‘N Sync: Similarities and Leader-Follower Relationships in International Business Cycles

James Graham*

June 23, 2014

Abstract

This paper analyzes international business cycle linkages, and considers New Zealand's place among them. I construct global and country-specific business cycles using principal components analysis on country data for GDP, consumption, investment, exports, industrial production, and employment. I then assess which countries' business cycles are similar using principal components analysis and a technique called hierarchical clustering analysis. I also assess the leader-follower relationships between countries using VAR models and network diagrams. I find that after accounting for the global business cycle, countries tend to cluster into Western- and Asian-country groups, and that Asian countries appear to be more central to the global economic network. New Zealand is not as strongly related to the global business cycle as other countries, however it is more similar to and influenced by Western countries than it is by Asian countries.

1 Introduction

The performance of New Zealand's economy is often thought to be tightly linked to the fortunes of its major trading partners. For this reason, it is important to understand which countries' business cycles are most similar to and have the biggest influence on New Zealand.

The interaction of business cycles across countries has been much investigated. Early studies considered international cross-correlations in business cycle variables, finding significant differences between the correlations implied by theory and those present in the data (Backus et al., 1993). In more recent literature, a popular approach focuses on the possibility that different countries' business cycles are driven by some common, global factor or regional factors. A group of authors (see Kose et al., 2003a; Crucini et al., 2011; Kose et al., 2012) use dynamic factor models to estimate these common factors, and find that global factors explain a significant proportion of the variance in countries' business cycles. Other authors have used the global vector auto-regression framework,

*The views in this paper do not necessarily reflect the views of the Reserve Bank of New Zealand. The paper is a work in progress and should not be cited. Any errors or omissions are entirely the author's.

which adapts the simple VAR model to allow large panels of data such as international business cycle variables (Greenwood-Nimmo et al., 2012).

However, models of the relationships between international business cycles often require difficult choices about the model restrictions needed to identify particular economic shocks or factors.

Alternative approaches that avoid significant modeling choices are adopted in the econophysics (i.e. economics-physics) literature. These include using lagged cross-correlations and principal components analysis to explore the relationship between countries' business cycles via network theory (Miśkiewicz and Ausloos, 2006; Ausloos and Lambiotte, 2007; Gligor and Ausloos, 2007; Redelico et al., 2009). These authors present a mix of findings showing both stable and unstable groupings of countries across different data sets and time periods. Separately, Diebold and Yılmaz (2013) take a similar but more econometric approach by combining unrestricted vector error correction models (VECMs) with the concepts of network theory to assess the relationships between international business cycles. They show that connectedness (i.e. different countries' degree of influence on each other) varies over time, but shows signs of a increasing trend in more recent years.

In assessing New Zealand's place amongst international business cycles, I opt to use simple, theory-free measures of country relationships that do not require complicated modeling assumptions. In doing so, I am able to focus entirely on the information provided by the data and describe countries' relationships using easy-to-understand graphical representations.

First, I use principal components analysis to summarize several business cycle components from New Zealand's major trading partners: GDP, consumption, investment, exports, industrial production, and employment. Second, given the first principal component explains the largest share of the data's variance, I assume it acts like a global business cycle and adjust all variables for its effects. Third, I consider the similarities of global cycle-adjusted country variables and business cycles using hierarchical clustering analysis – a technique more commonly used in the biological sciences. Finally, I explore leader-follower relationships between country business cycles using simple bivariate and multivariate VAR models.

I find that common global component in business cycle movements explains a reasonably large fraction of the variance in G7 country variables, with a smaller fraction owing to Asian countries and New Zealand being the least well explained. It is notable that only six percent of New Zealand's GDP is explained by movements in the common component, while New Zealand's exports are completely unexplained.

The hierarchical clustering analysis shows that country-specific business cycles fall into distinct Western and Asian country clusters. New Zealand's business cycle is is most similar to Western countries over the full sample, with some suggestion that it falls in with Asian countries over the sub-samples. An assessment of individual variables shows that New Zealand's business cycle variables – including exports – are much more like the Western countries' variables than Asian countries' variables.

The bivariate and multivariate VAR analyses are represented using network diagrams. The multivariate VAR analysis provides more useful information and suggests, again, that countries fall into Western and Asian-country clusters, where the Asian countries tend to have more influence on the New Zealand's trading partners. New Zealand is shown to follow other countries, rather than lead them, and is most strongly influenced by Western countries.

The paper is organized as follows. Section 2 describes the data used in the analysis, section 3 describes the principal components method used in constructing global and country-specific business cycles, section 4 describes the hierarchical clustering technique, section 5 describes the leader-follower analysis, and section 6 concludes.

2 Data

For the purpose of assessing the relationship between business cycles in New Zealand and the rest of the world, I use data for New Zealand's 16 largest trading partners.[1] The set of countries analyzed along with their trade weights as at February 2014 is described in table 1.

Business cycles are often measured simply as fluctuations in real GDP. However, variations in GDP may hide movements in other important macroeconomic variables. The NBER, for example, considers several variables in dating US business cycles: real GDP, employment, real income, retail sales, and industrial production.[2] Others have considered variables such as GDP, investment, and consumption (Kose, Otrok, & Prasad, 2012; King et. al, 1991), and GDP and unemployment (Blachard & Quah, 1989).

I consider a broad range of business cycle-related variables: real expenditure GDP (Y_t), real household consumption expenditure (C_t), real gross fixed capital formation (I_t), manufacturing industrial production (IP_t), merchandise exports(X_t), and the number of employed persons (E_t).[3]

The data capture many of variables in the analyses mentioned above, and also account for fluctuations in the tradable sector via exports, which are likely to be an important part of the business cycle for New Zealand and many of its open economy trading partners.

All data are seasonally adjusted and observed at a quarterly frequency. The data is log-differenced, representing percentage growth rates for each variable, and demeaned and standardized. Most countries have all data available from 2000Q1, and many have at least some data available from 1990Q1. Because principal components analysis can allow for missing data, the full sample period is

[1] We exclude India from this analysis despite a trade weight of 1.3% because we lack Indian data for many of the relevant economic time series.

[2] See the NBER's Business Cycle Dating Committee for details.

[3] Employment data is unavailable for Indonesia, and Malaysian consumption and investment data is only available from 2005. Overall employment data for China is unavailable, but we use the Haver series "Employment in Urban Units"

Table 1: New Zealand's trading partners and their trade weights

China	25.8	Singapore	1.9
Australia	15.8	Taiwan	1.8
US	8.5	Malaysia	1.8
Japan	6.1	Thailand	1.6
UK	3.4	Philippines	1.4
Korea	3.0	Hong Kong	1.2
Indonesia	2.2	France	0.9
Germany	1.9	Canada	0.9

1990Q1:2013Q4.[4] I consider the sub-samples 1990Q1:1999Q4 and 2000Q1:2013Q4, with the latter providing more informative data.

