimate to start this process; and our start values have no effect on the parameter estimates by the time we get to 1990. Our results are robust.

against differing temporal instabilities. The first is the fluctuations test of Ploberger et al. (1989), which detects *discrete* breaks at any point in time in the coefficients of a (possibly dynamic) regression. The second test is due to LaMotte and McWorther (1978), and is designed specifically to detect *random* parameter variation of a specific unit root form (our specification). We found that the random walk hypothesis for the parameters was justified for each country (results available on request). Finally we chose the fluctuations test for detecting structural breaks because the Kalman filter allows structural breaks at any point and the fluctuations test is able to accommodate this.[4] Thus, and in contrast to other tests, the fluctuations test is not restricted to any pre-specified (and hence untested) number of breaks.[5]

Once this regression is done, it gives us a time-varying AR(p) model. From this AR(p) we can then *calculate* the short–time Fourier transform as outlined below in order to *calculate* the associated time-varying spectrum.

2.3 Spectral Analysis

The power spectral density function (PSD) shows the strength of the variations of a time series at each frequency of oscillation. It decomposes the variance of a time series into the component that occurs at each frequency or cycle length. In a diagram it shows at which frequencies the variance or fluctuations are strong/powerful, and at which frequencies the variations are weak. For example, if a time series $X_t = \varepsilon_t$, where $\varepsilon_t \sim i.i.d.\left(0, \sigma^2\right)$ and σ is constant over time, the power spectrum would show constant variances across all frequencies: no frequency has a larger impact than any other frequency. However, if the data is dominated by long cycles or business cycles, then the diagram will show higher power (variances) at the low or middle frequency bands; and lower power at the high frequencies.

In order to calculate the spectrum from the estimated version of (2.2), we use the Fast Fourier Transform. The Fast Fourier Transform is an efficient algorithm for computing a

---

[4] Note that all our tests of significance, and significant differences in parameters, are being conducted in the time domain, *before* transferring to the frequency domain. This is because no statistical tests exist for calculated spectra (the data transformations are nonlinear and involve complex arithmetic). Stability tests are important here because our spectra are sensitive to changes in the underlying parameters. But, given the extensive stability and specification tests conducted, we know there is no reason to switch to another model that fails to pass those tests.

[5] The fluctuations test works as follows: one parameter value is taken as the reference value, e.g. the last value of the sample. All other observations are now tested whether they significantly differ from that value. In order to do so, Ploberger et al. (1989) have provided critical values which we have used in the figures (horizontal line). If the test value is above the critical value then we have a structural break, i.e. the parameters differ significantly from their reference values and vice versa. For reasons of limited space we have excluded the test diagrams from this paper, but report on the results. The diagrams are available from the authors upon request.

Discrete Time Fourier transformation (DTFT) at discrete points in time. It creates a *frequency domain* representation of the original *time domain* representation of the data: eqn (2.2). Thus, the spectra and coherences that follow are based on regressions done in the time domain, but then transformed into a frequency domain representation by the Fourier transform. However, we have allowed the coefficients in our regressions to vary over time. We therefore have to derive one DTFT for each point in time. These calculations define a sequence of short time Fourier transformations (STFT). In discrete time, this means the data to be transformed has been broken up into frames (which usually overlap each other). Each frame is then Fourier transformed, and the result added to a matrix which records its magnitude, phase and frequency at each time point. This can be expressed as:

$$STFT\{x[n]\} \equiv X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n} \tag{2.4}$$

In this case, *m* and *n* are different points in time; ω is the frequency and is continuous; j = √-1; and "*n-m*" is the estimation period of the current regression. In our application the estimation period is not constant, but increasing with each new observation. The squared magnitude of the STFT then yields the spectrogram of the function:

$$spectogram\{x_t\} \equiv \left|X(\tau,\omega)\right|^2 \tag{2.5}$$

The specific algorithm used to calculate the Fourier Transform in this paper is the Bluestein algorithm (Bluestein, 1968). This is a well-established algorithm; widely used in engineering (Boashash, 2003; Boashash and Reilly, 1992), but not commonly used in economics.

Finally Boashash and Reilly (1992) have shown that, once (2.2) has been estimated, its coefficients $\alpha_{i,t}$ can be used to calculate the short time Fourier Transform and the power spectra directly. That has the convenient property that the traditional formulae are still valid and may still be used, but they have to be recalculated at each point in time. The time-varying spectrum of the growth rate series can therefore be calculated as follows (Lin, 1997):

$$\mathrm{P_t}(\omega) = \frac{\sigma^2}{\left|1+\sum_{i=1}^{9} \alpha_{i,t}\exp(-j\omega i)\right|_t^2} \tag{2.6}$$

Hence, at any point in time, a power spectrum can be calculated instantaneously from the updated parameters of the model. And we are able to generate a power spectrum even if we have a short time series and even if that time series contains structural breaks.

Thus, when we present our empirical results, they are based on the time-varying STFT calculations; the only thing we need to do is to add a time dimension to show how the spectra and cross-spectra have changed over time. The result is a 3-dimensional diagram.

2.4 Cross-Spectral Analysis

We also need to investigate the linkage between different business cycles. In the frequency domain, the tool to do that is the coherence. The **spectral coherence** $\left(K_{XY}^2\right)$ is a statistic that can be used to examine the relation between two data sets. Values of the coherence always satisfy $0 \le K_{XY}^2 \le 1$. For a strictly proportional (linear) relationship between a single input x_t and single output y_t, the coherence will equal one. If x_t and y_t are completely unrelated, the coherence will be zero. If K_{XY}^2 is less than one but greater than zero, it is an indication that output y_t is being produced by input x_t as well as by other inputs. Hence, the coherence is nothing else than the R^2 at each frequency/cycle length. Since we are calculating the coherence using short time Fourier transforms, the coherences may also be time-varying.

Suppose now we are interested in the relationship between two variables $\{y_t\}$ and $\{x_t\}$, where $\{y_t\}$ is the Chinese growth rate and $\{x_t\}$ is the US growth rate for example. We assume that they are related in the following way:

$$V(L)_t \, y_t = A(L)_t \, x_t + u_t, \; u_t \sim \text{i.i.d.}\left(0, \sigma^2\right) \tag{2.7}$$

where $A(L)_t$ and $V(L)_t$ are filters, and L is the lag operator such that $Lz_t = z_{t-1}$. Notice that the lag structure, $A(L)_t$, is time-varying. That means we need to use a time-varying model (we use the Kalman filter again) to estimate the implied lag structure. That is

$$\begin{aligned} v_{i,t} &= v_{i,t-1} + \varepsilon_{i,t}, \text{ for i = 1, ..., p and } \varepsilon_{i,t} \sim \left(0, \sigma_{\varepsilon_i}^2\right) \\ a_{i,t} &= a_{i,t-1} + \eta_{i,t}, \text{ for i = 0, ..., q and } \eta_{i,t} \sim \left(0, \sigma_{\eta_i}^2\right) \end{aligned} \tag{2.8}$$

As before, we test for the random walk property using the LaMotte-McWorther test. And for structural breaks, we employ the fluctuations test (Ploberger et al., 1989). Finally, we use our previous general to specific approach to estimate (2.7); starting off with lag lengths of nine and p=q, and dropping those lags which were never significant (as we did before).[6]

As in Hughes Hallett and Richter (2004, 2006, 2009), we use the fact that the time-varying cross spectrum, $f_{YX}(\omega)_t$, using the STFT can be written as:

$$f_{YX}(\omega)_t = |T(\omega)|_t \, f_{XX}(\omega)_t \tag{2.9}$$

where $T(\omega)_t$ is the transfer or filter function is defined by (2.7), calculated as follows:

$$T(\omega)_t = \left(\frac{\sum_{b=0}^{q} a_{b,t} \exp(-j\omega b)}{1 - \sum_{i=1}^{p} v_{i,t} \exp(-j\omega i)} \right), \text{ for } t = 1, \ldots, T \tag{2.10}$$

The last term in (2.9), $f_{XX}(\omega)_t$, is the spectrum of predetermined variable. The spectrum of any *dependent* variable is then defined as (Jenkins and Watts, 1968; Nerlove et al., 1995):

$$f_{YY}(\omega)_t = |T(\omega)_t|^2 f_{XX}(\omega)_t + f_{vv}(\omega)_t \tag{2.11}$$

From (2.6) we get the time varying residual spectrum

$$f_{vv}(\omega)_t = \frac{f_{uu}(\omega)_t}{\left|1 - \sum_{i=1}^{p} v_{i,t} \exp(-j\omega i)\right|^2} \tag{2.12}$$

and the gain as $A(\omega)_t = |T(\omega)_t|^2$. Finally, given knowledge of $f_{YY}(\omega)_t$, $|T(\omega)_t|^2$, and $f_{XX}(\omega)_t$, we can *calculate* the time-varying coherence at each frequency as:

$$K^2_{YX,t} = \frac{1}{\left\{1 + f_{VV}(\omega)_t \Big/ \left(|T(\omega)_t|^2 f_{XX}(\omega)_t\right)\right\}} \tag{2.13}$$

The coherence measures, for each frequency, the degree of fit between x_t and y_t: that is, the R^2 between each of the corresponding cycles in x_t and y_t. The gain is the regression coefficient,

[6] The symmetry in the lag structure, and general to specific testing, allows the data to determine the direction of causality in these regressions. We do not report any results for the reverse causalities that were not accepted.

spillover or transmission effect of x_t on y_t. Hence $A(\omega)_t$ and $K^2_{YX,t}$ define the link between two variables at time t. However, neither the gain, nor the coherence take into account any leads, lags or shifts in the business cycle.

