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Characteristics of Business Cycles: Have they Changed?

Edited by
Oliver Holtemöller, Jörg Rahn and Michael H. Stierle

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Hausanschrift: Kleine Märkerstraße 8, 06108 Halle (Saale)
Postanschrift: Postfach 11 03 61, 06017 Halle (Saale)
Telefon: (0345) 77 53-60
Telefax: (0345) 77 53-8 20
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Editors' Biographies

Oliver Holtemöller is professor in economics (macroeconomics) at Martin-Luther-University Halle-Wittenberg and head of the department of macroeconomics at the Halle Institute for Economic Research (IWH). His research interests are macroeconomics, monetary theory and monetary policy, and applied econometrics and time series analysis. He studied economics, applied mathematics and practical computer science at the Justus Liebig University in Gießen. Having received a grant from the German Research Foundation, he participated in the doctoral programme 'Applied Microeconomics' at the Freie Universität Berlin and at the Humboldt-Universität zu Berlin from 1998-2001. Oliver Holtemöller obtained his doctoral degree from the Freie Universität Berlin in 2001. From 2001 to 2003, he was a collaborator in the National Research Center Quantification and Simulation of Economic Processes (SFB 373) at the Humboldt-Universität zu Berlin. From 2003-2009, Oliver Holtemöller was a junior professor in economics at RWTH Aachen University and a lecturer at the Academy of Business and Public Sector Management Aachen.

Michael H. Stierle is senior economist and co-ordinator for the macroeconomic forecasts at the European Commission, Directorate General Economic and Financial Affairs. He studied economics at Trier University and UNAM, Mexico City, and holds a PhD from Speyer University. He has worked in economic departments in the private financial sector as well as in academic research. He is a founding member and now Honorary Chair of INFER after chairing the network from 1998 to 2005. Michael's policy-oriented research is mostly concentrated on international economics, financial markets, growth and business cycles as well as regional economics.

Jörg Rahn is Chief Investment Officer at Marcard, Stein & Co., Family Office Bank in Hamburg. He studied mathematics and economics at Hamburg University and at the Rhodes University in Grahamstown (South Africa). He holds a PhD in economics from Hamburg University. For three years he worked at the German Council of Economic Experts where he was responsible for GDP growth forecasts of Germany and the rest of the world. His research is mostly focussed on international and monetary economics, financial markets and business cycles.

Preface*

The most recent economic downturn has shown that economic activity nowadays is still prone to large fluctuations. Despite a long tradition of research, the understanding of such fluctuations, namely business cycles, is still far from comprehensive. Moreover, in a developing world with new technologies, faster communication systems, a higher integration of world markets and increasingly better-skilled people the nature of business cycles changes continuously and new insights can be drawn from recent experience.

Several issues of business cycles have been in the focus of researchers lately. First of all the understanding of business cycles requires an identification of the driving forces behind the fluctuations and the dynamics of economic activity. With the knowledge of the drivers it would be helpful for policy-makers and business managers to construct an indicator that predicts the development and that indicates the turning points of economic activity.

The transmission of shocks from one economy, typically from the United States, to other economies is one aspect that has become increasingly important in a world of tightening trade and financial linkages. With the rising importance of economies such as China or India it is interesting to see if these countries could form a new regional block with a common business cycle and if the business cycle in East Asia has become increasingly independent from the one of the United States.

For policy-makers the synchronization of business cycles – across the world and in a monetary union in particular – is of notable interest. Whether the introduction of the euro has led to a synchronization of European business cycles is an important question to be addressed. A common movement of business activity would be beneficial for the work of the European Central Bank since diverging business cycles would increase the cost of foregoing the possibility of using counter-cyclical monetary policy. The results of such an analysis also matter for other regions planning to found a currency union.

Against such a background, this edition presents a selection of studies that cover a broad range of these issues. It focuses on three areas: explanation and description of business cycles (Part Two); transmission of shocks from the United States to Europe and other regions (Part Three); and, finally, the synchronization of business cycles in the Euro area (Part Four).

In this edition, we have included substantive contributions from renowned government and research institutes based in various European countries, which offer a diverse array of vantage points on the challenges for theory, empirics and normative statements. This

* The views expressed here are those of the editors only and do not necessarily correspond to those of the institutions where the editors are employed.

collection will be of particular interest to policy makers, planners and researchers seeking to understand business cycle behaviour, transmission of business cycle shocks to other countries, or the synchronization of business cycles in areas of common currencies such as the European Monetary Union.

This book is a compilation from the Conference of the International Network for Economic Research (INFER) in Brussels on January 24/25, 2008. Where appropriate, the papers have been updated before publication of this volume. We are indebted to all authors for their insightful contributions and for adhering to our deadlines in making this collection possible. We thank all the participants in the conference for their fruitful contributions to lively discussions in a friendly and helpful atmosphere. We thank Annika Klatt for editorial assistance.

Halle (Saale), August 2009

Oliver Holtemöller, Halle Institute for Economic Research (IWH)

Jörg Rahn, Marcard, Stein & Co.

Michael H. Stierle, European Commission

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PART ONE:
OVERVIEW

New Insights in Business Cycles: An Overview

Oliver Holtemöller, Jörg Rahn** and Michael Stierle****

Introduction

The quality of economic policy fundamentally depends on a clear understanding of how the economy works. For a long time, economists have divided economic analysis into growth theory and business cycle theory. Some economists, like for example Robert Lucas (1988), are convinced that the analysis of long-run economic growth is by far more important than the analysis of short-run fluctuations and business cycles. However, as already stressed by John Maynard Keynes (1923), "in the long run we are all dead", and governments and central banks all over the world try hard to stabilize macroeconomic aggregates like output, consumption and employment. Macroeconomic stability lowers the volatility of individual earnings and consumption, reduces workers' probability to be unemployed, and makes interest and inflation rates less volatile, meaning that economic planning is easier and therefore the allocation of resources more efficient.[1] Before we describe the contributions of this book to the literature on business cycle fluctuations and their implications, we briefly discuss some empirical facts about business cycles.

Empirical Facts about Business Cycles

Business cycles are empirically characterized by a cyclical co-movement of the main macroeconomic aggregates. The cyclical behaviour of time series can be uncovered by inspecting the sample spectral density (SSD). The spectral density shows the relative importance of cyclical fluctuations of a given frequency for the overall behaviour of the time series. Figure 1 shows the estimated smoothed spectral density of annual U.S. GDP growth rates between 1960 and 2006. It can be seen that the spectral density has a maximum at the frequency 0.17, which corresponds to a period length of 1/0.17 = 6 years, meaning that cyclical fluctuations with a period length of 6 years dominate the dynamics

* Corresponding author, Halle Institute for Economic Research, Kleine Maerkerstraße 8, 06108 Halle (Saale), Germany, Oliver.Holtemoeller@iwh-halle.de. The views expressed here are those of the authors only and do not necessarily correspond to those of the institutions where the authors are employed.

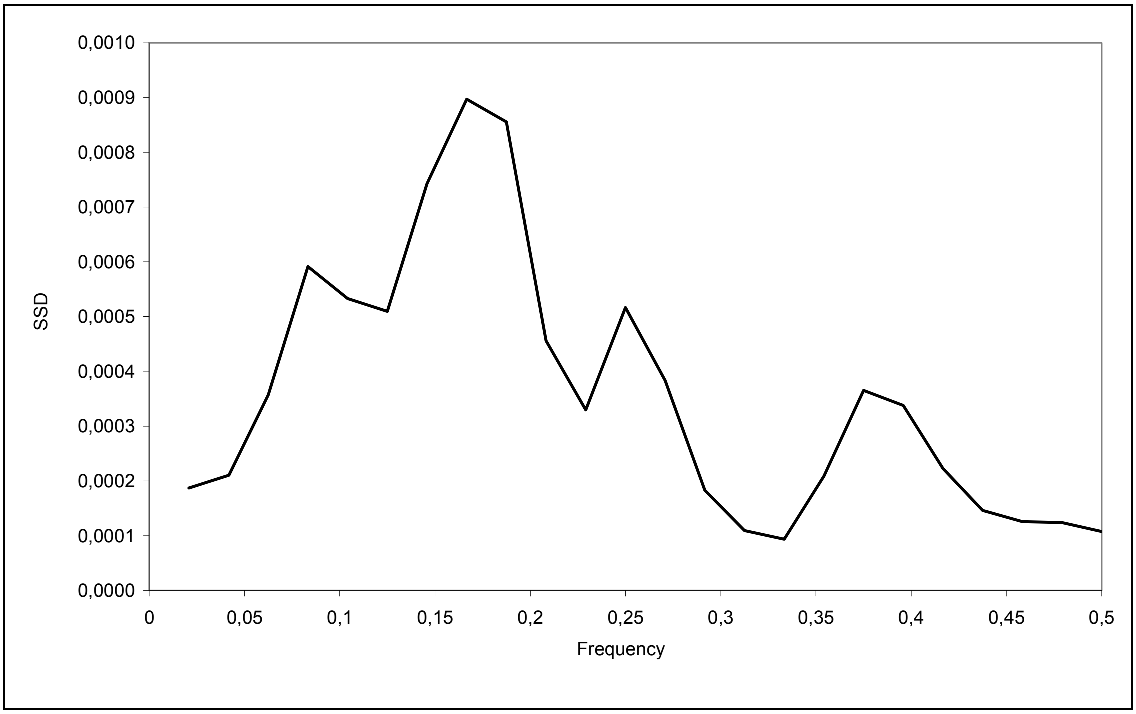
** Marcard, Stein & Co.

*** European Commission.

1 See *Barlevy* (2005) for a survey on 'The cost of business cycles and the benefits of stabilization.'

of U.S. GDP growth rates. Similar findings can also be reported for other countries. The co-movement of the macroeconomic aggregates is illustrated with help of Table 1.

Figure 1:
Sample Spectral Density of Annual U.S. GDP Growth Rates
- 1960-2006 -



Notes: SSD denotes the smoothed spectral density (modified Daniell smoother with a span of 3).

The table reports the means of consumption, investment, and current account shares in GDP, the standard deviations of output, consumption, investment, and current account, and their correlations with national output and U.S. output, respectively. The sample comprises 11 countries, namely the rich G7 (Canada, France, Germany, Italy, Japan, United Kingdom, United States) and the emerging BRIC (Brazil, Russia, India, China) countries. The standard deviations and the correlations are calculated from the cyclical (HP-filtered) components of the respective series. Consumption is the most important component of total output and has a share between 47% (Russia) and 74% (India). Investment shares in GDP lie between 15% (United Kingdom) and 29% (China). While investment accounts for a smaller share in output than consumption, it is by far more volatile than consumption, see the standard deviations in Table 1. The current account is less volatile than and mostly negatively correlated with output.

Accordingly, for the understanding of business cycles the dynamics of consumption and investment, which are both highly correlated with total output, have to be explained.

The papers in part two of this book aim at shedding some more light on the driving forces of consumption, investment and total output.

To some extent, there is also an international co-movement of macroeconomic aggregates. Especially, the business cycles of the U.S. and Canada and of the U.S. and the United Kingdom, respectively, are strongly correlated. The other countries in our sample exhibit lower contemporaneous correlations with the U.S., but that could also be caused by adjustment processes, which only would be revealed in a more detailed analysis.[2] Furthermore, there maybe higher correlations within certain regions, for example Europe or Asia. The papers in part three and four of this volume address international transmission of shocks and international business cycle synchronization in detail.

Table 1:
Descriptive Statistics for Macroeconomic Aggregates in G7 and BRIC Countries
- 1960-2006 -

	US	BR	CA	CN	DE	FR	IN	IT	JP	RU	UK
Mean											
C/Y	0.67	0.61	0.58	0.55	0.59	0.57	0.74	0.58	0.57	0.47	0.61
I/Y	0.16	0.20	0.18	0.29	0.21	0.20	0.20	0.22	0.27	0.24	0.15
CA/Y	−0.02	−0.02	0.02	0.04	0.00	0.00	0.00	0.00	0.01	0.11	0.00
Std. Dev.											
Y	0.02	0.04	0.02	0.07	0.02	0.01	0.02	0.02	0.03	0.07	0.02
C	0.02	0.04	0.02	0.05	0.02	0.01	0.02	0.02	0.02	0.05	0.02
I	0.06	0.09	0.05	0.10	0.04	0.05	0.04	0.05	0.06	0.19	0.06
CA/Y	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.04	0.01
Co-movement with Output											
C	0.86	0.45	0.82	0.82	0.82	0.84	0.76	0.79	0.90	0.59	0.85
I	0.88	0.91	0.80	0.85	0.83	0.88	0.51	0.84	0.96	0.97	0.87
CA/Y	−0.42	−0.54	−0.22	−0.50	−0.29	−0.46	−0.05	−0.51	−0.41	−0.36	−0.50
Co-movement with U.S.											
Y	1.00	0.11	0.79	0.15	0.29	0.28	0.00	0.25	0.02	0.01	0.71
C	1.00	−0.09	0.64	0.23	0.20	0.25	0.11	0.05	0.11	−0.42	0.59
I	1.00	0.35	0.33	0.08	0.30	0.10	0.29	−0.07	−0.05	−0.48	0.48
CA/Y	1.00	−0.24	−0.40	0.56	−0.05	−0.03	0.18	−0.04	−0.20	−0.56	0.22
N	47	47	47	47	36	47	47	47	47	18	47

Notes: The data is taken from the Worldbank's World Development Indicators. *C* denotes private final consumption, *I* gross fixed capital formation (investment), *CA* external balance (exports minus imports), and *Y* gross domestic product at constant prices in local currency. Standard deviations (Std. Dev.) and correlation coefficients (Co-movement) have been calculated after HP-filtering ($\lambda = 100$).

2 See *Chauvet* and *Yu* (2006), for example, for further empirical evidence on international business cycles in G7 and OECD countries.

Table 2:
Descriptive Statistics for Macroeconomic Aggregates in G7 and BRIC Countries
- Two Sub-samples -

	US	BR	CA	CN	DE	FR	IN	IT	JP	RU	UK
Mean	1960-1982										
C/Y	0.65	0.59	0.59	0.61	0.59	0.58	0.80	0.57	0.58		0.58
I/Y	0.15	0.25	0.18	0.25	0.22	0.21	0.18	0.23	0.27		0.14
CA/Y	−0.01	−0.03	0.01	0.09	−0.01	−0.01	0.00	0.00	0.00		0.01
Std. Dev.											
Y	0.02	0.05	0.02	0.09	0.02	0.01	0.03	0.02	0.03		0.02
C	0.02	0.05	0.02	0.06	0.02	0.01	0.02	0.02	0.02		0.02
I	0.06	0.10	0.04	0.11	0.05	0.04	0.04	0.06	0.06		0.03
CA/Y	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00		0.01
Co-movement with Output											
C	0.85	0.77	0.79	0.82	0.79	0.78	0.75	0.73	0.89		0.67
I	0.92	0.93	0.79	0.88	0.73	0.66	0.30	0.78	0.98		0.84
CA/Y	−0.31	−0.74	−0.52	−0.46	−0.44	−0.24	0.20	−0.44	−0.37		−0.34
Co-movement with U.S.											
Y	1.00	−0.09	0.79	0.07	0.93	0.30	−0.31	0.19	0.05		0.66
C	1.00	0.18	0.53	0.06	0.83	0.34	0.07	−0.14	0.43		0.32
I	1.00	0.19	0.34	−0.08	0.81	0.48	0.35	−0.07	0.12		0.46
CA/Y	1.00	−0.04	−0.46	−0.47	0.28	0.10	0.02	−0.23	0.02		−0.12
N	23	23	23	23	12	23	23	23	23		23
Mean	1983-2006										
C/Y	0.69	0.63	0.57	0.50	0.59	0.57	0.68	0.59	0.56	0.47	0.64
I/Y	0.17	0.17	0.19	0.32	0.20	0.19	0.22	0.20	0.27	0.24	0.16
CA/Y	−0.02	0.00	0.03	0.03	0.01	0.00	0.00	0.01	0.02	0.11	−0.01
Std. Dev.											
Y	0.02	0.03	0.02	0.03	0.01	0.01	0.02	0.01	0.02	0.07	0.02
C	0.01	0.04	0.02	0.03	0.01	0.01	0.01	0.02	0.01	0.05	0.02
I	0.06	0.08	0.06	0.10	0.04	0.05	0.04	0.04	0.04	0.19	0.06
CA/Y	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.00	0.04	0.01
Co-movement with Output											
C	0.91	0.24	0.91	0.93	0.78	0.88	0.88	0.85	0.89	0.59	0.91
I	0.88	0.90	0.82	0.86	0.86	0.97	0.86	0.90	0.94	0.97	0.88
CA/Y	−0.65	−0.31	0.06	−0.42	0.02	−0.48	−0.31	−0.59	−0.26	−0.36	−0.52
Co-movement with U.S.											
Y	1.00	0.54	0.85	0.27	−0.28	0.30	0.33	0.41	−0.18	−0.01	0.73
C	1.00	−0.14	0.84	0.26	−0.21	0.40	0.17	0.47	−0.50	−0.44	0.72
I	1.00	0.62	0.39	0.19	−0.10	−0.05	0.24	−0.06	−0.32	−0.49	0.53
CA/Y	1.00	−0.17	−0.39	0.56	−0.03	0.13	0.11	0.10	−0.25	−0.58	0.20
N	23	24	23	24	24	24	24	24	23	17	24

Notes: See notes to Table 1.

Of course, the empirical figures reported in Table 1 are not constant over time. The structure of economies is subject to substantial change.[3] In Europe, for example, the introduction of the single common currency, the Euro, was accompanied by a substantial change in monetary policy and therefore presumably also in the dynamics of macroeconomic aggregates. The BRIC countries and other emerging economies have started a dramatic catch-up process to the G7 countries and have reduced the volatility of output to a level that is similar to the G7 countries' volatility level. Furthermore, their co-movement with U.S. output has increased. This can be seen in Table 2, which reproduces the statistics of Table 1 for two sub-samples, namely 1960-1982 and 1983-2006. The changing nature of business-cycle dynamics is reflected in the style of the papers presented in this collection. All of them focus on specific periods and specific groups of countries, derive detailed new insights into business cycle fluctuations and their international differences. We now give a short summary of the main findings of the papers.

Part Two: Understanding the Driving Forces of Business

The driving forces of business cycles have been subject to dispute for a long time and are still not fully understood. What really drives business cycles is a highly relevant question, because this determines the optimal political response to business cycle fluctuations. The current theoretical literature on business cycles has strongly been influenced by the Real-Business-Cycle (RBC) revolution of the 1980ies, which was initiated by the seminal papers of Kydland and Prescott (1982) and Long and Plosser (1983).[4] The RBC theory states that economic fluctuations are caused by real factors, in particular technological or productivity shocks. While it has been shown by the proponents of this approach that RBC models are able to generate economic fluctuations that have – at least to a considerable extent – properties similar to observed aggregate macroeconomic data, many economists think that technological shocks are not the only source of business cycle fluctuations, see for example Galí and Rabanal (2004), who conclude that demand factors are the main driving factors of the business cycle. Blanchard (2008, p. 7) describes the state of macro as follows:

> "The joint beliefs that technological progress goes through waves, that perceptions of the future affect the demand for today, and that, because of nominal rigidities, the demand for goods can affect output in the short run, nicely combine to give a picture of fluctuations which, I believe, many macroeconomists would endorse today."

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3 A detailed analysis of changes in international business cycle dynamics can be found in *Stock* and *Watson* (2005).

4 See *King* and *Rebelo* (1999) for an excellent survey on RBC theory. For a broader overview including chapters on the history of business cycle theory as well as on different macroeconomic schools and their implications for business cycle theory see *Arnold* (2002). *Basu* and *Taylor* (1999) discuss the relation between theoretical business cycle models and international empirical evidence.

Consequently, the workhorse model for the analysis of short-run business cycle fluctuations today is a microfounded general equilibrium model in the style of the RBC theorists that is augmented by nominal rigidities and other imperfections. These augmentations give demand shocks a role in the explanation of business cycles without abandoning the rigorous formal approach to macroeconomics that has been put forward by RBC theorists. Nowadays, these augmented RBC models are labelled New Neoclassical Synthesis or New Keynesian models.[5] However, it is quite obvious that the relative importance of different economic shocks is not constant over time and across countries. Therefore, many recent works try to empirically identify the sources of business cycle fluctuations using modern time series and econometric techniques. The paper by Holtemöller and Schmidt (Chapter 2) is an example of this kind of macroeconometric research. Holtemöller and Schmidt use a small macroeconomic model of the New Neoclassical Synthesis type, which, firstly, is compatible with microeconomic optimization analysis and general equilibrium considerations that build the basis of pure RBC models, and, secondly, which also includes the Keynesian element of price stickiness, meaning that demand and monetary policy shocks affect the real allocation. In total, the model comprises four different economic shocks (technology, demand, cost-push, monetary policy). The model is estimated for Germany (1975-1998) using indirect inference methods. The estimated model suggests that output growth and consumption growth in Germany have been primarily caused by persistent productivity shocks while fluctuations in consumption share and output gap can mainly be attributed to demand shocks. Additionally, graphical illustrations of the four shocks are presented and discussed.

Investment is the basis of technological progress. Given the evidence on the importance of technological, or productivity, shocks, the current theoretical business cycle models are still relatively silent about investment decisions and the role of investment as a driving force of business cycles. Hillinger, in Chapter 3, readdresses the role of investment cycles in the explanation of business cycles. He argues that the theory of endogenous investment cycles has not given the attention it deserves when empirical evidence is taken into consideration. Using maximum entropy spectral analysis, Hillinger calculates investment cycles with a length of about 8 years and of about 4 years for the G7 countries. He then employs a second order accelerator, which incorporates adjustment costs both in the relation to the capital stock and the rate of investment in order to explain the observed mechanism. The results show a close fit of the underlying model to observed data.

In the final Chapter 4 of this part, Köberl and Müller discuss a quite fundamental question in business cycle research, namely how to measure business cycles. It has been forcefully stated, for example by McCallum and Nelson (1999), that commonly applied time series filters (HP-Filter or bandpass filters) are inappropriate for this purpose,

5 The book by *Galí* (2008) offers a discussion of the New Keynesian standard model an its application to business cycle analysis at the textbook level.

mainly because the link between the computed cyclical component and the output-gap definition in modern business cycle models, that is the difference between actual output and hypothetical flexible price output, is rather weak. Theoretically, the output-gap is a measure for the degree of capacity utilization – an economic variable that affects marginal costs and therefore the price-setting behaviour of firms. Köberl and Müller develop a business cycle indicator using business tendency survey data for Switzerland in order to directly infer capacity utilization from firms. It turns out that their indicator is closely related to GDP growth and can be used for nowcasting and short-run forecasting of GDP since it is earlier available than GDP growth data.

Part Three: The Transmission of Shocks across Countries and Regions

The papers in part three of the book are concerned with the international co-movement of national business cycle fluctuations. In Chapter 5, Schneider and Fenz analyze the relationship between the Euro area and the U.S. Using structural vector autoregressive analysis and sign restrictions, they are able to identify global and domestic shocks and their impact on Euro area and U.S. GDP, consumer prices and interest rates. They compute the corresponding forecast error variance decompositions and find out that, in the short run, domestic shocks explain the largest share of the forecast error variances in these variables. In the medium run (about 20 quarters), international factors gain importance and can account for about 40% in the forecast error variance of Euro area and U.S. GDP.

Hughes-Hallett and Richter, in Chapter 6, and Fidrmuc, Korhonen and Bátorová, in Chapter 7, focus on the Asian-Pacific region. Hughes-Hallet and Richter calculate frequency spectrums for national GDP growth rates and their coherence, that is, the correlation between the respective economic cycles. They identify two economic blocs, a China-centred bloc (Taiwan, Hong Kong) and a Japan-centred bloc (Korea, Malaysia, Singapore). According to their results, the overall link between the Asian-pacific countries and the U.S. weakens since the mid 1980s. China exhibits a coherence of about 50% and Japan even about 90% with the U.S., while the coherence between China and Japan is very low (about 10%). They extensively discuss the evolution of these and other figures over time and conclude that especially the China-related countries have considerably converged in recent time.

Fidrmuc, Korhonen and Bátorová explore the relationship between the business cycles in OECD countries on the one hand and China and India on the other hand. First, they calculate correlations of GDP growth rates at particular frequencies (dynamic correlations). They show that the correlations are relatively low at all frequencies, meaning that the business cycles in OECD countries and in China or India are quite different. In a second step, they regress the computed dynamic correlations on a factor that potentially explains a co-movement of business cycle fluctuations, namely bilateral trade. It turns out that trade intensity has a positive effect on the correlation of GDP movements at the short-run business-cycle frequencies but this effect is less important than for co-movement within OECD countries.

Part Four: The Synchronization of Business Cycles in the Euro Area

Chapters 8 and 9 in the final part four of the book are concerned with business cycle synchronization in the Euro area. Böwer and Guillemineau follow an approach that is similar to that of Fidrmuc et al. (Chapter 7). They calculate correlation coefficients of the business cycle components of Euro area members' GDPs over the sample 1980 to 2004. Using 8-year rolling windows, Böwer and Guillemineau show that the average bilateral correlation has increased from about 0.5 in the early 1980s to about 0.7 in the most recent window. Subsequently, they investigate multivariate correlations of these correlation coefficients and a set of possible determinants of business cycle synchronization. They conduct an extreme bounds analysis and document the robustness of the relationships between business cycle correlation and factors that may have an economic impact on these correlations. In line with earlier results, they find a robust positive relationship between bilateral trade and business cycle synchronization. Furthermore, they report robust relationships with business cycle correlations for variables that reflect bilateral differences in fiscal policy, competitiveness and stock market performance. Böwer and Guillemineau split the full sample into two sub-samples, the first one being 1980 to 1996 and the second one being 1997 to 2004. It turns out that the positive relationship between bilateral trade and business cycle correlation is only robust in the first sub-sample but fragile in the second one. Moreover, they find that none of the considered variables is robustly associated with bilateral business cycle fluctuations in the sense that robustness is confirmed for the full sample as well as for both of the two sub-samples. Therefore, the introduction of the Euro as a single currency seems to be related with a substantial change in the structural relationship between business cycles and factors explaining their synchronization. This finding makes clear that the determinants of business cycle synchronization are still not well understood and that more corresponding research is necessary. An important step towards a deeper analysis of business cycle synchronization is to carefully report and discuss the empirical facts. In the final paper of this volume, Gayer extensively describes the stylized facts of Euro-area business cycle convergence and synchronization. His contribution is twofold. Firstly, he shows to which extent business cycle synchronization measures, in particular standard deviations and correlation coefficients of national business cycle indicators, depend on the various decisions that have to be taken during their computation. He considers different indicators (GDP, industrial production and survey data), different window lengths for the calculation of time-varying standard deviations and correlation coefficients, and different cycle concepts (output-gap and growth rates). He finds that – irrespective of these multiple possibilities of computation – the level of synchronization of Euro-area business cycles is high, but not higher than in the first half of the nineties. Secondly, Gayer confronts the calculated time-varying correlation coefficients with a broad range of narrative evidence on business cycle and economic dynamics during the last 25 years. Two findings are in particular interesting and may be helpful for future research on business cycle synchronization: the international correlation of economic activity indicators seems to be systematically varying within a business cycle; and – compared to worldwide developments – synchronization in the Euro area has strongly increased in the early 1990ies, that is well before the introduction of the single European currency.

Conclusions

This conference volume reflects important aspects of the current state of business cycle research. To what extent economic policy, in particular monetary and fiscal policy, should and actually can stabilize macroeconomic fluctuations is a very lively discussed issue. Currently, economic policy makers and observers all over the world are concerned about the impact of increasing energy prices on macroeconomic stability, about the strength of real effects of the U.S. financial turmoil within the U.S., and about the transmission of these effects to other countries. Albeit these current issues are not explicitly addressed in this book, the reader obtains a broad overview of the variety of empirical and theoretical tools that business cycle research offers for their analysis. Business cycle analysts need a broad variety of tools because the characteristics of business cycles are both country-specific and time-varying. For the same reason, it is difficult to draw overall conclusions from all the papers presented in this volume. One conclusion, however, is possible: In order to be well prepared to cope with the current economic challenges, we still need to know more about the underlying drivers and the international transmission of business cycles.

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PART TWO: UNDERSTANDING THE DRIVING FORCES OF BUSINESS CYCLES

Identifying Sources of Business Cycle Fluctuations in Germany 1975-1998

Oliver Holtemöller * ***and Torsten Schmidt*** **

1. Introduction

We estimate a small dynamic stochastic general equilibrium (DSGE) model for Germany for the period from 1975 to 1998. We use the estimated model to identify the structural shocks, which have driven the business cycle, and to estimate the output-gap, which is an economically meaningful but unobservable variable. We compare our model-based output-gap to HP-filtered real GDP. The model-based decomposition seems superior to us because it relies on economic assumptions and not on a solely statistical decomposition. The period from 1975 to 1998 is interesting because several structural shocks occurred, for example the second wave of oil price shocks in the late 1970s and the shocks around the German reunification in 1990. Especially the nature of the economic shocks that origin in the German reunification are still not fully understood and have been subject to recent research, see Burda (2006) and Uhlig (2006), for example. We contribute to this literature by showing that the German unification was primarily accompanied by a pronounced demand shock but also followed by substantial negative productivity shocks.

This chapter is organized as follows. In Section 2, we present a small New Keynesian macroeconomic model, in Section 3, we describe our estimation approach, and the structural economic analysis follows in Section 4. Finally, Section 5 offers a brief summary and conclusions.

2. A Small Stylized Macroeconomic Model

We use a standard small New Keynesian macroeconomic model. Since these models have been discussed intensively in the recent literature, see for example Galí (2002), King (2000), McCallum and Nelson (1999a), Walsh (2003), and Woodford (2003), we only present our model specification without explaining it in greater detail. The endoge-

* Corresponding author, Halle Institute for Economic Research, Kleine Maerkerstraße 8, 06108 Halle (Saale), Germany, Oliver.Holtemoeller@iwh-halle.de. Holtemöller thanks the RWI Essen for financial support.

** RWI Essen.

nous variables of the model are consumption growth (Δc), output growth (Δy), consumption share in output (cy), short-term nominal interest rate (R), inflation rate (π) and output gap (yg). The main dynamics of the model are generated by three structural equations, namely an IS equation, a Phillips curve equation and a monetary policy rule, and four exogenous shocks.

Productivity Growth and Flexible Price Output

Like for example in McCallum and Nelson (1999b), we assume that the log flexible price (potential) output y^* is determined by an exogenous stochastic productivity process. More specifically, the change in the flexible price output follows an AR(1) process:

$$(1) \qquad y_t^* = y_{t-1}^* + x_{at}, \qquad x_{at} = \rho_a x_{a,t-1} + \varepsilon_{at}, \quad -1 < \rho_a < 1, \quad \varepsilon_{at} \sim N(0, \sigma_a^2).$$

IS Equation (IS)

The IS equation in New Keynesian macroeconomic models is derived from the optimizing behaviour of the representative household who seeks to maximize its utility while facing a budget constraint. Following the literature on estimated New Keynesian macroeconomic models, we allow for habit persistence in consumption. The resulting first order condition of the optimization problem is nonlinear and is therefore log-linearized. Since our model economy exhibits a stochastic trend in productivity, consumption does also follow a stochastic trend. Accordingly, we log-linearize a transformed version of the consumption Euler equation which does not contain the level of consumption but – like for example in Ireland (2001) – consumption divided by output, that is the consumption share cy. We show in the technical appendix that this procedure yields the following IS equation:

$$(2) \qquad E_t \begin{bmatrix} cy_t + a_1 cy_{t-1} + a_2 cy_{t+1} + a_3 cy_{t+2} + a_4 \Delta y_t \\ + a_5 \Delta y_{t+1} + a_6 \Delta y_{t+2} + a_7 \left(R_t - \pi_{t+1} \right) \end{bmatrix} = 0,$$

where the coefficients a_1 to a_7 follow directly from the inverse elasticity of intertemporal substitution σ and an habit persistence parameter h.

Resource Constraint (RC)

The resource constraint of the economy is given by

$$(3) \qquad Y_t = C_t + X_{gt},$$

where Y_t denotes output, C_t consumption, and X_{gt} comprises all other GDP components. We divide the resource constraint by flexible price output Y_t:

(4) $$YG_t = \frac{C_t}{Y_t^*} \cdot \frac{Y_t}{Y_t} + \frac{X_{gt}}{Y_t^*} = CY_t \cdot YG_t + \frac{X_{gt}}{Y_t^*},$$

such that after log-linearization around the steady state we have

(5) $$yg_t \approx \frac{cy}{1-cy} cy_t + x_{gt},$$

where x_{gt} is a stationary exogenous GDP shock:

(6) $$x_{gt} = \rho_g x_{g,t-1} + \varepsilon_{gt}, \quad -1 < \rho_g < 1, \quad \varepsilon_{gt} \sim N(0, \sigma_g^2).$$

Phillips Curve (PC)

Inflation dynamics are described by the New Keynesian Phillips curve, which is derived from the forward-looking behaviour of firms who know that prices will be sticky for some time and therefore consider expected future changes in marginal costs in the price setting decision. Under the assumptions that real marginal costs depend on the output gap and that a fraction γ_b of the firms is backward-looking, we obtain the hybrid Phillips curve:

(7) $$\pi_t = \gamma_b \pi_{t-1} + (1-\gamma_b)\beta E_t\left[\pi_{t+1}\right] + \kappa yg_t + x_{\pi t},$$

where $x_{\pi,t}$ represents a cost-push shock:

(8) $$x_{\pi t} = \rho_\pi x_{\pi,t-1} + \varepsilon_{\pi t}, \quad -1 < \rho_\pi < 1, \quad \varepsilon_{\pi t} \sim N(0, \sigma_\pi^2),$$

and κ is related to the degree of price stickiness (the lower κ, the higher price stickiness).[6]

Monetary Policy Rule (MP)

The model is closed by an interest rate rule, which reflects monetary policy:

(9) $$R_t = \tau_R R_{t-1} + (1-\tau_R)(\tau_\pi \pi_t + \tau_y yg_t) + x_{Rt}, \quad 0 \le \tau_R < 1, \quad \tau_\pi > 1, \quad \tau_y > 0,$$

where x_{Rt} is a monetary policy shock:

(10) $$x_{Rt} = \rho_R x_{R,t-1} + \varepsilon_{Rt}, \quad -1 < \rho_R < 1, \quad \varepsilon_{Rt} \sim N(0, \sigma_R^2).$$

The nominal interest rate R_t is the monetary policy instrument. It depends on the lagged interest rate (interest rate smoothing), inflation rate and output gap. It is well established

6 An empirical analysis of the Phillips curve for Germany can be found in *Tillmann* (2005).

in the literature that the interest rate policy by Deutsche Bundesbank until 1998 can be roughly described by such a simple interest rate rule, see Clarida and Gertler (1996).