3 Estimating the global business cycle

In order to approximate global and country-specific business cycles, I use principal components analysis (PCA). First, I extract the first principal component from the entire data set: every country's GDP, consumption, investment, exports, industrial production, and employment. As this factor explains the greatest share of the data's variance, I assume that it represents the global business cycle.

Indeed, figure 1 shows the evolution of the first principal component, which seems to capture several significant economic events: the recession of the early 1990s, the Asian crisis from 1997, the dot-com bubble collapse and September 11 terrorist attacks of the early 2000s, and the Global Financial crisis in 2008. There is also some indication of a steady increase in the mid-2000s preceding the GFC.

Second, using the estimated principal component coefficients for each variable, I remove the effect of the global cycle from each variable, producing global cycle-adjusted variables. Finally, the variables are grouped by country, and the first principal component of each of the country groups is assumed to represent its country-specific business cycle.

Table 2 shows how much of the variance of each variable for each country is explained by the global cycle. On average, the G7 countries', Malaysia, and Taiwan have the strongest connection to the global business cycle. Of the business cycle variables, countries' exports have the strongest connection to the global cycle, while employment has the weakest connection.

Among countries, New Zealand has the weakest connection to the global cycle on average. The global business cycle only accounts for six percent of New Zealand's GDP, six percent of investment, and zero percent of exports. The lack of explanation of exports is particularly stark, given the average country's

[4] In order to account for missing data, I run PCA on the covariance matrix of the data. If data is missing for any particular variable, the covariance between it and any other variable is simply based on less information than for two series with all data available.

Figure 1: First principal component from all data

exports are 56% explained by the global cycle. This may be due to the dependence of New Zealand's exports on dairy production, for which the effect of New Zealand-specific weather patterns are very likely orthogonal to the global business cycle. New Zealand's investment and employment, too, are only weakly explained, although the latter fact appears to common to most countries in the sample.

That New Zealand's business cycle lacks co-movement with the global business cycle is consistent with findings in the literature. Kose et al. (2003a) study a 60-country sample and estimate separate DFMs for GDP, consumption, and investment over the period 1960-1990. Their models include global, regional, and country-specific factors. They find that only 11% GDP, 9% of consumption, and 8% of investment in New Zealand are explained by global business cycles, which is comparable to the findings in table 2.

The results for GDP presented here are also similar to those in Kose et al. (2003a) for the US, Canada, France, Germany, Indonesia, and Korea. In contrast, for GDP in the UK, Japan, Hong Kong, Malaysia, Singapore I find much more explanation by the global business cycle.

Kose et al. (2003b) study a 76-country sample and estimate separate DFMs for GDP and consumption over the period 1960-1999. Their models include global and country-specific factors. They show that industrial countries have much stronger ties to the global cycle than developing countries. Over the 1981-1999 sub-sample they find that the global factor explains 27% of output and 23% of consumption in industrial counties, and 3% and 2% in developing countries, respectively.

In contrast, the current study finds less contrast between industrial and developing countries. The global business cycle explains, on average, 44% of output

Table 2: Percentage of variable variance explained by global business cycle

	Y	C	I	X	IP	E	Mean
New Zealand	6	20	6	0	31	7	12
China	20	8	2	59	37	0	21
Australia	7	28	10	34	34	18	22
United States	49	35	49	78	76	40	55
Japan	56	12	18	66	70	4	38
United Kingdom	56	17	15	47	70	19	40
Korea	38	19	11	69	48	6	32
Germany	63	0	32	57	75	2	38
Singapore	43	24	4	75	16	4	27
Taiwan	43	8	43	68	38	55	43
Thailand	23	18	20	51	20	0	22
Philippines	31	12	16	51	38	1	25
Hong Kong	51	25	11	53	18	11	28
France	67	15	51	51	75	22	47
Canada	53	45	67	74	48	52	57
Malaysia	72	–	21	70	56	0	44
Indonesia	10	6	6	56	4	–	16
Mean	37	18	22	56	44	15	

and 20% of consumption in industrial countries, and 31% and 11% in developing countries, respectively.[5]

4 Hierarchical clustering analysis

As the PCA shows, international business cycle movements exhibit evidence of a significant common component. Several studies consider whether there are also regional or group factors that affect countries' business cycles. For example, Kose et al. (2003a) find that with the possible exception of North America, there do not appear to be significant regional business cycle factors. Kose et al. (2012) consider countries grouped by their level of economic development and find that, in general, these country groups do not have large common business cycles.[6]

While it would be convenient if business cycle movements formed clusters by geographical location or degree of economic development, this may not be the case. Many studies pre-determine these groupings, and ignore the possibility of other groupings or that there are none at all. One non-deterministic method for exploring business cycle groupings is hierarchical clustering analysis, which is common in the biological sciences and has been used recently in the econophysics literature (see Gligor and Ausloos, 2007; Redelico et al., 2009; Ausloos

[5] I assume the industrial countries consist of: New Zealand, Australia, United States, Japan, United Kingdom, Korea, Germany, Singapore, Taiwan, Hong Kong, France, and Canada. The developing countries are: China, Thailand, Philippines, Malaysia, and Indonesia.

[6] However, there is some suggestion that these business cycles – small though they are – increased in importance over the latter part of the 20th century.

and Lambiotte, 2007).

Hierarchical clustering analysis compares pairs of variables, and groups them according to the degree of similarity between the observations associated with each variable. The similarity between between any pair of business cycles can be determined in many ways. The current paper adopts two of them. The first calculates the distance (i.e. the dissimilarity) between the business cycles of country i and j, denoted $d_{i,j}$, as:

$$d_{i,j} = \sqrt{\frac{1}{2}(1-\rho)}, \tag{1}$$

where ρ is the correlation coefficient between country i and j. The 'simple average' linkage clustering algorithm then groups countries according to the smallest distance, $d_{i,j}$, between them.[7]

The second method uses the principal components coefficients clustering algorithm (PCCCA) in Gligor and Ausloos (2007). This algorithm groups variables according to the similarities of the signs of their principal components coefficients. This is likely to be superior to the method above, as it uses information from all of the principal components as opposed to just the first component.