To distinguish changes in timing from changes in the importance of different cycles, we need to measure the phase shift between x_t and y_t. To do that, we need the *phase angle*. The phase angle measures the lead or lag relationship between two variables at each cyclical frequency. Formally:

$$\varphi(\omega) = \tan^{-1}\frac{-Q_{YX}(\omega)}{C_{YX}(\omega)} \tag{2.14}$$

where

$$C_{YX}(\omega) = f_{XX}(\omega)\sum_{j=0}^{\infty} a_j \cos\omega j, \quad \text{and} \quad Q_{YX}(\omega) = f_{XX}\sum_{j=0}^{\infty} a_j \sin\omega j\,. \tag{2.15}$$

The phase angle can therefore be written as

$$\varphi(\omega) = \tan^{-1}\left(\frac{\sum_{j=0}^{\infty} a_j \sin\omega j}{\sum_{j=0}^{\infty} a_j \cos\omega j}\right) \tag{2.16}$$

Hence, to calculate the phase angle, all we need to know are the coefficients a_j. However, in this paper we analyse a “standardised” phase angle, or *phase shift*:

$$\tau(\omega) = \frac{\varphi(\omega)}{\omega} \tag{2.17}$$

To see how to interpret the phase shift statistic, consider the following figure:

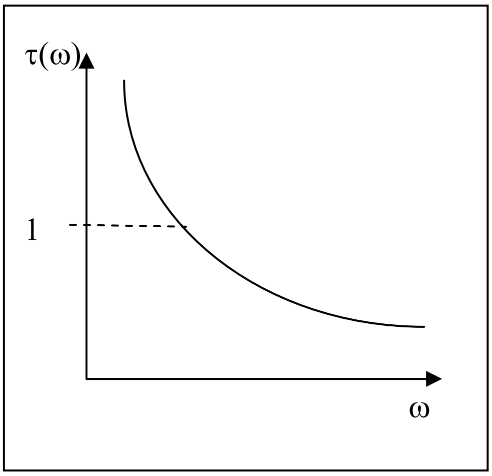

Figure 1: Assumed Shape of a Phase Shift

Figure 1 shows one variable is following the other at long cycles, with a delay of one quarter – peak to peak say. But for smaller cycles the delay is shorter. In efficient markets, the two processes should follow each other very closely, since agents are able to process new information relatively quickly. But in other cases there will be natural leads and lags depending on the production structure and degree of vertical integration

The formulae given above are for the time-invariant case. Since we get new values for a_j for each point of observation t, we can apply the above formulae for every point in time t. In other words the time-varying phase shift changes to:

$$\tau(\omega)_t = \frac{\varphi(\omega)_t}{\omega} \tag{2.18}$$

3 Empirical Results: Single Spectra

In this section and the next, we study the spectra and cross-spectra of output growth in China and Japan compared to the US, over the past 25 years. We take the US to be the leading economy ("economy of first resort"), at least at the start of the sample period, and analyse the changing relations between the US and the other two since the Asian financial crisis: 1996-7. Similar results for the changing relationships between the US and the UK, and the US vs. the Euro-zone, will be found in Hughes Hallett and Richter (2006) and can be taken as a benchmark for these comparisons.

For all countries we use the IMF's *International Financial Statistics* data. All GDP observations are quarterly data, already deflated by the IMF statistical service and expressed in US dollars. They are also seasonally adjusted by the IMF. Finally, we log difference the GDP data to give (quarterly) growth rates. We use data from 1987:4 to 2006:3. The sample actually starts earlier for the US (1982), and for Japan (1958), but the analysis will be restricted to the period following the stock-market/financial crash of 1987.

The resulting data are then fitted to an AR(p) or ADL(p,q) model as described above, and tested for stationarity, statistical significance, and a battery of diagnostic and specification checks before being converted to the spectra and cross-spectra that we need. The time domain regression results and tests are rather extensive and are available in full from the authors on request. We have attachedthough the regression results for the endof the sample.

a) **Spectra: US, Japan and China.** One striking feature of the individual spectra is that, in all three economies, the trend growth rate does not play an important role in terms of spectral power. Indeed, taking into account the vertical scale in each diagram, there is very little volatility in output growth of any kind in China after 1987 (figure 3), except at business cycle frequencies, and only then until the period of especially rapid trade growth and trade surpluses from 2004 onwards. Similarly, there is little output volatility in Japan except at the business cycle frequency in the Asian crisis period (1998-2002: figure 4). This is in stark contrast to the US spectrum (figure 2) which shows the declining power of trend growth after 1987, and mildly increasing volatilities at the short-to-medium cycle lengths over the same period. There is a clear persistence in her trend growth rates throughout nonetheless.

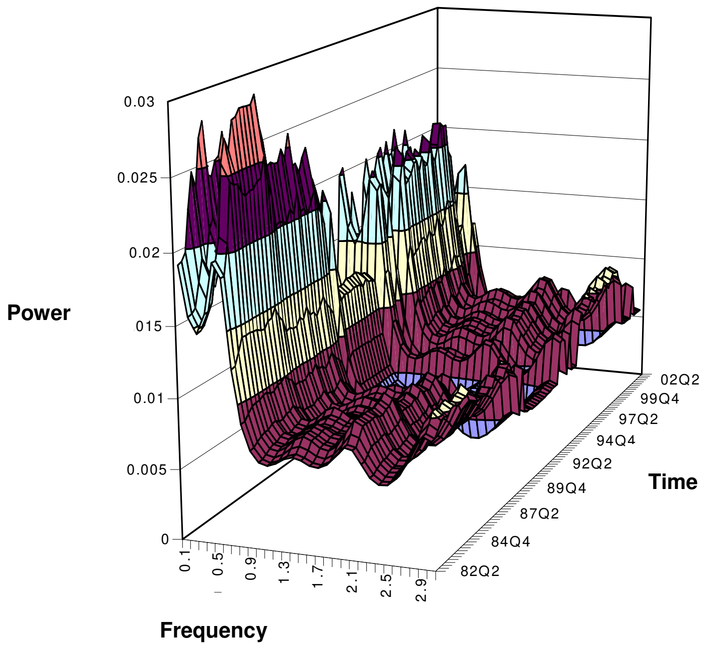

Figure 2: Spectrum of the US Growth Rate

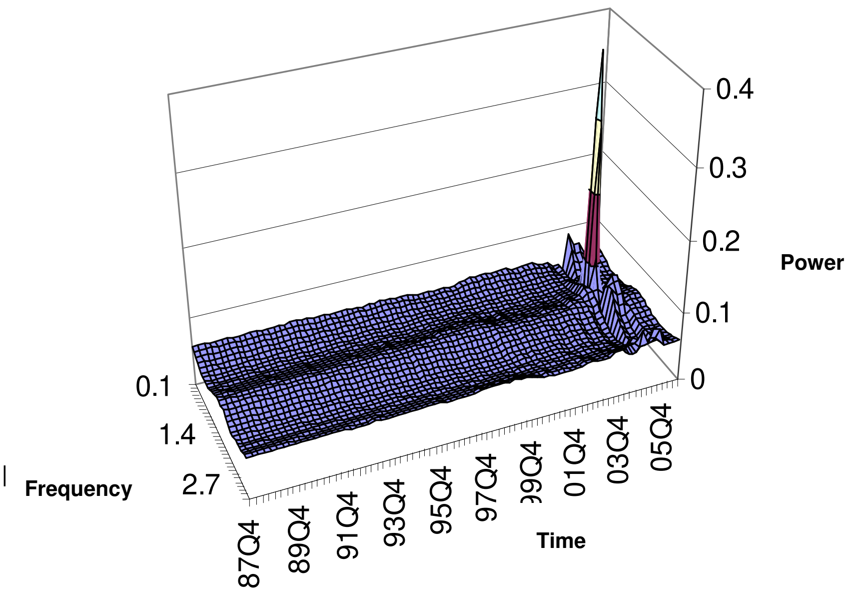

Figure 3: Spectrum of the Chinese Growth Rate

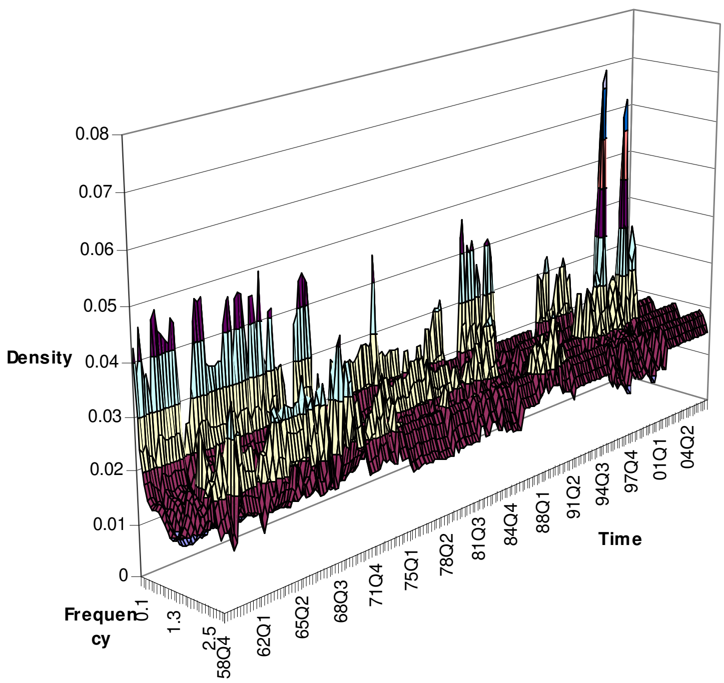

Figure 4: Spectrum of the Japanese Growth Rate

In making these points, we are drawing a clear distinction between persistent trends, meaning events whose effects on performance last a long time before dying away or being overtaken by subsequent events/changes; and constant growth trends whose effects are persistent and always the same in terms of economic performance. Obviously the former implies some variance in the outcomes, if only slowly changing, and hence some long cycle power in the associated spectrum. But the latter implies no effective variance in the outcomes, and hence no power in the corresponding spectrum at low frequencies (or anywhere else).