Additional Equations

The model is augmented with two additional equations, which represent definitions of observable variables. The growth rate of output is given by:

$$\Delta y_t = \Delta yg_t + \Delta y_t^*, \tag{11}$$

and consumption growth is equal to

$$\Delta c_t = \Delta cy_t + \Delta y_t. \tag{12}$$

Model Solution

Following Uhlig (1999), the complete model can be summarized in the following system of equations:

$$\begin{aligned} 0 &= Ay_{1t} + By_{1,t-1} + Cy_{2t} + Dz_t \\ 0 &= E_t\left[Fy_{1,t+1} + Gy_{1t} + Hy_{1,t-1} + Jy_{2,t+1} + Ky_{2t} + Lz_{t+1} + Mz_t\right] \\ z_t &= Nz_{t-1} + \varepsilon_t. \end{aligned} \tag{13}$$

The four variables cy_t, R_t, π_t and yg_t are specified as endogenous state variables $y_{1,t}$, and Δc_t and Δy_t are stacked in the vector $y_{2,t}$ of other endogenous variables. The vector z_t contains the four exogenous shocks x_{at}, x_{gt}, $x_{\pi t}$ and x_{Rt}. The matrices A, B, …, N are coefficient matrices with appropriate dimensions. ε_t is a multivariate normally distributed and serially uncorrelated shock vector with variance-covariance matrix Σ_ε. The model is solved numerically for the recursive law of motion of the endogenous variables using the Uhlig (1999) toolkit. The recursive law of motion can in turn be used to calculate impulse responses and to simulate the model. However, for this purpose the structural parameters have to be specified numerically.

3. Estimating the Stylized Macroeconomic Model

Indirect Inference Estimation of DSGE Models

The indirect inference approach (Gourieroux et al., 1993; Smith Jr., 1993) that we use is the Extended Method of Simulated Moments (EMSM) and proceeds as follows. In the first step, an auxiliary statistical model that summarizes the statistical properties of the relevant observable variables is estimated. In a second step, the same variables are generated artificially using the theoretical DSGE model and a vector of start values for the structural parameters that have to be estimated. For the simulated data we estimate the same statistical auxiliary model and compute a weighted distance between the two sets of auxiliary parameters (observed and simulated data). In the third step, this weighted distance is minimized numerically with respect to the vector of structural parameters. This procedure delivers consistent and asymptotically normally distributed estimates of the structural parameters. These estimates are not necessarily efficient, especially if it is feasible to estimate the model with maximum likelihood (ML) methods. However, it is well known that efficiency of ML estimation depends on the correct specification of the likelihood function. In case of non-normal exogenous shocks or misspecification, indirect inference may be more robust.

In the choice of the auxiliary model, we follow Smith Jr. (1993) and apply reduced form vector autoregressions (VAR). Reduced form VAR models without any restrictions are able to capture the dynamic behaviour of a given set of variables very well. An alternative to matching reduced form VAR coefficients is to match the impulse responses estimated from a structural VAR and the impulse responses implied by the theoretical model, like for example in Christiano et al. (2005). However, since Christiano et al. (2005) do not estimate the model-based impulse responses from simulated data but compute them directly from the recursive law of motion, the econometric theory that has been developed within the indirect inference literature cannot be directly applied. Furthermore, impulse response matching relies on the correct identification of economic shocks in small or medium scale SVARs, which is a difficult and often ambiguous task, see for example Canova and Pires Pina (2005) and Chari et al. (2005).

Preliminary Data Analysis

We use the following variables in our empirical analysis: short-term nominal interest rate (R), GDP deflator inflation rate (π), log real private consumption per capita in prices of 1995 (c), and log real GDP per capita in prices of 1995 (y). The data is for West Germany for 1975 to 1990 and for reunified Germany from 1991 to 1998. In total we have 96 quarterly observations. The data sources and precise definitions of the variables are given in a separate technical appendix.

Integration and cointegration properties. Log consumption per capita and log GDP per capita follow a long-run trend and are subject to a structural break due to the German reunification. Appropriate unit root tests show that both variables are integrated of order one, see Table 1. The table shows Augmented Dickey-Fuller *t*-Statistics together with the corresponding critical values. While our tests clearly suggests that log consumption (c) and log output (y) exhibit a unit root, the null hypothesis of a unit root is rejected for their respective growth rates and for the consumption share cy_t. In case of the consumption share it has to be considered, that a mean shift occurred in the first quarter 1991 due to the German reunification. Accordingly, log consumption and log output are cointegrated and share the same stochastic trend.[7] The inflation rate (π) is also found to be stationary. For the nominal interest rate (R) the null hypothesis of a unit root is not rejected. However, since unit root tests have low power for highly persistent stationary variables, we assume in the following – like many other studies as well – that the nominal interest rate is stationary in order to meet the requirements of our theoretical framework.

Adjustment for seasonality and German reunification. With exception of the interest rate, all considered variables exhibit a strong seasonal pattern. We adjust consumption and output growth rates, inflation rate and consumption share for deterministic seasonality and for the structural break due to German reunification in order to facilitate the subsequent computations. More precisely, we estimate for these variables autoregressive models with nonlinear least squares and augment these models with two sets of seasonal dummies (until 1990, from 1991 onwards) and with mean shift and impulse dummies for the first quarter of 1991. The AR order is chosen by adding additional AR terms until the residuals do not exhibit any serial correlation anymore. Subsequently, the adjusted variables are constructed by subtracting the deterministic terms from the original variables.

Table 1:
ADF Unit Root Tests

	Constant (A)		Constant and mean shift dummy (B)		Constant, time trend and mean shift dummy (C)		Broken time trend (D)	
	t-Stat.	*p*	t-Stat.	*p*	t-Stat.	*p*	t-Stat.	*p*
5% critical value	−2.892		−3.340		−3.760		−4.240	
GDP	−2.463	1	−2.100	0	−3.457	0	−3.997	0
Consumption	−2.006	4	−0.025	6	−2.316	4	−2.871	6
Inflation	−8.190	0	−9.254	0				
Interest rate	−2.189	1	−2.286	1				
Consumption growth	−13.128	0	−13.920	0				
GDP growth	−12.097	0	−3.807	6				
Consumption share	−2.487	0	−4.840	0				

Notes: The table shows Augmented Dickey-Fuller *t*-Statistics. The null hypothesis that a variable is integrated of order one is rejected, if the corresponding *t*-Statistic is smaller than the critical value. *p* is the lag order of the ADF auxiliary regression, which has been chosen according to BIC. The 5% critical values are taken from MacKinnon (1996) for alternative A, Perron (1990) for alternative B, and Perron (1989) for alternatives C and D. All alternatives include two sets of seasonal dummies, namely centered seasonal dummies for the whole sample and centered seasonal dummies multiplied by the mean shift dummy DS9101.

7 For testing the non-stationarity of the consumption share we apply unit root test critical values because we do not estimate a cointegration vector but consider directly the consumption share.

4. Structural Analysis

Estimation of the Model

The result of the numerical minimization of the weighted distance between the two sets of auxiliary parameters depends on the choice of the starting values. We have chosen a sophisticated random search strategy in order to deal with this problem. We have set the starting values to economically plausible values – partially relying on preliminary OLS regressions for the model equations. We perturbed these starting values several times and started the minimization again. Finally, we have chosen that specification that leads to the lowest weighted distance. Table 2 shows the corresponding starting values and the estimated structural parameters. During the estimation process, we have excluded the habit persistence parameter *h* from estimation because it turned out that other values than zero actually increase the weighted distance.

Table 2:
Estimated Structural Parameters

Parameter	Start values	Lower bound	Upper bound	Estimate	t-Statistic
IS equation					
σ	5.0000	1.0000	∞	20.1551	1.7490
h	0.0000	0.0000	1.0000	0.0000	
Phillips curve					
γ_b	0.3000	0.0000	0.9900	0.2045	0.2090
κ	0.1000	0.0100	∞	0.0100	0.1818
Monetary policy rule					
τ_R	0.9300	0.0000	0.9900	0.8515	13.1709
τ_y	1.0000	0.0000	∞	0.7482	0.4721
τ_π	1.5000	1.0100	∞	1.0137	1.6985
Productivity process					
σ_a	0.0070	0.0001	∞	0.0054	5.9795
ρ_a	0.0000	−0.9900	0.9900	0.0096	0.0383
GDP shock					
σ_g	0.0180	0.0001	∞	0.0012	1.2466
ρ_g	0.5400	−0.9900	0.9900	0.7522	3.0408
Cost push shock					
σ_π	0.0045	0.0001	∞	0.0024	2.0634
ρ_π	0.0000	−0.9900	0.9900	0.0003	0.0002
Monetary policy shock					
σ_R	0.0017	0.0001	∞	0.0023	13.7618

Notes: Indirect inference estimation with four observed variables (consumption share, inflation rate, interest rate and consumption growth rate), one lag in the auxiliary VAR model, and time series length multiplier 10. Coefficients without *t*-Statistics are not estimated but set a priori.

From the estimated model, the unobservable shocks and the output gap are uncovered using the Kalman filter. As suggested by Hamilton (1986), we run 2000 Monte Carlo simulations and draw the parameter vector from a multivariate normal distribution using the point estimates as mean vector and the estimated covariance matrix. The shocks and output gap, which we present in the next section, are 4-period centered moving averages of the means of the 2000 estimated state vectors.

Discussion of Empirical Results

Output gap. The model-based output gap is shown together with the annual GDP growth rate and the HP-filtered GDP in Figure 1 (actually, the figure shows 4-period centered moving averages of HP cycle and model-based output gap for illustrative purposes). The shaded areas in Figure 1 represent recessions in Germany according to the business cycle classification by Heilemann and Münch (1999). The model-based output gap coincides very well with the business cycle classification of Heilemann and Münch (1999), while HP-filtered output shifts the 1980-1982 recession to 1983. In this sense, we can confirm the statement of McCallum and Nelson (1999b) that the HP filter seems to be an inappropriate proxy for the output gap "because it does not properly reflect the influence of technology shocks". Additionally, it can be seen from Figure 2 that the output gap is mainly driven by demand shocks. This figure is generated setting all shocks but one to zero, respectively.

Figure 1:
Output Gap Decomposition

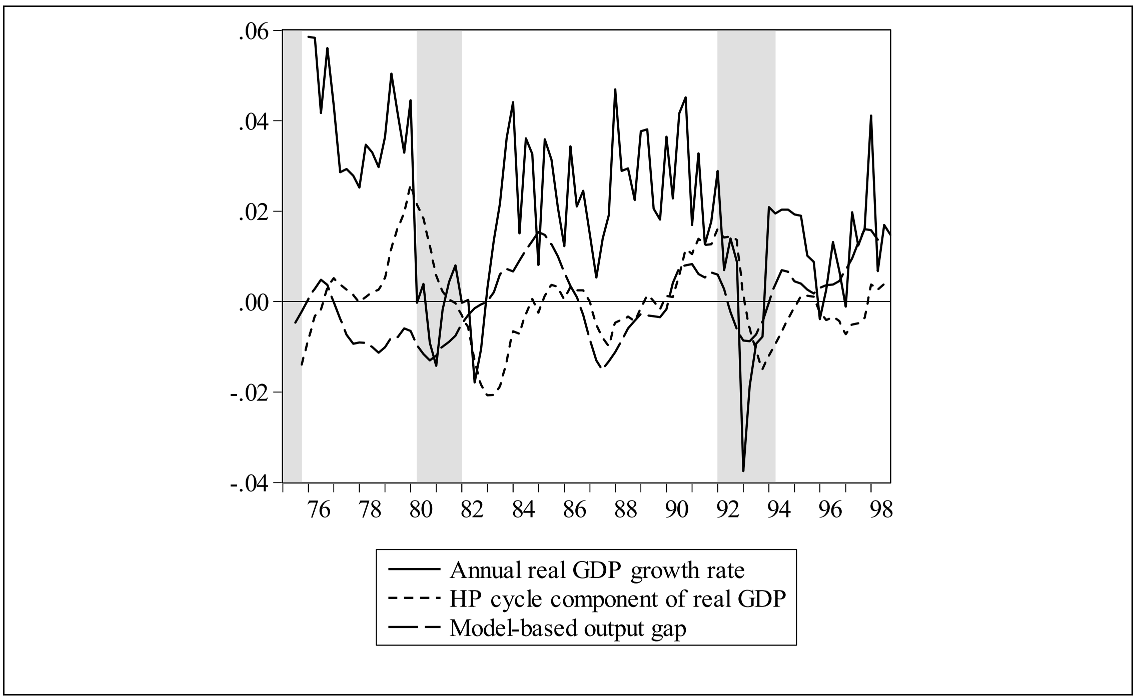
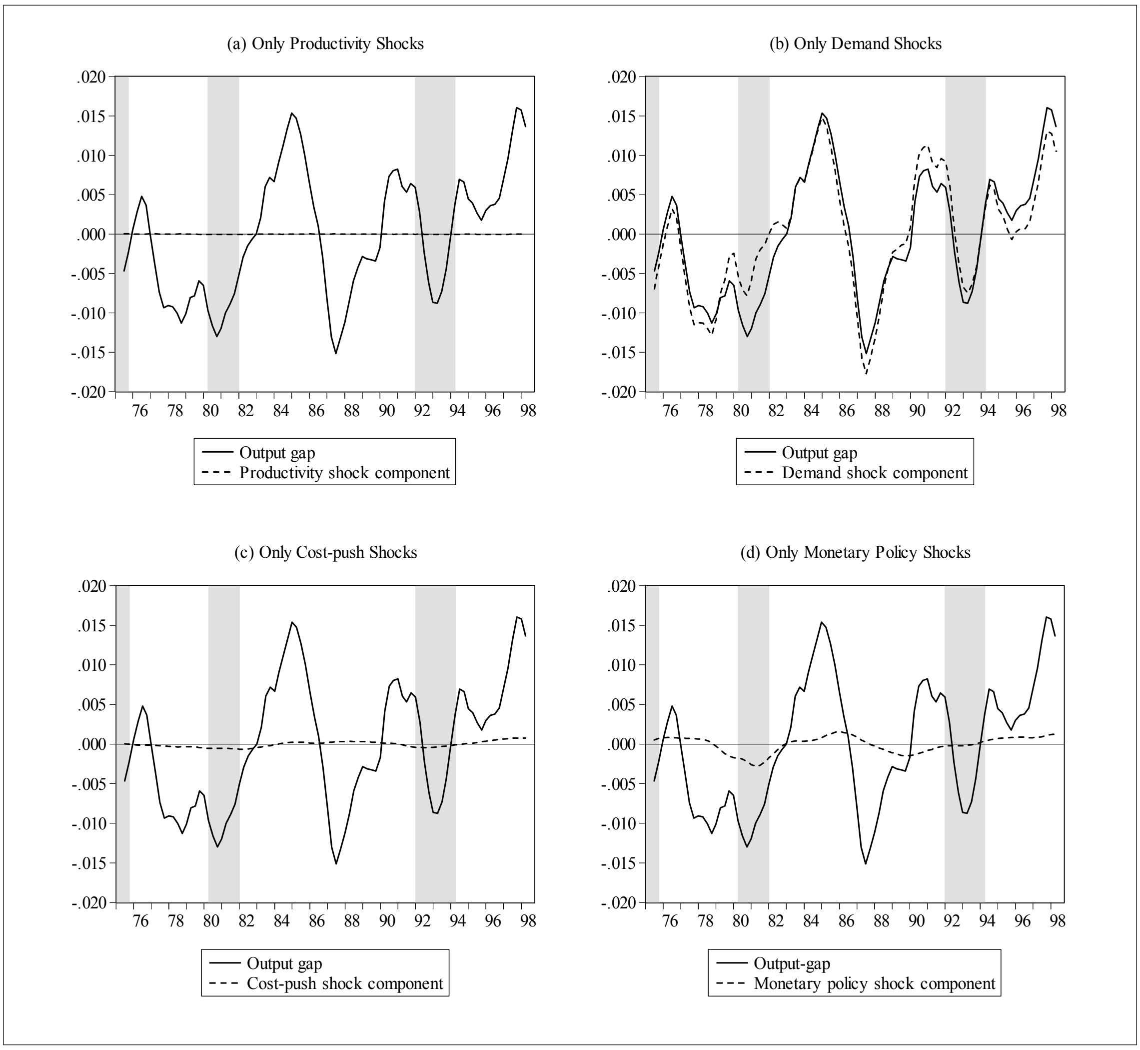


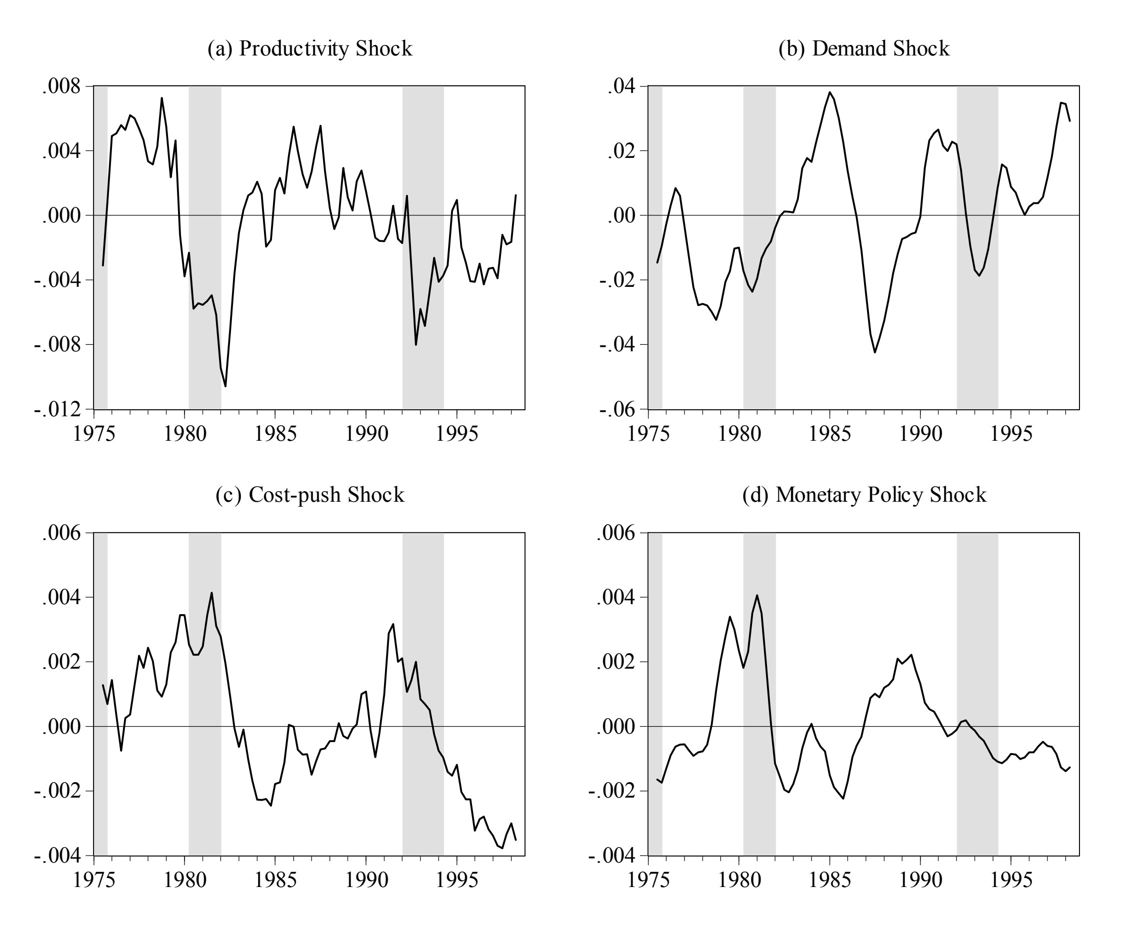
Figure 2:
Model Based Output Gap



The upper right figure shows how the output gap would have looked like if only the demand shock had been present, for example. It becomes clear that the productivity shock does not contribute to the explanation of the output-gap (see flat line in upper right panel of Figure 2 because the estimated autocorrelation coefficient of this shock is very close to zero. Therefore, permanent productivity shocks lead to an immediate adjustment of consumption to the new flexible price output level. This is in contrast to findings of DeJong et al. (2000) for the US. Their results suggest that shocks to total factor productivity play an important role in driving cyclical activity.

Structural shocks. The estimated structural shocks are shown in Figure 3. As Figure 3 highlights negative productivity shocks and negative demand shocks have jointly contributed to the recessions in the 1980ies and in the 1990ies. Similar to the results of Weber (1996), we find that the economic downturn in the early eighties can largely be attributed to permanent productivity shocks and that the output expansion in 1990/91 can be attributed to stationary demand shocks. The cost push shock reveals the inflationary pressure in the late 1970s due to oil price shocks and the inflationary pressure following the German reunification in the early 1990s. Interestingly, panel (d) shows that monetary policy has been quite restrictive before and during the recession in the early 1980s.

Figure 3:
Identified Structural Shocks



Business cycle accounting. The effects of the individual shocks on the observed variables and on the unobserved output gap can be summarized by correlation and relative variance statistics, which are provided in Table 3.[8] The left part of the table shows variance shares, that is the variance of the corresponding variable if only one shock is active divided by the corresponding variance if all four shocks are present. The right part of the table shows the correlation coefficients of one-shock-simulations and all-shock-

8 See *Chari* et al. (2007) for a detailed discussion of the business cycle accounting exercise using estimated structural models.

simulations. Our model specification suggests that output growth and consumption growth are primarily caused by persistent productivity shocks while fluctuations in consumption share and output gap can be mainly attributed to demand shocks. The inflation rate is not explained by the structural model because it is mainly driven by the cost-push shock. The interest rate is influenced by cost-push and interest rate shocks.

Table 3:
Business Cycle Accounting

Variable/Shock	Variance Share			
	Technology shock	GDP shock	Cost push shock	Monetary policy shock
Consumption share	0.00	1.04	0.00	0.01
Output gap	0.00	0.93	0.00	0.01
Inflation	0.00	0.01	1.02	0.00
Interest rate	0.00	0.40	0.14	1.09
Consumption growth	0.92	0.01	0.00	0.00
GDP growth	1.30	0.78	0.00	0.00
	Contemporaneous Correlation			
Variable/ Shock	Technology shock	GDP shock	Cost push shock	Monetary policy shock
Consumption share	0.30	1.00	−0.19	−0.17
Output gap	−0.27	0.99	0.30	0.32
Inflation	−0.22	0.05	0.99	−0.35
Interest rate	−0.24	−0.17	0.66	0.83
Consumption growth	1.00	0.59	0.12	−0.26
GDP growth	0.66	0.28	0.10	−0.05

5. Conclusions

We have presented an estimated small New Keynesian macroeconomic model for Germany from 1975 to 1998. We have calculated a model-based output gap, which coincides very well with other business cycle fluctuation classifications. Additionally, we have identified the economic shocks, which have driven the German business cycle in the sample period and shown how much these shocks contribute to the actual behaviour of output gap and observed data like output and consumption growth rates, inflation rate and interest rate. Our findings suggest that business cycle fluctuations measured by the output gap are mainly driven by demand shocks. However, productivity shocks have substantial effects on potential output and therefore are a main driver for output and consumption growth. The model presented in this paper is highly stylized. Furthermore, the robustness of the results has not been checked systematically. However, it can already be stated that the model-based approach to business cycle accounting that we have used is an interesting tool for structural business cycle analysis. The improvement and extension of the analysis will be subject to further research.

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Investment Cycles

*Claude Hillinger**

1. Introduction

The paper reports the principal findings of a long term research project on the description and explanation of business cycles. The research strongly confirmed the older view that business cycles have large systematic components that take the form of investment cycles. These quasi-periodic movements can be represented as low order, stochastic, dynamic processes with complex eigenvalues. Specifically, there is a fixed investment cycle of about 8 years and an inventory cycle of about 4 years. Maximum entropy spectral analysis was employed for the description of the cycles and continuous time econometrics for the explanatory models. The central explanatory mechanism is the second order accelerator, which incorporates adjustment costs both in relation to the capital stock and the rate of investment. By means of parametric resonance it was possible to show, both theoretically and empirically, how cycles aggregate from the micro to the macro level. The same mathematical tool was also used to explain the international convergence of cycles. I argue that the theory of investment cycles was abandoned for ideological, not for evidential reasons. Methodological issues are also discussed.

2. The History[9]

The paper deals with the empirical results developed at my institute (SEMECON) at the University of Munich. The motivation for this research can be better understood in the light of a brief historical survey. I focus on some 'stylized facts' of this history that I believe to be of continued relevance.

What I will refer to as 'traditional business cycle theory' developed roughly in the century between 1850 and 1950, largely outside of academic economics. Since Adam Smith, academic economics focused on elaborating the properties of the general economic equilibrium. In the case of Smith, the verbal description of the behavior of entrepreneurs contained a dynamic element, but with Walras the theory was cast in the mold

* University of Munich, SEMECON, Ludwigstr. 33/IV, 80539 Munich, Germany, hillinger@lmu.de.For helpful comments on earlier versions of the paper I am indebted to *Per Berglund* and *Nicolas Groshenny*.

9 The subject of this section is treated at greater length in *Hillinger* (2005) and more generally in *Hillinger* (2008).

of a static and timeless system of mathematical equations. The evident deviations from equilibrium that manifested themselves in recurring ‘crises’ were to the academic economists more an irritation, or a ‘friction’ than the subject of serious analysis.

Another related dichotomy arose in connection with the rise of socialism. For socialists, not the perfection of general equilibrium, but rather the imperfections of capitalism, including its recurrent crises, became the focus of their attention. The counterpart to Walras is Marx’s ‘Das Kapital’. Instead of the static mathematical perfection found in Walras, Marx gave a verbal description of a dynamic capitalistic process, punctured by periodic crises, that in his view would ultimately tear the system apart.

Most of the work done on business cycles was much less sweeping and spectacular; instead more narrowly focused and empirical. As described by Schumpeter (1954, p. 738) the recognition of the recurrence of economic depressions as part of a periodic process developed gradually in the course of the Nineteenth Century and replaced the earlier view of them as isolated events.

The first half of the Twentieth Century saw a vast increase in the availability of data with the consequence that business cycles could be more specifically localized in the different sectors of the economy. Matthews (1959) summarized what was known, or believed, about business cycles at that time. In essence, the argument was that business cycles are investment cycles and that there are three types. An inventory cycle in the 3-4 year range, an equipment cycle of 8-10 years and a building cycle of about 20 years. The evidence given was impressionistic, consisting of a few graphs of relevant time series. The explanation given was informal and involved the lagged adjustment of capital stocks to their desired levels. This adjustment is slowest for buildings, resulting in the longest cycle. For equipment, the adjustment speed is intermediate and so is the length of the cycle. The most rapid adjustment occurs with inventories so that here the cycle has the shortest period.

Interest in investment cycles essentially vanished after about 1960. The reason is not that they had ceased to exist, but that a number of both ideological and incidental factors worked against their being recognized. I list them below in a roughly chronological sequence.

a. The tectonic political and social changes that followed in the wake of the Great Depression had both favorable and unfavorable consequences for the study of business cycles. Favorable was the displacement of marginalist microeconomics from center stage and its replacement by macroeconomic concerns. Keynes’ (1936) General Theory became the most influential book of that age. The overall impact of the General Theory was not favorable to the study of business cycles.

The General Theory was motivated by Keynes’ belief that the Great Depression had heralded a fundamental structural change in the economies of industrialized nations. It was a change from the old business cycle, with its alternating ups and downs, to a state of permanent under employment. Formalized and reduced to its bare bones by Hicks in the form of the IS-LM model, this became the macroeconomics taught to generations of budding economists.

I have stressed that the General Theory was motivated by Keynes' vision of a post-Depression world of mature capitalism, characterized by stagnation and chronically deficient demand. Most of the General Theory elaborates a model of such an economy. However, in Chapter 22, Notes on the Trade Cycle, Keynes cast a backward glance at a world that he thought had ceased to exist. He attempted a brief explanation of economic cycles, which he explicitly described as a “nineteenth-century phenomenon”.

The building blocks for Keynes’ dynamic theory are contained in Chapters 5 and 12 on short- and long run expectations. The entrepreneur is described as making his current decisions on the basis of his expectations regarding the future. Future expectations are based on extrapolations from the past, but these may be strongly influenced by irrational and volatile factors of individual or mass psychology. Keynes discusses two fundamental decisions of the firm. In Chapter 5 it is the decision on how much to produce, which is related to short-term expectations regarding the demand for the product and also to current inventory levels. Chapter 12 is devoted to the firm's decision to invest in fixed capital. Here the decisive consideration is the relationship between the current cost of capital and its expected long-term yield. The current cost depends on the price of capital goods, the rate of interest and on costs of producing with old or new capital. The expected long-term yield depends on the expected long run evolution of market demand

Keynes’ attempt in Chapter 22 to construct an endogenous dynamic theory of economic cycles based on these building blocks, has remained rudimentary. The main reason appears to be that he devoted little effort to the task, since he regarded the chapter as no more than an historical aside. Also relevant is the fact that a logically tight description of the dynamics of an oscillatory process is virtually precluded by the rather diffuse verbal style of Keynes and earlier writers on economic cycles.

Considering these three chapters together, Keynes made a substantial contribution to the explanation of economic fluctuations, which was firmly in the tradition of the theories of investment cycles. In line with Keynes’ own belief that these chapters were of purely historical interest, they had no impact on the profession; they strongly influenced my work on business cycles.

b. The next great paradigm change in economics came with the decline of Keynesianism and rise of monetarism in the 60s and early 70s. This development was part of a broader political movement from Left to Right, exemplified by Margaret Thatcher in the UK and Ronald Reagan in the US. It involved a declining belief in the need for government intervention and a rising belief in the self regulation of markets. In macroeconomics this became the belief that economies are naturally stable and that the observed instability is the result of erratic monetary policies. Milton Friedman's proposal to forego all stabilization policies and let the money stock grow at a constant rate was the most radical expression of this view.

Monetarist's belief in a simple causation from money to both inflation and the real economy led them to oppose the kind of structural macroeconometric modeling practiced by the Keynesians. These models contained adjustment lags that could plausibly lead to overshooting and cyclical behavior. Monetarists thus took a further step away from the understanding of macroeconomic dynamics and business cycles.

c. The heyday of monetarism did not last very long; in the 1980s it began to divide into several branches. Academic macroeconomics came to be dominated by real business cycle theory and new Keynesian theory. Neither of these could plausibly relate to efforts at stabilization policies. Consequently there evolved a more applied branch of macroeconomics located primarily in central banks and other governmental organizations. Common to all of these was the assumption of 'shocks', either monetary or technological, as the cause of fluctuations. Paradoxically, the unexplained became the explanation. Macroeconomics in all of its variations moved ever further away from a belief in an endogenous dynamics.

d. Contemporary academic macroeconomics is characterized by the use of neoclassical representative agent models. This in spite of a voluminous literature that has demonstrated that there are no reasonable assumptions that allow one to deduce such a concept from the behavior of individual agents. At the applied level, the paradigmatic concept is the Taylor rule that gives a formal justification for an active monetary stabilization policy. The assumption and explanation of an endogenous dynamics features in neither the academic not applied branches of contemporary macroeconomics.

e. Currently, not only macroeconomics, but all of economics is once again in a transitional stage. The dominance of the neoclassical paradigm, along with the faith in the blessings of unfettered markets, is on the decline. It is my belief that the paradigms that have characterized economics in the 20th and early 21st Centuries have been excessively influenced by various ideologies and that we need a more down to earth empiricism that is also open to insights that economists have obtained in the past.

3. Investment Cycles in the Contemporary World

Investment in the Business Cycle, a First Look

I begin this section with some evidence on the role of investment in the business cycle taken from The American Business Cycle, edited by Gordon (1986). These contributions are intermediate in the following sense: The traditional theory of business cycles had faded, but the newer traditions of neoclassical macroeconomics, or of statistical testing in a time series context, had not yet come to dominate, at least not among the contributors to this collection. A consequence is that while the authors measure the contributions of investment to recessions, they make not attempt at determining cycles. The simplicity of the method used makes the results easy to interpret.

Table 1:
Contribution of Change in Real Fixed Investment to Change in Real GNP: Eight US Recessions
- 1948-1981 -

Period	Percent
1948:4-1949:4	18.8
1953:2-1954:2	12.7
1957:3-1958:2	45.8
1960:1-1960:4	61.4
1969:3-1970:4	43.1
1973:4-1975:1	55.2
1980:1-1980:2	59.2
1981:3-1982:4	34.0
Mean	41.3
Median	44.5

Source: Gordon and Veitch (1986).

I begin with the work on fixed investment in Gordon and Veitch (1986). They analyze how much fixed investment contributed to the decline in output during 13 US recessions between 1948 and 1982. The NBER dating is used for the timing of peaks and troughs. The variables are real quarterly GNP and fixed investment. Fixed investment is defined as the sum of the four categories: producer's durable equipment, nonresidential structures, residential structures and consumer durable expenditures. Both variables were detrended by an estimate of the trend value of real GNP. The principal conclusion is that measured as either a mean, or a median, the average contribution of fixed in vestment to the decline in detrended real GDP is above 40% and in some recessions around 60%.