The PCCCA is laid out below, where the value of the c^{th} principal component coefficient for variable i is given by $v_i(c)$. The PCCCA is:

1. Set the principal component coefficient counter $c = 1$
2. Compare the signs of the factor loadings for variables i and j:
    (a) If $v_i(c) \times v_j(c) > 0$, go to step 3
    (b) If $v_i(c) \times v_j(c) < 0$, go to step 4
3. Set $d(i,j) = \frac{1}{c}$ and stop.
4. Set $c = c + 1$ and return to step 2

Thus, the more principal components for which any two variables have same-signed coefficients, the more similar they are.[8] As above, I use the simple linkage clustering algorithm to group countries by the smallest distance between them.

I run the PCCCA on two sets of variables. First, I use the principal components coefficients from the PCA on all variables. This results in groups of variables, rather than countries. Second, in order to group countries together I re-run the PCA by extracting the first principal components from each country's data set, producing one country-specific business cycle factor for every country. I then run PCA on the set of country-specific factors. Essentially, this estimates the common component across countries' business cycles. Countries can then

[7] See the description of metrics and linkage criteria on the Wikipedia page hierarchical clustering for details. Programmes for hierarchical clustering analysis are readily available in Matlab.

[8] Note that the distance between any two variables with different signed coefficients declines linearly as c increases. This means that two variables whose coefficient signs diverge at $c = 2$ are much more dissimilar than two variables whose coefficient signs do not diverge until $c = 10$.

be grouped via the PCCCA using the principal component coefficients for each country. These principal component coefficients are reported in table 3 in the appendix.

4.1 Dendrograms

Hierarchical clustering analysis can be presented neatly via a diagram known as a dendrogram. In the dendrogram, each variable or country is represented by a leaf in the tree. Similarities are indicated by pairings of leaves. Variable pairs can then be connected to other variables or pairs by branches. The fewer branch-connections between any two variables, the more similar those variables are. Additionally, the lower is the height of a branch-connection between any two variables, the more similar those variables are. Similar groups of variables are coloured for ease of identification.

The analysis using the correlation method and PCCCA for the country business cycles is over the entire sample, and the two sub-samples 1990Q1:1999Q4 and 2000Q1:2013Q4. These dendrograms are presented in figure 2. The hierarchical clustering analysis for individual business cycle variables using the PCCCA is over the entire sample and is presented in figure 3.

The country business cycle dendrograms show that the PCCCA produces more clearly demarcated clusters, as well as more stable clusters over time than the correlation method. Nevertheless, the two hierarchical clustering algorithms produce broadly similar results.

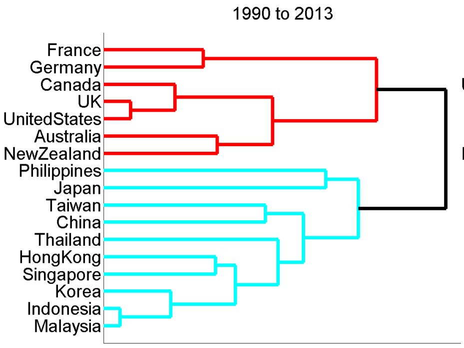
The clusters fall into two broad categories: Western and Asian countries. Under PCLCA, the countries in these broad clusters are stable over the different sample periods, with the exception of Australia, which begins in the Western group and moves to the Asian group, and Japan, which begins in the Asian group and moves to the Western group. In the 2000-2013 period, the Western group contains only G7 countries. Under the correlation method, there is no clear clustering for the 1990-1999 period, but the Western-Asian country split emerges for the 2000-2013 period, and over the whole sample.

Within the two large clusters, there are few groupings that are robust over time or method. The only obviously stable pair is France and Germany, which are paired under every sample period for the correlation method, and over the 2000-2013 and 1990-2013 samples for the principal component loadings clustering algorithm.

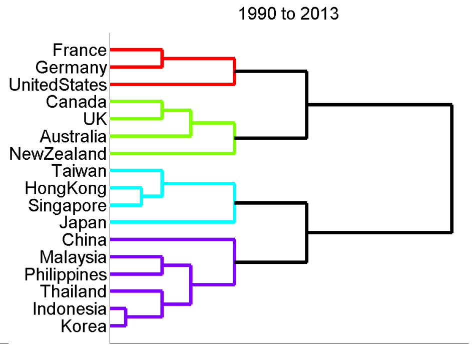
Although the correlation method over the 2000-2013 subsample splits the Asian cluster neatly into more developed (NIEs, Australia, China, and Malaysia) and less developed countries (ASEAN less Malaysia), this is not repeated under the PCLCA.

The relationship of New Zealand's business cycle to other business cycles is not entirely clear. Under both methods and over the entire sample period, New Zealand appears to fall into the Western country cluster. However, for both of the subsamples under the PCLCA, New Zealand is grouped with the Asian countries. In contrast, from 2000-2013 under the correlation method, New Zealand is grouped with the Western countries.