There may therefore have been change in these economies; but it is not a change that has altered the pattern of growth in the US in any significant way, or the growth patterns in China or Japan for that matter, except in the period after 2003. That is not to say that the relationship between these economies has not changed. But if it has, it must have been a change involving others outside the region; or, more likely, a change that involved a reallocation of roles between the economies of the Asia-Pacific area, rather than a change in their behaviour or dependency as such. The latter appears more likely because the pattern of structural (regime) breaks shows little in common taking each economy separately. Had they been settling into a new regime, there would have been something in common in the structural breaks as each economy entered that regime. As it is, the US is only showing structural breaks in 1996 and 2001 (the Clinton-Greenspan boom); while Japan shows breaks in 1977-80, 1983-92 and in 1994-2002 (boom times, then deflation); and China shows a series of small breaks in 1993, 1995 (the start and finish of the high inflation period), 1999-2000 and 2002 (the onset and end of deflation), and then a very large one in 2004-5 (expansion of trade, curtailing of Chinese imports). With a pattern like that, these breaks are far more likely to reflect changes in the domestic economies than in the trade or financial links between them.

(b) Commentary: The tentative conclusion at this stage is that there has been no significant change in the growth patterns of these three economies over the past two decades; with the exception of the increase in volatility at business cycle frequencies in Japan at the time of the Asian crisis, and from the liberalization in the Chinese economy and trade in 2001. Even so, the low spectral power in the two Asian economies implies they have enjoyed stable growth rates. That much they do have in common, and in contrast to the US. But it is not a new phenomenon.

4. Coherence, Gains and Spillovers

We turn now to the coherence between the economic cycles of our Asian economies at different frequencies – and whether those coherences have been increasing or decreasing. These results provide a test of the hypothesis that our two Asian economies form a coherent economic block, more similar in performance than with those outside the group, and whether their dependence on the US economy has decreased as the strength of the linkages in Asia has increased. In addition, we can test the proposition that, if exchange rates are pegged, then business cycles will converge as trade and financial links strengthen. This is an important matter as Artis and Zhang (1997), and Frankel and Rose (1998, 2002), argue that this is likely to happen as trade and financial links intensify. On the other hand, Kalemli-Ozcan et al (2003), Hughes Hallett and Piscitelli (2002), Baxter and Kouparitsas (2005), and Peersman and Smets (2005) show that it has not happened elsewhere. So it may not happen in the Asian case either. The point is that China has maintained a pegged exchange rate with the US throughout this period, whereas Japan has not. We can examine the coherences (gains, phase shifts) directly and attribute the results to the exchange rate regime over and above the increased trade and financial flows. The results below show that Japan, with her floating exchange rate, has maintained a far closer degree of cyclical convergence with the US than has China with a fixed rate and no tendency for the coherences to increase. A fixed rate therefore appears to be neither necessary, nor sufficient for inducing convergence.

(a) Coherence and Spillovers: the US and China. Take the China-US relationship first ("the US affects China", figure 5)[7]: we can see that the coherence declined gradually from 1987 to 2001, but remained at a fairly high level of 0.4 to 0.5 throughout. However it increased again, rather abruptly, from 2001 to imply a stronger if somewhat uncertain association between US growth and Chinese growth at the short, long, and (most of all) business cycle frequencies from 2004 to 2006.

[7] Note that each coherence/gains relationship implies a direction of causality, and hence different degrees of association or spillover effects, depending on whether we are looking at how much US growth affects growth in China or how much Chinese growth affects the US performance. Hence we get different results, and different implications, depending on whether the underlying regressions (2.7) specify Chinese growth as a function of US growth; or US growth as a function of Chinese growth. Coherences may therefore imply one growth pattern is more closely associated/dependent on another, than holds in reverse (the dependence or association of the second on the first). Coherence therefore measures the general closeness of fit between two variables x and y, rather than the simple correlation coefficient which is symmetric. Gains likewise measure the numerical impact of growth in one economy on that in another, and vary with the direction in which the linkage is supposed to run.

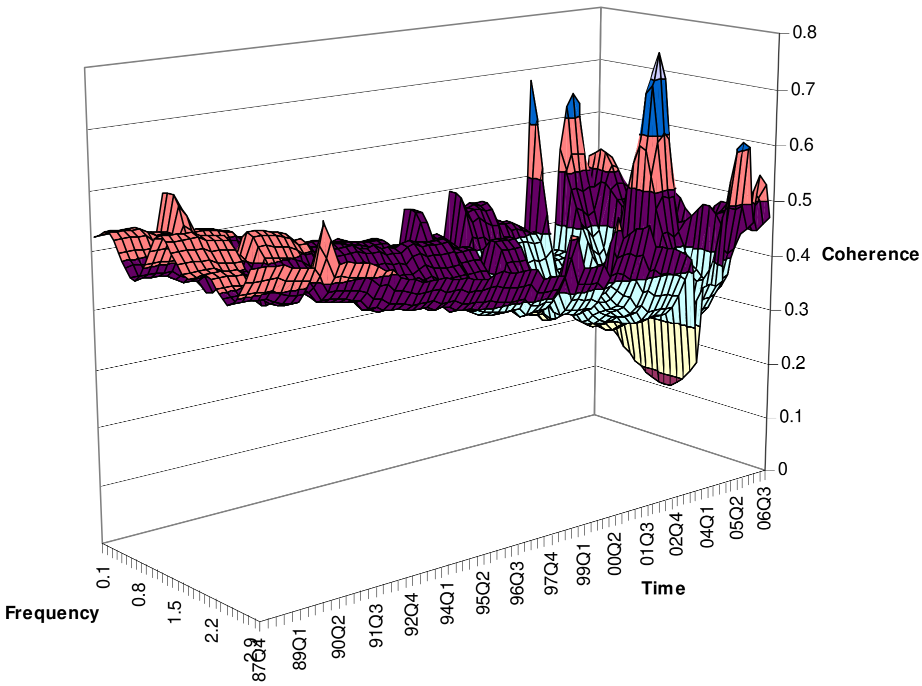

Figure 5: Coherence between China and the US

The gains, figure 6, however show that the impact of variations in US growth on China has been quite small until 2002, with multipliers of below 0.08 per unit change in the US and declining. But then there is a sudden increase in the US influence at short, long and business cycle frequencies in 2003-4; such that, by 2005, the spillovers onto China had settled back to the levels of 1990-91. So there is partial support for our initial hypothesis, but not quite as expected: US dominance and economy of first resort effects have indeed been declining with respect to China, but only slowly and only up until 2002. The recent surge in trade with the US, based as it is on expanding Chinese exports and domestic substitution of imports[8], has restored much of the US influence on China although it remains at a fairly low level.

[8] It is very clear in the data that Chinese exports and imports have grown at equal speeds since 2000, at rates of 30 percent annually in the period 2002-2004. But then import growth stopped altogether in 2004; and only edged back up to 10% in 2007, while export growth remained above 20% throughout. As a result China's trade surplus tripled in 2005, and then doubled again in 2007.