Next I turn to Blinder and Holtz-Eakin (1986) on inventory fluctuations. Here the focus is on the contribution of the change in real inventory investment to the change in GNP. Both variables are detrended by Gordon's estimated trend of real GNP. Key results are shown in Table 2. Looking at this table and seeing that the three largest contributions average near 200%, the reader is likely to rub his eyes in disbelief. This disbelief will be even greater when he recalls that inventory investment is on average only about one percent of GDP. The results do call for some explanation.

Let me say first of all, that having long worked on inventory fluctuations the results are not surprising to me. Both in the work done at my University of Munich seminar SEMECON and in other studies that I have seen, the contributions of inventory fluctuations to short run fluctuations in GDP tend to lie between 50 and 100%, with the 100% mark sometimes passed. A contribution of more than 100% means that other components moved predominantly in a contrary direction to GDP. The median contribution of 74.5% is quite typical.

The three very large contributions are not plausible descriptions of reality; their genesis can be explained as follows: Inventory investment is by far the most unreliably estimated component of GDP. Essentially it is computed as the difference between output and final sales, so that errors on both sides of the accounts enter. Many countries do not report a statistical discrepancy for the NIPAs, simply amalgamating the discrepancy with the inventory investment. Note that the three largest discrepancies occur when the changes in GNP are smallest. An error of given magnitude has the biggest impact on the contribution measure in these cases.

The two tables cover the same recessions, though with different data sets, as is indicated by slight differences in the dating of turning points. It is interesting to add the two kinds of contributions to get a measure of the contribution of total investment. When this is done, excluding the three recessions with very large inventory contributions, we find a mean contribution of 78% and a median contribution of 64%.

A conservative summary of these results is that investment accounts on average for more than 60% of cyclical fluctuations. This despite the fact that fixed investment averages only about 20% of GDP and inventory investment only about one percent. An empirically oriented theory of economic fluctuations must start with such elementary observations and proceed by refining and explaining them. The traditional theory of investment cycles has done this, albeit in an unsystematic manner.

The Spectral Analysis of Business Cycles in the Major Industrialized Economies

I turn to evidence on investment cycles obtained at my institute SEMECON at the University of Munich. This evidence relies heavily on maximum entropy spectral analysis which is a much more efficient method for determining the characteristics of a short time series then classical spectral analysis. It involves fitting a short AR-process, usually of order 3-5, and then determining the frequency domain properties from the roots of the fitted process.[10]

10 *Woitek* (1996) and *Süssmuth* (2003, Ch. 3) discuss the SEMECON methodology of time series analysis including maximum entropy spectral analysis. *Heintel* (1998) is an efficient method for determining the order developed at SEMECON.

The empirical evidence reported in this subsection is a summary of Table 4.2 in Süssmuth (2003). The countries examined are the G7: Canada, France, Germany, Italy, Japan, UK and USA. Annual deflated figures were obtained from EUROSTAT for the main components of the NIPAs: consumption (CON), total private investment (TPI), gross fixed capital formation (GFCF), inventory investment (II), exports (EXP), imports (IM), and government (GOV). TPI is the sum of GFCF and II. A modified Baxter-King filter was used to detrend the series. The sum of detrended components defines detrended GDP.

The order of the fitted AR-process was determined by the Bayesian order statistic of Heintel (1998). The statistic determined orders ranging from 2 to 5. There was not a single series that had no cycle, most had two. The longest cycle estimated was the 9.7 year fixed investment cycle in Canada. The shortest was the 2.8 year inventory cycle in Japan. Both period and modulus of each cycle were computed from the roots of the estimated AR-process. The precision of the estimates, as measured by the standard error, was quite high throughout.

Table 2:
Contributions of Inventory Investment to Changes in Real GNP: Thirteen Recessions
- 1948-1981 -

Period	Change of Real GNP	Change of Inventory Investment	Percent Contribution of Inventories
1948:4-1949:4	−7.1	−13.0	183
1953:2-1954:2	−20.2	−9.2	46
1957:3-1958:1	−23.0	−10.5	46
1960:1-1960:4	−8.6	−18.0	209
1969:3-1970:4	−7.3	−12.3	168
1973:4-1975:1	−60.7	−38.0	63
1980:1-1980:2	−35	−1.6	5
1981:3-1982:4	−45.1	−38.8	25
Mean	−25.9	−17.7	93
Median	21.6	−12.7	74.5

Source: Blinder and Holtz-Eakin (1986).

Table 3 reports the median values of the principal parameters. The first line refers to the long, the second to the short cycle. Two cycles, with the typical periods of the fixed investment cycle and the inventory cycle are in evidence in almost all series. The associated moduli near 8, in some cases 9, indicate quite pronounced cycles. The R-squares are low, but it must be remembered that the series fluctuate about zero.

The table confirms two theoretical predictions made in later sections: The long cycle is present in II, but the short cycle is not present in GFCF. The GFCF cycle has a period of twice the length of the II cycle.

A further interesting result presented by Süssmuth pertains to the estimated combined GDPs of the G7 and EURO-15[11] countries. The results are reproduced in Figure 1. Both cycles are clearly evident in the aggregate GDPs. The estimates are highly significant and the moduli large. A precise 2:1 relationship is again found between the long and the short cycle.

The evidence for investment cycles as quasi-cycles presented here is clear cut. It is duplicated in the other studies quoted above.

Table 3:
Median Statistics of Investment Cycles in G-7 Economies*

	GDP	CON	TPI	GFCF	II	EXP	IM	GOV
Period	7.1 3.6	7.3 3.7	8.1 3.9	6.5	6.2 2.8	6.2	6.0	7.1 3.9
Modulus	0.8 0.8	0.8 0.8	0.9 0.8	0,9	0.8 0.8	0.8	0.8	0.8 0.8

* Most countries had no short cycle in GFCF, EXP and IM.
Source: Süssmuth (2003).

The Second Order Accelerator and the Explanation of Investment Cycles

The second order accelerator (SOA) is meant to be the behavioral explanation of the observed quasi-cyclical behavior of investment. The SOA is a second order differential equation in fixed investment, or in output in the case of the inventory cycle. It generalizes the first order flexible accelerator that has been a workhorse of applied econometrics, where it has been used to model investment in fixed capital. The SEMECON research has used the SOA for modeling both fixed and inventory investment. A substantial literature derives the flexible accelerator from the assumption of adjustment costs.[12] A derivation of the SOA based on adjustment costs is given in Hillinger, Reiter and Weser (1992). The derivations given here are more intuitive and simpler.

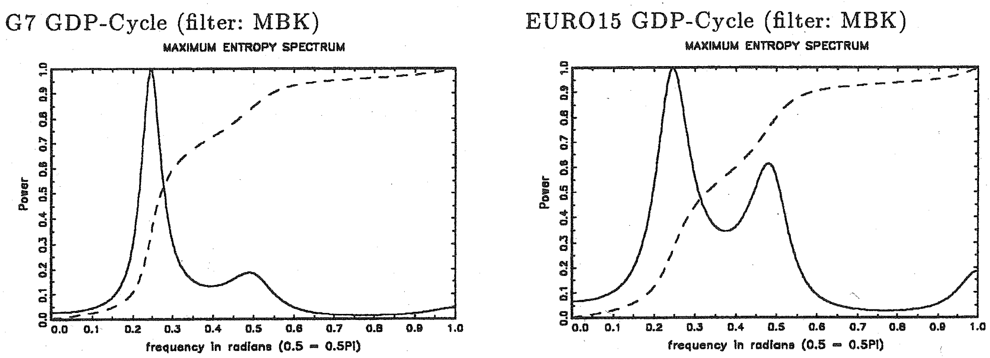
First Derivation. The simplest derivation of the SOA is to regard it as a transformation from the observed cycles in the frequency domain to a dynamic equation in the time domain that is capable of generating the cycles. Such equations are required both for purposes of modeling and for prediction. Since the observed behavior involves a cycle, the simplest differential equation that can generate the observed behavior is a second order equation capable of having a pair of complex roots.

11 The Euro zone before the latest accessions.

12 For a review see *Maccini* (1987).

Figure 1:
Spectra of G-7 and EURO-5 GDPs

Supranational GDP series' spectra (filter: MBK)



G7:

per.[a]	mod.[a]	adj. R^2	ord.
8.206 (3.203)	0.906 (0.001)	0.389	5
3.963 (1.084)	0.804 (0.027)		

EURO15:

per.[a]	mod.[a]	adj. R^2	ord.
8.324 (1.048)	0.854 (0.012)	0.307	5
4.076 (1.259)	0.833 (0.014)		

Source: Süssmuth (2003).

The fixed investment cycle has generally been observed in gross fixed investment. From time to time the statistical agencies also publish data on the stock of fixed capital. Differencing yields net investment and differencing again gives the change in investment. If K_f is the stock of fixed capital, the continuous time analogues are K_f, DK_f, D^2K_f. Relating these in a linear differential equation gives

(1) $$D^2K_f = \alpha DK_f + \beta K_f$$

as the SOA equation for fixed investment.

To model the inventory cycle, let $K_{i,t}$ now be the stock of inventories at the beginning of period t. The change in inventories is the difference between output and sales: $K_{i,t+1} - K_{i,t} = Q_t - S_t$. For an individual manufacturing firm S would be sales and Q production; for a national economy, S is final sales and Q is total output, i.e. GDP. The equation then states the national accounts identity that inventory investment is the difference between GDP and final sales. In continuous terms $DK_i = Q - S$.

The crucial difference to fixed investment is that the firm only controls its output, which is the input to its inventory stock; sales, the outflow from the inventory stock, is determined by the firm's customers. Accordingly, the homogeneous part of the SOA equation for inventories is written as a differential equation in Q:

(2) $$D^2Q = \alpha DQ + \beta Q.$$

Second Derivation. A derivation of the SOA that has more economic content involves a generalization of the standard flexible accelerator, a work horse of much empirical econometrics. In a continuous formulation it is

(3) $$I_f = \mathrm{D}K_f = b\left(K_f^* - K_f\right),$$

where I is net investment and K^* the desired capital stock. That a capital shortage or surplus cannot be instantly removed is particularly evident in the continuous case, since investment would have to be infinite. The SOA goes one step further to assume that the dependent variable in (3) should be desired investment I_f^* and that actual investment adjusts to it in a further equation. There are many reasons why investment cannot make sudden jumps. Production equipment is usually made to order and takes time to produce, particularly if the supplier is already operating at capacity. In the case of surplus capital, it would be unwise to immediately junk a machine when it is not fully utilized. The SOA model thus is

(4) $$I_f^* = b(K_f^* - K_f),$$

(5) $$\mathrm{D}I_f = c(I_f^* - I_f)\cdot$$

Since $I_f = \mathrm{D}K_f$, the two equations can be combined to give a second order equation in K_f:

(6) $$\mathrm{D}^2K_f + c\mathrm{D}K_f + cbK_f = cbK_f^*.$$

The roots are

(7) $$x_{1,2} = \frac{1}{2}\left[-c \pm i\sqrt{4bc - c^2}\right].$$

The solution is periodic for $c < 4b$ and always damped. An interesting special case occurs when b » c Then the homogeneous part of (6) can be approximated by

(8) $$\mathrm{D}^2K_f = a(K_f^* - K_f), \quad a = bc.$$

This is referred to as the single parameter SOA. It implies, in the absence of shocks, a constant amplitude cycle with period

(9) $$P_f = \frac{2\pi}{\sqrt{a}} \quad ,$$

This is the simplest formulation that reproduces the key stylized fact, recognized in the traditional theory of business cycles, that the period of the cycle is inversely proportional to the speed of adjustment.

The SOA for Inventory Investment. The intuitive derivation of the SOA for inventory investment is similar, but a bit more complicated, because now production Q must be considered as an inflow to the inventory stock and final sales S as an outflow. The stock of inventories in this model is K_i. With suitable operationalization of the variables, the model can be applied to a firm, a sector, or a national economy.

(10)
$$Q^* = S^* + b(K_i^* - K_i),$$
$$\mathrm{D}Q = c(Q^* - Q),$$
$$\mathrm{D}K_i = Q - S.$$

The first equation states that the desired level of output is equal to the medium term expected level of final demand plus a component to adjust actual inventories to the desired level. The second equation stipulates that production is adjusted towards the desired level. The final equation is an identity that gives the actual rate of change of the inventory stock as the difference between production and final sales.

Differentiating the last equation, making various substitutions and taking S, S^* and K_i^* and as exogenous, we find the same homogeneous equation in K as in (6). The dynamic analysis is therefore exactly the same as in the case of the fixed investment cycle.

Third Derivation. The third derivation of the two SOA equations was given in Hillinger, Reiter and Weser (1992). It is based on the assumption that the firm minimizes a stream of expected discounted quadratic adjustment costs. Given a sufficiently high discount rate, it is shown that an SOA with complex roots is implied both in the case of fixed investment and in the case of inventory investment.

Equipment Cycle and Inventory Cycle Interaction

The two SOA mechanisms can be combined in a simple macroeconomic model. For this purpose I define residual demand $S_r = S - I_f$. Residual demand thus includes all components of GDP other than the two investment variables. To enable the simplest possible analysis of the interaction of the two cycles, it will be assumed here that S_r is exogenous. All variables are again to be considered as deviations from trend so that we have a pure cycle model. The desired stock of fixed capital K_f^* has been set at its equilibrium level of zero. The desired inventory stock is given by $K_i^* = \upsilon(S_r + I_f)$. Inventory investment having a shorter horizon than fixed investment, K_i^* is allowed to fluctuate with current demand. The model incorporating the two SOA equations is

(11)
$$\mathrm{D}I_f = -b_f c_f K_f - c_f I_f$$
$$\mathrm{D}K_f = I_f$$
$$\mathrm{D}Q = b_i c_i \left[v\left(S_r + I_f\right) - K_i \right] - c_i (Q - S_r - I_f)$$
$$\mathrm{D}K_i = Q - S_r - I_f.$$

In matrix notation this can be written as

(12)
$$\mathrm{D}\mathbf{x} = \mathbf{Ax} + \mathbf{Bs},$$

where

(13)
$$\mathbf{x} = \left[I_f, K_f, Q, K_i \right]^T$$
$$\mathbf{s} = S_r$$
$$\mathbf{A} = \begin{bmatrix} -c_f & -b_f c_f & 0 & 0 \\ 1 & 0 & 0 & 0 \\ c_i \left(1 + b_i v\right) & 0 & -c_i & -b_i c_i \\ -1 & 0 & 1 & 0 \end{bmatrix}$$
$$\mathbf{B} = \left[0, 0, c_i \left(1 + b_i v\right), -1 \right]^T .$$

The model has a particularly simple structure. The first two equations do not have an input from the rest of the system and produce the pure fixed investment cycle. The remaining two equations generate the inventory cycle. Since I_f is an input to this second subsystem, the fixed investment cycle will also be present in output and inventory investment. This feature was pointed out to me by Klaus Schüler shortly after I had first formulated the model. It is confirmed by the evidence summarized in Table 3 as well as by other data that we have examined. This is what is usually meant by a predictive confirmation in science: The prediction by a model of certain features of the data that had not been noticed previously.

If the one-parameter OAS equations are used, the model becomes simpler still and has the system matrix

(14)
$$\mathbf{A} = \begin{bmatrix} 0 & -a_f & 0 & 0 \\ 1 & 0 & 0 & 0 \\ a_i v & 0 & 0 & -a_i \\ -1 & 0 & 1 & 0 \end{bmatrix},$$

with the eigenvalues

(15)
$$\lambda_{1,2} = \pm i \sqrt{a_f}, \quad \lambda_{3,4} = \pm i \sqrt{a_i} \cdot$$

The SOA and the Conceptualization of Disequilibrium Dynamics

In physics, there are elementary conceptualizations that underlie the understanding of dynamic phenomena. The basic concept is inertia, the property of a moving object to continue unchanged motion unless acted upon by an external force. For periodic motions, as of a pendulum, the key concepts are kinetic energy, due to the bodies' inertia, and potential energy, a form of stored energy capable of exerting a subsequent force. The SOA allows an interpretation of investment cycles in precisely these terms.

In my theory of investment dynamics, the investment flow is the analog of kinetic energy and the capital stock provides the potential energy. Firms plan their investment over a long horizon. This involves such activities as developing new products, entering new markets, or building new production facilities. Once embarked upon, such activities are difficult and costly to change. Firms invest because they wish to increase their capital stock. The inertia of investment typically leads to an overshooting of the target. Excess capacity develops and exerts a downward pressure on investment.

Schematically the situation is depicted by a phase diagram in Figure 2a. The capital stock is on the horizontal, net investment of the vertical axis, both in deviations from equilibrium. In Quadrant I, there is excess capital, so investment, while positive, is slowing down and becomes zero where excess capital is at a maximum. Analogous to potential energy, the excess capital stock continues to decelerate investment into the negative range in Quadrant II. When the equilibrium capital stock is reached, disinvestment continues in Quadrant III so that a capital shortage develops. The point at which disinvestment ceases corresponds to the maximum capital shortage. Investment is positive in Quadrant IV and the capital shortage is gradually eliminated. Investment is now maximal and the economy passes again into quadrant I in which excess capacity is built up. The phase diagram was drawn for a constant amplitude cycle, but an explosive or damped cycle is equally possible.

Figure 2b plots an empirical phase diagram based on German fixed capital and net investment, 1970-1989, in deviations from trend. With some very minor exceptions near the bottom of the second cycle, the movement is exactly as predicted by the theoretical phase diagram. The first cycle is damped, the second of constant amplitude.

The ME spectrum of German fixed investment is shown in Figure 2c. There is a sharp peak at 8.33 years. A measure of the importance of the peak is the peak power. It gives the fraction of the total power (area) of the spectrum in a range of plus, minus 10% of the peak frequency. The peak power in this case is almost 70%. A second cycle at 4.2 years has vanishing power and cannot be identified visually.

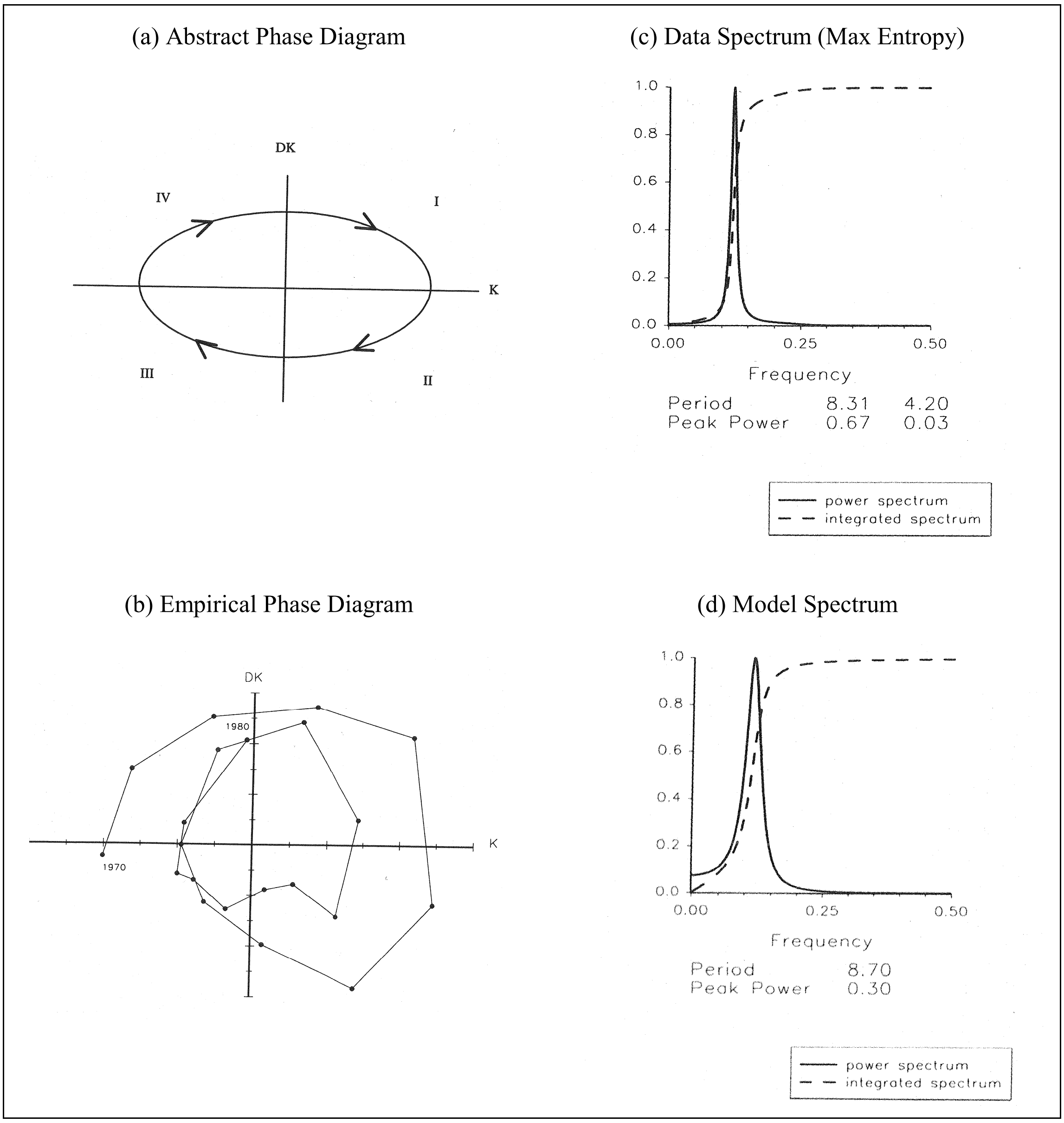
To take the analysis one step further, a second order differential equation was fitted to the data. The result was

$$D^2K_f = -0.221DK_f - 0.526K_f. \qquad (16)$$

The spectrum of this equation is given in Figure 2d. The period at 8.7 years is close to that of the ME spectrum. The peak power at 0.3 is lower, indicative of more damping as is also evidenced by the broader peak.

My conclusion from the analysis of this section is that that the analyzed data set has a cyclical pattern and that is clearly revealed by the visual methods taken from the physical sciences.

Figure 2:
Visual Analysis of the Equipment Cycle Germany
- 1970-1989 -



Source: Hillinger (1996).

An analysis of the inventory cycle can be given along similar lines, but it is more complex because inventory investment is equal to production minus sales and is therefore not under the complete control of the firm.

In Hillinger and Konrad (1993), similar ideas were applied to the analysis of foreign exchange disequilibria. The 'potential energy' in this case is a country's stock of net foreign assets and the 'kinetic energy' is the current account balance of trade in goods and services. Here the main complication is the so called 'J-curve' phenomenon according to which an exchange rate movement in response to a trade imbalance will actually worsen the imbalance before it can improve. A calibration of the model yielded a 10 year cycle. Currently, the huge and persistent US deficit is again at the center of the international economic agenda. I believe that our model provides a better basis for analyzing this phenomenon than neoclassical models of instantaneous adjustment of foreign trade and capital markets.

4. Structural Econometric Modeling of Investment Cycles

As briefly stated in the introduction, the methodology underlying the research reported in this paper was inspired by that of the natural sciences, particularly concerning the separation of description and explanation with respect to observed empirical regularities. The borrowing from the natural sciences went beyond this general principle to the use of specific mathematical/statistical tools that are used especially in physics and engineering when dealing with dynamical systems. One descriptive tool that has already been described is maximum entropy spectral analysis. At the descriptive level it can be used to summarize salient features of the observations. A proposed model can serve as an explanation of the observed regularities if the model output has the same characteristic spectrum as the observations.

In this context it is illuminating to discuss the different meanings of the terms 'prediction', and 'confirmation', in natural science and in econometrics. In econometrics, 'prediction' refers to observations on a time series that are predicted by a model. In natural science 'prediction' refers to a pattern that is generated by a model and is confirmed if found in the data. A proposed explanatory model is refuted if the patterns that it predicts are not found in the data. In contrast to this, econometrics uses a statistical concept of confirmation based on significance tests.[13]

Explanatory dynamic models in the natural sciences take the form of differential equations, i.e. they are formulated in continuous time. In the econometric mainstream models are formulated as discrete difference equations. This assumption of discreteness was apparently adopted without much reflection as a seemingly obvious consequence of the discreteness of the observations. Discreteness is equally a property of observations in the natural sciences and there are weighty reasons why econometric models should be formulated in continuous time. These have been elaborated in a substantial literature on continuous time econometrics. Since the SEMECON econometric models of investment cycles are in this tradition, it is discussed in the next subsection.

13 A critical view of the statistics based econometric methodology is offered by *Keuzenkamp* (2000).

Continuous Time Econometrics

The history of continuous time econometrics and its relationship to mainstream econometrics is a strange one. Elementary common sense suggests that economic dynamics, both theoretical and empirical, should be formulated in terms of differential equations. A discrete model implicitly assumes that firms make all decisions at the end of a period, say a quarter, for the following period. In between, the decision making staff presumably goes fishing or falls into a Rip Van Winkle like stupor. In reality decisions, big or small, are made on a daily, some even on an hourly basis. Moreover, even if all firms made their decisions at fixed intervals, these would not be the same for different firms. For consumers the situation is not different; each day some loose their jobs, others find one; some are born, other die and many other events affect consumer behavior, individually or collectively. The overall result is surely that if we could observe economic time series at very close intervals we would see a continuous movement.[14]

During the period of large scale, structural macro-econometric modeling, mainstream econometric theory was occupied in dealing with the consequences of the decision to model in discrete time. The typical model was of the form $x_t = \mathrm{B}x_t + \mathrm{C}x_{t-1}$, and further terms involving exogenous and random variables. The dependent variable of one equation thus appeared as an explanatory variable in another. Simultaneity was viewed as the principal problem and such solution concepts as two-or three stage least squares, partial- or full information maximum likelihood were offered as solutions.

Already Strotz (1960) had pointed out that simultaneity is the consequence of the specification error involved in discrete modeling. In the natural sciences, where dynamic phenomena are modeled as differential equations, simultaneity was never an issue.

Post 1950s mainstream econometrics evolved from traditional, discrete statistical theory and this mold proved to be impervious to the arguments referred to above. After the rise of neoclassical macroeconomics, an additional barrier between mainstream econometrics and continuous time econometrics arose from the fact that, in empirical applications, the latter employed a disequilibrium framework,[15] incompatible with rational expectations and real business cycle macroeconomics.

The SEMECON research described in the present paper may be regarded as a confluence of the two streams of traditional investment cycle theory and continuous time econometrics.

A significant contribution to continuous time econometric theory was made at SEMECON by Michael Reiter and is the basis for the empirical results of the next sub-

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14 In financial markets very high frequency data have actually become available and are being modeled in continuous time.

15 A thorough discussion of disequilibrium continuous time econometrics is *Wymer* (1996).

section. Estimation in continuous time econometrics had been highly computationally intensive and consequently restricted to mainframe computers. Reiter's contribution was based on the continuous time Kalman filter developed in Harvey and Stock (1985). This led to two substantial advantages. A pragmatic advantage was a dramatic reduction in computation, allowing the estimation to be done on a desktop computer. A more fundamental gain was the possibility opened by the Kalman filter to differentiate between errors in the equations and errors in the variable. As expected, inventory investment showed large errors in the variable. The two types of error have entirely different implications for dynamics.[16]

Empirical Results

In this subsection I present results taken from Hillinger and Reiter (1992), where we aimed at testing the simplest possible models of the equipment cycle, the inventory cycle and their interaction. The criterion of simplicity has been at the heart of the progress of the natural sciences. It is diametrically opposed to the idea on which the large scale macroeconomic models were based, that including ever more detail increases 'realism' and hence model performance. Moreover, that fact that a very simple model, in which the stock of fixed capital is the driving force, can explain the dynamics of fixed investment, justifies the designation 'fixed investment cycle'. Similarly, the term 'inventory cycle' is justified by the simple model with the inventory stock as driving variable. The simple model of their interaction is capable of generating the stylized facts mentioned earlier.

Table 4:
Cyclical Interaction in USA; One Parameter Model
- 1960-1986 -

Parameters	Estimated value	Standard error	
a_f	0.926	0.098	
a_i	6.984	0.483	
v	0.123	0.025	
P_f	6.531	0.345	
P_i	2.378	0.082	
Equation	R^2	MSE	Autocorrelation
Fixed investment	0.691	17.000	–0.024
Fixed capital	0.923	9.230	–0.213
Production	0.783	21.191	–0.092
Inventories	–0.052	10.830	–0.004
Invent. investment	0.485	10.423	–0.083

16 This work is described in *Reiter* (1995, Chs. 12, 13).

For each model two alternative specifications were considered. If the two parameter SOA model implied a modulus near unity, the single parameter version was tried and if satisfactory adopted. For reasons of space, only a highly condensed summary is given here.

The equipment cycle equation (1) was fitted to German data; the inventory cycle model (11) was fitted to UK data; finally, the models of cyclical interaction (11) and (14) was fitted to US data. The results were impressive throughout. Here I report some results for the US. Both the two parameter and single parameter SOA versions gave excellent results. Table 4 gives the results for the single parameter version corresponding to (14). All coefficients are highly significant. In judging the R^2s, it should be kept in mind that the data were in deviation form and two cyclical series that have the same period can have a negative correlation due to a difference of phase.

Figure 3 plots the model predictions against the observations. Beyond 1980 an out of sample forecast over a 6 year period is shown. The two years ahead lower turning point is hit perfectly. The five year ahead upper turning point is also timed perfectly, but the amplitude is too great.

5. The Aggregation Problem for Investment Cycles

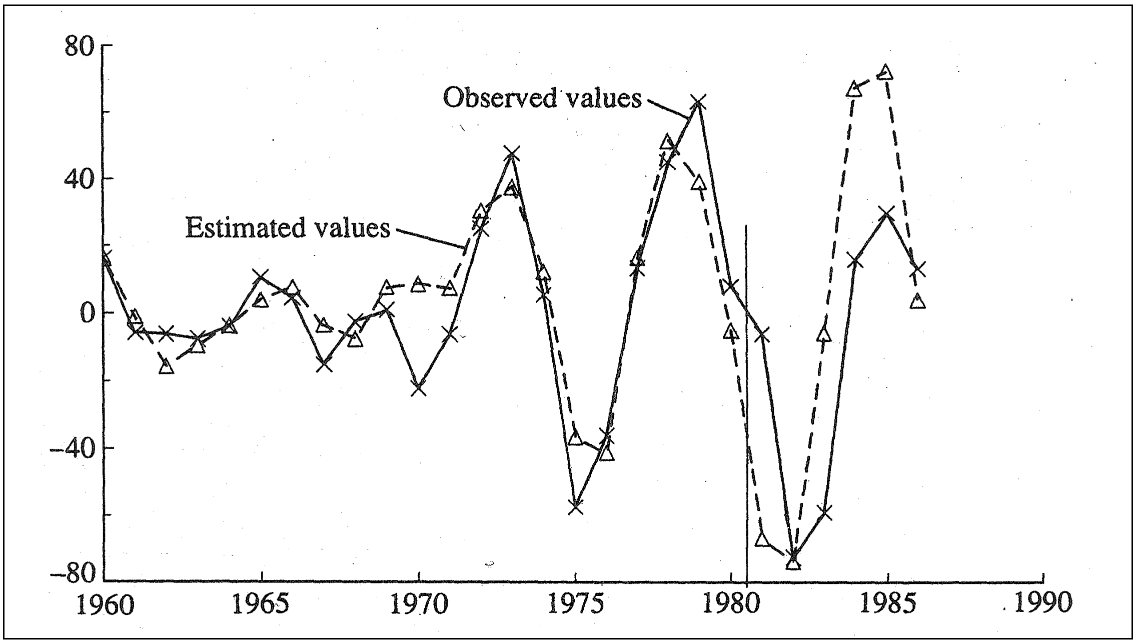
The Problem of Cyclical Aggregation

I have long been critical of neoclassical macroeconomics for ignoring the fact that that no reasonable justification for the use of the representative agent concept can be derived.[17] I had long been aware of the fact that the same criticism applies to my own work on investment cycles, though in a somewhat attenuated form. In the case of neoclassical macroeconomics there are the twin problems that the macro-level cannot be deduced from the micro-level and that the macro level has not performed satisfactorily against macro-data. As described in the previous sections, the SEMECON approach to the modeling of investment cycles found stable relationships in the data, both descriptively in the frequency domain, and as explanatory structural models in the time domain. The first problem though, a rigorous derivation from microeconomics, remained unsolved for a long time. Ultimately, this too was solved and the solution is described in the following sub-sections. Because the subject is quite complex, particularly in the empirical implementation, I have decided to give here a very abbreviated and purely verbal

17 This criticism is elaborated in a longer version of the present paper (*Hillinger*, 2005), as well as in *Hillinger* (2008).

discussion. The interested reader can find a full discussion in Süssmuth (2003) and in Süssmuth and Woitek (2005).

Figure 3:
USA: Private Net Fixed Capital Formation Model of Cyclical Interaction, Single Parameter Version Estimation 1960-1980
- Forecasts 1981-1986 -



Source: Hillinger and Reiter (1992).

Parametric Resonance and the Aggregation of Cycles

The SOA equations can be plausibly justified as explanations of the investment and production behavior of individual firms. However, even if many firms have SOA's with similar periods, these would not add to visible cycles at the aggregate level. Even small differences in period lengths imply constantly changing phase differences between the cycles of individual firms. Firm specific shocks would also lead to a random distribution of the phases of cycles. The result at the aggregate level would be essentially random.

I had long been aware of the problem and also had thought that the answer must come from physics in the form of a resonance model. Resonance phenomena in physics are well known. For example, if a number of tuning forks with similar, but not identical, inherent frequencies are placed close to each other, they tend to agree on a common frequency and phase. The opportunity to explore this conjecture presented itself in 1993 when a young man named Thilo Weser presented himself at my office. He had just obtained his Ph.D. in physics and wanted to obtain one in economics as well. For his dissertation in economics he took on the problem just described. It turned out that there are many resonance models in physics. One of these appeared promising, the model of parametric resonance.