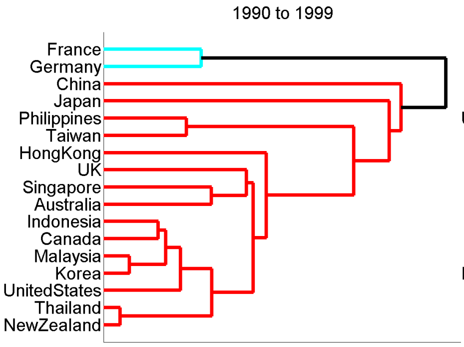
Figure 2: Dendrograms



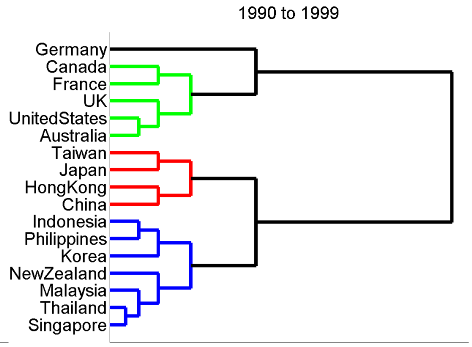
(a) Correlation method



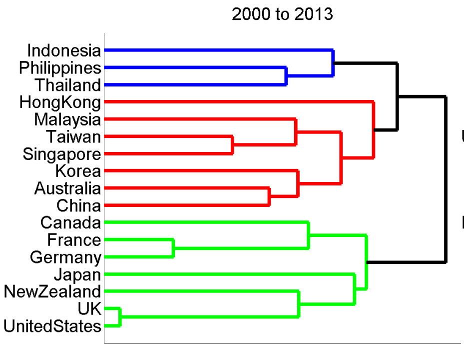
(b) PCCCA



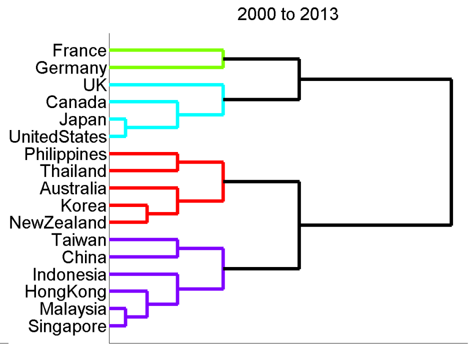
(c) Correlation method



(d) PCCCA



(e) Correlation method



(f) PCCCA

Figure 3: Dendrogram with all variables, 1990-2013

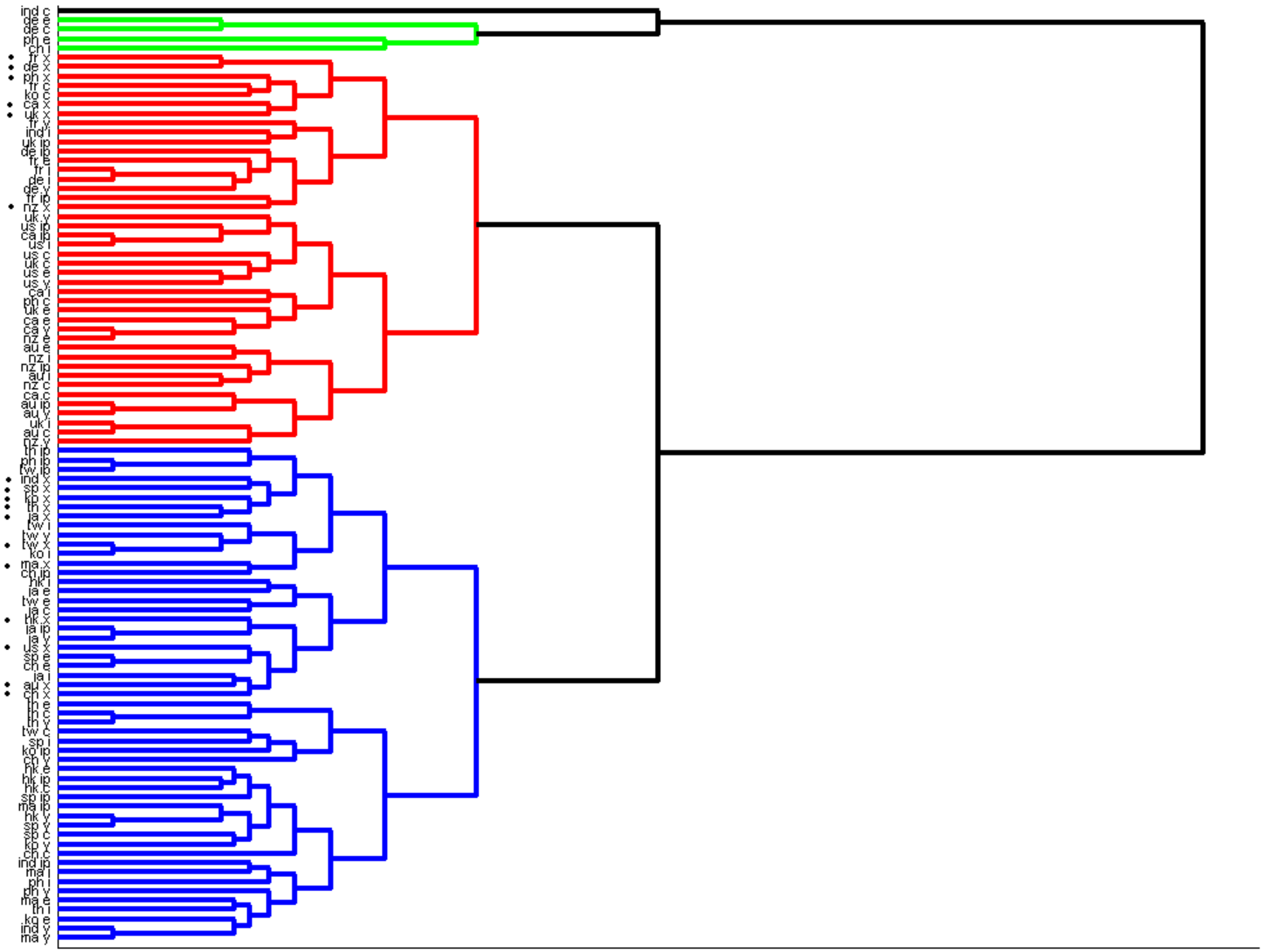


Figure 3 presents the PCCCA using the entire data set in one step (i.e. run the algorithm on the first PCA using the whole data set). The dendrogram confirms, with more detail, the presence of the Western and Asian country clusters. All but two of the leaves in the blue cluster are variables from Asian countries, while all but three of the leaves in the red cluster are variables from western countries.

Some variables also tend to cluster together. For example, exports (marked in the graph with black dots) are clustered only within the top red sub-cluster and the top blue sub-cluster. Moreover, some countries' variables are closely clustered together. For example, France's variables all fall within the top red sub-cluster, and Japan's all fall within the top blue sub-cluster. Interestingly, for several countries, exports are relatively distantly related to their other variables. For example, both Canada and New Zealand's exports fall into the top red sub-cluster, with their other variables in the bottom red sub-cluster; and for both the US and Australia, exports fall into the top blue sub-cluster, while their other variables are in the bottom red sub-cluster.

5 Leader-follower analysis

Hierarchical clustering analysis shows which countries' business cycles are most similar, either with respect to pairwise correlations or similarities in connection to common global components. However, the analysis cannot describe the source of fluctuations driving them. In order to do so, many papers in the literature attempt to identify the macroeconomic shocks driving these business cycles. The DFM literature, for example, concentrates on the global, regional, or country source of a business cycle's movements. Others have tried to identify specific economic shocks using structural VAR models (see Stock and Watson, 2005; Ahmed et al., 1993). And yet another literature studies international business cycles via the theory-first approach of DSGE modeling and estimation (see Justiniano and Preston, 2010).

I propose a technique called leader-follower analysis, which does not attempt to identify the source of shocks, but does attempt to identify which countries' business cycle movements lead others. This allows the representation of movements in international business cycles via network diagrams.

The following sections describe two methods of leader-follower analysis for country business cycles. In each method, the country business cycles used are adjusted for the global business cycle. The relationships between countries, then, are taken to reflect fluctuations associated with the countries themselves rather than the global business cycle.