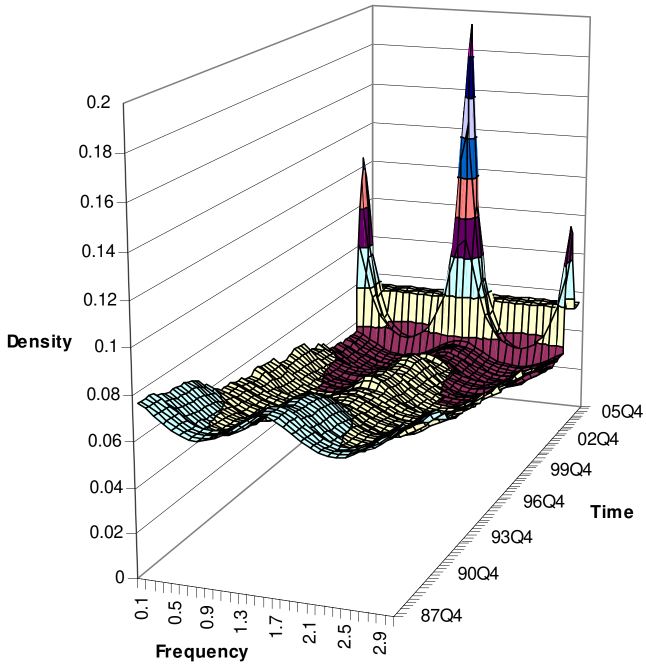

Figure 6: Gain China – US

In the light of the above results, it is important to see if the counterpart is true: i.e. if China's impact on the US economy has also been increasing. We might expect to see the China to US gains and coherence increasing with the expansion of trade and financial flows between the two, in the same way as the US to China coherence and gains have increased. And to some extent we do. The US-China coherence (figure 7) is rather low, but falls steadily (from 0.1 to 0.05) up until 2001 just as the China-US coherence did. It then jumps back up to 0.1, and more strongly to 0.3 at the business cycle frequency. It then remains at that level.

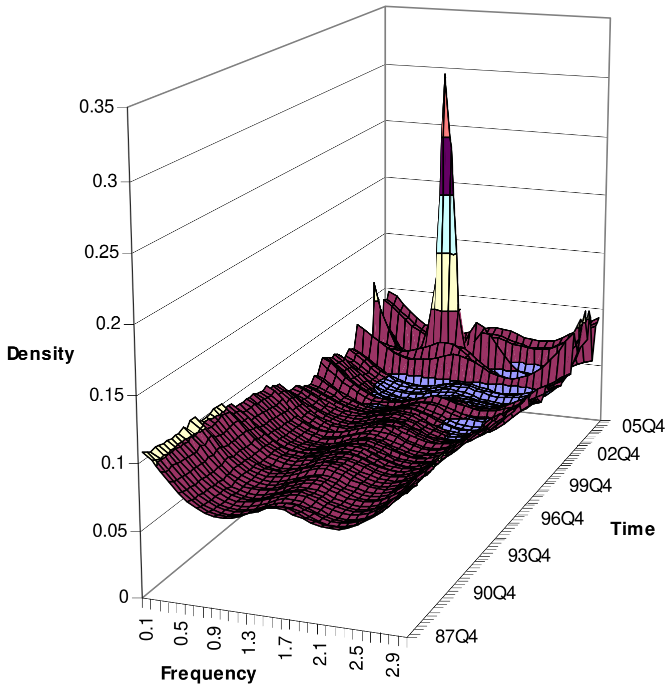

Figure 7: Coherence between the US and China

In the same way, the US-China gain (figure 8: the impact of Chinese growth on the US) is high but falls steadily until 2001, and then recovers sharply thereafter to values similar to those of the early 1990s – again similarly to the China-US case[9].

[9] We observe this more in the long and short cycles than in business cycles. That suggests a change in the phase relationship. If there is such a change, then the strength of coherence or gain must increase at some frequency, and decrease at another, while the change itself takes place. See our test for changing phase shifts and changes in the product mix (consumption goods, process inputs, components, and investment goods) in section 5.

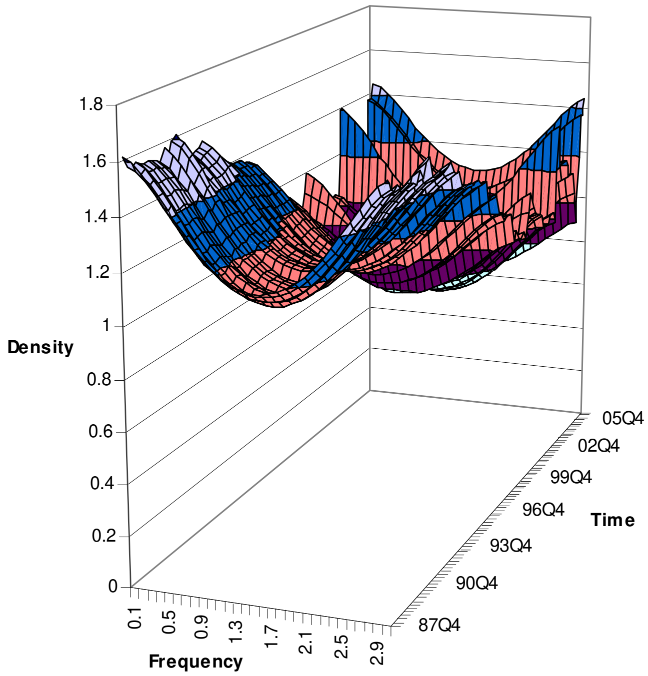

Figure 8: Gain US - China

Those results might therefore suggest a *mutual* dependence between China and the US, in place of the presumed leadership of the US economy in the 1980s and 1990s. However this would be wrong due to the asymmetries in the linkage**.** The US to China linkage has a high coherence but a low gain, while the China to US linkage has a low coherence but high gain. Such asymmetries reveal the pattern of dependency or leadership in this case. It appears that the US has the power to *shape* the cycle in China – this is the coherence part – through her control of monetary and financial conditions (interest rates, supply of capital, exchange rates); while China has the power to influence spillover effects onto the US, and hence the *size* of the cycle (this is the gain effect), through the outsourcing of manufactures, and cheap components or intermediates for the US economy. This fits in neatly with the facts. Chinese imports of process goods, intermediates and components now account for 42% of total imports; those from the US having risen by a factor of 8 since 1992 (and by 3 times since 2001), and those from Japan by 12 times since 1992 (2½ times since 2001). Similarly Chinese process exports, components and intermediates are 53% of total exports, with those going to the US up by a factor of 4¾, and those going to Japan up 15 times, since 1992.

These results give a more nuanced view of the relationship between the US and China. It is consistent with the idea that China has gained greater influence through its expansion of trade; but at the cost of dependence on foreign monetary conditions (risking thereby inflation, excess liquidity, asset bubbles, uncertainties in short term financing). However, the key point is that this relationship is not new. It has been in this form since the 1980s; even if it has become stronger, but more uncertain, since 2000.

(b) Coherence and Gains: the US and Japan. The Japan-US relationship presents a simpler picture (figures 9 and 10). The coherence here shows a steady but surprisingly strong linkage between Japanese growth and US growth. That association may be stronger at long cycles, and may have weakened in the past 5 years, but the changes are very small. The gains however (the impact of US income movements on Japanese growth) show larger changes; those spillovers fall from around 0.3 in the 1970s and 1980s, especially at long cycles and in short term volatility, to about 0.15 now. But that is still twice as large as the impact of the US on China. And at business cycle frequencies, the spillovers are twice that strength again after 2001. These results therefore also support our original hypothesis; but only weakly because the linkage between US-Japanese business cycles is increasing (if anything) at the end of the sample, and because the constant coherence means there will be correspondingly few changes in the Japan to US relationship. We do not report that relationship separately therefore.