The simplest way of joining two dynamic systems is linearly, with the output of one becoming the input of the other. This merely leads to a superposition of cycles, with each retaining its original period. The resonance phenomenon requires a nonlinear interaction. In the parametric resonance model, the nonlinearity takes the form of the output of one oscillator directly impacting the parameters of the other.

If several oscillators are connected as specified by the parametric resonance model, the following predictions can be deduced:

First Prediction. Oscillators whose initial periods and phases are sufficiently close to each other will resonate, in the sense that they will 'agree' on a common average period and a common average phase. Resonance also leads to an increase in the amplitudes of the individual oscillations, possibly converting stable to unstable oscillations.

Second Prediction. Resonance involving a phase reversal is also possible. In this case two cycles agree on an average period, with the peak of one corresponding to the trough of the other.

Third Prediction. Resonance is also possible among oscillators whose frequencies are integer multiples of each other. The larger the multiple separating the two cycles, the weaker is the effect. The only case that we have considered is the 2:1 relationship between fixed investment and inventory cycles that has already been mentioned.

Macro Evidence. Regarding the third prediction, I have already mentioned that the fixed investment cycle and the inventory cycle have an approximate 2:1 relationship in the G-7 countries. Hillinger and Sebold-Bender (1992) investigated the two types of cycle for 15 OECD countries. They found median values of 6.3 years for the fixed investment and of 3.0 years for the inventory cycle; this is very close to the 2:1 ratio.

The second prediction has not played any role in our research. However, Matthews (1959), discusses at some length that the building cycle in the UK and the US had the opposite phase. When the UK was depressed, the flows of both capital and immigration from the UK to the US peaked, contributing to the boom there.

An Econometric Study of the Aggregation of Cycles

In a first study of the aggregation of cycles via parametric resonance Weser (1992) employed simulations in order to demonstrate the first and third predictions of the model in the context of the fixed investment and inventory cycles. The analysis was carried forward by Süssmuth (2003) who studied aggregation empirically, both with disaggregated US data, as well as with data on the international aggregation of cycles. The following discussion is based on his work.[18] In particular, I will describe the aggregation of the fixed investment cycle within the US economy and leave out the part that deals with the international aggregation of the inventory cycle.

The foundation of the analysis is the SOA of fixed investment modified to incorporate the parametric resonance effect as defined in Weser (1992). The basic idea is that the investment behavior of the individual firm is affected by the level of aggregate investment. The individual firm tends to invest more when the investment of other firms is high and it will invest less if the investment of other firms is low. This is an instance of what in the modern literature is referred to as 'herding'. There are several explanations that are not mutually exclusive. One is simply mass psychology; Keynes' 'animal spirits'. Another reason is managers' risk aversion. If a manager's decision to invest misfires, he is in a better position if he can say that most managers had acted similarly. Finally, firms are very concerned about market share. A firm may fear to lose market share if it invests less aggressively than others.

The empirical study used annual US data from 1958-1962 on real capital spending for 450 SIC 4-digit industries. This highly disaggregated data set comes as close to the level of individual firms as is possible while still including the set of all manufacturing firms. The objective was to explain the cyclical properties of the aggregate, i.e., of manufacturing fixed investment (MFI).

A first step in the analysis of the disaggregated date was to fit an AR (2) process. In the case of 430 sectors, that yielded periods of 2.5-7.6 years, with a mean of 4 years. The moduli were in the range 0.23-0.96 with a mean of 0.6. The remaining 20 series, mainly in the textile and food industries, were excluded from subsequent computations. Their contribution to the aggregate variance is negligible. The fact that around 96% of manufacturing industries exhibit an endogenous cyclical dynamics contradicts the position of the neoclassical mainstream.

To simplify the computations, 135 series were selected that together explained 82% of the aggregate variance. Using the spectral measure of squared coherency (sc), 110 of the 135 were selected as highly coherent with the aggregate and therefore as being logical candidates for a coherent group exhibiting the resonance phenomenon.

Further, rather complex econometric steps focused on the coherent set led to re-estimates of their dynamic parameters along with a resonance parameter for each group. Monte Carlo simulations were made of the entire complex system in order to evaluate the spectral properties of MFI as implied by the model and to compare this result with the spectrum obtained directly from the data. The basic result is given in Table 5. The

18 A related journal article is *Süssmuth* and *Woitek* (2005).

results are certainly good enough to confirm parametric resonance as a feasible explanatory model for cyclical aggregation.

Table 5:
Cyclical Aggregation in US Manufacturing Fixed Investment

	Model generated	Empirical
Period in years	5.63	4.55
Modulus	0.81	0.75

Source: Süssmuth (2003).

6. Some Notes on the more Recent Literature

I have discussed the that the theory of investment cycles, more generally the idea of an endogenous, cyclical process has almost completely disappeared from modern macroeconomics. I stress the 'almost', since from time to time publications do appear that contain at least some elements related to the older theories. I give here an impressionistic survey of some, mainly of a survey nature. A comprehensive survey of empirical evidence, as well as of older and newer theories of business cycles is given by Zarnovitz (1992).

A Symposium on Business Cycles appeared in the Spring 1999 issue of the Journal of Economic Perspectives. I quote here some relevant passages from the Introduction to the Symposium by De Long (1999):

> "Nearly every long economic expansion in the United States generates intellectual currents claiming that the boom-bust business cycle is over, that there is a 'new economy'." (p. 19).

Much earlier, Haberler (1958) began the preface to his famous review of business cycle theories by stating that "The business cycle has often been declared dead." (p. VII). In relation to the business cycle, economists evidently also have a cyclical pattern of amnesia.

Victor Zarnowitz presents a different approach: the over-investment approach according to which each boom contains within it the seeds of the subsequent recession, and each recession contains within it the seeds of the subsequent boom. Observers of business cycles have long felt that this approach contains profound truth – yet it has never been well-integrated into old Keynesian, new Keynesian, monetarist, or new classical business cycle theories. Just what is it about the structure of capitalist market economies that causes real economic activity to rise and fall in ways that seem to show certain regularities? My assessment at least is that economists will not be able to claim that they understand the business cycle until they have successfully integrated Zarnowitz's approach-which is Wesley C. Mitchell's approach as well-with that of other, currently more popular approaches.

Fuhrer and Schuh (1998) is the proceedings volume of a conference on business cycles held at the Fereal Reserve Bank of Boston. I quote from the Foreword by the Bank's president Cathy E. Minehan:

> "The topic of our forty-second annual economic conference is one of i the most important but perplexing issues in all of economics: What causes business cycles? [...]"

Business cycle theory suggests that unanticipated good or bad 'shocks' occur periodically and create fluctuations around a long-run trend. Monetary and fiscal policy then must act to smooth the fluctuations. But I think most of us can agree that shocks are a less than fully satisfying explanation of the business cycle. What economic behavior lies behind these shocks? What causes consumers to alternate between spending sprees and retrenchment? Why is investment spending so volatile, and what causes businesses to suddenly layoff large numbers of workers at a time, or even close down altogether? Do monetary and fiscal policies contribute to economic fluctuations?

As discussed in Hillinger (1992b), the first formal business cycle models developed at the beginning of the econometric movement were based on the idea of a gestation lag in fixed investment. The idea was resurrected in the well known article by Kydland and Prescott (1982). The same idea was used by Tarjan (1992a) to explain cycles of socialist economies.

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Business Cycle Measurement: A Semantic Identification Approach Using Firm Level Data

Eva Köberl and Christian Müller***

1. Introduction

Economic theory is very often based on concepts of equilibrium. Market solutions are derived from the idea of intersection of demand and supply, markets clear when the right price is quoted. Likewise, individual decisions such as the choice of optimal inputs in terms of quantity and prices can be modelled by equilibrium approaches where a solution obtains given market structure, profit maximisation objectives and certain state variables. A matter of interest thereby is, how this equilibrium looks in practice: What is this equilibrium like? When and how is it achieved? And, how do deviations from this equilibrium which can be interpreted as business cycle fluctuations, look like? These questions are not easy to answer as they depend strongly on the definition of equilibrium.

The literature provides various methods to extract information about business cycle movements. For example, the Hodrick-Prescott-Filter (Hodrick and Prescott, 1997) extracts the difference between trend and cyclical component, which is often interpreted as the business cycle, or the short-lived deviation of actual output from its trend path. There are several other filters such as the Baxter-King-filter (Baxter and King, 1999) available which we may characterise as technical filters. A second branch of business cycle measures uses economic theory and econometrics to calculate deviations of actual output from potential output. For doing so, economic theory needs to provide a way for calculating potential output. A natural choice in this case is a hypothetical production function which is then put to the data, for example. Due to its economic underpinning we may call this class of business cycle measures economic filters.

In our approach, we choose yet another way. We use statements of firms about their capacity utilisation on a quarterly frequency and compare these statements to an implicit desired level of capacities. The structure of the data allows us to derive a typical dynamic pattern of actual and desired capacity utilisation on a firm level. Based on this pattern and on the semantic content of the particular survey question we are able to define

* Corresponding author, ETH Zurich, Swiss Economic Institute, Weinbergstr. 35, 8092 Zurich, Switzerland, koeberl@kof.ethz.ch.

** Zurich University of Applied Sciences.

positive shocks, negative shocks and the equilibrium. Owed to the fact that the basis for our identification is a semantic analysis we call this approach semantic filter.

After having extracted the business cycle measure we will compare it to actual GDP growth. We find that our indicator provides excellent ex-ante forecasts for GDP two quarters ahead.

It might be noteworthy that our identification strategy is relatively simple and could be applied to several other countries. Due to its simplicity and robustness with respect to information updates it might be considered as a basis for comparisons of the stance of the business cycles across countries.

The remainder of the paper is structured as follows. In Section 2 the framework of the business cycle measurement is described, including details on the data and the empirical methodology used. Section 3 presents the results and performance of the constructed indicator and Section 4 concludes.

2. Business Cycle Measurement: Framework

The Data and its Semantic Content

Quite contrary to the usual aggregated analysis we use micro data on the firm level. The data source is the Swiss Economic Institute's (KOF) quarterly business tendency survey in the Swiss manufacturing industry. The data is available from 1999 first quarter to 2007 third quarter and consists of 25,119 observations. There are two questions related to capacity utilisation. First, it is asked whether the technical capacities are currently too high, just right or too low (judgment). Secondly, firms are asked to quantify the capacity utilisation within the past three months in percentage points, where the firms can choose from a range of 50% to 110% in five percentage steps. From the latter we can calculate the percentage change in capacity utilisation from t to $t + 1$ and compare this to the judgment about availability of capacities given by the firm in t.

The answer to the judgment question is interpreted as follows. A 'too low' is equivalent to a desire for expanding capacities, regardless of adjustment costs or flexibility of technical capacities. Hence, this should result in a reduction in capacity utilisation in the future, whether it is achieved through changes in technical capacities or just variations in capacity utilisation by e.g. sales from stock. Likewise, a 'too high' statement implies the wish for increasing capacity utilisation by lowering capacities or production in stocks, for example.

The key to identify shocks in the economy is our ability to match the qualitative answer which tells whether or not firms are in need of more capacity and the change in their actual capacity utilisation. For example, if firms indicate that their technical capacities are too low and we observe that their use of capacity utilisation increases it is safe to say that this particular firm has been hit by a (positive) shock.

Semantic Cross Validation

The above interpretation requires some cross-checking with economics. Therefore, we next examine whether or not the data is consistent with basic considerations about plausible firm behaviour. Borrowing from nonparametric econometrics we label this method semantic cross validation, where economics provides the benchmark for assessing the semantic interpretation. The first analysis will be based on contingency tables suggested by Ivaldi (1992). It is constructed as follows (see Table 1). The rows describe the judgment of the firms in t about their current technical capacity; '+' stands for 'too high', '=' for just right, '–' for too low. In the columns, the possible outcomes in capacity utilisation changes are listed. A '+' means that the level of capacity utilisation has been augmented between t and $t + 1$, a '=' stands for an unchanged level and '–' means a lower level. On the basis of this classification of nine different states of the firms, we are able to identify states that can be associated with either positive or negative shocks. The remaining states will be considered equilibrium situations, or states during which adjustment takes place.

Table 1:
Principle Structure of the Contingency Table

		realisation		
		–	=	+
	–	*mm*	*me*	*mp*
judgment	=	*em*	*ee*	*ep*
	+	*pm*	*pe*	*pp*

When looking at state *pm*, for example, firms positioned in this field consider their capacities in t as 'too high', but from t to $t + 1$ their degree of capacity utilisation still declines. Using the previous arguments we can classify this state as a situation of a negative shock to the particular firm. The argumentation for state *mp* is similar. As capacities in t are stated as 'too low' and the capacity utilisation rises anyway in the next quarter, we can classify *mp* as a state of a positive shock. The equilibrium derived from this observations is the state *ee*, where capacity is 'just right' in t and hence there follows no change in capacity utilisation in $t + 1$.

Following the same logic *mm* and *pp* characterise periods of adjustment towards the desired position, while the interpretation of *me* and *pe* is not that clear cut. Empirically (Müller und Köberl, 2007) it seems that *em* and *ep* are very close to the pure equilibrium situation while *me* and *pe* lean towards secondary positive and negative shock states.

For the sample in our study the repartition of percentage shares to the different states are summarised in Table 2. The table shows a few interesting features. For example, the majority of firms find itself in a situation where capacities are sufficient (*ee*). When firms express a desire for more capacities (judgment '–') they decrease (realisation '–') their capacity utilisation more often than they increase it (2.7 vs. 2.4). Equivalently, when firms report 'too high' capacities, an increase in capacity utilisation follows in the next period with the highest probability. By contrast, shocks to this plausible pattern occur not very frequently (positive shock *mp*: 2.4, negative shock *pm*: 2.8). Müller and Köberl (2007) show that once being hit by a positive shock the typical adjustment path of a firm is *mp* → *mm* → *ep* → *em* → *ep* … . In other words, after a positive shock firms start to adjust capacity utilisation downward (*mm*) before they enter a period of sustained switching between the near equilibrium states.

Table 2:
Empirical Contingency Table

sample 1999-2007		realisation –	realisation =	realisation +
judgment	–	2.7	3.0	2.4
	=	25.4	30.1	25.7
	+	2.8	3.5	4.4

Notes: The table entries report the shares of firms who judge their capacities according to the row labels and likewise experience a change in capacity utilisation as indicated by the column headers.

All in all, we may conclude that the semantic interpretation of the data provided in the previous subsection very well corresponds to what is economically plausible. Therefore, we are confident in continuing regarding *mp* as a measure of a positive and *pm* as a measure of a negative shock respectively.

Construction of the Indicator

In this section we describe the calculation of the business cycle indicator. Let x_t be either of the nine shares described in Table 1. For example, in case of a negative shock, $x_t = pm_t$.

Our business cycle measure is given by

(1) $$bc_t = x_t - \mu_t, \quad \mu_t = \hat{x}_{t+1} \,|\, x_t .$$

For obtaining $\hat{x}_{t+1}$ we use an approximation of the system by a discrete Markov-chain of order one. We make two important assumptions.

ASSUMPTION 1. (Markov chain) Firms at state s_j, $1 \le j \le 9$ in period t will move to state s_k, $1 \le k \le 9$ with a constant probability $p_{j,k}$.

ASSUMPTION 2. (Homogeneity) The firms in our sample are homogeneous with respect to their typical response pattern, that is $p_{j,k}$ does not vary across firms.

We suggest that the move from $s_{j,t}$ to $s_{k,t+1}$, $1 \leq k \leq 9$ is ruled by a 9-dimensional Markov-chain. We thus define the probabilities

(2) $$p_{j,k} = \text{Prob}(s_{k,t+1}|s_{j,t}), \quad j, k \leq 9,$$

(3) $$\sum_{k=1}^{9} p_{j,k} = 1 \quad \forall \quad j = 1,...9 \cdot$$

where j and k denote either of the 9 states defined before. In order to find the adjustment paths of the firms, we estimate the transition probabilities to move from $s_{j,t}$ to $s_{k,t+1}$ each quarter. Multiplying the transition probability matrix by the present (at time t) 9 × 9 matrix of the shares of firms in each of the nine states, we get the hypothetical steady-state of the economy in $t + 1$. This we compare to the actual steady-state in $t + 1$. As we are able to distinguish between positive and negative shocks on a semantic basis, the interpretation of positive and negative values of the business cycle indicator changes. In the empirical analysis we focus on $x_t = em_t$ as it provides the best model fit when estimating quarterly GDP. The state *em* empirically represents a state close to equilibrium (Müller and Köberl, 2007).

3. Application

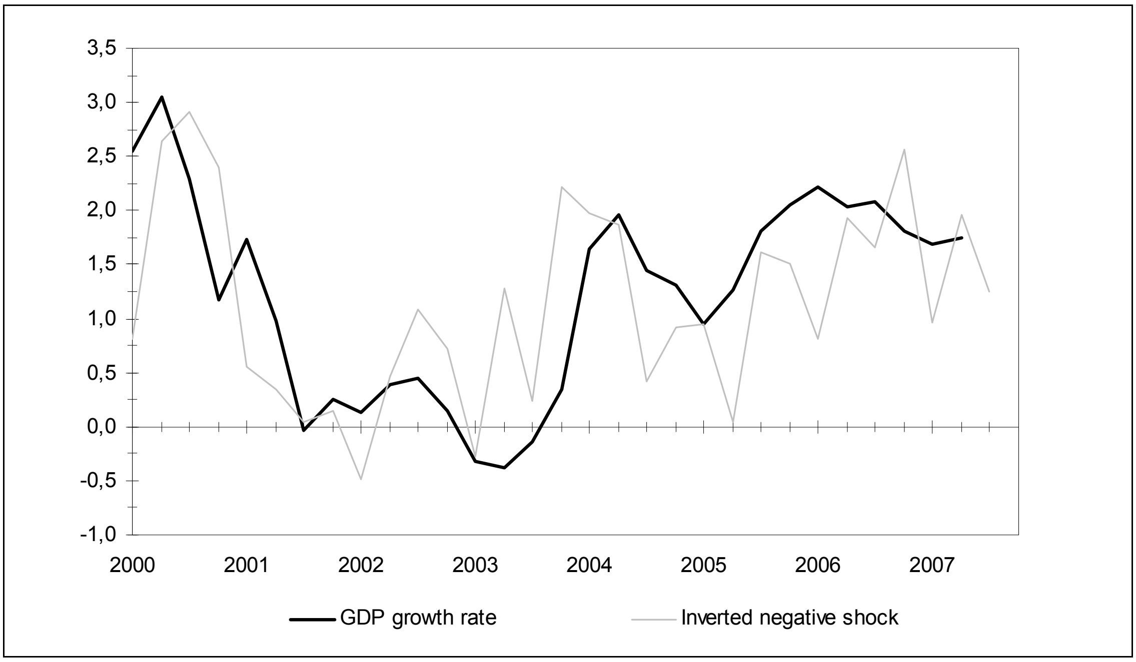
Before turning to the econometric exercise let us have a look the business cycle indicator. Figure 1 displays $bc_t = em_t - \hat{e}m_{t+1}|em_t$, that is the negative shock in the vicinity of the equilibrium state of the economy. The figure is scaled to make the time series comparable. Furthermore, the figure is standardised to the year-on-year growth rate of quarterly real GDP. To make the picture even more accessible, the negative shock has been inverted (multiplied by −1) and then plotted against quarterly real GDP. By simple visual analysis the correlation between the two series appears pretty large. In fact, the contemporaneous correlation between the GDP growth rate and bc_t is −0.60 while the correlation with GDP growth one quarter ahead amounts to −0.50.

Notice that the business cycle indicator is not smoothed or filtered in any way. Therefore, it appears rather spiky in comparison to the filtered GDP growth. Next, we turn to estimation and forecasting GDP growth with the new indicator.

Estimating and Forecasting GDP Growth

One important desirable property of a business cycle indicator is its ability to track and possibly forecast GDP growth. Our proposal has a publication lead of one quarter. It therefore has the potential of being a good nowcasting tool.

Figure 1:
Business Cycle Measure: Inverted Negative Shock to the Economy



For deriving the most appropriate model we use the following strategy. We first specify a general model for quarterly GDP growth as the dependent variable. The list of exogenous and predetermined variables comprises four lags of quarterly GDP, the contemporaneous business cycle measure and three of its lags, three seasonal dummies (*sd*), and a constant. We then let PcGets (see e.g. Hendry and Krolzig, 2004) choose the best model subject to not deleting the constant at any step of the selection procedure. The sample for model selection is 2000 second quarter to 2006 first quarter which admits a valid ex-ante forecasting comparison. The resulting model reads (absolute t-values in parentheses below the coefficient estimates):

$$\Delta y_t = -0.92 em_t^{(3)} - 3.48 sd_{2,t} - 1.68 sd_{3,t} + 1.28 \quad (4)$$

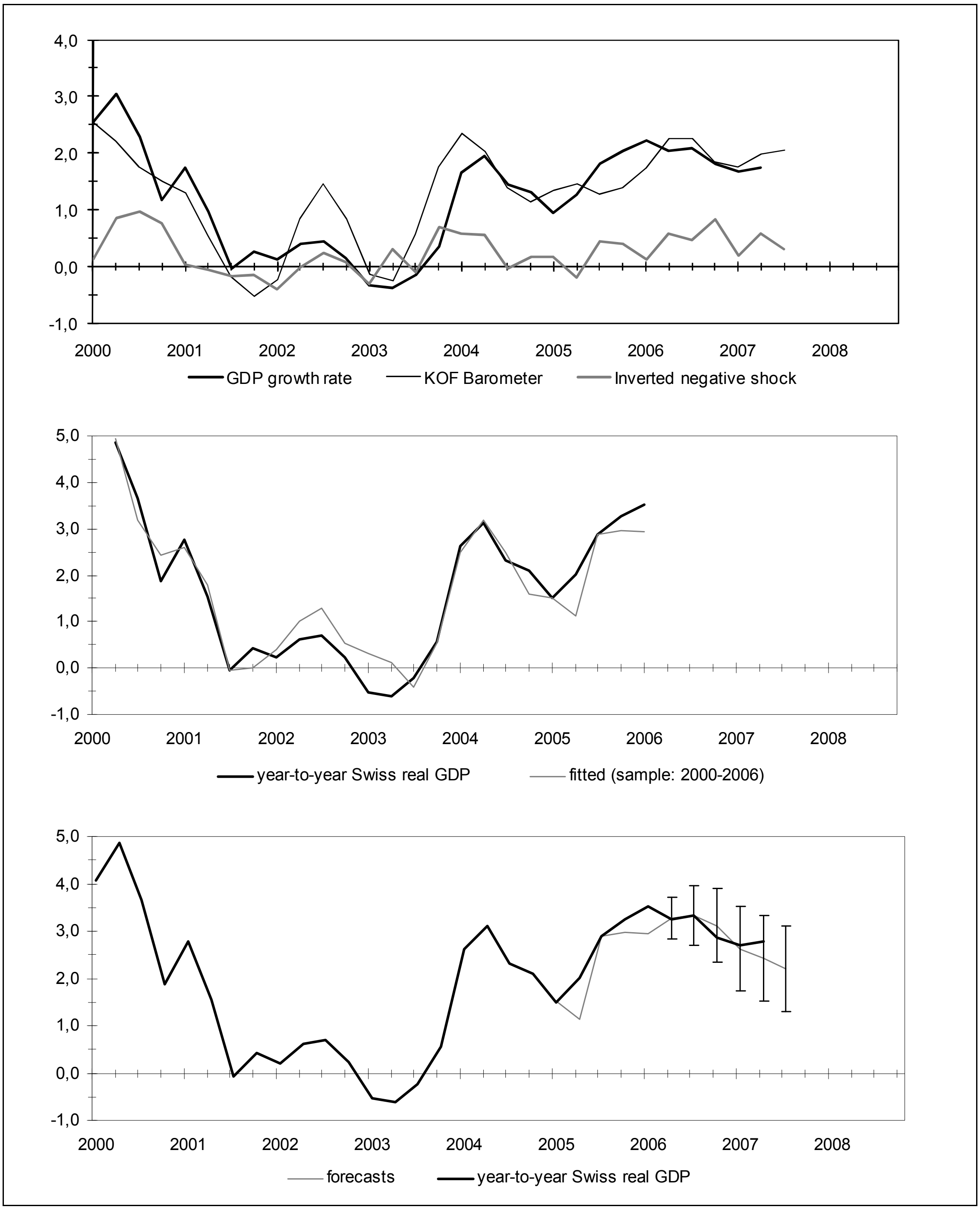
$$\qquad\quad (2.48) \qquad (9.90) \qquad (6.39) \qquad (4.18)$$

$$\hat{\sigma} = 0.521 \qquad \qquad \overline{R}^2 = 0.87 \quad (5)$$

The null hypothesis of no autocorrelation up to order four and normality of the residuals cannot be rejected at any conventional level of significance. Hence, the properties of the estimation are very satisfactory and the business cycle indicator appears statistically significant and has the theoretically correct sign.

To complete the application we use Equation (4) for forecasting. Notice that both model selection and estimation did not include observations after 2006 first quarter. Therefore, we may perform truly ex ante forecasts for the quarters up until 2007 second quarter. The forecast is depicted in Figure 2.

Figure 2:
Business Cycle Indicator and Forecasting: $x_t = em_t$



Quite obviously, the forecasting performance is pretty impressive. Not only are the realised values within the 95% confidence bounds throughout the forecasting period, the absolute deviations are also very small.

Another observation can be made in the top panel of Figure 2 where in addition to quarterly year-to-year growth of real GDP the current official business cycle indicator of KOF is plotted. The correlation between all three series is rather high. The official series requires considerably more resources for calculation though.

The middle panel of the figure displays the fitted values of the regression. Obviously, the fitted line is much smoother than the original business cycle measures. They therefore offer a possibility to report a more conventional business cycle measure. However, our approach to business cycle measurement is based on identifying shocks. It is not clear that smoothness as such is a desirable property for shocks.

To conclude this section, we could show that our business cycle indicator does indeed provide valuable information for gauging GDP growth. It is a useful tool for both nowcasting and short-horizon forecasting.

4. Summary and Conclusion

In this paper we describe the derivation of a business cycle indicator that is based on a semantic identification of shocks hitting the economy. We are able to identify positive and negative shocks. The new business cycle indicator has a publication lead one quarter and can be used for one quarter ahead forecasting real GDP growth. On top of that, our indicator is very easy to compute.

Further research will – among others – be devoted to set the indicator in relation to simultaneous economic decisions by firms such as price setting.

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PART THREE: THE TRANSMISSION OF SHOCKS ACROSS COUNTRIES AND REGIONS

Business Cycle Fluctuations in the US and the Euro Area: Comovement and Shock Transmission

Martin Schneider and Gerhard Fenz***

1. Introduction

It is widely acknowledged that the US is the leading economy in the world. The US-business cycle is typically believed to lead the business cycle in other world regions. Moreover, the role of the US as a locomotive for the world economy should lead to a asymmetric transmission of business cycle shocks from the US to the rest of the world. However, with the emergence of the European Economic and Monetary Union, an economic market evolved with size and economic power similar to the US. This raises the question whether the transmission of shocks is still unidirectional running from the US to the euro area only or if the European business cycle also has a significant influence on the US. Most studies find that the US economy leads the European economies (e.g. Osborn, Pérez and Sensier, 2005) and that the transmission of European shocks to the US economy is not strong. However, there is also evidence that shows some impact of European business cycle fluctuations on the US economy. Pérez, Osborn and Artis (2006) find an increasing impact of EU-15 on the US economy over time. In the recent past about one fifth of output fluctuations in both regions can be attributed to shocks in the other country.

The focus of our paper is on the linkages between the US and the euro area business cycles. We first analyse their comovement by means of static and dynamic correlation measures. By using spectral analysis, we are not only able to describe the synchronization of both economies at business cycle frequencies, but also to determine which business cycle is leading or lagging the other one. The main part of the paper deals with the identification of global and country specific US and euro area shocks. We identify global and country specific shocks simultaneously. This allows us to investigate the transmission of country specific shocks from the US to the euro area as well as from the euro area to the US. Moreover, we identify three different country specific shocks in each of the two country blocks: a supply shock, a demand shock and a monetary policy shock. To this end, we set up a VAR model with the US and the euro area as separate

* Corresponding author, Österreichische Nationalbank, Otto Wagner Platz 3, 1090 Vienna, Austria, martin.schneider@oenb.at. We like to thank Fabio Canova, Sandra Eickmeier, Oliver Holtemöller, Sylvia Kaufmann for fruitful discussions and comments. The views expressed in this paper do not necessarily reflect the official viewpoint of the Oesterreichische Nationalbank.

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regional blocks plus a block with global variables. We identify the global shocks by means of a conventional Cholesky decomposition. The identification scheme for country specific shock is based on the idea of imposing sign restrictions on impulse responses introduced by Faust (1998), Canova and de Nicolo (2003) and Canova (2005).

The paper is organized as follows. In Section 2 the results on the business cycle synchronization between the US and the euro area are presented. In Section 3 we analyse the transmission of business cycle shocks between the US and the euro area. In Section 3, we discuss the two-country VAR model, the identification of shocks, and the empirical results on the shock transmission. Finally, we summarize our findings and draw some conclusions in Section 4.

2. Comovement of US and Euro Area Output

With the European Economic and Monetary Union, a new economic market evolved with size and economic power similar to the leading world economy, the US. Both the US and the euro area have a population of about 300 Million people and a share in world GDP of more than 20%. Both markets can be considered as rather closed economies. The euro area has a higher share of exports in percent of GDP than the US. Around 15% of euro area total exports are going to the US and vice versa. In the course of the catching up of other world regions the bilateral trade shares are declining in relative terms (i.e. in percent of total exports) but – due to globalization – increasing in absolute terms (i.e. bilateral exports in percent of GDP). Consequently, trade remains an important channel for the transmission of shocks between both regions. With the surge in international financial flows and the technological revolution in the information and communication sector, new channels are gaining importance (see Eickmeier, 2007). International financial market linkages are steadily increasing between the US and the euro area. For instance, bilateral shares in the stocks of active and passive foreign direct investment are reaching almost 20% in both regions.

As both regions together account for almost half of world GDP, analysing business cycle linkages between the US and the euro area remains of particular interest. Moreover, the establishment of the euro area and the subsequent convergence of business cycles across member countries trigger questions like whether the European business cycle is now less influenced by economic development in the US or whether the transmission of shocks from the euro area to the US is becoming stronger.

An empirical analysis of business cycle linkages since 1970 shows stable relations between both regions with one episode of apparent disconnection at the beginning of the nineties. During the 70ies both business cycles moved hand in hand driven by substantial global shocks that hit the world economy (oil price shocks). In the 1980s, the business cycles showed a less strong but still high synchronization. At the beginning of the

1990s, the correlation between the US and the European cycle broke down almost completely – a consequence of the 1991 US recession that was mainly caused by domestic factors and, presumably more important, German reunification.

Table 1:
Static and Dynamic Measures of GDP Comovement in the US and the Euro Area

	Static correlation[1]			Dynamic coherency[2]	Dynamic correlation[2]
	Contemp.	Maximum			
1972Q1 - 2006Q3	0.42	0.59	(3)	0.43	0.49
1972Q1 - 1989Q4	0.58	0.68	(2)	0.61	0.64
1990Q1 - 2006Q3	0.29	0.58	(4)	0.29	0.38
1995Q1 - 2006Q3	0.50	0.79	(3)	0.51	0.60
	Delay[2, 3] (quarters)	Granger causality (p-value)[4]			
		US -> EA		EA -> US	
1972Q1 - 2006Q3	−1.65	0.00		0.00	
1972Q1 - 1989Q4	−1.43	0.00		0.04	
1990Q1 - 2006Q3	−1.40	0.00		0.00	
1995Q1 - 2006Q3	−1.71	0.00		0.00	

[1] Numbers in brackets refer to lag (+) / lead (−) (in quarters) of the euro area relative to the US with maximum correlation. – [2] At business cycle frequencies (i.e. 6 to 32 quarters). – [3] −(+): US leads (lags) euro area. – [4] H_0: region 1 does not Granger-cause region 2.

Source: The author's own calculations.

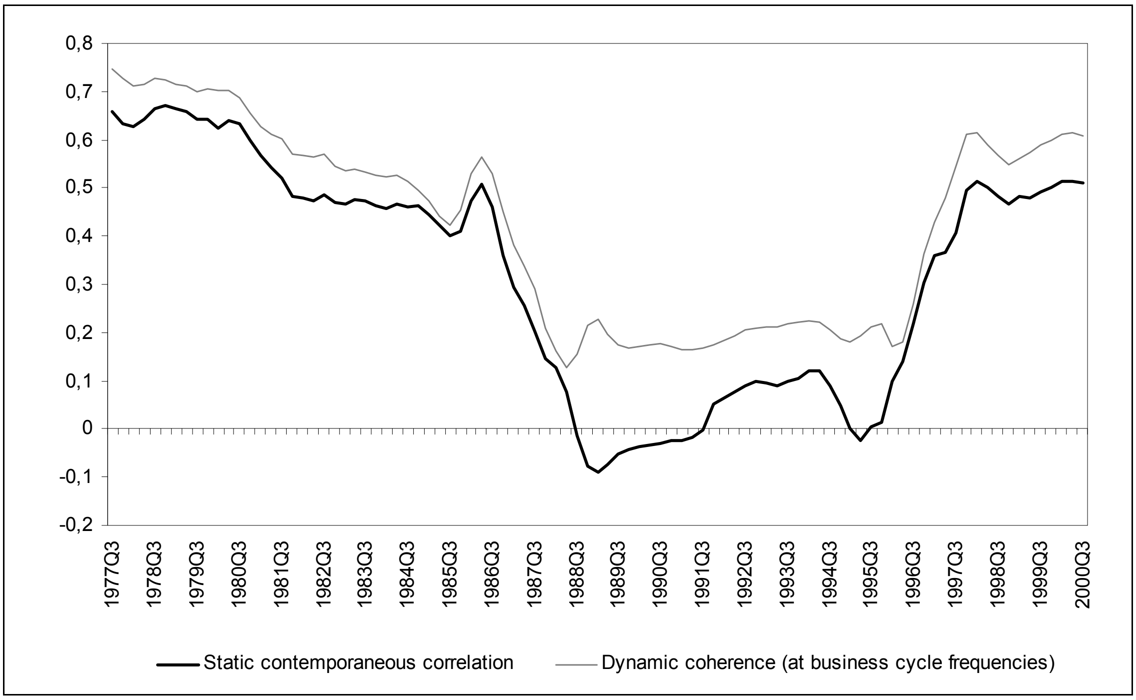
However, the almost simultaneous occurrence of the recession in the US and major European economies in 2001 challenged the belief that business cycles in the US and the euro area became disconnected. Indeed static and dynamic correlation measures indicate that the dynamics in the first half of the nineties were rather an exception than a new trend. Our results in Table 1 and Figure 1 confirm findings by Perez, Osborn and Sensier (2003) and others. Business cycle linkages between the US and the euro area are remarkable stable over time. Static and dynamic correlation measures of HP-filtered GDP for different periods and ten-year-rolling-windows indicate that both economies moved only in the first half of the nineties out of phase while the comovement seems to be stable and strong in all other episodes. Moreover, results for the maximum contemporaneous static correlation and for the delay in the frequency domain show that the US economy is constantly leading the euro area.