5.1 Bivariate leader-follower analysis

In this section, I determine leader-follower relationships in business cycles between country pairs using simple bivariate VAR models and Granger causality tests. This is an econometric extension of the comparison of bi-directional lagged correlations used in two studies from outside of the economics literature: one concerning leader-follower relations within pigeon flocks, the other concerning leader-follower relationships in music listening preferences.[9] In the econo-physics literature, Ausloos and Lambiotte (2007) use a similar, simple lagged correlation method to construct network structures of countries using GDP data.

The basic VAR(n) model for any two variables, $x_{i,t}$ and $x_{j,t}$, is denoted

$$x_{i,t} = \alpha_{ii,1} x_{i,t-1} + ... + \alpha_{ii,n} x_{i,t-n} + \alpha_{ij,1} x_{j,t-1} + ... + \alpha_{ij,n} x_{j,t-n} + \varepsilon_{i,t} \tag{2}$$

$$x_{j,t} = \alpha_{jj,1} x_{j,t-1} + ... + \alpha_{jj,n} x_{j,t-n} + \alpha_{ji,1} x_{i,t-1} + ... + \alpha_{ji,n} x_{i,t-n} + \varepsilon_{j,t}. \tag{3}$$

In our case, $x_{i,t}$ is the business cycle for country i; $\alpha_{ii,n}$ is the response of country i to itself at the n^{th} lag; $\alpha_{ij,n}$ is the response of country i to country j at the at the n^{th} lag; and $\varepsilon_{i,t}$ is the error term for the country i equation. Note that the error terms in the VAR model are not identified as country-specific shocks. The appropriate number of lags, n, is determined by the BIC.

For any given pair of countries i and j, the Granger causality test indicates whether one country leads the other, there is a bi-directional relationship, or there is no relationship. Where the tests indicate a bi-directional relationship, it may be useful to consider the relative size of the VAR equation coefficients. For example, it may be the case that the relationship between countries is stronger from j to i than it is from i to j.

5.2 Multivariate leader-follower analysis

Bivariate VARs and Granger causality tests provide a very simple method for analysing leader-follower relationships among countries' business cycles. However, this method is likely to suffer from the endogeneity problem. For example, a relationship between country i and j may actually be due to some other factor such as a third country k.

To account for this, I follow the method of Diebold and Yılmaz (2013) and employ a multivariate VAR that includes the business cycles of all countries in the sample. As noted in section 1, isolating the effect of a shock to country i on country j requires a difficult choice of identification method and associated model restrictions. Diebold and Yılmaz (2013) avoid such difficulties by employing the generalized forecast error variance decomposition (GFEVD) described in Pesaran and Shin (1998). Rather than referring to the influence of particular shocks, the GFEVD describes the degree of variation in country j which is accounted for by variations in country i. While the variations in country i may be due to a variety of underlying shocks, the GFEVD can describe the extent

[9] Both papers compare simple bi-directional lagged correlations between the directions of movement of different variables. In *Hierarchical group dynamics in pigeon flocks*, Nagy et al. (2010) use GPS data that tracks individual pigeons while flying, and compare the movements of each pair of pigeons within the flock. The study finds that the flock is hierarchical, with identifiable leader pigeons for most flights. In *The geographic flow of music*, Lee and Cunningham (2012) use data from online music streaming services and observe the changes in music listening traffic to compare pairs of cities in the data set. The study finds that trends in music are often set by particular cities e.g. Atlanta, Pittsburgh, Montreal, Oslo, and Paris.

to which movements in i, wherever and however they originate, are passed on to j.

Diebold and Yılmaz (2013) use multivariate VARs and the GFEVD method to assess the connectedness of global business cycles. I adapt this method to leader-follower analysis. First, I calculate several useful measures of connectedness between country business cycles within a network, defined by Diebold and Yılmaz (2013) as:

- Pairwise directional connectedness: the proportion of country j's variance explained by country i's variance, denoted $C_{j \leftarrow i}$.
- Net pairwise directional connectedness: the net effect of country i on j, given by the difference between the two pairwise directional connectedness countries j and i. Denoted $C_{ji} = C_{i \leftarrow j} - C_{j \leftarrow i}$.
- Total directional connectedness *to* others: the proportion of variance i contributes to all other countries, given by the sum of the pairwise directional connectedness measures from country i to all countries $j \neq i$. Denoted $C_{\bullet \leftarrow i} = \Sigma_{j=1, j \neq i}^{N} C_{j \leftarrow i}$
- Total directional connectedness *from* others: the proportion of variance i explained by all other countries, given by the sum of the pairwise directional connectedness measures to country i from all countries $j \neq i$. Denoted $C_{i \leftarrow \bullet} = \Sigma_{j=1, j \neq i}^{N} C_{i \leftarrow j}$
- Net total directional connectedness: the net effect of country i on all other countries $j \neq i$. Denoted $C_i = C_{\bullet \leftarrow i} - C_{i \leftarrow \bullet}$.
- Total connectedness: the average effect of all countries effects on other countries. Denoted $C = \frac{1}{N} \sum_{j,i=1, j \neq i}^{N} C_{j \leftarrow i}$

Table 4 in the appendix reports the GFEVD for every variable, and also each of the connectedness calculations described above. The table should be read as the country in column j explaining the country in row i. Note that because the shocks in the multivariate VAR are not orthogonalized, the proportion of the variance of country i explained by all countries under the GFEVD may exceed 100%. For ease of reading, I normalize the proportions explained so that row sums add to 100% (see Diebold and Yılmaz, 2013).

The main leader-follower analysis presented in this paper concentrates on the flow of business cycle movements between each country pair. Hence, net pairwise directional connectedness is the most useful concept for our purposes. If $C_{ji} = C_{i \leftarrow j} - C_{j \leftarrow i} > 0$, country i has a greater influence on country j than j has on i. That is, country i leads country j. These leader-follower relationships are presented in a network diagram in section 5.3.

5.3 Network diagrams

Rather than reporting the results of the bivariate and multivariate VAR analyses in tables, I represent the results in network diagrams. In these diagrams, nodes represent countries and edges (i.e. arrows) represent the direction of business cycle movements between countries. All network diagrams are produced in Gephi, an open source network graphing software (see Bastian et al., 2009).

Note that for the bivariate VAR analysis, I only graph results for the Granger causality tests at the 10% significance level.[10] For the multivariate VAR analysis, I graph the net pairwise directional connectedness for each country pair.