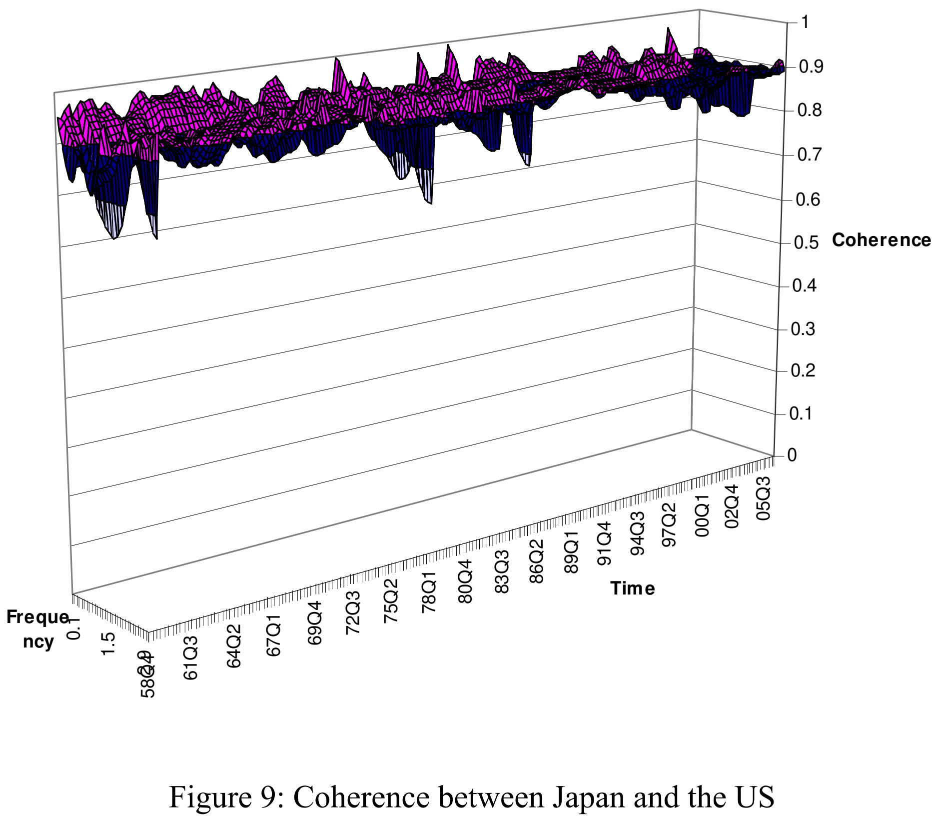

Figure 9: Coherence between Japan and the US

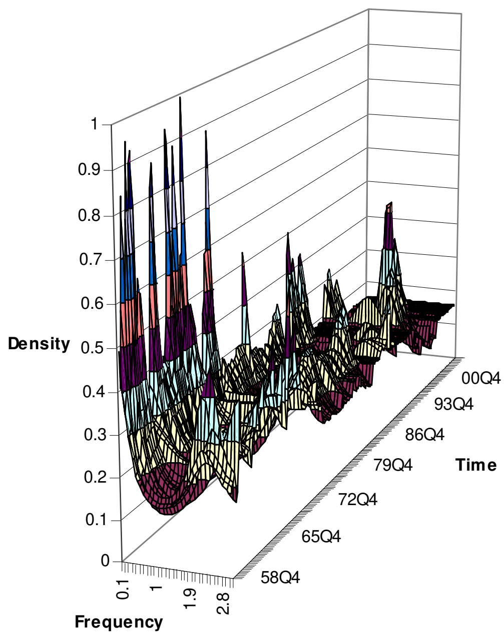

Figure 10: Gain Japan - USA

(c) Coherence and Gains: China and Japan. The Japan-China (China influences Japan) coherence (figure 11) is very low throughout at 0.1, but shows distinct increases in 1997 and in 2003 where the relationship starts to show a significant increase in volatility. At that point the transmissions from China are mainly to the business cycle frequencies in Japan. However, the coherences remain small, no more than for China influencing the US, and smaller (by factors of 5 to 6) than the US's coherences with China or Japan.

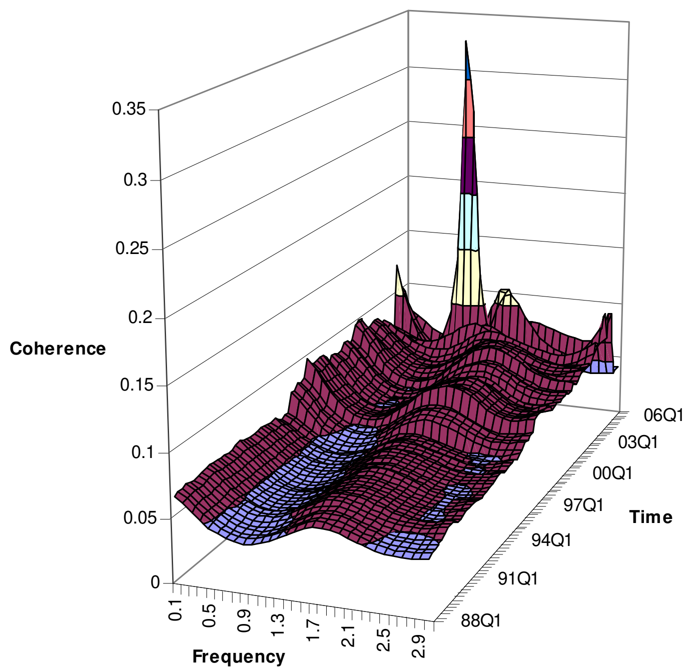

Figure 11: Coherence between Japan and China

The gains (figure 12) mean-while are smaller again at 0.02-0.03, although they too show an increase in 1997 at the short and long frequencies before tailing off again after 2003. This is consistent with Japan evolving separately from China, even though one might have expected more linkage between the two as Chinese components are increasingly used and manufactures increasingly consumed in Japan; and as more Japanese equipment or investment goes to China. However, the fact that the same thing is also happening in the US means that Japan and the US continue to behave in the same way with respect to each other despite their changing roles in the Asian economy. Since China's role in either partner economy is the thing that has been changing, it is her relationship with the US and Japan that has changed; not those elsewhere in the region.

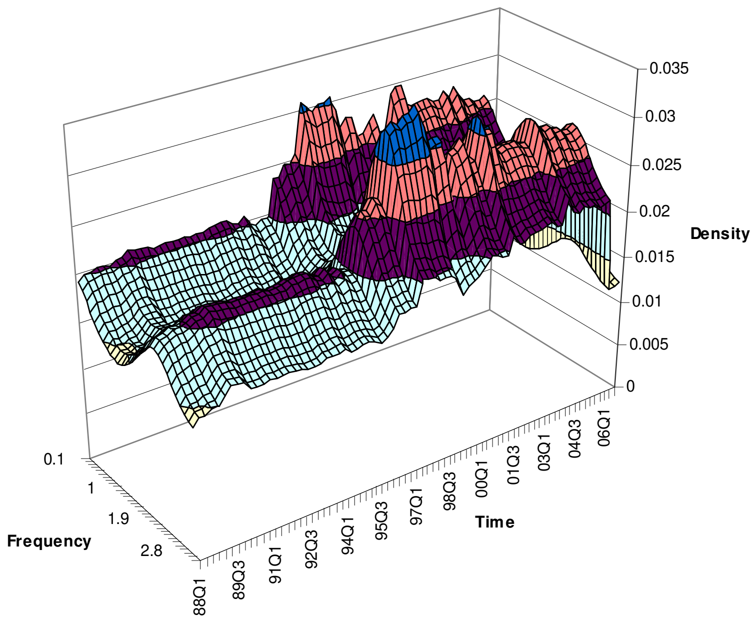

Figure 12: Gain Japan - China

Together with the above, the reverse relationship (Japan influences China, figs. 13-14) shows something of the same pattern as the China-US relationship, although much less clearly marked because of the decade of depression in Japan. Like in the US comparisons, Japan's influence on China shows low coherence and high gains; but China's influence on Japan has a high coherence and low gains. In the China-Japan case however, these linkages are weaker: the ratio of coherence to gain is 4:1 for China-Japan and 1:2 (in the 1990s) for Japan-China, compared to 10:1 and 1:12 for the China/US counterparts. And the picture has been confused by the loss of any form of (statistically significant) linkage during Japan's decade of depression (1993-2004). As one might expect, as Japan sank into depression her influence on China vanished, even if China's weak but strengthening influence on Japan did not. Consequently the China-Japan linkage shows a lot of uncertainty, especially with the Japanese attempts at revival in 1996 and 1999, while the Japan-China one does not. But the successful revival in 2004 restores more than the status quo ante, and fairly evenly so across most frequencies. In summary, we can draw the same conclusions as we did in the China/US case: China can influence the size of the cycle in Japan, but Japan exerts some influence over the shape/existence of the cycle in China. However the effects are more limited than in the US linkage. And Japan's influence on China is spread over the long (investment), short (monetary financing), and business (network production and consumables) cycles, whereas China's influence on Japan is mostly at business cycle frequencies (out-sourced production, components).