Given the leading properties of the US economy it is not surprising that the US economy „Granger causes" the euro area. However and maybe more surprisingly there is also clear evidence for reverse causality.[19]

19 Simple *Granger* causality tests for different lags show that this result holds for the first and third lag but not for the second and fourth lag.

Both bits of information – stable business cycle linkages and reciprocal Granger causality – indicate that analysing the transmission of country specific shocks in both directions from the US to the euro area and from the euro area to the US simultaneously is of particular interest.

Figure 1:
Static Correlation and Dynamic Coherence of GDP Comovement in the US and the Euro Area (10-Years Centred Moving Averages)



Source: The authors' own calculations.

3. Transmission of Business Cycle Shocks between the US and the Euro Area

A Two-Country VAR Model

We analyze the transmission of structural shocks within a two-country VAR model including the US and the euro area. In addition, a block of two global variables controls for international developments. The identification of the structural shocks follows the sign restriction approach suggested by Canova (2005). We simultaneously identify demand, supply and monetary policy shocks for both the US and the euro area.

The VAR model consists of eight endogenous variables. Each regional block includes real GDP as a measure of real activity, the CPI as a measure of inflation, and short-term interest rates (three-month money market rate) as proxy for monetary policy. Additionally, two global variables enter the VAR: real world trade and the HWWI index of raw material prices. These two variables control for international disturbances. All variables (with exception of the interest rates, which are in levels) are in logs and have been detrended using the HP-filter.[20] The model is given by:

$$(1) \qquad \begin{bmatrix} x_t^{GL} \\ x_t^{US} \\ x_t^{EA} \end{bmatrix} = \begin{bmatrix} B_{11}(L) & 0 & 0 \\ B_{21}(L) & B_{22}(L) & B_{23}(L) \\ B_{31}(L) & B_{32}(L) & B_{33}(L) \end{bmatrix} \begin{bmatrix} x_{t-1}^{GL} \\ x_{t-1}^{US} \\ x_{t-1}^{EA} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{GL} \\ \varepsilon_t^{US} \\ \varepsilon_t^{EA} \end{bmatrix}$$

where $(\varepsilon_t^{GL}, \varepsilon_t^{US}, \varepsilon_t^{EA})' \sim (0,\Sigma)$, $\Sigma = blockdiag(\Sigma_{\varepsilon^{GL}}, \Sigma_{\varepsilon^{US}}, \Sigma_{\varepsilon^{EA}})$. x_t^{GL} represents the set of global variables, x_t^{US} the set of US variables and x_t^{EA} the euro area variables. We assume that the global variables (world trade and the HWWI-index) are not influenced by US and by euro area variables. The underlying structural model is given by:

$$(2) \qquad \begin{bmatrix} C_{11} & 0 & 0 \\ C_{12} & C_{22} & C_{12} \\ C_{12} & C_{12} & C_{12} \end{bmatrix} \begin{bmatrix} x_t^{GL} \\ x_t^{US} \\ x_t^{EA} \end{bmatrix} = \begin{bmatrix} G_{11}(L) & 0 & 0 \\ G_{21}(L) & G_{22}(L) & G_{23}(L) \\ G_{31}(L) & G_{32}(L) & G_{33}(L) \end{bmatrix} \begin{bmatrix} x_{t-1}^{GL} \\ x_{t-1}^{US} \\ x_{t-1}^{EA} \end{bmatrix} + \begin{bmatrix} u_t^{GL} \\ u_t^{US} \\ u_t^{EA} \end{bmatrix}$$

where $(u_t^{GL}, u_t^{US}, u_t^{EA})' \sim (0,I)$ and u_t^m is the vector of structural disturbances of region m. The model was estimated with quarterly data ranging from 1983Q3 to 2006Q2. The optimal lag length is one and was selected according to the Schwarz information criterion.

Simultaneous Identification of Structural Shocks

Our approach to identify structural shocks is a straightforward extension of the identification scheme proposed by Faust (1998), Canova and de Nicoló (2003) and Canova (2005). The crucial idea is to identify underlying structural shocks by using sign restrictions on the impulse responses to orthogonalized disturbances. We start by orthogonalizing the variance covariance matrix of the innovations (Σ) by means of a Cholesky decomposition $\Sigma = PP'$. This gives us a vector of orthonormal residuals $\tilde{\varepsilon}_t^m \sim (0,I)$. However, this orthogonalization is by no means unique since for any orthonormal matrix $Q: QQ' = I$, $\Sigma = \tilde{P}\tilde{P}' = PQQ'P'$ is an admissible decomposition. Thus, we can construct a set of admissible decompositions by using different orthonormal matrices Q. Within the class of orthonormal matrices, rotation matrices are a reasonable candidate to

20 The euro area data we use are from the area wide model (AWM) database, the US data from the Bureau of Labor Statistics, world trade figures from the International Financial Statistics (IMF) and the HWWI-index from the Hamburgische WeltWirtschaftsInstitut database. Data reach from 1982Q1 to 2006Q2.

consider. They allow us to cover the whole space of Q matrices in a straightforward way. Rotation matrices use sine and cosine functions to rotate the orthogonalized residuals. In a VAR system with N variables there are $N(N\text{-}1)/2$ bivariate rotation angles. Since we are interested in the identification of structural shocks for the US and the euro area only, we keep the original Cholesky decomposition for the two global variables. We decided to order world trade first thereby assuming that there is a contemporaneous effect of world-trade-innovations to the HWWI index but not vice versa.

The next step is to identify decompositions with a meaningful economic interpretation. We aim to identify three structural shocks – a demand shock, a supply shock and a monetary policy shock for both the US and the euro area. Following Canova (2005), we rotate the orthogonalized disturbances and impose sign restrictions on the impulse responses to structural shocks. According to standard macroeconomic theory, a positive demand shock will generate a positive response of output and a rise in inflation. Monetary authorities will increase interest rates thereby generating a positive co-movement between all three variables. Contrary, a positive supply shock will increase output but decrease prices. In that case, monetary policy faces a trade-off between price stability and the output goal. Hence, theory gives us no clear guidance for the reaction of interest rates. Finally, a positive monetary policy shock is defined by a decrease of the interest rate and increases in output and inflation. These sign restrictions can be derived from a large set of theoretical models. We impose these restrictions on the contemporaneous reaction of the variables only. They are consistent with the standard textbook aggregate-demand aggregate-supply framework as well as with more advanced models like DSGE models in the line of Smets and Wouters (2003). We do not impose any sign restrictions on the spillovers of domestic idiosyncratic shocks on other countries or the global variables. Hence, these variables are free to react to the shocks in the foreign country.[21] We identify the shocks by taking 50,000 draws with a Metropolis-Hastings algorithm.

Responses to Structural Shocks

The forecast error variance decomposition of US and euro area GDP gives us important insights into the driving forces of the business cycle fluctuations (see Table 2). First and foremost, the FEVD for both countries is strikingly similar. In the medium run, domestic shocks account for about 60% of business cycle fluctuations in both the US and the euro area. International shocks explain 25% and spillovers from the other country the remaining 15% of the US (euro area) forecast error variance. These results confirm findings by Canova, Ciccarelli and Ortega (2004) Kose et al. (2003) and Perez, Osborn and

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21 *Paustian* (2007) investigates the conditions, under which the sign restriction approach is able to pin down the correct sign of unrestricted responses. He finds that the number of variables whose impulse responses are restricted, the number of periods for which the restrictions are imposed and the relative variance of the shocks determine the precision, with which the unrestricted responses can be estimated.

Artis (2006), that about 1/3 of GDP fluctuations are explained by global factors. Moreover, Perez, Osborn and Artis (2006) show that in the recent past – similar to our results – about one fifth of output fluctuations in both countries can be attributed to spillovers from the other country. Second, in the short run the euro area seems to respond stronger to foreign shocks (global shocks and spillovers from the US) than the US. Third, the influence of domestic shocks is dominating but declining with the forecast horizon in both countries. Fourth, domestic supply shocks are the most important source of fluctuations in the medium run with a share of about 30%. The only noticeable difference between the US and the euro area concerns the importance of monetary policy shocks. For the US, we find that 11% of the forecast error variance are explained by monetary policy shocks in the medium run. This is consistent with other empirical findings (Christiano, Eichenbaum and Evans, 1999).[22] In the euro area, monetary policy shocks explain 16% of the variance after 20 quarters.

Table 2:
Forecast Error Variance Decomposition for US and Euro Area GDP

	US GDP										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.00	0.00	0.00	0.30	0.35	0.30	0.95	0.03	0.02	0.00	0.05
4 quarters	0.04	0.02	0.06	0.40	0.30	0.18	0.87	0.03	0.01	0.03	0.07
8 quarters	0.09	0.11	0.20	0.34	0.23	0.12	0.70	0.04	0.02	0.04	0.10
12 quarters	0.10	0.15	0.25	0.31	0.20	0.12	0.63	0.07	0.01	0.04	0.12
20 quarters	0.09	0.16	0.25	0.29	0.19	0.11	0.60	0.08	0.03	0.04	0.15
	Euro area GDP										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.06	0.03	0.09	0.05	0.00	0.09	0.14	0.33	0.22	0.22	0.77
4 quarters	0.04	0.05	0.09	0.04	0.01	0.05	0.09	0.43	0.14	0.25	0.82
8 quarters	0.04	0.06	0.10	0.03	0.04	0.05	0.12	0.39	0.17	0.22	0.78
12 quarters	0.04	0.13	0.16	0.05	0.05	0.04	0.13	0.33	0.19	0.18	0.70
20 quarters	0.04	0.20	0.23	0.05	0.04	0.04	0.13	0.30	0.18	0.16	0.63

WT: World trade, HW: HWWA-index, Sup: Supply shock, Dem: Demand shock, Mon: Monetary policy shock.

Source: The authors' own calculations.

Concerning prices (see Table A1 in the appendix), direct spillovers from the US to the euro area and vice versa are small in the short run. While spillovers from the euro area

22 The fact that monetary policy shocks account only for a negligible part of output and inflation fluctuations does not imply that monetary policy itself has no effect. The systematic component of monetary policy may still have a significant effect on output and prices.

to the US remain small in the medium run, spillovers from the US to the euro area become somewhat more important. At a horizon of 20 quarters, US shocks explain 17% of the CPI forecast error variance in the euro area while euro area shocks account for only 6% of US CPI. Global shocks play a very important role in explaining inflation innovations. They contribute between 1/3 and 1/4 to the variance at a horizon of one quarter and around 1/2 in the medium run. This result is in line with evidence from the literature. Ciccarelli and Mojon (2005) find that a common global factor is an important source of variability of inflation in 22 OECD countries. The impact of country-specific factors for inflation computed by Mumtaz and Surico (2007) is also comparable to our results. Any identification scheme that imposes zero restrictions on the contemporaneous impact would therefore lead to misleading results. Finally, monetary policy shocks account for a considerable part of variations in the short term interest rates only in the short run – especially in the euro area. However, this share declines with the forecast horizon to 8% in the US and 16% in the euro area. In the long run, the bulk of interest rate variance in the US is explained by demand shocks (see Evans and Marshall, 1998 for a similar finding), while supply shocks are the dominating factor in the euro area.

4. Summary and Conclusions

This paper analyses business cycle linkages between the US and the euro area. Static and dynamic correlation measures of HP-filtered GDP indicate a stable and strong comovement over the past decades with one notable exception. At the beginning of the nineties both economies moved out of phase triggered by the effects of German reunification. Results for the delay in the frequency domain show that the US economy is constantly leading the euro area, confirming the role of the US as the leading world economy. More surprisingly, we find strong evidence of reciprocal Granger causality indicating that spillovers from the euro area to the US are non-negligible. We analyze the reciprocal transmission of business cycle shocks between both regions within the framework of a two country VAR model. Based on the sign restriction approach proposed by Canova (2005), we simultaneously identify global and country specific shocks and investigate the transmission of country specific shocks in both directions. Our findings show that forecast error variance decompositions of GDP for the euro area and the US have a very similar pattern. In the short run, the variance of output fluctuations is mainly caused by domestic shocks. In the medium run, the influence of global shocks and – albeit to a lesser extent – of spillovers increases. Nevertheless, domestic shocks still explain about 60% of fluctuations. Direct spillovers between both countries remain rather limited and account for not more than 15%, while global shocks account for 25% of the forecast error variance. Thus, we find that after controlling for global shocks, spillovers from euro area specific shocks to the US are of similar size and importance than spillovers from US shocks to the euro area.

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Appendix

Table A1:
Detailed Results for the Forecast Error Variance Decomposition

	US GDP										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.00	0.00	0.00	0.30	0.35	0.30	0.95	0.03	0.02	0.00	0.05
4 quarters	0.04	0.02	0.06	0.40	0.30	0.18	0.87	0.03	0.01	0.03	0.07
8 quarters	0.09	0.11	0.20	0.34	0.23	0.12	0.70	0.04	0.02	0.04	0.10
12 quarters	0.10	0.15	0.25	0.31	0.20	0.12	0.63	0.07	0.01	0.04	0.12
20 quarters	0.09	0.16	0.25	0.29	0.19	0.11	0.60	0.08	0.03	0.04	0.15
	Euro area GDP										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.06	0.03	0.09	0.05	0.00	0.09	0.14	0.33	0.22	0.22	0.77
4 quarters	0.04	0.05	0.09	0.04	0.01	0.05	0.09	0.43	0.14	0.25	0.82
8 quarters	0.04	0.06	0.10	0.03	0.04	0.05	0.12	0.39	0.17	0.22	0.78
12 quarters	0.04	0.13	0.16	0.05	0.05	0.04	0.13	0.33	0.19	0.18	0.70
20 quarters	0.04	0.20	0.23	0.05	0.04	0.04	0.13	0.30	0.18	0.16	0.63
	US Consumer price index										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.08	0.25	0.33	0.35	0.17	0.12	0.63	0.03	0.00	0.00	0.04
4 quarters	0.12	0.42	0.55	0.24	0.13	0.07	0.43	0.02	0.00	0.00	0.02
8 quarters	0.12	0.47	0.59	0.19	0.13	0.05	0.37	0.03	0.01	0.00	0.04
12 quarters	0.12	0.45	0.57	0.19	0.14	0.05	0.38	0.03	0.02	0.00	0.05
20 quarters	0.11	0.45	0.57	0.18	0.14	0.05	0.37	0.03	0.03	0.00	0.06
	Euro area Consumer price index										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.01	0.21	0.23	0.01	0.04	0.00	0.05	0.35	0.33	0.04	0.72
4 quarters	0.02	0.33	0.35	0.04	0.06	0.00	0.09	0.24	0.27	0.04	0.56
8 quarters	0.01	0.45	0.46	0.05	0.07	0.00	0.12	0.16	0.21	0.04	0.42
12 quarters	0.01	0.49	0.50	0.04	0.10	0.00	0.14	0.13	0.18	0.04	0.36
20 quarters	0.01	0.48	0.49	0.04	0.13	0.00	0.17	0.13	0.16	0.04	0.34
	US short term interest rate										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.06	0.06	0.13	0.00	0.52	0.21	0.74	0.06	0.06	0.02	0.14
4 quarters	0.08	0.05	0.13	0.01	0.63	0.17	0.81	0.02	0.03	0.01	0.06
8 quarters	0.09	0.06	0.15	0.03	0.60	0.11	0.73	0.05	0.06	0.01	0.12
12 quarters	0.11	0.11	0.21	0.04	0.51	0.08	0.63	0.10	0.06	0.00	0.16
20 quarters	0.14	0.11	0.25	0.03	0.45	0.08	0.56	0.12	0.06	0.01	0.19
	Euro area short term interest rate										
	Global			US				EA			
	WT	HW	Sum	Sup	Dem	Mon	Sum	Sup	Dem	Mon	Sum
1 quarter	0.08	0.03	0.11	0.00	0.01	0.00	0.01	0.02	0.38	0.47	0.88
4 quarters	0.04	0.05	0.09	0.04	0.01	0.05	0.09	0.43	0.14	0.25	0.82
8 quarters	0.04	0.06	0.10	0.03	0.04	0.05	0.12	0.39	0.17	0.22	0.78
12 quarters	0.04	0.13	0.16	0.05	0.05	0.04	0.13	0.33	0.19	0.18	0.70
20 quarters	0.04	0.20	0.23	0.05	0.04	0.04	0.13	0.30	0.18	0.16	0.63

WT: World trade, HW: HWWA-index, Sup: Supply shock, Dem: Demand shock, Mon: Monetary policy shock.

Source: The author's own calculations.

Table A2:
Cumulated Response of US and Euro Area GDP to Structural Domestic Shocks in Both Countries

	US GDP					
	US			EA		
	Sup	Dem	Mon	Sup	Dem	Mon
1 quarter	−0.24	0.20	0.19	0.06	0.04	0.01
4 quarters	0.67	0.57	0.40	0.16	0.06	0.18
8 quarters	1.06	0.83	0.51	−0.04	−0.07	0.35
12 quarters	1.21	0.92	0.65	−0.32	−0.06	0.42
20 quarters	1.13	0.89	0.79	−0.51	0.21	0.52
	EA GDP					
	US			EA		
	Sup	Dem	Mon	Sup	Dem	Mon
1 quarter	−0.09	−0.02	0.13	0.25	0.21	0.20
4 quarters	−0.22	0.05	0.16	0.85	0.38	0.64
8 quarters	−0.12	0.32	0.02	1.13	0.03	0.85
12 quarters	0.09	0.51	0.00	1.05	−0.32	0.83
20 quarters	0.26	0.43	0.14	0.82	−0.39	0.76

Sup: Supply shock; Dem: Demand shock; Mon: Monetary policy shock

Source: The author’s own calculations

Are the Asian-Pacific Economies Converging?

*Andrew Hughes-Hallett and Christian Richter**

1. Introduction

This paper investigates a popular hypothesis, that the emergence and industrialisation of China as one of the world's largest trading economies, and the increasing sophistication of Japan as a financial and manufacturing centre, has changed the pattern of dependencies and hence spillovers between the economies of the Asia-Pacific area. The US was long regarded the dominant economy in the region, and hence the locomotive or 'economy of first resort' through its consumption of intermediate products, trade in sophisticated manufactures, supply of capital, and financial stability where there were fixed exchange rates.

But the rise of China as a major trader in cheaper manufactures and intermediates, and Japan as a provider of sophisticated manufactures and source of finance (particularly after the 1987 stockmarket crash and the Asia crisis) may have changed all that. These two economies may have become just as important as trading partners and locomotive economies for the other Asian economies; and may now have significant spillovers on the US too. Moreover their rapidly expanding foreign asset stocks, acquired through large and continuing trade imbalances in the region, gives them a certain influence over monetary conditions (even if exchange rates have become a little more flexible). In that case the pattern of spillovers may have changed, perhaps to the point that they have become locomotives for the region, while the US is now playing a supporting, stabilising or beggar-thy-neighbour role.

The changes we test directly for in this paper are whether enhanced trade and financial integration effects have led to an increased convergence (coherence, correlation) between the Asian economies. We focus on the coherence; and then ask, to what extent are growth cycles becoming more correlated in the Asia-Pacific region? Is there evidence of cyclical convergence at business cycle frequencies (the focus for policy purposes), or at any other frequencies? Does this imply a common business cycle? Cyclical convergence is an essential condition for the continued success of fixed exchange rates and their implied reliance on foreign monetary conditions. As this paper focuses on coherences in a

* Corresponding author, Kingston University, Faculty of Arts and Social Sciences, Penrhyn Road, Kingston upon Thames, Surrey KT1 2EE, United Kingdom. We gratefully acknowledge financial support from the Leverhulme Trust. We are grateful for very helpful comments by Jarko Fidrmuc.

related paper we investigate the spillover effects in Asia (Hughes-Hallett and Richter, 2008).

At present a selective reading of the literature on cyclical convergence in other contexts (jurisdictions) could lead to almost any conclusion, and to find a way to measure the extent and characteristics of the linkages/dependencies between economies is not easy. In this paper we show how spectral analysis can be used to answer such questions, even where data samples are small and where structural breaks and changing structures are an important part of the story. We need a spectral approach to determine the degree of convergence at different frequencies and cycles. The inconclusive results obtained in the past, particularly in the Euro area, may have been the result of using a correlation analysis which averages the degree of convergence across all frequencies and imposes a symmetric degree of dependence between the cycles. That is problematic because two economies may share a trend or short term shocks, but show no coherence between their business cycles for example. Or they may have an asymmetric relationship in which one leads the other because of size, trade links or capital ownership (economy of first resort); or because of their industrial structure as suppliers or consumers of each others products (Chaplygin et al., 2006), or because of an influence over monetary conditions and finance (Hughes-Hallett and Richter 2008).

The existing studies in this literature make it very clear that previous results have been 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 difficulty highlighted in particular by 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 selection of a smoothing parameter, such as in the HP algorithm and equivalent to an arbitrary band-pass selection (Artis et al. 2004).
iv) We use a coherence measure which generalises the conventional correlation and concordance measures.

However, any spectral approach is tied to a model based on a weighted sum of sine and cosine functions. 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 non-differentiable functions, 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, 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 commented 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). Once again, a time-varying spectral approach, which separates out changes at different cyclical frequencies in the economy, is going to be needed to provide the flexibility to capture these features. Similarly it will be needed if we are to be able to accommodate the structural breaks which must be expected with China emerging as one of the world's largest trading economies; and with the increasing sophistication of the Japanese economy, with increasing financial integration and investment flows, changes to the size and composition of trade imbalances, changes to the supply chain of components/inputs to China or Japan, and the strengthening of monetary institutions.

2. Time Frequency Analysis: An Outline

Time Varying Spectra

Spectral analysis decomposes the variance of a sample of time series data across different frequencies. The power spectrum itself shows the relative importance of the different cyclical components in creating movements in that data, and hence describes the cyclical properties of a particular time series. It is assumed that the fluctuations of the underlying data are produced by a large number of elementary cycles of different frequencies which combine together to produce the overall, directly observed cycle. Furthermore, it is usually assumed that the contribution of each component cycle is constant throughout the sample.

However, as Chauvet and Potter (2001) show for the US, business cycles cannot be assumed to be constant over time. Hence the spectrum would not be constant over time due to the changing weights associated with each of the elementary cycles. A 'traditional' frequency analysis cannot handle that case. But in recent years a time frequency approach has been developed which can do so. It depends on using a Wigner-Ville distribution for the weights (see for example Matz and Hlawatsch 2003). In this paper we use a special case of the Wigner-Ville distribution, namely the 'short time Fourier transform' (STFT). The STFT catches structural changes (here interpreted as changes of the underlying lag structure in accordance with Wells 1996), but assumes local stationarity. We employ the STFT for two reasons: first, the time series we analyse are already in log-differenced form (see Equation (1) below) so stationarity may be assumed. Moreover, standard unit root tests performed on our data (specifically ADF and the Phillips-Perron tests, available on request) confirm that assumption. Finally, the available results on similar data (Campbell and Mankiw 1987, Clark 1987, Todd 2003, Watson 1986) also confirm that conclusion. Secondly, if the time series is stationary, then the STFT and the Wigner-Ville distribution coincide (Boashash 2003).

All the data collected for this paper are real GDP from the OECD main indicators. We use seasonally adjusted quarterly data from 1980:1 to 2005:1. Growth rates are then defined, using GDP data, as follows:

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

Next we employ a two step procedure. As Evans and Karras (1996) point out, if business cycles are to converge, they have 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 of each of the growth rates separately. Then we estimate the bilateral links between the cycles in those growth rates. In order to allow for the possible changes in the parameters, we employ a time-varying model by applying a Kalman filter to the chosen AR(p) model as follows:

(2) $$y_t = \alpha_{0,t} + \sum_{i=1}^{9} \alpha_{i,t} y_{t-i} + \varepsilon_t$$

with

(3) $\alpha_{\mathrm{i,t}} = \alpha_{i,t-1} + \eta_{i,t},$ for $i = 0,\ldots,9$

and ε_t, η_t ~ i.i.d. $(0, \sigma^2_{\varepsilon,\eta_i})$ for $i = 0,\ldots,9$.

In order to run the Kalman filter we need initial parameter values. The initial parameter values are obtained by OLS using the entire sample (see also Wells 1996).[23] Given these start values, we then estimate the parameter values in (2) using the Kalman filter. To do this we employ a general to specific approach, eliminating insignificant lags using the strategy specified below. 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 the set of diagnostic tests shown in the tables that follow, to confirm the specification found. The final parameter values are therefore filtered estimates, independent of their start values.

Using the above procedure 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 but not others; or it might never be significant. The parameter changes are at the heart of this paper as they imply a change of the lag structure and a change in the spec-

23 Obviously, using the entire sample implies that we neglect possible structural breaks. The initial estimates may be biased therefore. The Kalman filter will then correct for this since, as *Wells* (1996) points out, the Kalman filter will converge to the true parameter value independently of the initial value. But choosing initial values which are 'close' to the true value accelerates convergence. Hence we employ an OLS estimate to start. But our start values have no effect on the parameter estimates by the time we get to 1990. Our results are robust.

tral 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 was estimated again. If the AIC criterion was less than before, then that lag was completely excluded. 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 minimises the AIC criterion, and leads to a parsimonious specification. Finally, we tested the residuals in each regression for auto-correlation and heteroscedasticity.

The specification, (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) 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, the LaMotte and McWorther (1978) test, is designed 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). We chose the fluctuations test for detecting structural breaks because the Kalman filter allows structural breaks at any point and this fluctuations test is able to accommodate this.[24] Thus, and in contrast to other tests, the fluctuations test is not restricted to any pre-specified number of breaks.[25]

Once this regression is done, it gives us a time-varying AR(p) model. From this AR(p) we can calculate the short-time Fourier transform (STFT), as proposed by Gabor (1946), in order to calculate the time-varying spectrum.

Calculating Single Spectra. Boashash and Reilly (1992) and Boashash (2003) show that the STFT can always be expressed as a time-varying discrete fast-Fourier transform calculated for each point in time. This transforms the time series signal into the frequency domain at each point. It also has the convenient property that the 'traditional' formulae for the coherence and the gain are still valid, but have to be recalculated at each point in time. The time-varying spectrum of the growth rate series can therefore be calculated as (see also Lin 1997):

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24 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 transformations are nonlinear and may involve complex arithmetic). Stability tests are important here because our spectra could be sensitive to changes in the underlying parameters. But with the stability and specification tests conducted, we know there is no reason to switch to another model that fails to pass those tests.

25 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 parameter value differs significantly from the reference value and vice versa.

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

where ω is angular frequency and j is a complex number ($j^2 = -1$). Hence the advantage of this method is that, at any point in time, a power spectrum can be calculated instantaneously from the updated parameters of the model.

Time Varying Cross-Sprectra

Moving to the next step, we can now estimate the relationships between two variables. By transferring the time domain results into the frequency domain, we can show how the relationship between two economies has changed in terms of individual frequencies. That is, we are able to investigate whether any convergence took place over time; and, if so, at which frequencies. As a measure of that relationship, we use the coherence.

Suppose we are interested in the relationship between two variables, $\{y_t\}$ and $\{x_t\}$ say, where $\{y_t\}$ might be the Japanese growth rate and $\{x_t\}$ the US growth rate. We assume that they are related in the following way:

(5) $$V(\mathrm{L})_t y_t = A(\mathrm{L})_t x_t + u_t,\ u_t \sim (0,\sigma^2)$$

where A(L) and V(L) are filters, and L is the lag operator such that $\mathrm{L}y_t = y_{t-1}$. Notice that the lag structures, A(L) and V(L), are time-varying. We use the same specification as (3):

(6)
$$\upsilon_{i,t} = \upsilon_{i,t-1} + \varepsilon_{i,t}, \quad \text{for} \quad i = 1, \ldots, p \quad \text{and} \quad \varepsilon_{i,t} \sim (0, \sigma^2_{\varepsilon_i})$$
$$a_{i,t} = a_{i,t-1} + \eta_{i,t}, \quad \text{for} \quad i = 1, \ldots, p \quad \text{and} \quad \eta_{i,t} \sim (0, \sigma^2_{h_i})$$

As before, we tested 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 again use our general to specific approach to Estimate (6); starting off with lag lengths of nine and $p = q$, and dropping those lags which were never significant (as before).[26]

Having estimated the coefficients in (6), we can calculate the gain, coherence and cross spectra based on the time-varying spectra just obtained. That allows us to overcome a major difficulty in this kind of analysis: namely that a very large number of observations would usually be necessary to carry out the necessary frequency analysis by direct estimation. This may be a particular problem in the case of structural breaks, since the subsamples would typically be too small to allow the associated spectra to be estimated directly.

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26 The symmetry in the lag structure, and our general to specific testing strategy, means that we can allow the data to determine the direction of causality in these regressions.

Calculating Cross-Spectra. Following Hughes-Hallett and Richter (2002, 2003a, 2003b, 2004), we use the fact that the time-varying cross spectrum, $f_{YX}(\omega)_t$, using the STFT is given by

(7) $$f_{YX}(\omega)_t = T(\omega)_t f_{XX}(\omega)_t$$

where $T(\omega)$ is the transfer function which is calculated using the short time Fourier transform of the weights $\left\{a_j\right\}_{j=-\infty}^{\infty}$. As noted above, the traditional formulae can be used to do this at each point in time. The last term in (7), $f_{XX}(\omega)_t$, is the spectrum of the predetermined variable. That spectrum may be time varying as well. Next, we calculate the time-varying gain as:

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

for $b = 0, \ldots, q$ and $i = 1, \ldots, p$

The last term in (7), $f_{XX}(\omega)_t$, is the spectrum of predetermined variable. This spectrum may be time varying as well.

However, in this paper we are interested in the coherence and in the decomposition of the changes to that coherence over time. So we need to establish expressions for the coherence and gain between X_t and Y_t. The spectrum of any dependent variable is defined as (Jenkins and Watts 1968, Wolters 1980):

(9) $$f_{YY}(\omega)_t = \left|T(\omega)\right|^2 f_{XX}(\omega)_t + f_{vv}(\omega)_t$$

From (5) we get the time varying residual spectrum

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

and the gain as $|A(\omega)_t| = |T(\omega)_t|^2$. Given knowledge of $f_{YY}(\omega)_t$, $|T(\omega)_t|^2$, and $f_{XX}(\omega)_t$, we can now calculate the coherence as

(11) $$K_{YX,t}^2 = \frac{1}{\left\{1 + f_{vv}(\omega)_t \middle/ \left(\left|T(\omega)\right|^2 f_{xx}(\omega)_t\right)\right\}}$$

The coherence is equivalent to the R^2 of the time domain. The coherence measures, for each frequency, the degree of fit between X and Y or the R^2 between each of the corresponding cyclical components in X and Y. Hence, the coherence measures the link between two variables at time *t*. For example, if the coherence has a value of 0.6 at frequency 1.2, then this means that country *X*'s business cycle at a frequency of 1.2 determines country *Y*'s business cycle at this point in time by 60%. In this paper, we are concerned only with the coherence, not the gain or phase shift elements.

Last, but not least, a note on the figures shown in the following two sections. We first present the time-varying spectra and then the coherences. One can see from these figures that the spectra change. However, one cannot infer directly from those figures that the changes in the spectra are also statistically significant. The figures for the time-varying spectra have to be accompanied by the fluctuation test results. Once a structural break has been identified by the fluctuations test, the results of that change will show up as significant in the corresponding spectrum or cross-spectrum.

3. Single Spectra

In this section and the next, we study the spectra and cross-spectra of output growth in selected Asian economies compared to the US, or compared to China or Japan, over the past 20 years. We take the US, China and Japan to be the potential leading economies ('economies of first resort') in the Asia-Pacific area, and analyse the changing relations between them; and between them and the other emerging economies of the region (Korea, Taiwan, Malaysia, Hong Kong and Singapore) since the Asian financial crisis in 1996-1997. Similar results for the US and the UK, and for the Eurozone, can be found in Hughes-Hallett and Richter (2006) and used as a benchmark for these comparisons. We use quarterly, seasonally adjusted data for real GDP in all eight economies, log differenced to obtain growth rates. The resulting series were then fitted to an AR(*p*) model as described above, and tested for stationarity, statistical significance, and a battery of other diagnostic and specification checks. Our data start in 1987Q4 or earlier, and finish in 2006Q3 in each case.

According to Evans and Karras (1996) a necessary condition for convergence is that countries follow the same data generating process. Hence, the first step in our analysis is to compare the business cycle characteristic of the individual countries. We ordered countries according to their similarities. So the next section investigates the Japanese bloc (including its major trading partner, the US); and the second section discusses the Chinese bloc.

The Japan Bloc

Figure 1 shows the spectrum of the US growth rate. This spectrum is based on an AR(9) process (see Table 1). The table shows the final regression with all parameters significant.