The networks can be interpreted as follows. First, between any two countries, there may be a one-way edge, a two-way edge, or no connection at all. For the bivariate VAR analysis, a directed edge (arrow) from country i to j exists if the business cycle of country i Granger-causes that of country j. For the multivariate VAR analysis, a directed edge exists if the net pairwise directional connectedness from i to j is positive, $C_{ji} > 0$.

Second, the weight (thickness) of an edge from i to j represents the strength of the leader-follower relationship between those countries. For the bivariate VAR analysis, the weight of an edge is determined by the size of the bivariate VAR coefficient $\alpha_{ji,1}$.[11] For the multivariate VAR analysis, the weight of an edge is determined by the value for the net pairwise directional connectedness, $C_{ji} > 0$.

Third, the size of a country's node is determined by its 'weighted degree', which is the number of leader-follower relationships associated with that country, weighted by the strength of those relations. Note that the weighted degree metric does not depend on the direction of a country's relationships. Countries are ranked by their weighted degree, where larger nodes indicate more and/or stronger leader-follower relationships and smaller nodes indicate fewer and/or weaker leader-follower relationships.

Fourth, the colour of a country's node is determined by its 'weighted out-degree', which is the number of leading relationships that the country has, weighted by the strength of its influence on other countries. Countries are ranked by their weighted out-degree, where countries that are more red are stronger leaders, countries that are more blue are stronger followers, and purple countries have a mix of leader and follower relationships.

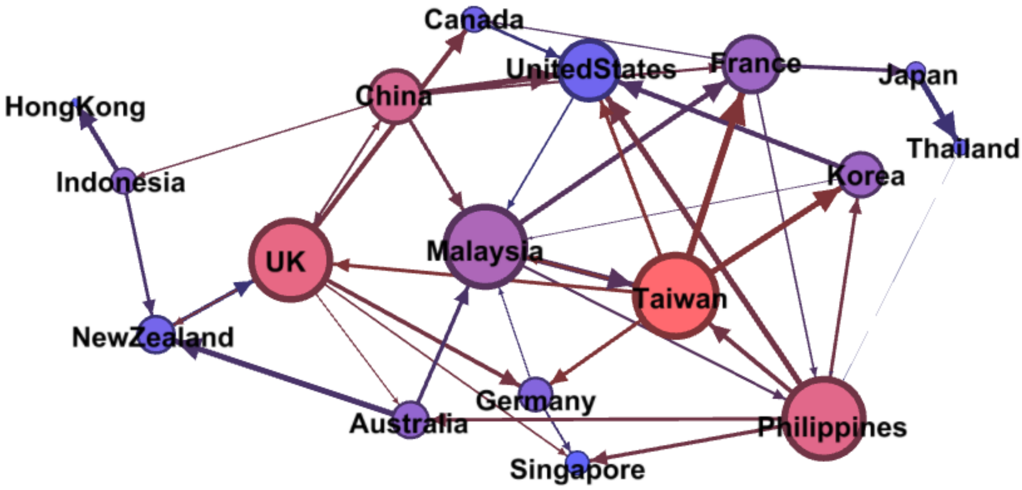
Finally, the layout of the nodes in the diagram is determined by the Force Atlas 2 algorithm provided by Gephi. This algorithm arranges country nodes so that they are closer to other countries with which they have relationships. The algorithm produces networks in which nodes with more and/or stronger relationships form centralized clusters, while nodes with fewer and/or weaker relationships lie on the periphery. Visually, we can see that larger nodes are more connected to others, and thus tend to be more central to the network. Because countries are placed close to others with whom they have relationships, regions of the network may suggest possible sub-groups of inter-connected countries.

Figure 4 shows the results of the bivariate VAR and Granger causality analysis. The most connected countries are the UK, Malaysia, Taiwan, and the Philippines. Among these well-connected countries, Taiwan has the most and/or

[10] Although the significance level is essentially arbitrary, the smaller the significance level, the fewer country pairs pass the test, which results in a more sparse network. The 10% level results in a network in which no single country or cluster of countries is separated from the other countries in the network.

[11] Although some coefficients can be negative, I set the edge-weights to reflect the absolute value of the relevant coefficients.

Figure 4: Leader-follower relationships: bivariate VAR



strongest leading relationships, followed by the UK and Philippines. Malaysia has a mix of leading and following relationships. Many of the small open economies in the sample tend to have fewer and/or weaker connections, but also tend to be followers. Examples include New Zealand, Australia, Hong Kong, and Singapore. Although some obvious country pairs such as New Zealand and Australia, and Canada and the US are closely connected, Germany and France are neither connected, nor related to the same groups of countries.

Overall, the network does not appear to show country clusters that reflect geographical proximity. For example, European countries do not cluster together, Asian countries are spread throughout the network, and New Zealand and Australia are closer to the UK and Germany than they are to other countries in the Asian region. This lack of clustering by geographical region is consistent with the network analysis of countries' GDP growth in Ausloos and Lambiotte (2007). However, my finding may be due to the adjustment for the global cycle. It might be the case that geographic neighbours' business cycles are similar, but only to the extent that neighbours follow the global cycle in the same way; their country-specific business cycles may be unrelated. This would be consistent with the finding in Kose et al. (2003a) that regional business cycles account for very little of the variance in countries' output, consumption, and investment.