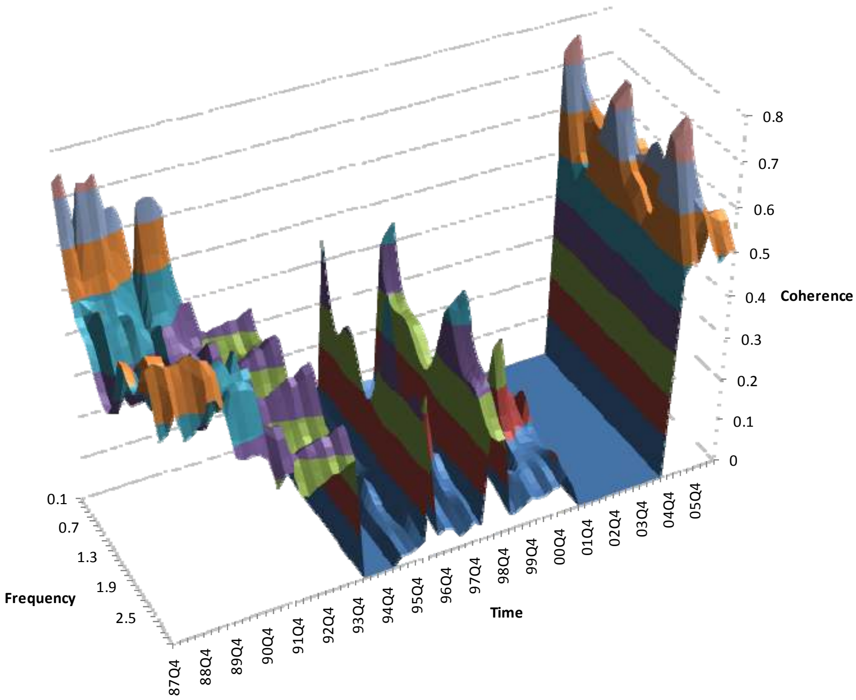

Figure 13: Coherence China – Japan

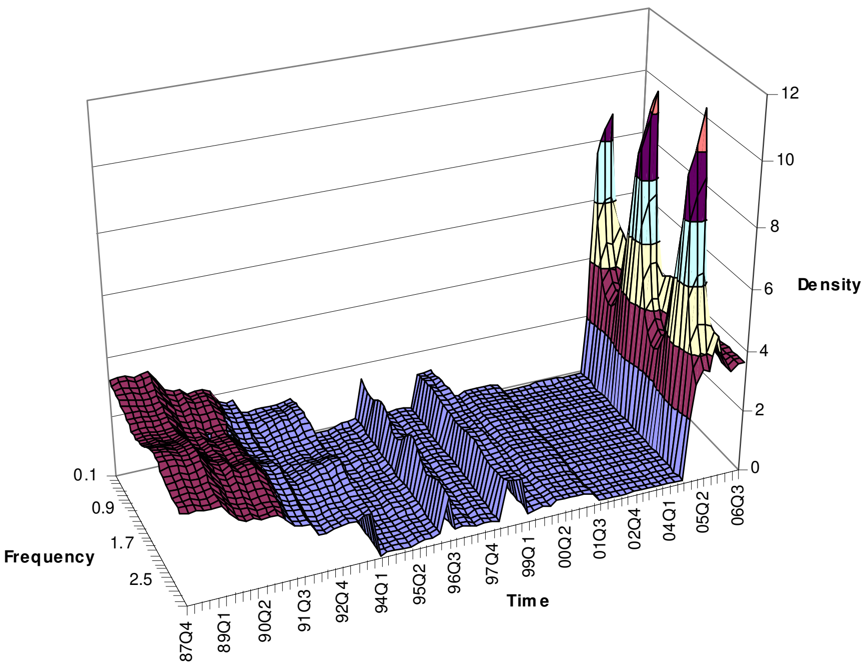

Figure 14: Gain China - Japan

5. Phase Relationships

We turn now to the phase (or time) shifts between the cycles in these economies. To make this systematic across cycles, we use the phase shift measure at (2.18) rather than correlations computed between cycles at arbitrarily imposed leads and lags (as has been done in previous investigations: Chaplygin et al, 2006). These phase shift calculations give quite a lot of information on the industrial structure and demand patterns which have given rise to the linkages identified in the last two sections. They are therefore needed to provide some insight into why those linkages have arisen and what they depend on.

(a) China and the US: Figures 15 and 16 show the phase relationships between China and the US. Recall that a positive phase shift means that the dependent variable's economy [in the sense of (2.7)] leads the other one at that cycle length. Figure 15 therefore shows that the US economy leads the Chinese economy at all the low frequency cycles, from frequencies of 0 to 0.4, by up to 3 quarters. This implies a degree of dependency on the US for long term developments derived from the US demand for intermediate inputs, components, and from the Chinese need for materials and finance.

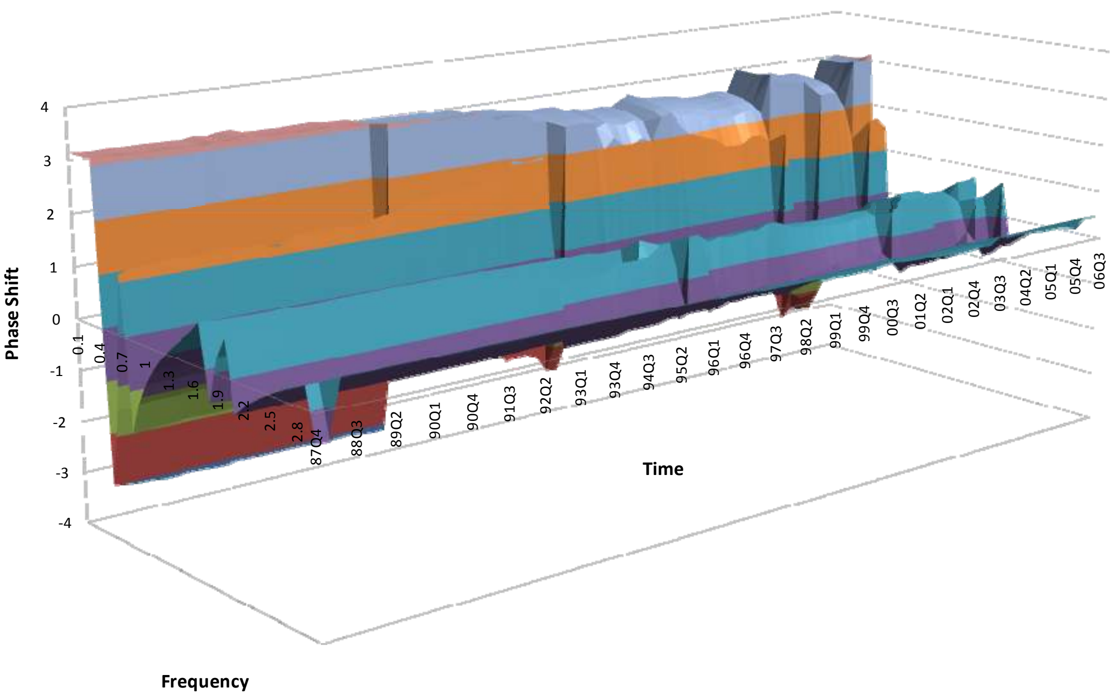

Figure 15: Phase Shift US- China

This interpretation is consistent with an estimated lead time of 3 quarters, or about 9 months, in the long cycles. The lead time itself declined a little from 1992 to1999, to become unstable in 2000-03, but was restored to its previous value of 3 quarters in 2005. There are also other leads and lags of interest. At business cycle frequencies, they are a mixed bag with the US lagging China at frequencies of 0.4 to 0.6; but leading China in the 0.6-0.7 range, and then lagging again at 0.7 to 1.0. In this part of the story the lead times are all quite short, 1-2 quarters, whereas the lag times are longer at 3 quarters. This part of the diagram represents the impact of US demand for intermediates, and the Chinese need for materials and financing on the US business cycle (the lead terms); and the effects of consumption or investment spending in China (lag terms). There are further small phase shifts at the short cycles, probably reflecting financing arrangements, but they are not very important.

The reverse picture, China-US, shows that China has a very minor lead over the US when the causality runs from the US to China: perhaps one month for the long cycles, and none at business cycle lengths (figure 15). Effectively changes in the US have their impacts in China right away or with a 1 month delay.

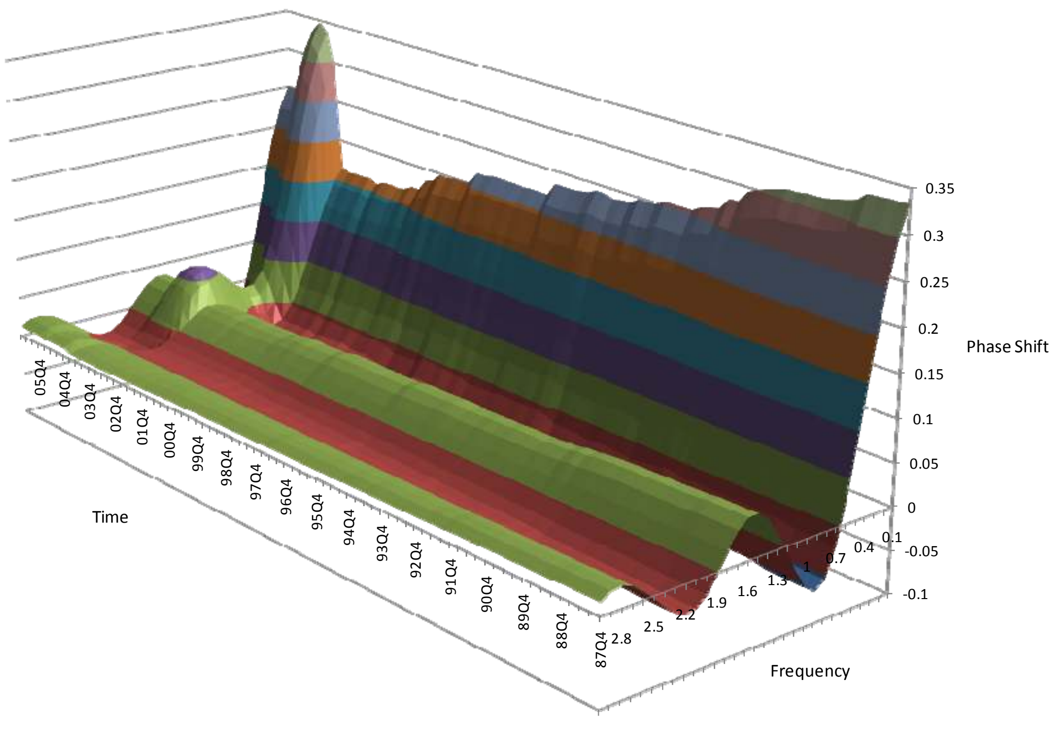

Figure 16: Phase Shift China - US

(b) China and Japan: Figures 17 and 18 show that the phase shifts between China and Japan are much weaker. In fact they are statistically insignificant for half the sample in the China-Japan case, and with such short lags in the Japan-China case as to be uninteresting. We can conclude that the impacts of any changes in China on Japan are transmitted instantly. However, the impact of changes in Japan on the Chinese economy was effectively zero after 1993 until 2005. Where there is some impact, Japan appears to have had the same effect on China as the US did, but with longer lead times. In recent years, China has led Japan by up to 10 quarters (3-4 years) in the longer cycles. This must reflect Japanese financing and FDI in China, and her demand for intermediates and components (the network trade). There are also lags of 1-2 years at business cycle frequencies, which may reflect Japanese consumption of Chinese manufactures.