Figure 1:
Spectrum of the US Growth Rate

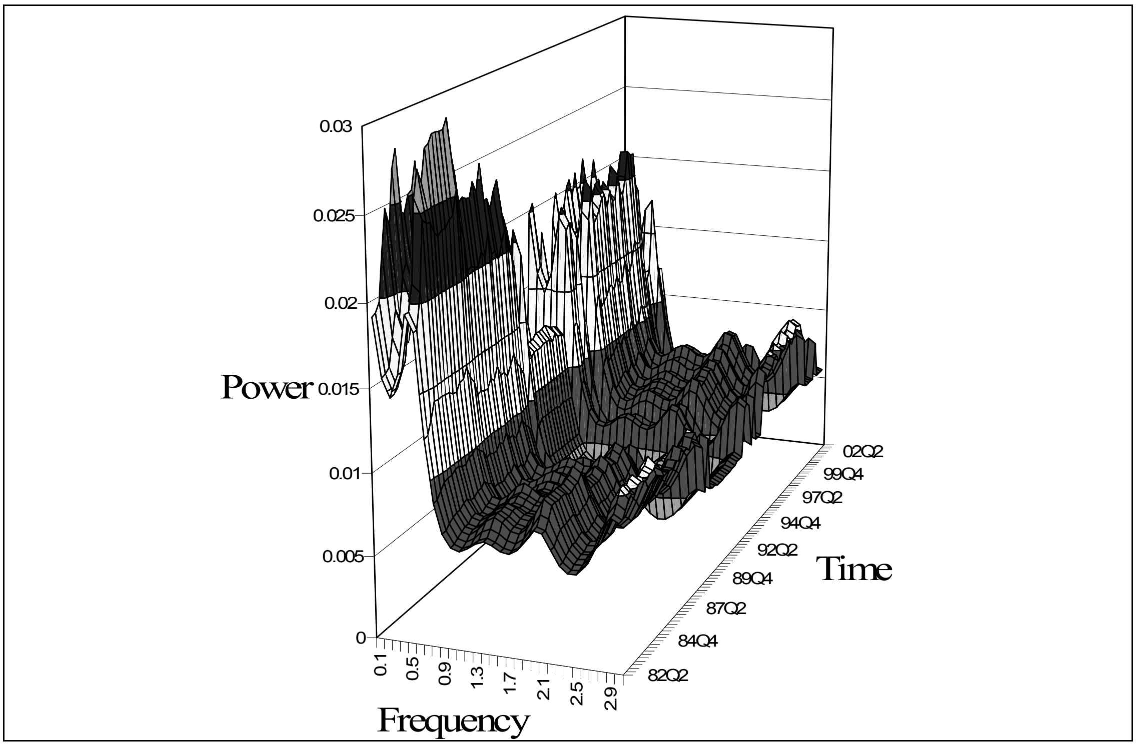

Table 1:
Regression Results of the US Growth Rate

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

The spectrum shows that the US business cycle used to be dominated by a long cycle at a frequency of 0.5, which is equivalent to a 12 quarter cycle. However, the dominance of that cycle is decreasing over time. Clearly visible also is the financial problems of the early 1990s which led to increased uncertainty reflected here in the break down of the long cycle.

Figure 2:
Spectrum of the Japanese Growth Rate

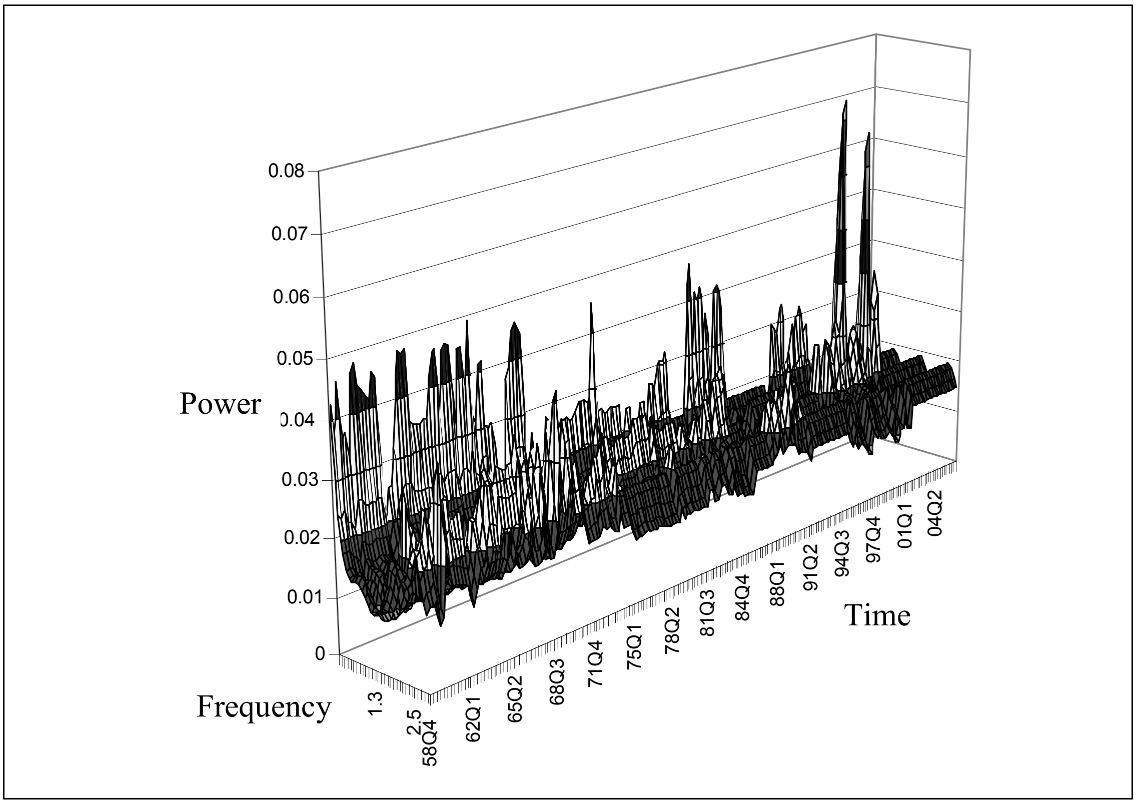

Table 2:
Regression Results of the Japanese Growth Rate

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	0.0134
R^2	0.6110	Standard Error of Estimate	0.0162
Mean of Dependent Variable	0.0113	Sum of Squared Residuals	0.0288
Akaike (AIC) Criterion	0.0175	Ljung-Box Test: Q*(24)	28.6232
Variable	Coeff	Std Error	t-Stat
Constant	0.0023	0.0003	7.8921
DLJPGDP{2}	−0.1911	0.2439	−0.7835
DLJPGDP{3}	0.0655	0.1310	0.4999
DLJPGDP{7}	0.1579	0.0269	5.8707

Figure 2 shows the Japanese spectrum. The Japanese spectrum is based on an AR(7) model (see Table 2). Like in the US the dominant cycle is the long cycle. But the spectrum is more volatile than the US. But like the US the dominance of the long cycle is decreasing. Towards the end of the sample two new cycles emerge: at a frequency of 1.3 or 4.8 quarters and at a frequency of 2.5 or 2.5 quarters. The financial crisis in Japan has clearly contributed to the decline of the long cycle and the appearance of shorter cycles. Yet, the long cycle did not completely disappear. And noise is not as important as in the US. So there are similarities between the US spectrum and its changes, although, the Japanese spectrum is more volatile than the US spectrum. Thus, despite the similarity between the two countries, there is diversity in terms of volatility. So similarity and diversity go hand in hand. This is a new result. Finally, the similarity of the two spectra suggests that there must be a close link between the two countries, which will be confirmed when we look at the coherence between the two national cycles.

Figure 3 shows the Korean spectrum. The Korean spectrum is based on an AR(3) model (see Table 3). The Korean spectrum appears to be stable apart from an interruption in the early 90s.

The Korean spectrum is characterized by a cycle at a frequency of 0.8 or 7.8 quarters. However, that cycle collapsed during the early 90s when a temporary cycle at a frequency of 1.9 or 3.3 quarters appeared. That cycle disappeared again at the end of the nineties, only to reappear at the end of the sample. Comparing this spectrum with Japan and the US it is clear that Korea is characterized by a long cycle, but is generally less volatile than in Japan. Moreover, noise has a bigger impact on the business cycle, much like the US. And like in Japan, there is a new business cycle emerging at the end of the sample. So there seems to be a common development between Japan and Korea at the end of the sample, and similar behaviour during the rest of the sample.

Figure 4 shows the Malaysian spectrum. The Malaysian spectrum is based on an AR(5) model. The Malaysian spectrum appears to be fairly stable over the sample period. It is basically characterized by a cycle at a frequency of 1.3 or 4.8 quarters. Interestingly, the long cycle is not as important in Malaysia as it was in the US, Japan or Korea. The medium cycle is always dominant, although its weight has been decreasing since the mid 90s. The business cycle is also affected by noise like in the US and Korea. However the financial crisis of the 90s has a different effect on Korea and Malaysia, than on Japan and the US. It increases uncertainty in all countries. But while uncertainty increases the weight of the shorter cycles in Korea, in Malaysia the weight of the long cycle deceases (whilst the weight of the short cycle is constant), increasing the relative weight of the short cycle. Hence, the financial crisis was not as severe in Malaysia as in Korea or China. We get same result for Singapore. The Singapore spectrum is displayed in Figure 5, and is based on an AR(7) model (Table 5). Like the Malaysian spectrum, Singapore is fairly stable over the sample period. It is characterized by a long cycle at a frequency of 0.7 or 8.9 quarters and a medium cycle at frequency 1.3 or 4.8 quarters. A short cycle is

Figure 3:
Spectrum of the Korean Growth Rate

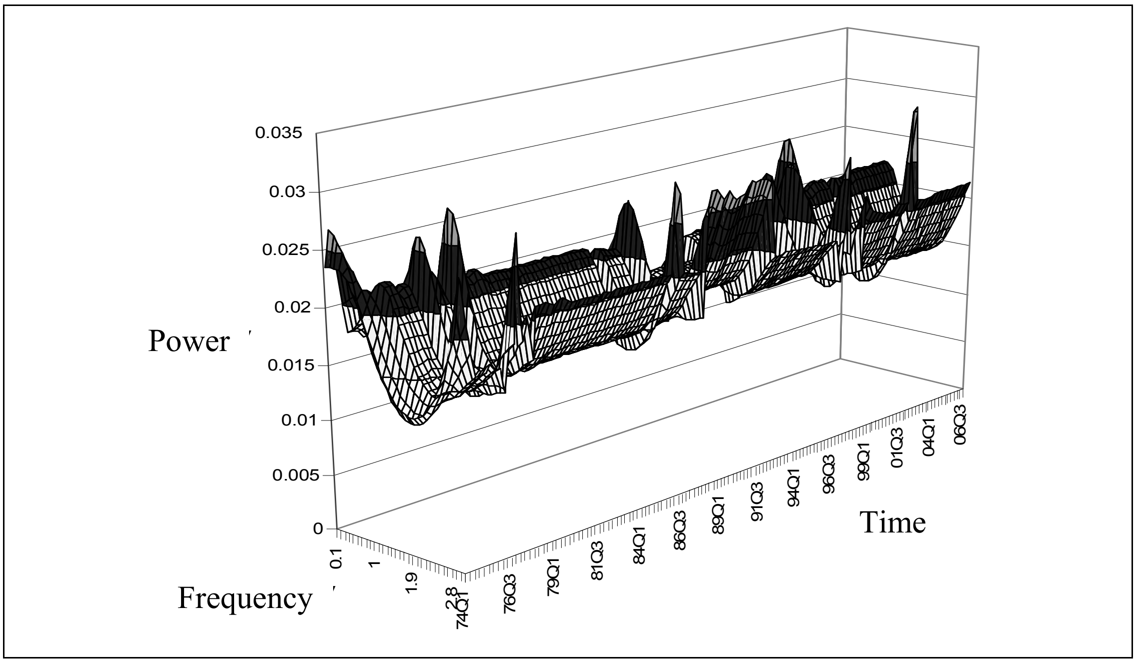

Table 3:
Regression Results of the Korean Growth Rate

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLKORGDP	Quarterly Data From	1972:01 To 2006:03
Usable Observations	139	Std Error of Dependent Variable	0.0154
R^2	0.7169	Standard Error of Estimate	0.0172
Mean of Dependent Variable	0.0166	Sum of Squared Residuals	0.0397
Akaike (AIC) Criterion	0.0182	Ljung-Box Test: Q*(24)	23.8878
Variable	Coeff	Std Error	t-Stat
Constant	0.0147	0.0115	1.2733
DLKORGDP{1}	0.0146	0.1362	0.1073
DLKORGDP{2}	−0.0484	0.1471	−0.3291
DLKORGDP{3}	−0.2260	0.0352	6.4235

also present, stronger than the medium cycle, at a frequency of 2.5 or 2.5 quarters. Interestingly, towards the end of the sample the long run cycle gains weight; and it does not lose any significant weight during the financial crisis in the 90s. By contrast, the medium cycle does lose some weight towards the end of the sample while the short term cycle gains some weight. Hence Singapore shares medium cycle behaviour with Japan and Malaysia; and short run cycle behaviour with Korea; and stability over the financial crisis period with Malaysia.

Figure 4:
Spectrum of the Malaysian Growth Rate

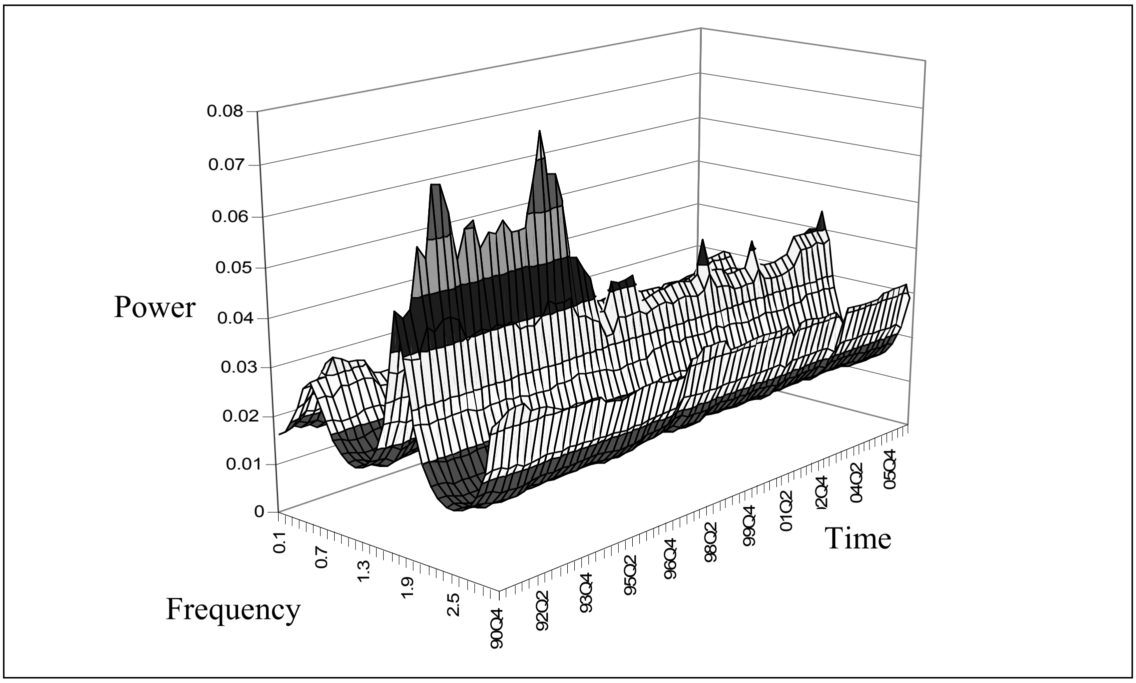

Table 4:
Regression Results of the Malaysian Growth Rate

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLMAGDP	Quarterly Data From	1989:03 To 2006:03
Usable Observations	69	Std Error of Dependent Variable	0.0184
R^2	0.7459	Standard Error of Estimate	0.0210
Mean of Dependent Variable	0.0153	Sum of Squared Residuals	0.0286
Akaike (AIC) Criterion	0.0265	Ljung-Box Test: Q*(16)	14.7848
Variable	Coeff	Std Error	t-Stat
Constant	0.0094	0.0120	0.7842
DLMAGDP{2}	−0.0874	0.0460	−1.9016
DLMAGDP{4}	0.1486	0.0369	4.0269
DLMAGDP{5}	−0.3865	0.0505	−7.6561

Figure 5:
Spectrum of the Singapore Growth Rate

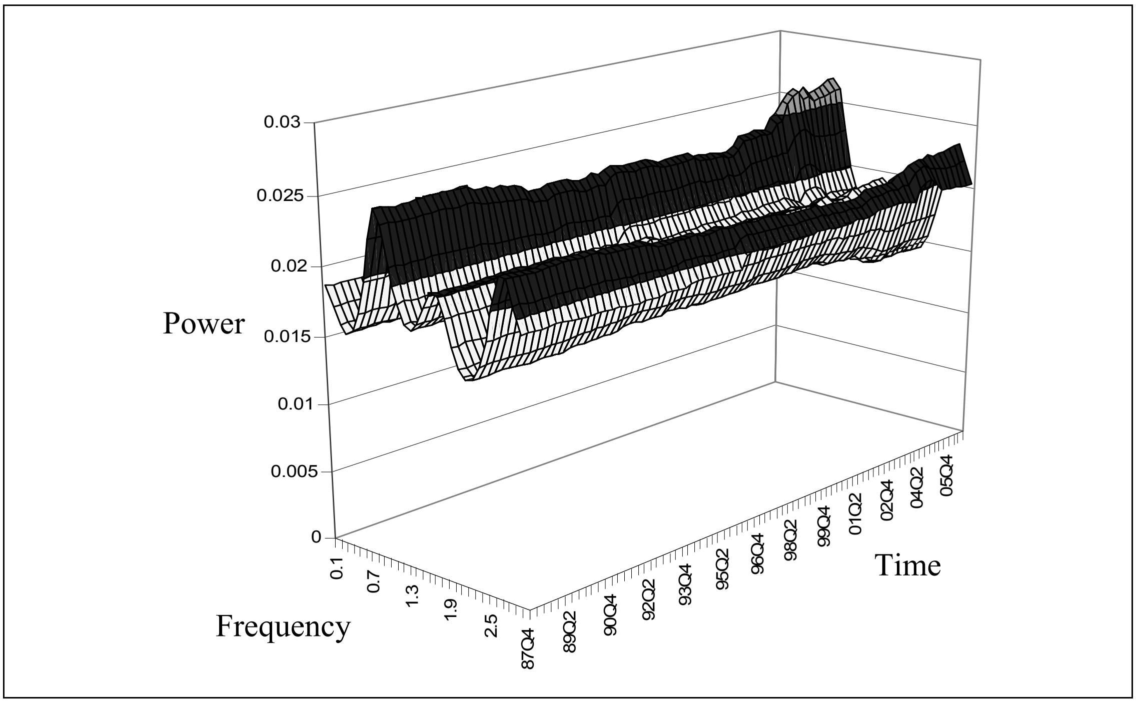

Table 5:
Regression Results of the Singapore Growth Rate

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLSINGDP	Quarterly Data From	1986:03 To 2006:03
Usable Observations	81	Std Error of Dependent Variable	0.0171
R^2	0.6495	Standard Error of Estimate	0.0186
Mean of Dependent Variable	0.0168	Sum of Squared Residuals	0.0271
Akaike (AIC) Criterion	0.0216	Ljung-Box Test: Q*(18)	22.4491
Variable	Coeff	Std Error	t-Stat
Constant	0.0103	0.0094	1.0944
DLSINGDP{3}	−0.1810	0.0287	−6.3147
DLSINGDP{7}	0.1450	0.0258	5.6189

The China Bloc

The Chinese spectrum is shown in Figure 6. This spectrum is based on an AR(4) process. One striking feature is that the spectrum is very stable until 2004. The main cycle is medium term at a frequency of 1.4 or 4.5 quarters. However, the long run cycle and short term noise matter at the end of the sample.

The main cycle of 4.5 quarters is a feature shared with Malaysia, Japan and to a smaller extent with the US. However, the striking feature is that this cycle is the main cycle whilst in those other countries, it is not. In those other economies, other cycles dominate, and to a greater extent than in China, which is why we have tentatively grouped those countries into a separate bloc. The coherence analysis to follow will give a clearer picture of that distinction and lead to some revisions to our classification.

If we compare the spectrum of China with that of Taiwan, one can immediately recognize the similarity and why China forms a separate bloc from the Japanese bloc. Figure 7 shows the Taiwanese spectrum, which is based on an AR(8) model (see Table 7). Although that specific-ation differs from the Chinese case, the spectra themselves are very similar. The main cycle is at a frequency of 1.5 or 4.2 cycles. So the Taiwanese business cycle may be slightly shorter, but it has less power and the long cycle matters to the same degree as in China.

However, there are some smaller differences: there is another cycle at a frequency of 0.8 or 7.8 quarters. In the year 2000, the weight of that cycle is increasing, but it remains far less strong than the main cycle at 4.2 cycles and its importance decreases towards the end of the sample. Moreover, Figure 7 reveals that the structural break appears at about the same time as in China (2004), but takes longer to return to the weight that it had prior to the shock.

Last but not least, we have another economy in the Chinese bloc, namely Hong Kong. The spectrum for Hong Kong looks much more volatile than the Chinese and Taiwanese spectrum (Figure 8). Yet Hong Kong's main business cycle is at a frequency of 1.3 or 4.8 quarters, which is almost the same as for China and Taiwan. The other important features are the long cycle and short term noise. The Hong Kong spectrum is based on an AR(7) model: Table 8.

However, in contrast to China and Taiwan, the importance of the medium cycle has been decreasing over time. At the end of the sample, the weight of the medium cycle is no greater than the weight on the other two cycles. Moreover, in 1999 another cycle appeared namely at a frequency of 1.9 or 3.3 quarters. Interestingly, from the beginning of the appearance of this cycle it is as important as the one at 4.8 quarters.

Figure 6:
Spectrum of the Chinese Growth Rate

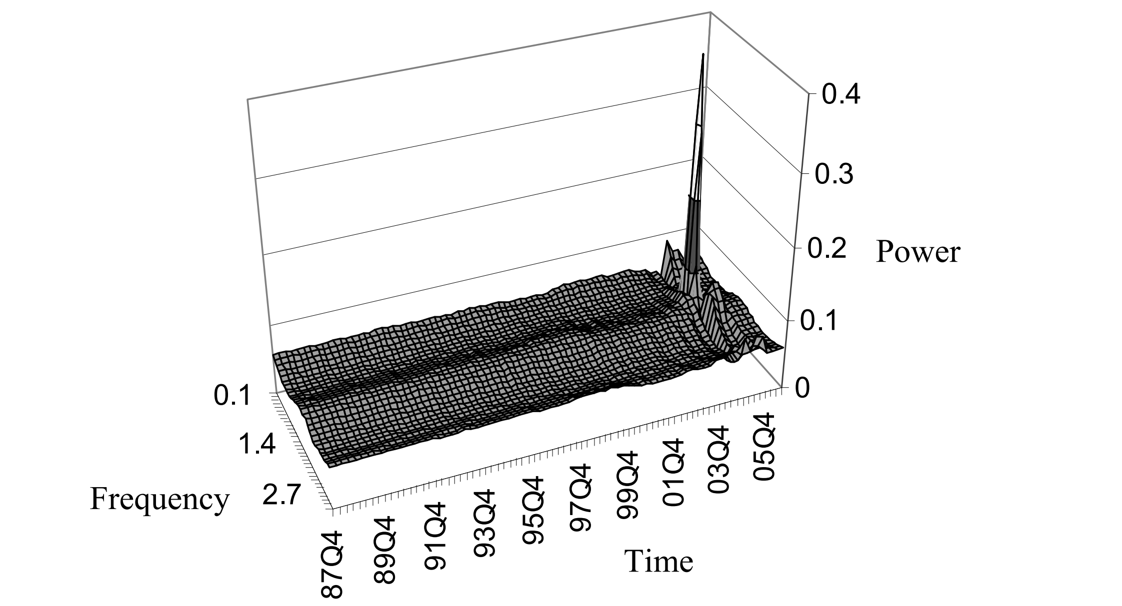

Table 6:
Regression Results for the Chinese Growth Rate

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	0.0503
R^2	0.6267	Standard Error of Estimate	0.0518
Mean of Dependent Variable	0.0192	Sum of Squared Residuals	0.2090
Akaike (AIC) Criterion	0.0600	Ljung-Box Test: Q*(18)	15.8562
Variable	Coeff	Std Error	t-Stat
Constant	0.0310	0.0282	1.0977
DLCHGDP{3}	0.0230	0.1252	0.1839
DLCHGDP{4}	0.1223	0.0545	2.2458

Figure 7:
Spectrum of the Taiwanese Growth Rate

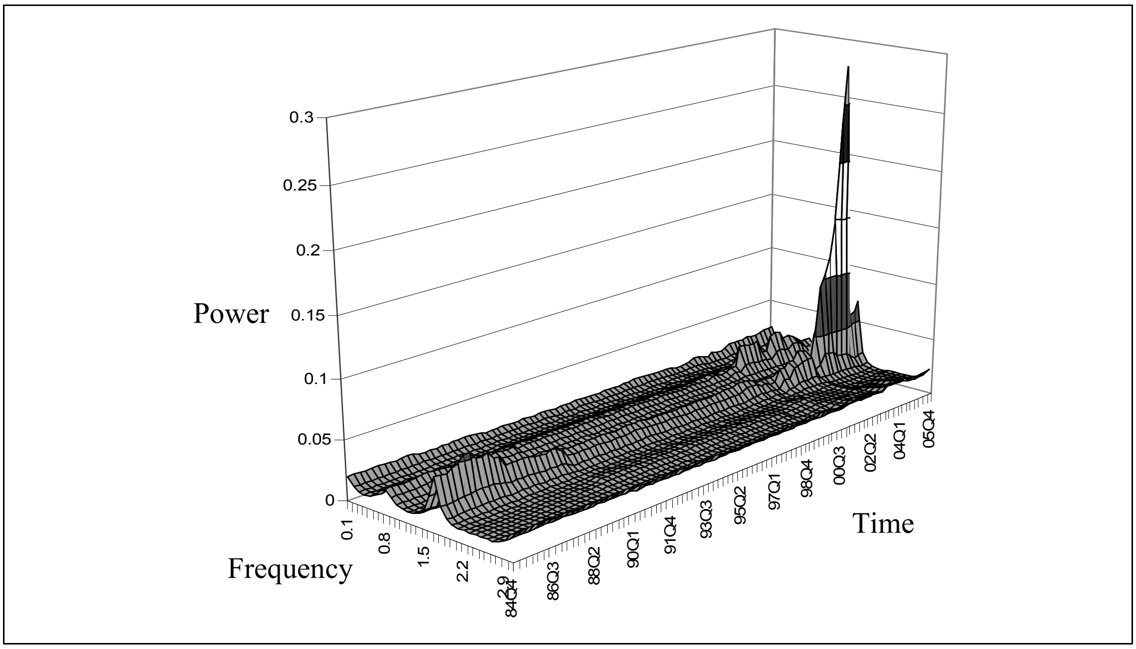

Table 7:
Regression Results for Taiwan

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLTWGDP	Quarterly Data From	1983:01 To 2005:04
Usable Observations	92	Std Error of Dependent Variable	0.0140
R^2	0.7973	Standard Error of Estimate	0.0146
Mean of Dependent Variable	0.0152	Sum of Squared Residuals	0.0186
Akaike (AIC) Criterion	0.0182	Ljung-Box Test: Q*(20)	20.2988
Variable	Coeff	Std Error	t-Stat
Constant	−0.0058	0.0064	−0.9183
DLTWNGDP{4}	0.3604	0.0623	5.7889
DLTWGDP{5}	−0.2081	0.0596	−3.4939
DLTWGDP{7}	0.2815	0.1467	1.9180
DLTWGDP{8}	0.3674	0.0359	10.2278

Figure 8:
Spectrum of Hong Kong

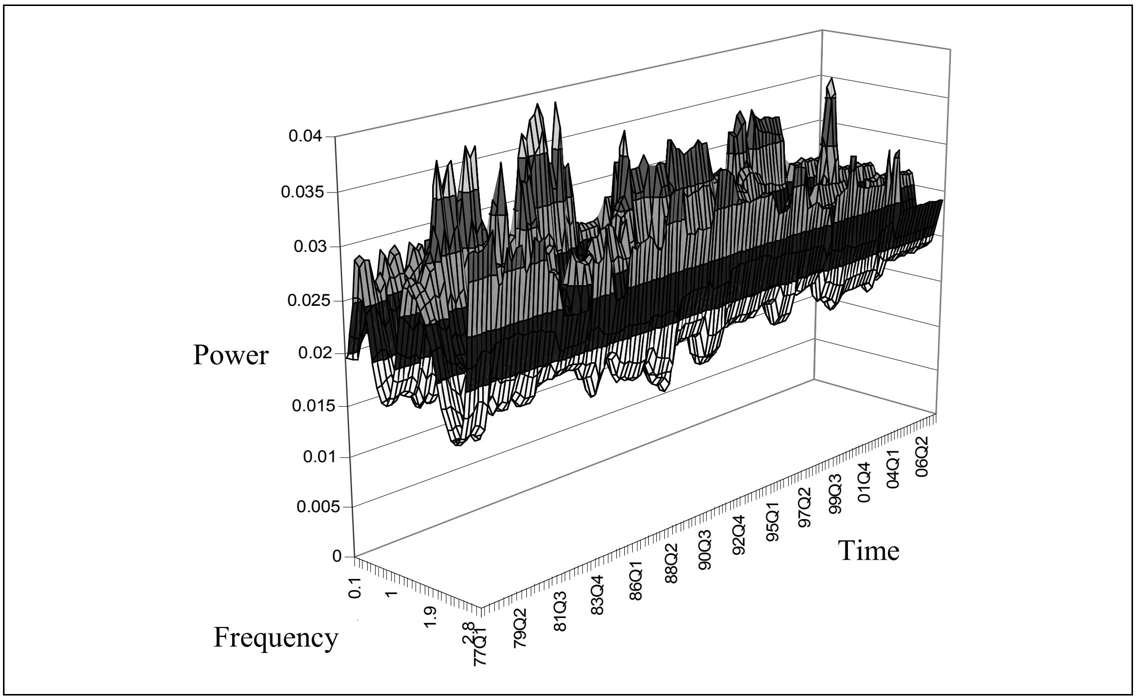

Table 8:
The Regression Results for Hong Kong

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLHKGDP	Quarterly Data From	1975:01 To 2007:02
Usable Observations	130	Std Error of Dependent Variable	0.0235
R^2	0.5316	Standard Error of Estimate	0.0219
Mean of Dependent Variable	0.0155	Sum of Squared Residuals	0.0607
Akaike (AIC) Criterion	0.0233	Ljung-Box Test: Q*(23)	25.2098
Variable	Coeff	Std Error	t-Stat
Constant	0.0176	0.0076	2.2991
DLHKGDP{4}	0.1426	0.0949	1.5000
DLHKGDP{5}	0.0662	0.0987	−0.6651
DLHKGDP{7}	−0.1855	0.0338	−5.3264

It is also interesting to note that since 1999 the spectrum has been much smoother than for the rest of the sample. So it seems that the return to China has led to less uncertainty. But like in Taiwan recent years have seen another business cycle appear, not seen in China. In addition, Hong Kong business cycle behaviour is also similar to that in Japan with respect to volatility. Japan is volatile until about 2004 and then calms down (Figure 2). Obviously, the date is different in Hong Kong, but both have a common business cycle volatility that has been reduced in recent years. That makes Hong Kong a special case: there are features close to China, but also to other regional power, Japan. To resolve this ambiguity, and the questions in the Japan grouping, we must turn to an analysis of the coherences.

4. Increasing Coherence between Asian Economic Cycles?

We turn now to the coherence, or correlations, between the economic cycles of our Asian economies at different frequencies – and whether those coherences have been increasing or decreasing in recent years. These results supply a test of the hypothesis that the Asian economies form a coherent economic group, more similar in their performance than with those outside the group, and that their dependence on the US economy has decreased as the strength of the linkages between them has increased.

We are primarily interested in coherence at business cycle frequencies because of what it implies will be demanded from policy makers and market responsiveness; and of price and wage flexibility in particular. But short and long cycle coherences are important too, for their ability to transmit persistent shocks or short term volatility.

Coherence among the Big Three: The US, China and Japan

We first examine the coherences between the larger economies in the Asia-Pacific region. Taking the China-US relationship first ('US affects China', Figure 9),[27] we can see that the coherence has been gradually declining from 1987 to 2001; but has remained at a fairly high level of 40% to 50% throughout (although some cycles went outside this band).

However it increased again rather abruptly from 2001, to imply a stronger if somewhat uncertain (there are several interruptions to this increased coherence) influence of US growth on China at the long, short, and (most of all) at the business cycle frequencies

[27] Note that each coherence 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. We therefore get different results, and different implications, depending on whether the underlying regressions specify Chinese growth as a function of US growth rates; or US growth as a function of Chinese growth. Coherences can therefore imply one growth pattern is more closely associated or dependent upon another, than holds in reverse (being the dependence/association of the second on the first). Coherence therefore measures a generalized closeness of fit or association between two variables x and y, rather than just the simple correlation coefficient between them which implies a symmetric relationship.

from 2004 to 2006. From Table 9 we can see that these fluctuations are largely caused by the Chinese lag and not by the US lag, whose value remained constant and stable over the entire sample.

Thus US dominance and ‘economy of first resort’ effects have indeed been declining with respect to China, but slowly and only up until 2002. The recent surge in trade with the US, based as it is on expanding exports and the domestic (Chinese) substitution of imports, has restored much of the US influence on China although that influence is remains rather small.