Figure 5: Leader-follower relationships: multivariate VAR

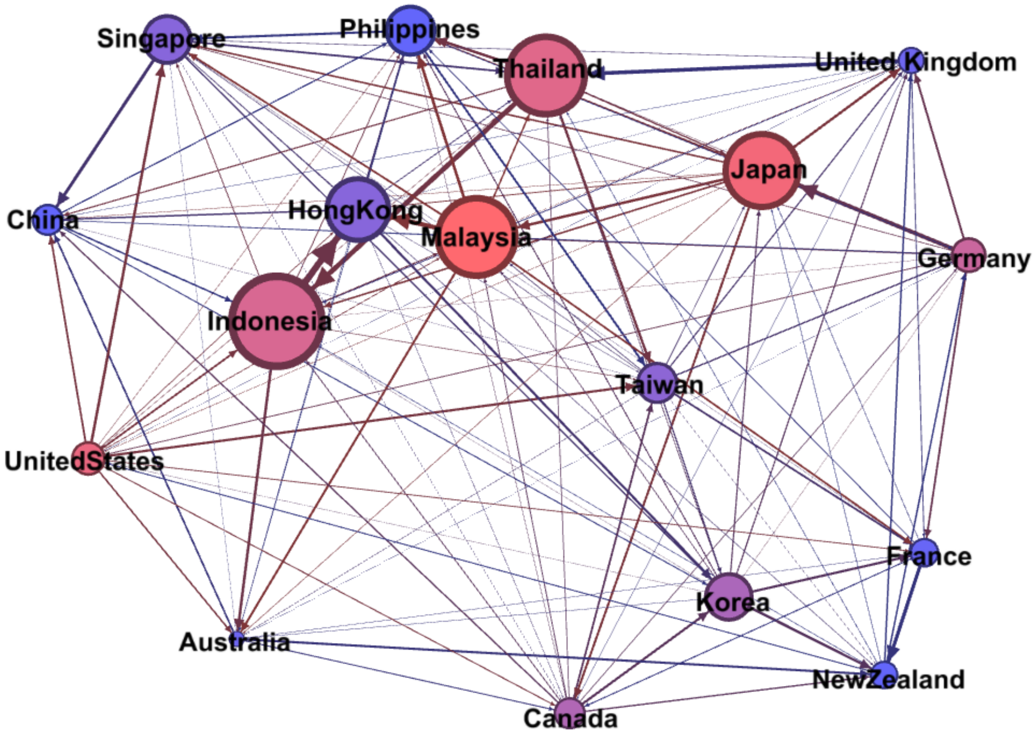


Figure 5 shows the results of the multivariate VAR and connectedness analysis. The most connected countries are Indonesia, Thailand, Malaysia, and Japan. In general, Asian economies form the most connected group of countries and are clustered in the center of the network, with Indonesia, Malaysia, and Hong Kong being the most closely related. Among these well-connected Asian countries, Malaysia and Japan have the most and/or strongest leading relationships. Interestingly, China has fewer and/or weaker relationships than other Asian countries, and is also a strong follower of others.

Western country nodes are smaller than Asian country nodes, and fall on the periphery of the diagram suggesting less connectedness. Of the Western countries, the US and Australia are most closely related to the Asian cluster of countries. Of the Western countries, only the US and, to a lesser extent, Germany tend to have leading relationships.

The multivariate VAR analysis shows more clustering by Asian and Western country regions than the bivariate VAR analysis. This suggests that third-country effects are affecting the results produced by the latter.

Across the two analyses, the US does not appear to play a central role: it is a medium-sized follower in the bivariate VAR analysis and a small leader in the multivariate VAR analysis. This is likely due to the effect of adjusting each country's business cycle for movements in the global cycle. While this removes a significant amount of co-movement between cycles, it avoids the endogeneity problems involved in assessing leader-follower relationships in the presence of a significant global business cycle.

New Zealand is a follower in this analysis, although it has several small leading relationships. Interestingly, most of its relationships are with Western countries: Australia, the UK, Germany, France, and Canada.

6 Conclusion

In this paper I analyze similarities and leader-follower relationships in international business cycles using two novel and economic theory-free techniques. The first, uses hierarchical clustering analysis to assess similarities between country-specific business cycles, and also countries' business cycle variables. The second, uses bivariate VARs and Granger causality tests, and a multivariate VAR and connectedness measures to assess leader-follower relationships.

I find that a common global component in business cycle movements explains a reasonably large fraction of the variance in G7 country variables, with a smaller fraction owing to Asian countries and New Zealand being the least well explained. It is notable that only six percent of New Zealand's GDP is explained by movements in the common component, while New Zealand's exports are completely unexplained.

I then find evidence that similarities in country-specific business cycles form two large clusters: Western and Asian countries. New Zealand seems to be more similar to the Western cluster, with some suggestion that it falls in with Asian countries over different sub-samples. An assessment of individual variables shows that New Zealand's business cycle variables – including exports – are much more like the Western countries' variables than Asian countries' variables.

Finally, I find that Asian countries tend to be more connected to and have more influence on New Zealand's trading partners than Western countries. This can be seen in their centrality to the network of business cycle movements. New Zealand is not especially well-connected to other countries in the business cycle network. To the extent that it is connected, it is found to follow other countries, rather than lead them. Moreover, New Zealand is most strongly influenced by Western countries, rather than Asian countries.

These results are somewhat surprising. New Zealand's economic fortunes are often thought to depend on the state of the global economic environment, yet New Zealand's business cycle variables do not appear to be significantly connected to movements in the rest of the world. Moreover, while New Zealand's exports to China and the rest of Asia continue to rise, we might expect New Zealand's business cycle to be more dependent on movements in those countries. Yet New Zealand still seems to be more influenced by the West than it does by Asia. I leave it to future studies to reconcile these puzzles.

References

Shaghil Ahmed, Barry W Ickes, Ping Wang, and Byung Sam Yoo. International business cycles. *The American Economic Review*, pages 335–359, 1993.

M. Ausloos and R. Lambiotte. Clusters or networks of economies? a macroeconomy study through gross domestic product. *Physica A: Statistical Mechanics and its Applications*, 382(1):16–21, 2007.

David Backus, Patrick J Kehoe, and Finn E Kydland. International business cycles: theory and evidence. Technical report, National Bureau of Economic Research, 1993.

Mathieu Bastian, Sebastien Heymann, Mathieu Jacomy, et al. Gephi: an open source software for exploring and manipulating networks. *ICWSM*, 8:361–362, 2009.

M. J. Crucini, M. A. Kose, and C. Otrok. What are the driving forces of international business cycles? *Review of Economic Dynamics*, 14(1):156–175, 2011.

Francis X Diebold and Kamil Yılmaz. Measuring the dynamics of global business cycle connectedness. Technical report, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania, 2013.

M. Gligor and M. Ausloos. Cluster structure of eu-15 countries derived from the correlation matrix analysis of macroeconomic index fluctuations. *The European Physical Journal B*, 57(2):139–146, 2007.

Matthew Greenwood-Nimmo, Viet Hoang Nguyen, and Yongcheol Shin. Probabilistic forecasting of output growth, inflation and the balance of trade in a gvar framework. *Journal of Applied Econometrics*, 27(4):554–573, 2012.

Alejandro Justiniano and Bruce Preston. Can structural small open-economy models account for the influence of foreign disturbances? *Journal of International Economics*, 81(1):61–74, 2010.

M. A. Kose, C. Otrok, and C. H. Whiteman. International business cycles: World, region, and country-specific factors. *american economic review*, pages 1216–1239, 2003a.

M. A. Kose, E. S. Prasad, and M. E. Terrones. How does globalization affect the synchronization of business cycles? *American Economic Review*, pages 57–62, 2003b.

M Ayhan Kose, Christopher Otrok, and Eswar Prasad. Global business cycles: convergence or decoupling? *International Economic Review*, 53(2):511–538, 2012.

C. Lee and P. Cunningham. The geographic flow of music. In *Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012)*, pages 691–695. IEEE Computer Society, 2012.