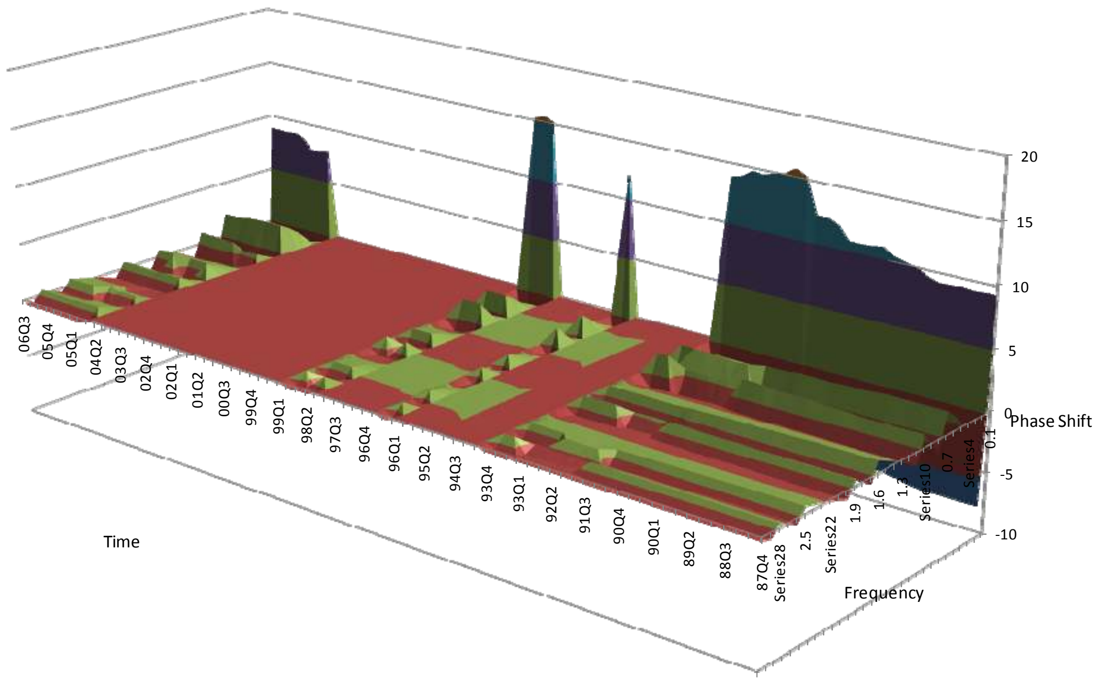

Figure 17: Phase Shift China - Japan

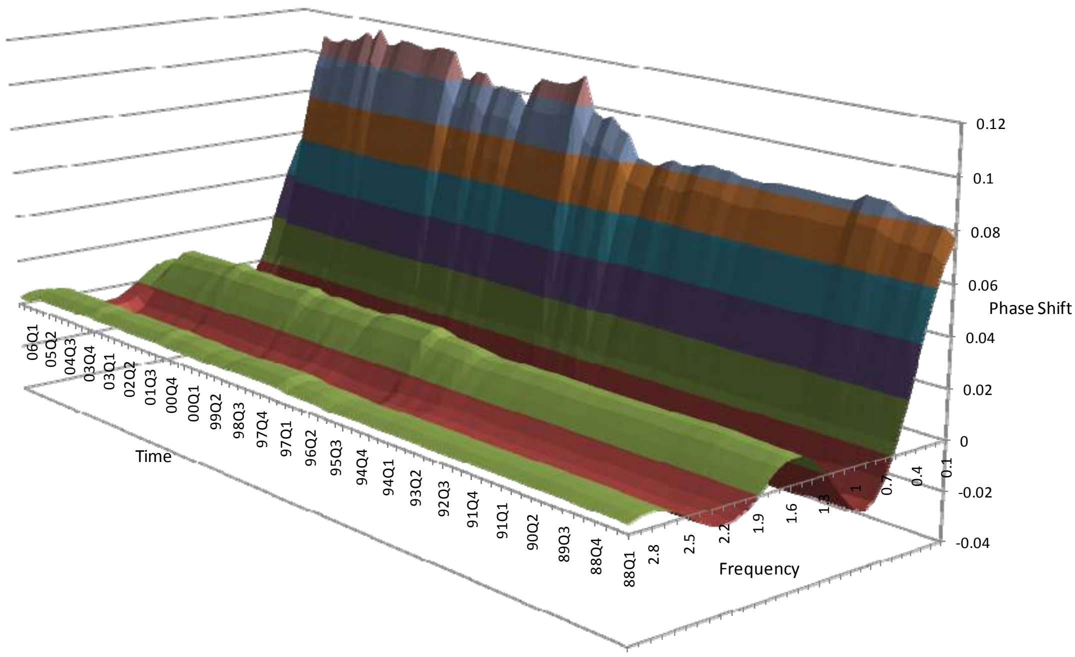

Figure 18: Phase Shift Japan - China

(c) Japan and the US: There are no phase shifts in this case, as might be inferred from the very high coherences (almost 1) between the US and Japanese growth cycles reported earlier. That means the US and Japanese cycles are more or less in line with one another; the phase shifts are zero.

6. Conclusions

This paper has examined the links and leadership-dependency relationships in the Asia-Pacific area over the past 20 years in terms of spillovers and lead/lag relationships between China, Japan and the US; and whether US hegemony has been reduced by the strengthening of the links between Asian economies.

Our results indicate that:

a) The economic links with the US have indeed weakened, and those elsewhere may have strengthened. However, this is not new. It has been happening steadily since the mid-1980s, and it has now been partly reversed by the unbalanced expansion of Pacific trade.

b) The linkage with the US is more complex than usually supposed. It appears that the US still influences the shape and existence of cycles elsewhere through her control of monetary conditions where exchange rates are pegged (China); but China has some control of the size of the cycles at home and elsewhere through the strength of her trade in consumption, components and intermediate goods. Since the changes with respect to Japan are very similar, the Japan-US relationship is largely unchanged.

c) There is no evidence that fixed exchange rates encouraged convergence despite increasing trade and financial links; most likely because of the capacity of misaligned (undervalued) exchange rates to generate excess liquidity, easy credit, and domestic asset bubbles.

d) The phase shift calculations show a fairly complex patterns of lead and lag relationships in which China appears to respond more or less immediately to changes in US or Japanese growth patterns, but the US and Japan adjust to changes in China with leads or lags of a year or two in their long or business cycles. These leads and lags identify the industrial structure, and the demand pattern, in the links between these economies.

References

Artis, M. and Zhang W. (1997), 'International Business Cycles and the ERM: Is there a European Business Cycle?', *International Journal of Finance and Economics* **2**, 1-16.

Artis, M., M. Marcellino and T. Priorietti (2004), 'Dating the Euro Area Business Cycle', In L. Reichlin (Ed.), *The Euro Area Business Cycle: Stylised Facts and Measurement Issues* (London: Centre for Economic Policy Research).

Baxter, M. and M. A. Kouparitsas (2005), 'Determinants of Business Cycle Comovement: a Robust Analysis', *Journal of Monetary Economics* **52**, 113-158.

Bluestein, L. I. (1968), 'A Linear Filtering Approach to the Computation of the Discrete Fourier Transform', *Northeast Electronics Research and Engineering Meeting Record* **10,** 218-219.

Boashash, B. (2003), 'Time Frequency Signal Analysis and Processing', (Oxford: Elsevier).

Boashash, B. and A. Reilly (1992), 'Algorithms for Time-frequency Signal Analysis', in B. Boashash (Ed.): *Time-Frequency Signal Analysis - Methods and Applications* (Melbourne: Longman-Cheshire).

Canova, F. (1998), 'Detrending and Business Cycle Facts', *Journal of Monetary Economics* **41**, 475-512.

Canova, F. and H. Dellas (1993), 'Trade Dependence and the International Business Cycle', *Journal of International Economics* **34**, 23-47.

Chaplygin, V., A. Hughes Hallett and C. R. Richter (2006), 'Monetary Re-integration in the ex-Soviet Union: A Union of Four?', *Economics of Transition* **14, 47-68.**

Evans, P. and G. Karras (1996), 'Convergence Revisited', *Journal of Monetary Economics* **37**, 249-265.

Fidrmuc, J. and I. Batorova (2008), 'China and the World Economy: A Dynamic Correlation Analysis of Business Cycles', *UNU-WIDER DP 2008/02* (Helsinki: United Nations).

Frankel, J. and A. Rose (1998), 'The Endogeneity of the Optimal Currency Area Criteria', *Economic Journal* **108**, 1009-25.

Frankel, J. and A. Rose (2002), 'An Estimate of the Effect of a Common Currency on Trade and Income', *Quaterly Journal of Economics,* **117**, 437-66.

Harding, D. and A. Pagan (2001), 'Extracting, Analysing and Using Cyclical Information', *mimeo*, (Canberra: Australian National University).