The Japan-US relationship presents a rather simpler picture. The coherence shows a steady but surprisingly strong linkage between Japanese growth and US performance (Figure 11). That association may be stronger at long cycles, and may have weakened in the past 5 years, but those effects are very small. Hence as far as Japan is concerned, the US is still the dominating influence on Japan’s business cycle.[28]

Increasing Coherence towards a Global Business Cycle?

To show that the Asian region as whole does not converge towards a global business cycle, as represented by the US, we examined the coherences of the other (smaller) economies with the US. It turned out that none of the smaller Asian economies converge towards the US. As an example we show here the impact the US has on South Korea.

In contrast to the China-US and Japan-US coherences reported above, that between Korea and the US is weak: 2% at the end of the sample, in place of 50% to 90% in the China-US and Japan-US cases (Figure 12 and Table 12). The profile appears to be similar to the China-US case but the timing is different. The coherence gradually diminishes, almost to zero, until 1998; and then jumps to its highest sustained level in the sample period, with more coherence at the long and trend cycle end of the spectrum. But even then, the coherence remains low compared to the Japanese-US case. So if there is an emerging Japan-Korea(-US) bloc, as the earlier single spectra and Japan-US results had suggested (and which the Korea-Japan results that follow also suggest), then the Korea component is only just now starting to emerge in the wake of the Asia crisis.

Similarly, like China, the other small economies (Taiwan, Singapore, Hong Kong, Malaysia) experienced a weakening of their linkage to the US since the 1980s. They also show low coherences and falling gains from US activity, but coherences and gains that pick up again in the period 2000-2001.

28 The results are based on the regression shown in Table 11.

Figure 9:
Coherence between China and the US

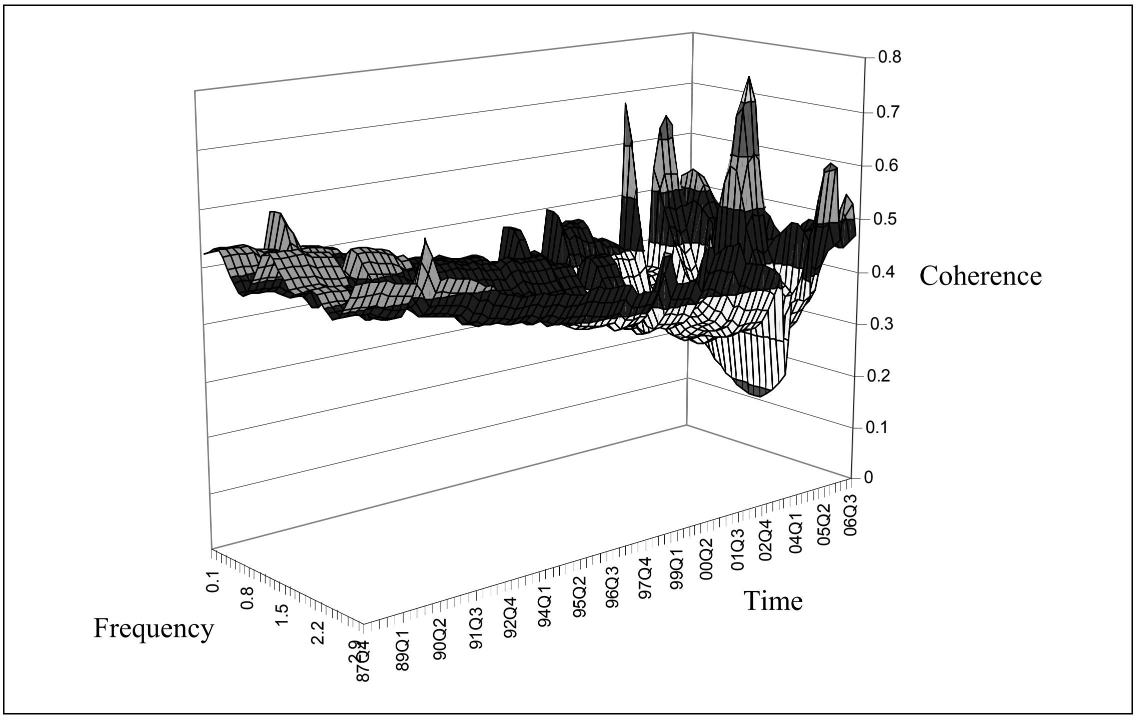

Table 9:
Regression Results between China and the US

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	0.0503
R^2	0.7515	Standard Error of Estimate	0.0887
Mean of Dependent Variable	0.0192	Sum of Squared Residuals	0.2389
Akaike (AIC) Criterion	0.1029	Ljung-Box Test: Q*(18)	18.8275
Variable	Coeff	Std Error	t-Stat
Constant	−0.0112	0.0300	−0.3731
DLCHGDP{4}	0.1135	0.1152	0.9847
DLUSGDP{5}	0.0548	0.0123	4.4499

Figure 10:
Coherence between Japan and USA

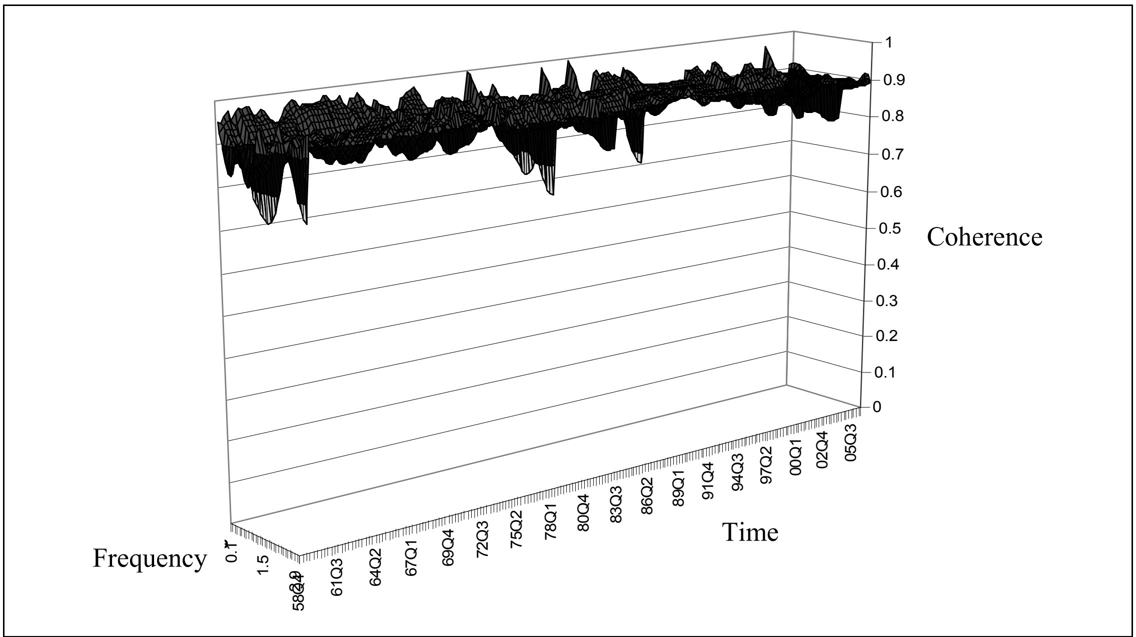

Table 10:
Regression Results between Japan and US

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	0.0134
R^2	0.6159	Standard Error of Estimate	0.0173
Mean of Dependent Variable	0.0113	Sum of Squared Residuals	0.0589
Akaike (AIC) Criterion	0.0188	Ljung-Box Test: Q*(24)	32.2215
Variable	Coeff	Std Error	t-Stat
Constant	0.0004	0.0025	0.1603
DLJPGDP{2}	−0.1511	0.2635	−0.5733
DLJPGDP{3}	0.0757	0.1411	0.5365
DLUSGDP	0.0014	0.0002	5.7452

Figure 11:
Coherence between Korea and US

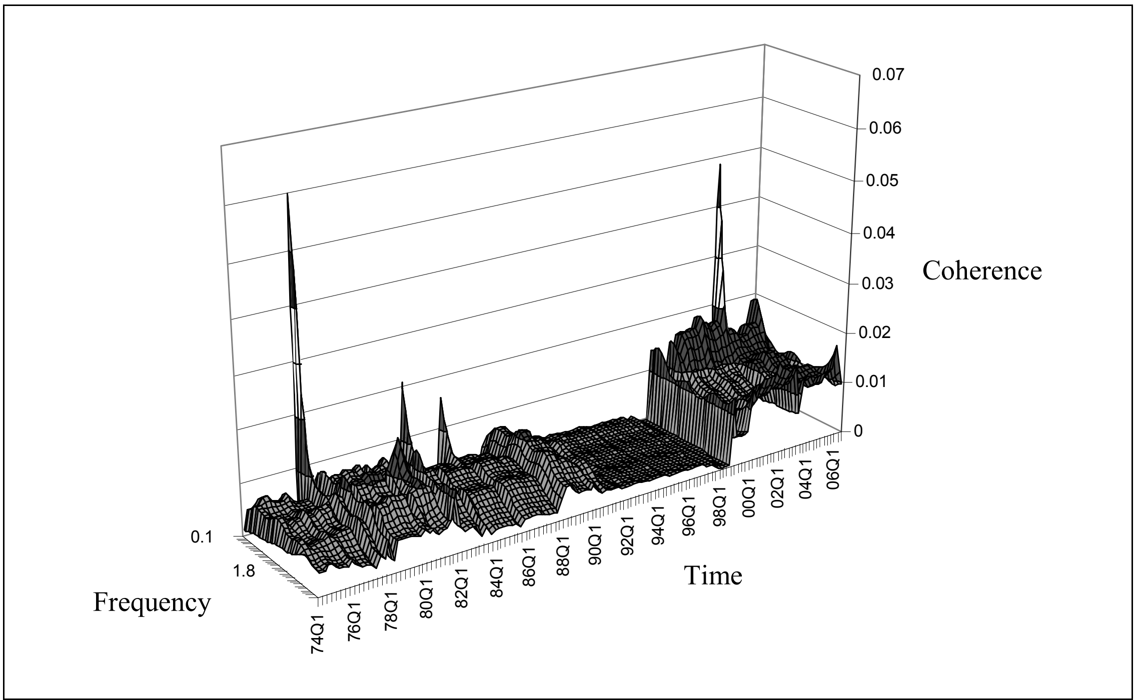

Table 11:
Regression Results between Korea and US

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLKORGDP	Quarterly Data From	1972:01 To 2006:03
Usable Observations	139	Std Error of Dependent Variable	0.0154
R^2	0.7701	Standard Error of Estimate	0.0173
Mean of Dependent Variable	0.0166	Sum of Squared Residuals	0.0397
Akaike (AIC) Criterion	0.0188	Ljung-Box Test: Q*(24)	24.6896
Variable	Coeff	Std Error	t-Stat
Constant	−0.0016	0.0093	−0.1704
DLKORGDP{1}	0.0719	0.0293	2.4526
DLKORGDP{2}	0.1471	0.0073	20.1077
DLUSGDP{1}	0.0109	0.0039	2.7979
DLUSGDP{4}	−0.0018	0.0011	−1.7146

Figure 12:
Coherence between Korea and Japan

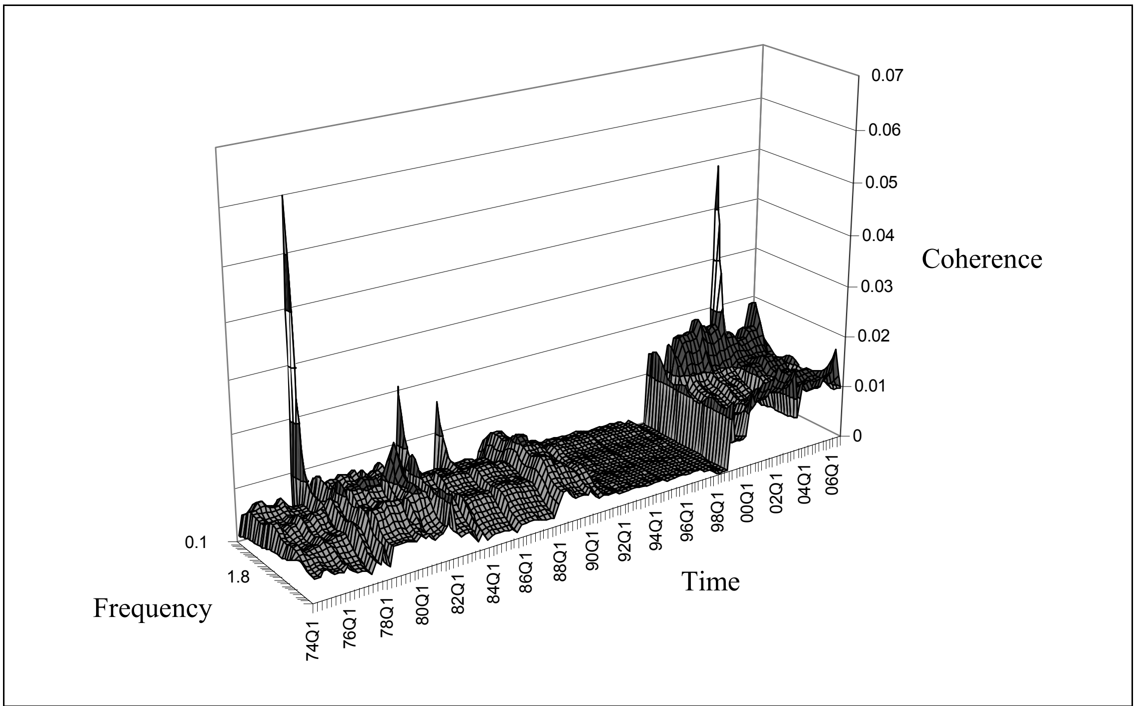

Table 12:
Regression Results between Korea and Japan

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLKORGDP	Quarterly Data From	1972:01 To 2006:03
Usable Observations	139	Std Error of Dependent Variable	0.0154
R^2	0.7714	Standard Error of Estimate	0.0167
Mean of Dependent Variable	0.0166	Sum of Squared Residuals	0.0373
Akaike (AIC) Criterion	0.0183	Ljung-Box Test: Q*(24)	29.5794
Variable	Coeff	Std Error	t-Stat
Constant	0.0164	0.0093	1.7645
DLKORGDP{1}	−0.0029	0.0963	−0.0301
DLKORGDP{3}	−0.4159	0.2141	−1.9421
DLKORGDP{7}	−0.0790	0.0151	−5.2342
DLJPGDP{1}	0.2162	0.0632	3.4220
DLJPGDP{3}	0.2254	0.1382	1.6311

The Coherence between the Smaller Asian Economies

The Japanese Bloc. In this section, we focus on the Japan bloc as identified in Section 3. This will serve to highlight, that Japan has a bigger impact on some countries than on others.

The coherence between Korea and Japan is reasonably strong, at 25% in the 90s, rising to 40% after 1999, but very volatile. Moreover it has a similar profile to the China-US coherence, with a gradually diminishing coherence in the 90s, and a sharp increase in the long cycles and the business cycle frequencies with the increase in Asian trade after 1999. Thus if there is an emerging Japan-Korea(-US) bloc, it is only just now evolving with the link to the US through Japan. That it is detaching itself from the rest of East and South East Asia can be seen from the very low levels of coherence and gains for Japan-China and Korea-China; and from the fact that, unlike what happens within the China bloc, those gains fall significantly after 2003 (see Figure 13). Turning to Malaysia, the coherence with Japan is steady if fluctuating with different cycle lengths (Figure 13).

At an average of 40%, it is quite strong but shows a lot of additional uncertainty around the Asia crisis period (1995-2001). It also appears that the strength of that coherence has been building at the business cycles, and possibly weakening among the long cycles since 1999, consistent with Malaysia's position of a supplier of components and materials to Japan. But these changes are small, and not yet comparable to the strengthening coherence in the China-US or Korea-Japan relationships. That is consistent with a continuing similarity, but weakening linkage with Japan – as would happen if blocs start to separate.

Singapore shows a rather clearer picture of the same thing. Like Malaysia, the Singapore's coherence with Japan show slight decline from 1990, and a stronger one in the late 1980s, to reach a similar value of around 40% now. The lows and uncertainties of the Asia crisis are also clear to see. Then from 2003 things stabilise, with a small build up again at the long, short and business cycle frequencies. Taiwan shows the same pattern; see below. But, again like Malaysia, this is a restoration on the status quo ante and nothing like the increases in co herence seen in the China-US or Korea-Japan cases. The similarity of these results and their similarity to the Malay-Japan and China-US results, gives a clearer picture of an evolving China based group separating itself from the Japan-Korea bloc which remains more closely allied to the US. But to establish that firmly we need to check that the counterpart changes have also occurred in the coherences with China.

Figure 13:
Coherence between Malaysia and Japan

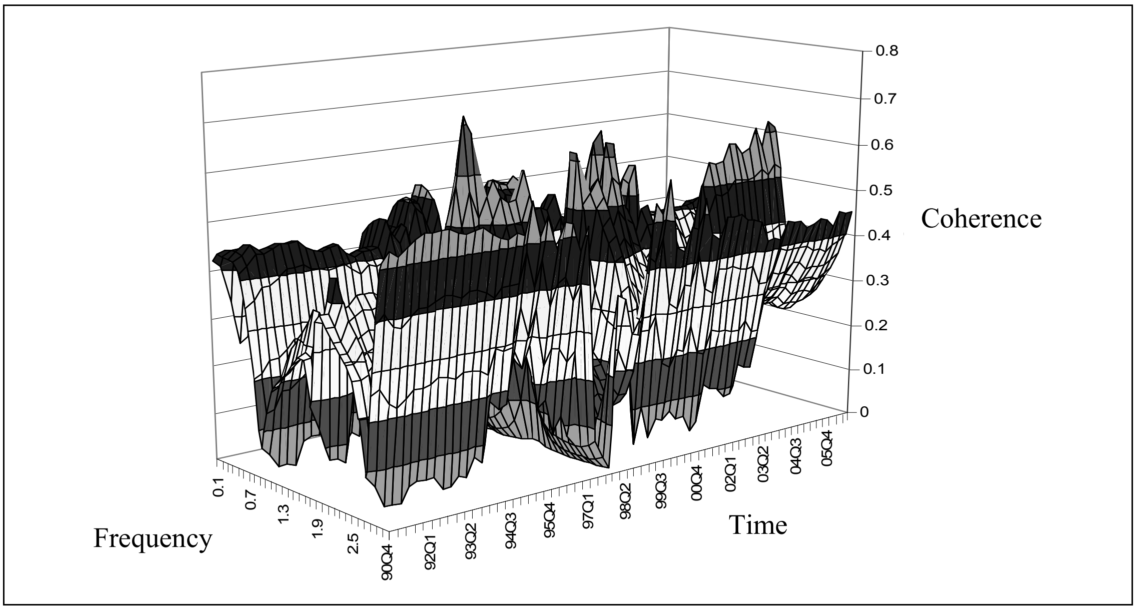

Table 13:
Regression Results between Malaysia and Japan

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLMAGDP	Quarterly Data From	1989:03 To 2006:03
Usable Observations	69	Std Error of Dependent Variable	0.0184
R^2	0.8211	Standard Error of Estimate	0.0187
Mean of Dependent Variable	0.0153	Sum of Squared Residuals	0.0217
Akaike (AIC) Criterion	0.0229	Ljung-Box Test: Q*(16)	22.0435
Variable	Coeff	Std Error	t-Stat
Constant	0.0045	0.0091	0.4931
DLMAGDP{2}	0.0434	0.0375	1.1576
DLMAGDP{4}	0.1948	0.0355	5.4858
DLMAGDP{5}	−0.4151	0.0468	−8.8767
DLMAGDP{7}	0.1154	0.0366	3.1522
DLJPGDP	0.7208	0.1642	4.3893
DLJPGDP{7}	−0.0637	0.0468	−1.3626

Figure 14:
Coherence between Singapore and Japan

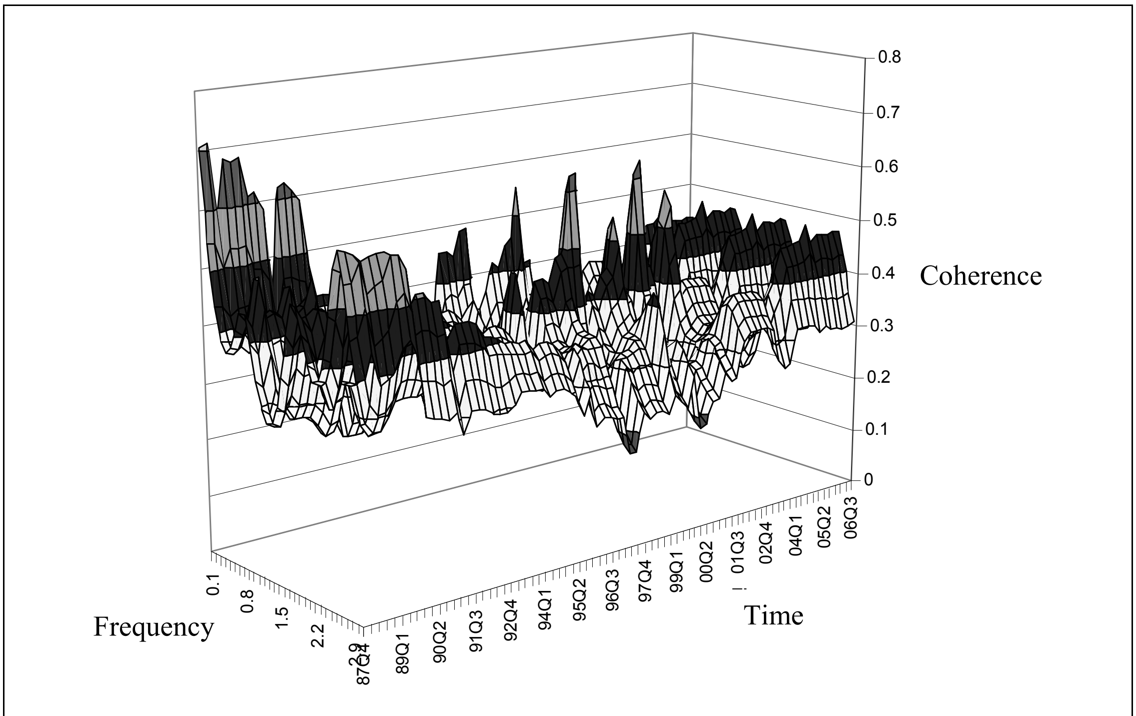

Table 14:
Regression Results between Singapore and Japan

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLSINGDP	Quarterly Data From	1986:03 To 2006:03
Usable Observations	81	Std Error of Dependent Variable	0.0171
R^2	0.5258	Standard Error of Estimate	0.0168
Mean of Dependent Variable	0.0168	Sum of Squared Residuals	0.0220
Akaike (AIC) Criterion	0.0195	Ljung-Box Test: Q*(18)	22.5129
Variable	Coeff	Std Error	t-Stat
Constant	0.0079	0.0049	1.6214
DLSINGDP{7}	0.2500	0.1185	2.1102
DLJPGDP	0.6477	0.1221	5.3028

The Chinese Bloc. We review the coherences between Japan and China, and Korea and China, separately from the coherences of the smaller economies (Malaysia, Taiwan, Singapore and Hong Kong) with China, to allow for the fact that there may be two blocs in the Asia-Pacific region: one based on Japan (possibly involving the US) and one based on China.

The Japan-China (China influences Japan) coherence is very low throughout our sample, at 10% or less, 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 to the short, long, but mainly business cycle frequencies in Japan. However, the coherence remains small: no more than for China influencing the US, and far smaller (by factors of 5 to 6) than the US's coherence with China or Japan. This is consistent with a Japan bloc developing separately from a China bloc, even though one might have expected some linkage between the two as Chinese components are increasingly used, and manufactures consumed, in Japan; and as more Japanese equipment or investment goes to China. The fact that the same thing is also happening between China and the US means that Japan and the US continue to behave in the same way with respect to China despite their, and China's, changing roles in the Asian economy.

Taiwan shows the closest relationship to and most influence from China. Our Taiwan-China coherence is substantially higher, at 40% to 50% in 2004, than the other China coherences (including with the US) or the Korea-Japan coherence. Moreover there has been a precipitous rise since 2002 (possibly since 1999), with the power concentrating at the long and business cycle frequencies (and away from the short/intermediate frequencies). That suggests a shift in phase and product structure has taken place with an increase in consumer goods traded either way and intermediate inputs to Taiwan at business cycle frequencies; and increased financing from Taiwan to provide the long cycle connection. Interestingly, these effects are now even less than the apparently declining influence of Japan on Taiwan.

The coherence between Hong Kong and China is perhaps the best example for the appearance of convergence. At the start of the sample, that coherence is about 70% for the long run cycle.

Over time, more and more cycles have a coherence of close to 100%. However, not all cycles are at 100%. Nevertheless, over time the Hong Kong economy became closer to the Chinese one and that fact is expressed in the convergence of the cycles.

Figure 15:
Coherence between Japan and China

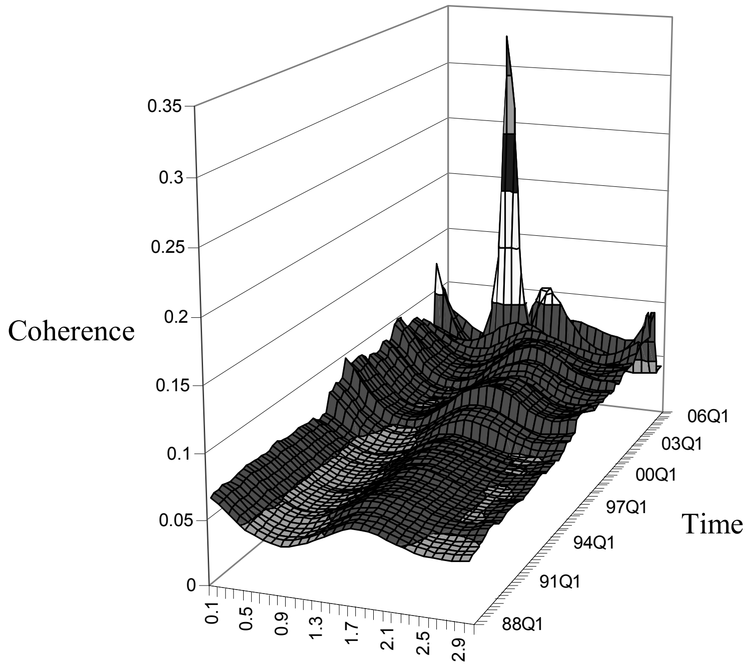

Table 15:
Regression Results between Japan and China

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	0.0134
R^2	0.6633	Standard Error of Estimate	0.0102
Mean of Dependent Variable	0.0113	Sum of Squared Residuals	0.0078
Akaike (AIC) Criterion	0.0112	Ljung-Box Test: Q*(17)	17.5585
Variable	Coeff	Std Error	t-Stat
Constant	−0.0000	0.0056	−0.0015
DLJPGDP{1}	−0.0299	0.0175	−1.7088
DLJPGDP{3}	0.1258	0.0461	2.7286
DLCHGDP{5}	0.0132	0.0034	3.8569

Figure 16:
Coherence between Taiwan and China

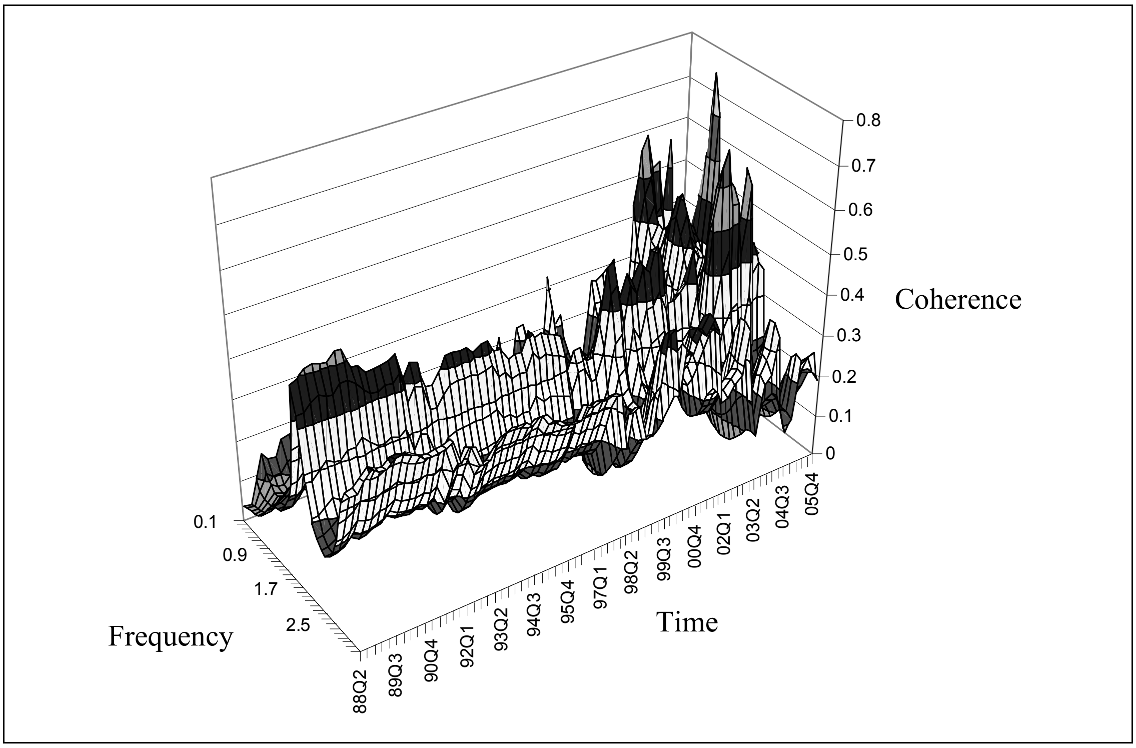

Table 16:
Regression Results between Taiwan and China

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLTWGDP	Quarterly Data From	1987:01 To 2005:04
Usable Observations	76	Std Error of Dependent Variable	0.0140
R^2	0.4906	Standard Error of Estimate	0.0121
Mean of Dependent Variable	0.0152	Sum of Squared Residuals	0.0102
Akaike (AIC) Criterion	0.0141	Ljung-Box Test: Q*(17)	20.4284
Variable	Coeff	Std Error	t-Stat
Constant	0.0041	0.0016	2.4983
DLTWGDP{4}	0.3566	0.0636	5.6097
DLTWGDP{5}	−0.1895	0.0343	−5.5325
DLTWGDP{7}	0.3925	0.0626	6.2706
DLCHGDP{1}	0.0466	0.0156	2.9918
DLCHGDP{2}	−0.0808	0.0559	−1.4453

Figure 17:
Coherence between Hong Kong and China

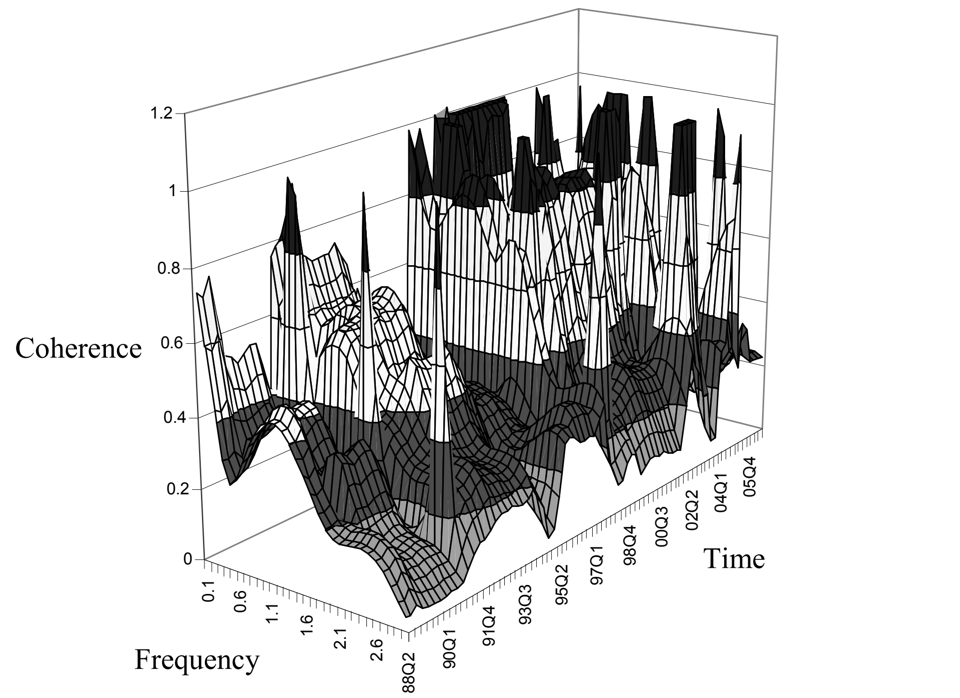

Table 17:
Regression Results between Hong Kong and China

VAR/System – Estimation by Kalman Filter			
Dependent Variable	DLHKGDP	Quarterly Data From	1987:01 To 2006:03
Usable Observations	79	Std Error of Dependent Variable	0.0235
R^2	0.6231	Standard Error of Estimate	0.0170
Mean of Dependent Variable	0.0155	Sum of Squared Residuals	0.0213
Akaike (AIC) Criterion	0.0193	Ljung-Box Test: Q*(17)	18.1543
Variable	Coeff	Std Error	t-Stat
Constant	0.0086	0.0006	13.2630
DLHKGDP{4}	0.1078	0.0267	4.0337
DLHKGDP{6}	−0.0824	0.4591	−0.1794
DLCHGDP	0.0698	0.0634	1.1015
DLCHGDP{1}	0.0883	0.0489	1.8052

5. Conclusion

The contribution of this paper has been to examine the hypothesis that there are two blocs emerging in the Asia-Pacific area over the past 20 years. We also investigated whether this has changed the size or direction of the spillovers between economies, whether it has reduced US hegemony in the region by strengthening the links between Asian economies. We find:

a) That the links with the US have indeed weakened, and those within a bloc centred on China have been strengthening;

b) But this is not a new phenomenon. It has been happening steadily since the mid-1980s, and it has now been largely (but not completely) reversed by the unbalanced expansion of trade.

c) There are two Asian blocs emerging; one based on Japan whose relationship with the US remains unchanged, and one based on China where there have been substantial changes. The links between those two blocs are weak and uncertain; the primary difference between them resting on the flexibility of their exchange rates and the consequent control of domestic monetary and financial conditions.

d) Of the countries examined, Japan-Korea(-US) form one group; and China-Taiwan-Hong Kong the other, with Malaysia and Singapore as part-time members of each group (perhaps veering to Chinese sphere of influence now). The strongest changes are found in the China bloc, where there seems to have been some reallocation of activities.

f) These results, and the subtleties which allow us to distinguish the behaviour of different countries and classify them into different groups, highlight why it is so important to use the digital filter as we have used it here. The high resolution shows what countries have in common and what not. Other methods which use the time domain or the frequency domain alone cannot do this.