J. Miśkiewicz and M. Ausloos. An attempt to observe economy globalization: the cross correlation distance evolution of the top 19 gdp's. *International Journal of Modern Physics C*, 17(03):317–331, 2006.

M. Nagy, Z. Ákos, D. Biro, and T. Vicsek. Hierarchical group dynamics in pigeon flocks. *Nature*, 464(7290):890–893, 2010.

H Hashem Pesaran and Yongcheol Shin. Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1):17–29, 1998.

F. O. Redelico, A. N. Proto, and M. Ausloos. Hierarchical structures in the gross domestic product per capita fluctuation in latin american countries. *Physica A: Statistical Mechanics and its Applications*, 388(17):3527–3535, 2009.

James H Stock and Mark W Watson. Understanding changes in international business cycle dynamics. *Journal of the European Economic Association*, 3 (5):968–1006, 2005.

Table 3: Principal component coefficients for country business cycles

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th	17th
New Zealand	0.14	0.16	0.32	0.46	-0.32	-0.37	-0.16	0.23	0.25	0.23	-0.30	-0.25	0.10	0.01	-0.10	0.12	-0.14
China	0.17	0.14	-0.43	0.19	0.23	-0.01	-0.47	-0.02	-0.17	-0.23	-0.23	-0.19	-0.35	-0.37	-0.14	-0.04	-0.08
Australia	0.19	0.16	0.07	0.47	0.38	0.10	-0.21	-0.08	-0.15	0.35	0.31	0.44	0.06	0.15	0.04	0.19	0.09
United States	0.32	-0.31	0.18	0.03	-0.15	-0.29	0.04	-0.36	-0.14	-0.20	0.19	0.15	-0.30	0.23	-0.29	-0.10	-0.42
Japan	0.26	-0.19	0.15	-0.02	-0.30	0.45	-0.49	0.12	0.18	-0.34	0.04	0.22	0.34	-0.04	0.05	-0.11	-0.02
United Kingdom	0.26	-0.30	0.24	0.14	0.06	-0.09	0.23	0.06	-0.20	-0.25	0.01	-0.11	0.05	-0.25	-0.26	0.19	0.65
Korea	0.24	0.24	-0.19	0.38	-0.02	0.40	0.50	0.15	0.29	-0.18	0.11	-0.09	-0.14	0.13	-0.16	-0.26	-0.05
Germany	0.26	-0.27	-0.12	-0.19	0.21	0.17	-0.11	0.32	-0.19	0.26	-0.28	-0.24	0.03	0.58	-0.20	-0.04	0.03
Singapore	0.22	0.18	-0.35	-0.20	-0.10	-0.13	0.17	-0.14	0.11	0.09	-0.38	0.48	0.32	-0.09	-0.38	0.14	0.02
Taiwan	0.28	0.27	-0.17	0.01	-0.16	-0.15	0.05	-0.14	-0.48	-0.01	0.22	-0.32	0.52	0.01	0.18	-0.25	-0.04
Thailand	0.19	0.51	0.51	-0.33	0.42	-0.10	0.00	0.14	0.02	-0.27	-0.12	0.07	-0.02	0.04	-0.01	-0.17	-0.05
Philippines	0.21	0.19	0.17	-0.28	-0.35	0.33	0.07	0.20	-0.30	0.37	0.16	-0.01	-0.30	-0.33	-0.12	0.22	-0.13
Hong Kong	0.23	0.01	-0.28	-0.12	-0.19	-0.43	-0.05	0.51	0.09	-0.06	0.25	0.27	-0.25	0.09	0.30	-0.10	0.21
France	0.30	-0.34	-0.05	-0.05	0.38	-0.06	0.22	0.19	0.21	0.05	0.07	-0.09	0.22	-0.35	0.25	0.23	-0.45
Canada	0.33	-0.14	0.11	-0.04	0.01	0.05	0.02	-0.36	0.18	0.40	-0.27	0.02	-0.18	-0.18	0.33	-0.49	0.23
Malaysia	0.26	0.16	-0.05	-0.03	-0.12	0.11	0.06	-0.29	0.03	-0.23	-0.21	-0.11	-0.16	0.29	0.47	0.58	0.08
Indonesia	0.15	0.12	-0.10	-0.28	0.07	-0.07	-0.24	-0.24	0.51	0.14	0.46	-0.35	0.02	0.04	-0.29	0.13	0.19

Table 4: Connectedness of country business cycles

	NZD	CHN	AUS	USA	JAP	UKM	KOR	GER	SGP	TWN	THL	PHL	HKG	FRA	CAN	MA	IND	$C_{i\leftarrow\bullet}$
NZD	4	1	24	0	0	1	16	11	4	1	1	1	1	22	8	1	4	96
CHN	1	11	10	14	3	0	0	0	19	2	8	1	10	1	14	2	1	86
AUS	11	0	21	12	4	1	1	10	1	3	1	4	2	0	0	14	16	80
USA	6	3	3	21	9	10	12	7	0	4	5	1	1	1	11	7	1	81
JAP	3	1	1	7	2	2	8	25	0	5	17	6	2	10	0	3	6	96
UKM	10	2	1	9	17	6	8	12	3	7	4	0	0	3	5	10	3	94
KOR	1	6	3	11	1	1	6	1	21	17	0	2	16	0	14	0	0	94
GER	20	4	11	2	0	0	0	28	0	9	4	5	1	1	8	6	0	99
SGP	1	0	2	16	10	0	13	4	3	3	0	19	5	0	8	11	7	99
TWN	0	1	1	18	1	0	10	1	0	0	21	13	4	3	12	9	4	98
THL	4	1	1	3	9	27	4	6	11	6	2	0	10	1	4	12	0	99
PHL	1	8	0	3	15	0	8	1	6	1	16	0	11	5	2	17	6	100
HKG	1	1	4	5	7	1	2	1	2	2	5	0	0	0	1	27	41	100
FRA	1	1	2	6	7	8	14	12	1	14	1	0	0	6	12	14	0	93
CAN	0	6	6	17	13	7	0	4	9	1	0	0	3	18	15	0	0	84
MAL	1	4	1	11	19	9	4	15	0	13	3	0	0	3	5	0	8	96
IND	7	10	0	12	16	8	1	1	2	1	30	1	1	0	5	2	3	97
$C_{\bullet\leftarrow i}$	68	49	70	146	131	75	101	138	79	89	116	53	67	68	109	135	97	
C_i	-28	-37	-10	65	35	-19	7	39	-20	-9	17	-47	-33	-25	25	39	0	