Hughes Hallett, A. and L. Piscitelli (2002), 'Does Trade Cause Convergence?', *Economics Letters* **75**, 165-170.

Hughes Hallett, A. and C. Richter (2004), 'Spectral Analysis as a Tool for Financial Policy: An Analysis of the Short End of the British Term Structure', *Computational Economics* **23**, 271-288.

Hughes Hallett, A. and C. Richter (2006), 'Is the Convergence of Business Cycles a Global or Regional Issue? The US, UK, and Euroland', *International Journal of Finance and Economics*, 11, 177-94.

Hughes Hallett, A. and C. Richter (2009), 'Economics in the Backyard: How Much Convergence is there between China and her Special Regions?', *The World Economy,* June 2009.

Jenkins, G. M. and D. G. Watts (1968), '*Spectral Analysis and its Applications*', (San Francisco: Holden-Day).

Kalemli-Ozcan, S., B. Sorensen and O. Yosha (2003), 'Risk Sharing and Industrial Specialisation: Regional and International Evidence', *American Economic Review* **93**, 903-918.

Kocenda, E., and J. Hanousek (1998), 'Integration of Emerging Equity Markets: Major Asian Players', *Korean Economic Review* **14**, 99-114.

LaMotte, L. R., and A. J. McWorther (1978), 'An Exact Test for the Presence of Random Walk Coefficients in a Linear Regression', *Journal of the American Statistical Association* **73**, 816-820.

Lin, Z. (1997), 'An Introduction to Time-Frequency Signal Analysis', *Sensor Review* **17**, 46-53.

Nerlove, M., D. M. Grether and J. L. Carvalho (1995), '*Analysis of Economic Time Series',* (New York: Academic Press).

Peersman, G., and F. Smets (2005), 'Industry Effects of Monetary Policy in the Euro Area', *Economic Journal* **115**, 319-342.

Ploberger, W., W. Krämer and K. Kontrus (1989), ' New Test For Structural Stability in the Linear Regression Model', *Journal of Econometrics* **40**, 307-318.

Shin, K. and Y. Wang (2004), 'Trade Integration and Business Cycle Co-movements: the case of Korea with other Asian countries', *Japan and the World Economy* **16**, 213-230.

Sato, K. and Z. Zhang (2006), 'Real Output Co-movements in East Asia: any evidence for a monetary union?', *World Economy* **29**, 1671-1689.

Shin, K. and C-H. Sohn (2006), 'Trade and Financial Integration in East Asia: effects on co-movements', *World Economy* **29**, 1649-1669.

Stock, J. H. and M. W. Watson (2002), 'Has the Business Cycle Changed and Why?', *NBER Working paper* **No 9127,** Cambridge, MA**.**

Wells, C. (1996), '*The Kalman Filter in Finance*', (Dordrecht: Kluwer Academic Publishers).

APPENDIX: The Time Domain Regression Results

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLUSGDP	Quarterly Data From	1981:04 to 2006:01
Usable Observations	87	Degrees of Freedom	79
Centered R^2	0.2804	R Bar^2	0.2440
Uncentered R^2	0.7335	$T * R^2$	61.617
Mean of Dependent Variable	0.0079	Std Error of Dependent Variable	0.0061
Standard Error of Estimate	0.0053	Sum of Squared Residuals	0.0022
Akaike (AIC) Criterion	0.0058	Ljung-Box Test: Q*(9)	18.1554
Variable	Coeff	Std Error	T-Stat
Constant	0.0021	0.0018	1.1368
DLUSGDP{1}	0.3173	0.0932	3.4043
DLUSGDP{2}	0.2615	0.0896	2.9172
DLUSGDP{5}	-0.1835	0.0809	-2.2677
DLUSGDP{9}	0.1583	0.0669	2.3679

Table 1: Regression Results of the US Growth Rate

VAR/System - Estimation by Kalman Filter

Dependent Variable	DLCHGDP	Quarterly Data From	1986:03 to 2006:03
Usable Observations	81	Std Error of Dependent Variable	0.0502523692
R^2	0.62668	Standard Error of Estimate	0.0517675790
Mean of Dependent Variable	0.0192415504	Sum of Squared Residuals	0.2090308143
Akaike (AIC) Criterion	0.06003	Ljung-Box Test: Q*(18)	15.8562
Variable	Coeff	Std Error	T-Stat
Constant	0.0309714823	0.028215885321	1.097661190261
DLCHGDP{3}	0.0230286004	0.125233414390	0.18388543089
DLCHGDP{4}	0.1223207713	0.054466167098	2.24581199317

Table 2: Regression Results for the Chinese Growth Rate

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLJPGDP	Quarterly Data From	1956:04 To 2006:03
Usable Observations	200	Std Error of Dependent Variable	0.0133742511
R^2	0.61097	Standard Error of Estimate	0.0161841229
Mean of Dependent Variable	0.0112672038	Sum of Squared Residuals	0.0288
Akaike (AIC) Criterion	0.01753	Ljung-Box Test: Q*(24)	28.6232
Variable	Coeff	Std Error	T-Stat
Constant	0.002256952	0.000285975647	7.89211097477
DLJPGDP{2}	-0.191069969	0.243873373248	-0.783480240960
DLJPGDP{3}	0.065477484	0.130986360529	0.499880172289
DLJPGDP{7}	0.157928096	0.026901229076	5.87066470552

Table 3: Regression Results of the Japanese Growth Rate

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLCHGDP	Quarterly Data From	1986:03 To 2006:03
Usable Observations	81	Std Error of Dependent Variable	0.0502523692
R^2	0.75146	Standard Error of Estimate	0.0886966903
Mean of Dependent Variable	0.0192415504	Sum of Squared Residuals	0.2389229410
Akaike (AIC) Criterion	0.10286	Ljung-Box Test: Q*(18)	18.8275
Variable	Coeff	Std Error	T-Stat
Constant	-0.011188398	0.029987965239	-0.373096280996
DLCHGDP{4}	0.113482839	0.115247578376	0.984687407113
DLUSGDP{5}	0.054765564	0.012307197747	4.449880887521

Table 4: Regression Results between China and the US

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLUSGDP	Quarterly Data From	1986:03 To 2006:03
Usable Observations	81	Std Error of Dependent Variable	0.5064543417
R^2	0.66606	Standard Error of Estimate	0.5080642573
Mean of Dependent Variable	0.0192415504	Sum of Squared Residuals	20.134084588
Akaike (AIC) Criterion	0.58919	Ljung-Box Test: Q*(18)	17.8252
Variable	Coeff	Std Error	T-Stat
Constant	0.4585070334	0.294045977540	1.559303879218
DLUSGDP{2}	0.1454246122	0.019634219737	7.40669168996
DLCHGDP{5}	1.2437476003	0.172272983415	7.21963232804

Table 5: Regression Results US – China

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLJPGDP	Quarterly Data From	1956:04 To 2006:03
Usable Observations	200	Std Error of Dependent Variable	0.0133742511
R^2	0.61593	Standard Error of Estimate	0.0173362495
Mean of Dependent Variable	0.0112672038	Sum of Squared Residuals	0.0589069271
Akaike (AIC) Criterion	0.01878	Ljung-Box Test: Q*(24)	32.2215
Variable	Coeff	Std Error	T-Stat
Constant	0.000393816	0.002456501088	0.160315955281
DLJPGDP{2}	-0.151056368	0.263478632647	-0.573315438993
DLJPGDP{3}	0.075729208	0.141141569878	0.536547864196
DLUSGDP	0.001351646	0.000235266939	5.74515766527

Table 6: Regression Results between Japan and US

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLJPGDP	Quarterly Data From	1986:04 To 2006:03
Usable Observations	80	Std Error of Dependent Variable	0.0133742511
R^2	0.66326	Standard Error of Estimate	0.0101585433
Mean of Dependent Variable	0.0112672038	Sum of Squared Residuals	0.0078428962
Akaike (AIC) Criterion	0.01123	Ljung-Box Test: Q*(17)	17.5585
Variable	Coeff	Std Error	T-Stat
Constant	-0.000008579	0.005626312484	-0.001524779775
DLJPGDP{1}	-0.029911361	0.017503885862	-1.708841158021
DLJPGDP{3}	0.125815674	0.046109210344	2.728645165450
DLCHGDP{5}	0.013221779	0.003428064709	3.856922246047

Table 7: Regression Results Japan - China

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLCHGDP	Quarterly Data From	1986:03 To 2006:03
Usable Observations	81	Std Error of Dependent Variable	0.0502523692
R^2	0.31272	Standard Error of Estimate	0.0558988779
Mean of Dependent Variable	0.0192415504	Sum of Squared Residuals	0.2312266567
Akaike (AIC) Criterion	0.06376	Ljung-Box Test: Q*(17)	12.3611
Variable	Coeff	Std Error	T-Stat
Constant	0.036323083	0.008120564047	4.472975374280
DLCHGDP{3}	0.081669663	0.037051062870	2.20424614663
DLCHGDP{5}	0.014302885	0.145844159196	0.098069642520
DLJPGDP	0.067646075	0.118533509127	0.570691573751
DLJPGDP{7}	-3.579857673	1.222277777339	-2.92884133151

Table 8: Regression Results China - Japan