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Dynamic Correlation Analysis of Business Cycles of the Emerging Asian Giants: The Awakening

*Jarko Fidrmuc**, *Iikka Korhonen*** *and Ivana Bátorová****

1. Introduction

Globalization has been one of the major events in the world economy in the last two decades. China and India played only a marginal role in the world economy before the 1990s. While China was a predominantly agrarian economy before 1980, it is now to a large extent a modern industrial economy with booming urban regions. Furthermore, high trade growth was supported by large investment flows (see Eichengreen and Tong, 2005, and Lane and Schmukler, 2007). Not surprisingly, growth in China has changed the distribution of economic activities across the world. Between 1980 and 2006, the share of Chinese GDP in the world economy increased from 1.7% to 5.5% (valued at market exchange rates, the share would be higher if purchasing power adjusted prices were used). Now, China is one of the most important exporting and importing nations worldwide. India seems to follow the development path of China more recently (see Winter and Yusuf, 2007; Ysuf et al., 2007), although India concentrates more on services than on the manufacturing sector than China. Moreover, in 2006 India's share of the global output was only 1.9%.

New structure of the world economy has also important implications on business cycles around the world. The increasing weights of the emerging countries, especially the trade shares of the largest Asian countries (China and India), have lead to higher global growth. Moreover, global economic prospects are less influenced by few large economies (especially the US and Germany) than before. This may make the countries less vulnerable to the demand shocks in a particular region, which is also referred to as decoupling of business cycles in the recent literature (see Kose et al., 2008).

* Corresponding author, Ludwig-Maximilians-University Munich, Historicum, Schellingstr. 12, 80539 Munich, Germany, jarko.fidrmuc@lrz.uni-muenchen.de. The usual disclaimers apply. We appreciate the research assistance by Yin Xia. We benefited also from comments by Katharina Fidrmuc-Helmstedt, Gerhard Illing, Tomasz Kozluk, Michael Funke, Tuuli Koivu, Aaron Mehrotra, Juraj Zeman, Pavol Brunovský and seminar participants at the Comenius University Bratislava in May 2007, as well as Eiji Ogawa and seminar participants at the Hitotsubashi University Tokyo in December 2007, and Jörg Rahn.

** Bank of Finland.

*** Comenius University.

In turn, business cycles have become also more globalized recently. The literature on business cycle synchronization stresses the importance of foreign trade and capital flows. Thus, the emergence of Asian giants (China and India) as large trading nations and targets for international investment is likely to have a significant impact on the business cycles of its partner countries. As far as the intensity of trade and financial relations with the emerging Asian giants is largely different between the countries, the exposure to globalization may possibly explain the recent differences in business cycle developments.

This may be especially important for European countries. On the one hand, we observed a joint EU cycle until the 1980s (see Artis and Zhang, 1997, Fatas, 1997), which may have disappeared despite previous expectations in the 1990s (see Artis, 2003). On the other hand, the exposure to globalization, which can be proxied by trade intensity with China and India, is very different between the EU countries. The UK, Germany, Finland and the Netherlands are examples of countries linked intensively to South and Southeast Asia, while the remaining countries have rather a moderate intensity of economic relationships with this region.

Trade flows are generally seen as important factors of business cycles. However, their effects on international business cycles are ambiguous. On the one hand, Frankel and Rose (1998) find a robust positive relationship between trade intensity and correlation of business cycles between OECD countries. This reflects also high shares of intra-industry trade between these countries. On the other hand, globalization may result in an increased specialization patterns around the world. Krugman (1993) argues that this is likely to cause business cycle divergence between countries.

There is already a rich literature on trade between South Asian countries and the developed countries (see Bussière et al., 2008). Other authors look also at the determinants of the business cycles in South East Asia. Among others, a special issue of World Economy was devoted to this issue (see de Grauwe and Zhang, 2006). However, there are only few papers about the synchronization of business cycles in developed countries and in emerging economies. The exceptions from this (see Hughes-Hallett and Richter, 2008, and Kose et al., 2008) concentrate on the description of stylized facts of business cycles in various regions. This paper extends this discussion with the analysis of factors of business cycle convergence and divergence between OECD countries and the two largest emerging economies in Asia (Asian giants).

The main results of our paper are as follows. First, we show that business cycles in China and India are very different from those of OECD countries, which favors the decoupling hypothesis. Second, trade flows between OECD countries and China have had so far low effects on the comovements in both Asian emerging economies and OECD countries, although surprisingly they have increased the comovements at the short-run frequencies (especially in China). This stands in a contradiction to the positive relationship between trade and business cycle similarities between OECD countries documented well in the earlier literature and confirmed in our paper for the OECD countries. Finally, we show that trade and financial flows have lowered the degree of business cycle synchronization between OECD countries.

The paper is structured as follows. The next section presents a literature survey on determinants of international business cycles with special focus on emerging economies. Section 3 introduces the concept of dynamic correlations between emerging Asia and OECD and discusses the stylized facts and similarities of business cycles in both regions. Section 4 analyses the determinants of dynamic correlation of business cycles in Asian giants and in developed countries. Section 5 investigates the impact of China on the degree of business cycles synchronization between OECD countries and the last section concludes.

2. Determinants of Business Cycle Synchronization

Economic development is determined both by domestic (for example aggregate demand shocks and budgetary policy) and international factors (external demand and international prices for traded goods). In open economies, the latter are playing an increasingly important role and often determine also domestic policies, which try to insulate the economy from adverse external economic shocks. Originally, Frankel and Rose (1998) showed that trade, and more generally economic integration among the countries, can result in increased synchronization of individual business cycles since trade links serve as a channel for the transmission of shocks across countries. In line with these considerations, Kenen (2000) shows in a Keynesian model that the correlation between two countries' output changes increases with the intensity of trade links. In turn, Kose and Yi (2006) analyze this issue in an international real business cycle model and conclude that, although the model suggests a positive relation between trade and output co-movement, quantitatively only small effects are obtained.

However, this hypothesis of positive relationship between trade business cycles was not generally accepted. For example, Krugman (1993) points out that, as countries become more integrated, they increasingly specialize. That is, the importance of asymmetric or sector-specific shocks increases in the process of economic integration. This pattern may be more appropriate for the explanation of business cycles in China.

In the empirical literature, the role of trade links has been studied extensively in this context. Despite theoretical ambiguities, several authors have demonstrated that countries trading more intensively, exhibit also a higher degree of output co-movement (see e.g. Frankel and Rose, 1998, and Baxter and Kouparitsas, 2005). However, it is not trade relations per se which may induce business cycle synchronization. Indeed, Frankel and Rose's hypothesis underlines that bilateral trade is mainly intra-industry trade, although this indicator does not directly enter their analysis. Basically, the idea is that specialization increases the exposure to sector specific shocks and these shocks are transmitted via intra-industry trade. Fontagné (1999) discusses the relation between intra-industry trade and the symmetry of shocks in a monetary union. Fidrmuc (2004) and Artis et al. (2008) show that intra-industry trade is a better indicator for business cycle asymmetries than simple trade intensities.

As far as China and India specialize vertically, this channel may possibly be less relevant for their business cycles. Actually, the specialization forces discussed by Krugman (1993) can dominate, which can cause divergence of business cycles between the emerging Asian giants and their trading partners.

So far, literature on business cycle correlation has concentrated mainly on developed economies. However, a number of studies have looked at business cycle correlation in Eastern Asia. For example, Sato and Zhang (2006) find common business cycles for the East Asian region. Moreover, Shin and Sohn (2006) find that trade integration (but much less financial integration) enhances the comovements of output in East Asia.[29] Kumakura (2005) finds that the share of electronic products in foreign trade increases business cycle correlation for the countries around the Pacific. Also Shin and Wang (2004) find that trade is a significant determinant of business cycle correlation for East Asian countries. So far, very few papers have looked at the correlation of business cycles between China and other emerging Asian economies and those of the OECD countries. Hughes-Hallett and Richter (2008) analyse the declining importance of the USA in Asia. Kose et al. (2008) find that there has been a convergence of business cycles within the groups of OECD countries and emerging markets (including also non-Asian countries) but a decoupling of business cycles between these two groups.

3. Dynamic Correlation Analysis of Business Cycles in the Asian Giants

The correlation analysis is the most basic approach which has been applied in literature to study the degrees of synchronization between economic variables. The most common measure of co-movement between time series is the classical correlation, which is also commonly used in literature on business cycle correlation. Unfortunately the classical correlation is associated with two main drawbacks: First, it does not allow for a separation of idiosyncratic components and common co-movements. Second, it is basically a static analysis that fails to capture any dynamics in the co-movement. An alternative measure of synchronization in the case of business cycles is the dynamic correlation, which was proposed by Croux et al. (2001).

29 *Kočenda* and *Hanousek* (1998) document a high degree of convergence and integration of the Eastern Asian capital markets.

Let x and y be zero-mean real stochastic processes. Let $S_x(\lambda)$ and $S_y(\lambda)$ be the spectral density functions of x and y and $C_{xy}(\lambda)$ be the co-spectrum, $-\pi \le \lambda \le \pi$. So the dynamic correlation, $\rho(\lambda)$, equals to

(1) $$\rho_{xy}(\lambda) = \frac{C_{xy}(\lambda)}{\sqrt{S_x(\lambda)S_y(\lambda)}}.$$

Similarly to standard correlation coefficient, the dynamic correlation is defined between –1 and 1.

We use quarterly GDP data according to International Financial Statistics of the IMF. For developed countries, the time series start in the 1970s or 1980s. For India, we use IMF data between 1993 and 2006. If seasonal adjustment is required, we use the U.S. Census Bureau's X12 ARIMA procedure, which was performed for the whole available period.

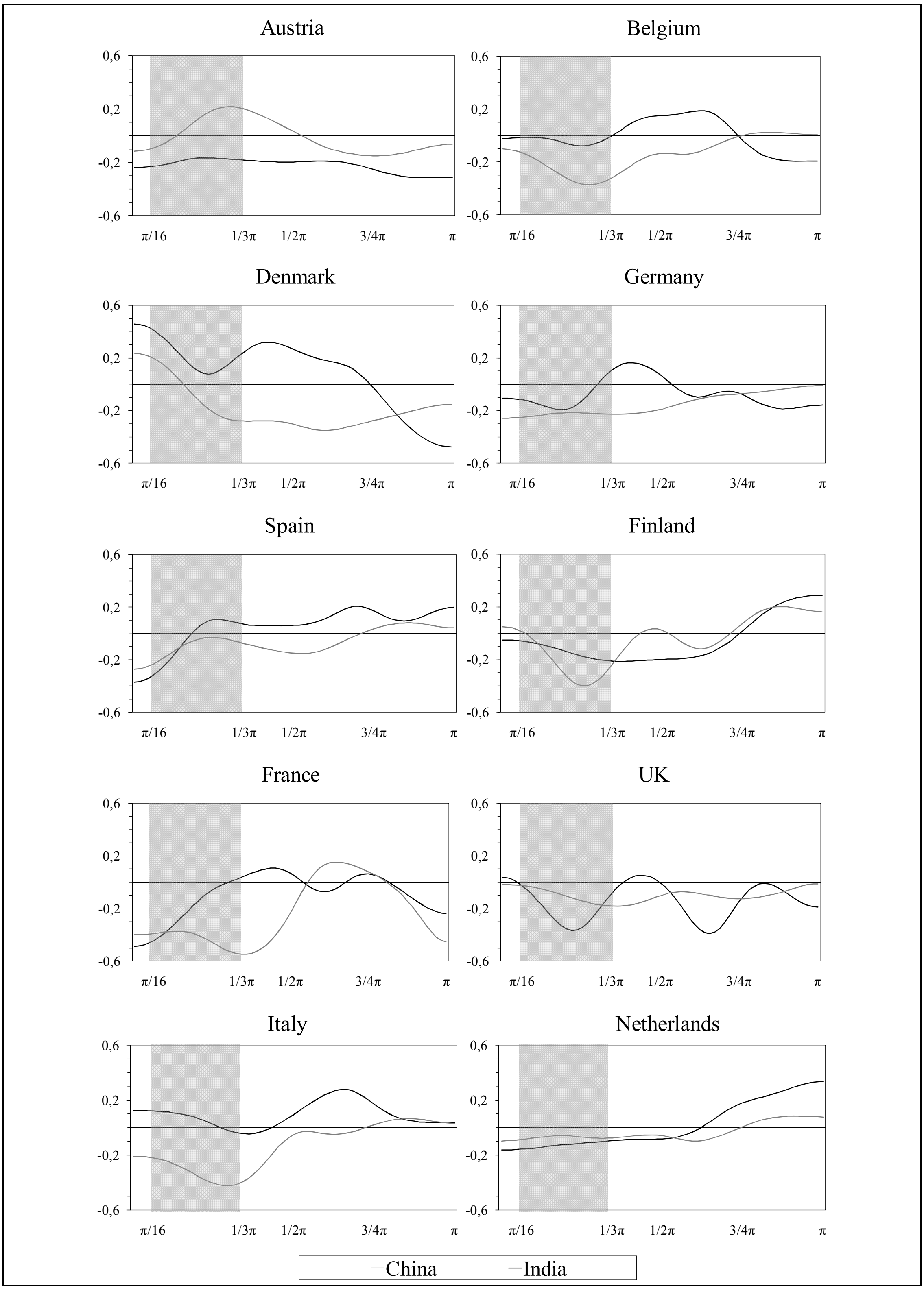
However, it is more difficult to find appropriate quarterly data for China in international sources. Therefore, we use national quarterly data in current prices, which was deflated by the CPI. However, we have to keep in mind that these time series have been subject to a major revision recently. So far, only annual data are available according to the new methodology.[30] As before, we adjusted this time series by the same procedure as for other countries. Furthermore, the time series start in 1992. This restricts our analysis to the period between 1992 and 2006.

Figure 1 presents dynamic correlations of business cycles in both Asian emerging economies and in selected developed economies between 1992 and 2006. As usual in literature, we differ between three components of the aggregate correlation. First, the long-run movements (over 8 years) correspond to the low frequency band below $\pi/16$. Second, the traditional business cycles (that is, cycles with a period between 1.5 and 8 years) belong to the medium part of the figure (marked as a shadow area) between $\pi/16$ and $\pi/3$. Finally, the short-run movements are defined by frequencies over $\pi/3$. Although it is usual to neglect these developments in literature, we will look at them here because the short-run dependences of economic development may be more important in the case of China and India.

We can see that business cycles in Asian emerging economies and selected developed economies vary significantly over the frequencies. In turn, the pattern is remarkably similar for China and India, which contrasts to the pattern of dynamic correlations between developed economies. In particular, the OECD countries show usually high dynamic correlations for the business cycle frequencies and long-term comovements (see Croux et al, 2001).

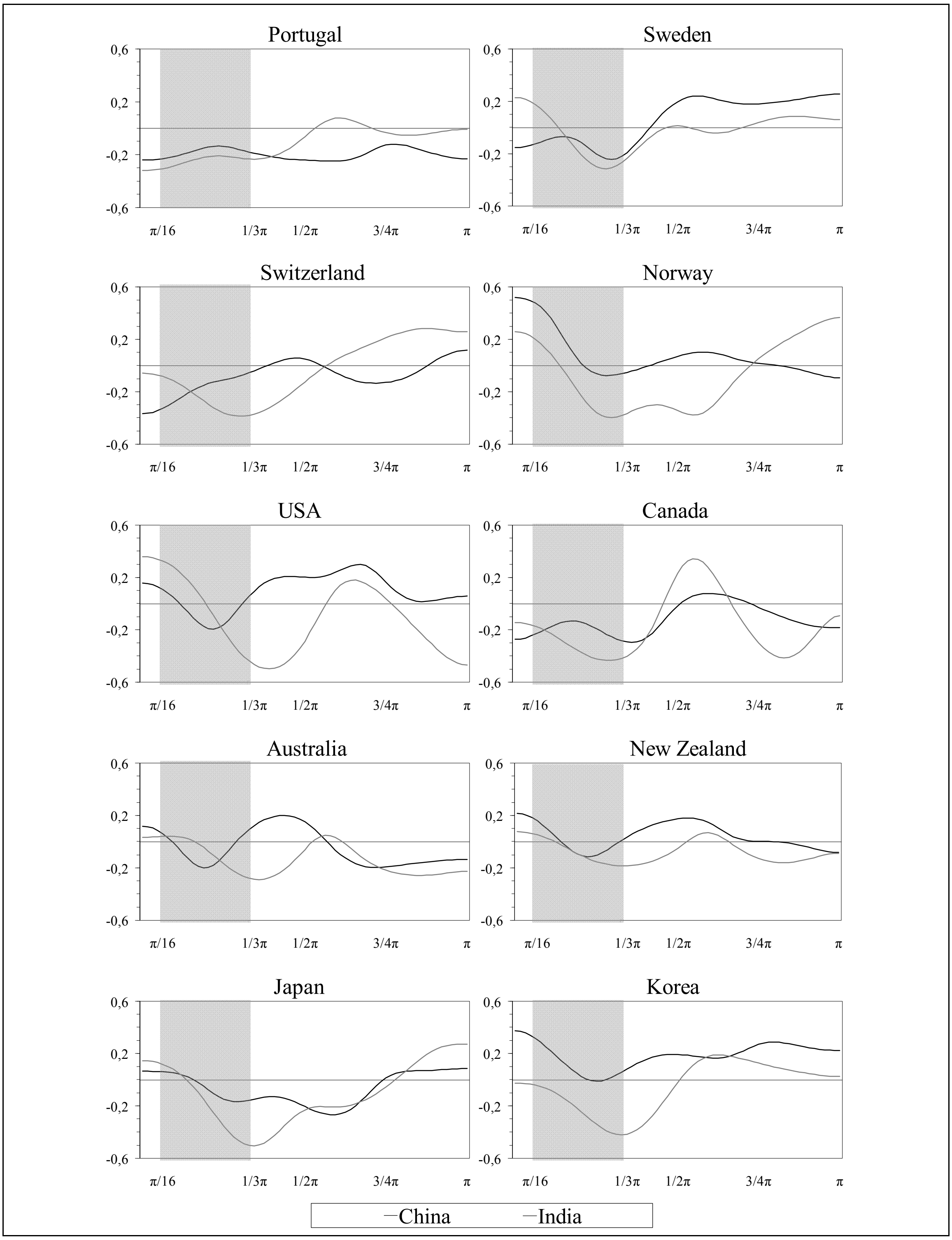
30 The impact of the revision on correlations should be moderate if the dynamic properties of the time series remained the same.

Figure 1a:
Dynamic Correlations of China and India with Selected Countries, 1992-2006



Note: Business cycle frequencies are marked by the shadow area.

Figure 1b:
Dynamic Correlations of China and India with Selected Countries, 1992-2006



Note: Business cycle frequencies are marked by the shadow area.

In general, the pattern of dynamic correlations with the OECD countries is remarkably similar for China and India (see especially the results for the Netherlands, Finland, and Japan). However, dynamic correlations are usually slightly lower for India than for China for the whole interval of frequencies.

Only few countries show comparably high positive correlation of the long-run cycles with China and India. These countries include especially the non-European OECD countries (USA, Korea, Australia, and Japan). To a lesser degree, we can see also small positive correlations of the long-run development in Denmark, Norway, and perhaps the UK. In general, the non-European OECD countries trade more intensively with China than the remaining countries of our sample, which may go towards explaining the extent of business cycle correlation. For India no clear pattern of trade could be discerned.

We can see a more homogenous picture for the traditional business cycle frequencies (between $\pi/16 \approx 0.2$ and $\pi/3 \approx 1$). In general, negative correlations of business cycles in both China and India and business cycles of the OECD countries dominate, which confirms the decoupling hypothesis for both countries. Our results are also similar to the earlier findings by Shin and Sohn (2006) and Sato and Zhang (2006). As before, also the non-European OECD countries show a positive correlation at the lower range of the interval (close to eight years).

Finally, we can see also large differences between various short-run frequencies. In general, the dynamic correlations tend to increase at the right end of the spectrum (see Figure 1), but it reaches positive values usually only in China. This would correspond to strong business linkages between suppliers from China and final producers in the developed countries. Among the European countries short-term correlation appears to be high for Finland, Netherlands and Sweden. For China, the short-run correlations are high also for the USA and Korea, but only marginally positive for Japan. All these countries can be characterized as having highly intensive relationships to China over a longer period. Short-run correlation with the Indian business cycle is positive for Finland, Norway and Switzerland, even though their trade with India is quite low. Therefore, the result may be a statistical artifact, or some other factors are affecting the degree of business cycle correlation.

4. Factors Explaining the Pattern of Dynamic Correlations

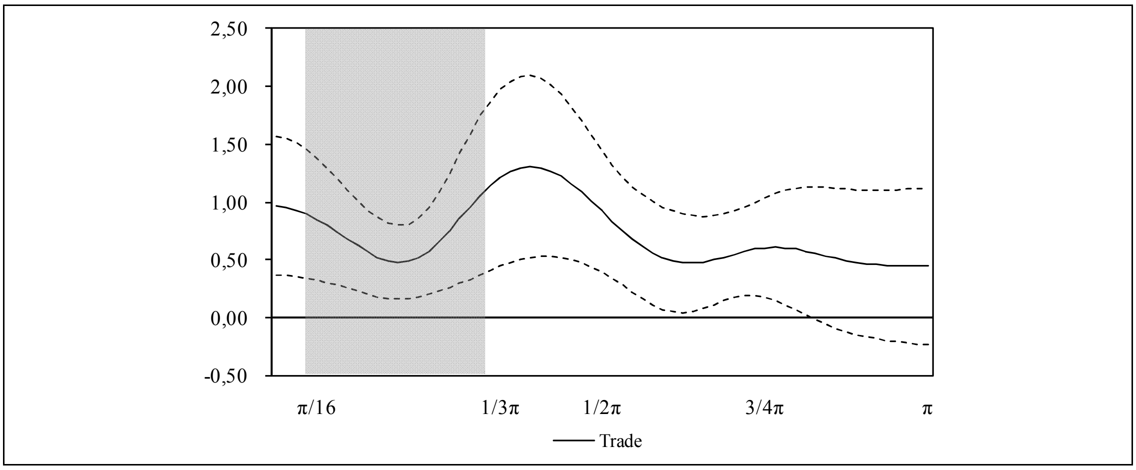
In addition of stylized facts of the previous section, we briefly assess trade intensity as a potential determinant of business cycle synchronization between the Asian emerging economies and the OECD countries. In particular, we test whether the extent of foreign trade between a country and the emerging Asian giants influences dynamic correlations at the individual frequencies. The more intensive a country has trade links with the emerging Asian countries, the stronger should be the synchronization of the comovements (especially of business cycles) with the region. Furthermore, the degree of synchronization may be different for different frequencies, because e.g. different economic policies may cause divergence between the business cycles. We use foreign trade data from the IMF's Direction of Trade statistics to calculate the average shares of China and India in exports and imports of the OECD countries between 1995 and 2006. This period captures the rapid growth of China's foreign trade.

In the previous section we calculated the dynamic correlation between the Chinese and Indian GDP growth and growth in 20 OECD countries. As we saw earlier, correlations differ greatly between the OECD countries. Therefore, we estimate the set of following estimations for the dynamic correlation at all frequencies λ,

(2) $$\rho_j(\lambda) = \beta_1(\lambda) + \beta_2(\lambda)\log(x_j) + \varepsilon_j(\lambda).$$

Trade intensity is the single explanatory variable, which is denoted by x. It is defined as the ratio of bilateral trade (average of exports and imports) recorded between the OECD country j and the China or India to GDP of the analyzed OECD countries. This indicator shows the importance of both Asian countries from the perspective of the OECD countries. We have 20 observations for all country pairs with China and India, giving 40 observations for each frequency. We present the parameter β_2 for the explanatory variables and the individual frequencies in Figure 2.

Figure 2:
Regression Results, Determinants of Dynamic Correlations of Business Cycles of OECD Countries with Business Cycle of the Asian Giants



Note: Confidence bands are constructed as 1.96 standard errors. Business cycle frequencies are marked by the shadow area. For better comparison, explanatory variables have been rescaled to yield coefficients of the same size.

Although the results have to be taken very cautiously, the findings confirm largely the stylized facts of the previous section. Integration between the OECD countries and the Asian giants tends to have low but significant effects on dynamic correlation of GDP at the business cycle frequencies. In turn, trade intensity has a positive effect on the correlation of GDP movements at the short-run frequencies (see Figure 2), although it becomes insignificant at the right-hand side of the spectrum. This result stands in a contrast to positive relationship found usually for the OECD countries in the earlier literature following Frankel and Rose (1998), which we also confirmed for dynamic correlations of business cycles of OECD countries (see the left block of Figure 3). In particular, trade intensity has the highest effects on dynamic correlation at the long-run frequencies for the OECD countries.

Thus, we are able to identify some linkages between foreign trade and dynamic correlations. More extensive trade ties do increase business cycle correlation, although the effect seems to be felt mostly in the short-run business cycle frequencies.

5. Globalization and Business Cycles of OECD Countries

The stylized facts of the previous sections show that the business cycles in China and in the OECD countries are largely not synchronized. Furthermore, the intensity of economic links with China differs largely between the OECD countries. This can influence the business cycles of the individual OECD countries as shown partially in the previous section. In addition to increased synchronization of movements at particular frequencies, the synchronization between OECD countries may decline as a result of different exposure to the 'globalization' shock, which is proxied by the trade of the OECD countries with China and India. Alternatively, different specialization patterns achieved during the globalization period may lead also to increasing dissimilarities in business cycles of the OECD countries despite similar exposure to trade and financial integration with China and other emerging markets.

Therefore, we extend our analysis to the business cycles between the OECD countries. We follow Frankel and Rose (1998) and estimate the following specification for the individual frequencies,

(3) $$\rho_{ij}(\lambda) = \gamma_1(\lambda) + \gamma_2(\lambda)b_{ij} + \delta(\lambda)x_i + \delta(\lambda)x_j + \omega_{ij}(\lambda),$$

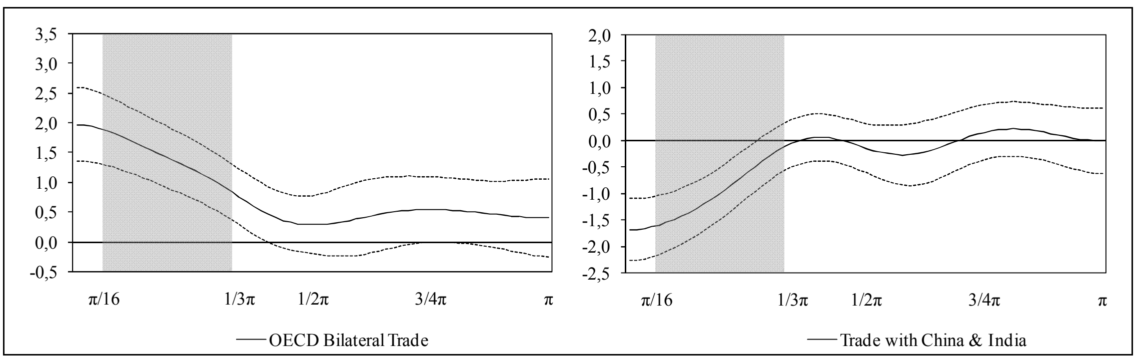
where ρ is the bilateral dynamic correlation at frequency λ and b_{ij} stands for trade to GDP ratio of OECD countries i and j. Furthermore, x represents the trade intensity (the average of exports and imports) with China or India used in the previous section, which is computed as total trade of, for example, an OECD country i with China and India and divided by GDP of countries i. The same definition is used for the exposure of globalization shock in country j. We restrict the coefficient for trade with China or India, δ, to be the same for both countries i and j, as the differences between them are caused by different ordering of the countries in the data matrix (note that we use only one half of the all possible combinations of *n* countries, because the indicators are the same (except for possible errors in trade statistics) for the country pair *i* and *j* as well as for the pair *j* and *i*).

Because estimating (3) by OLS may be inappropriate (see Imbs, 2004), we use two stage OLS. This reflects that bilateral trade flows might be influenced by exchange rate policies. Therefore, trade intensities have to be instrumented by exogenous determinants of bilateral trade and financial flows. Such instruments are provided by the well-known gravity model (see, for example, Bussière et al., 2008) including the log of GDP and GDP per capita, log of distance between trading partners, a dummy for geographic adjacency, countries with a common language, and a dummy for the 15 earlier member states of the EU and the NAFTA.

The results are reported in Figure 3. We can see that the positive relationship between business cycle similarities and the degree of trade integration is fully confirmed for the business cycle frequencies as well as for the long-run frequencies in OECD countries. Somewhat surprisingly, the relationship is positive but no longer significant for the short-run frequencies.

In contradiction to trade integration between OECD countries, Figure 3 shows that the trade intensity with the Asian giants is negative and highly significant especially at the longer-term business cycles frequencies. This pattern is the same if we include China or India in separate regressions, although it seems to be stronger for China.[31] This confirms our hypothesis that high intensity of trade and financial links to the Asian emerging economies has a negative effect on country's synchronization with business cycles of other OECD countries. For the short-run frequencies, the estimated coefficients are insignificant and only in few cases they have positive signs.

Figure 3:
Regression Results, Determinants of Business Cycle of OECD Countries



Note: Confidence bands are constructed as 1.96 standard errors. Business cycle frequencies are marked by the shadow area. For better comparison, explanatory variables have been rescaled to yield coefficients of the same size.

31 The detailed results are available upon request from authors.

6. Conclusion

Globalization has been one of the major events in the world economy in the past two decades. During this gradual process, several emerging countries have gained in economic weight and started to influence economic developments also in other countries. This development has been dominated especially by the Chinese economic growth, supported by export expansion to and investment from developed countries. Within few years, China has become an important factor of growth of the global economy. More recently, this development has been followed by India and possibly also by some other smaller emerging economies. Increasingly, these countries could also influence the business cycles of their trading partners.

We show that the business cycles between the economic development in emerging Asian giants and in developed economies are largely different. Many transnational companies use emerging markets as a part of their production chains and this is especially true for the Asian economies. Despite of this, most developed countries show a negative correlation with China and India for the traditional business cycles (cycles with periods between 1.5 and 8 years), which is generally discussed as decoupling of business cycles. However, many countries show higher correlations of the short-run fluctuations.

It seems that countries, which have more intensive economic relationship with China and India, have also higher dynamic correlation with these economies. This seems to be especially true for the long-term developments. However, trade integration is playing less important role for the convergence of business cycles than documented for business cycles between the OECD countries. In sum, our first results confirm a special position of the emerging Asian giants in the business cycles of the world economy. Despite the increased trade links between the countries, both China and India behave rather differently from the rest of the world economy. This may correspond to the replacement of production from the OECD countries to the emerging Asian economies.

Finally, we show that countries engaged intensively in trade with the emerging Asia tend to have a lower degree of synchronization of business cycles with other OECD countries, although the effects are relatively small especially for the business cycle frequencies. This stands in a contrast to the effects of trade and financial integration between the OECD countries, which show a positive and strong relationship between the degree of synchronization and of business cycles and trade.

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PART FOUR:
THE SYNCHRONIZATION OF BUSINESS CYCLES IN THE EURO AREA

Endogeneity of Optimum Currency Areas: What Can We Learn from the Determinants of Business Cycle Synchronization across the Euro Area?

Uwe Böwer and Catherine Guillemineau***

1. Introduction

This paper examines the underlying factors of business cycle synchronization in the euro area. We investigate a variety of potential determinants of cycle synchronization in the context of European monetary integration and check the robustness of the results by conducting an extreme-bounds analysis. Among traditional explanatory factors, trade-related variables emerge as robust determinants of business cycle synchronization but a few policy and structural indicators also appear to have some explanatory power.

Since the advent of EMU, business cycles have been highly correlated across euro area countries. Yet, inside the monetary union, euro area countries still experience different degrees of synchronization of their business cycles. Knowing what are the factors driving business cycle differentials among euro area countries and how these factors have evolved through time, can help to analyse better growth developments in the euro area. Various studies have shown that European business cycles have become increasingly synchronous (see for example Artis and Zhang, 1997 and 1999; Massmann and Mitchell, 2004; Gayer, 2007). Applying Markov Switching VAR models, Artis et al. (2004) find evidence of a distinct European business cycle. Few academics have, however, explored the underlying factors behind cycle synchronization in Europe. Baxter and Kouparitsas (2004) and Imbs (2004) analysed large samples of both developing and industrialised countries and found trade flows, specialisation, and financial integration to be important factors for business cycle synchronization. Their results are, however, not unequivocal and seem to depend on the country and time samples chosen.

In this paper, we specifically address the factors that are related to business cycle synchronization in the euro area countries. We test the standard determinants and consider a

* Corresponding author, European Commission, Av. de Beaulieu/Beaulieulaan 1, 1160 Brussels, Belgium. The authors would like to thank Antonello d'Agostini, Nicholai Benalal, Juan-Luis Diaz del Hoyo, Jean Imbs, Beatrice Pierluigi and Nick Vidalis as well as participants of the European Economic Association Meeting 2006 in Vienna and seminar participants at the European Central Bank, the European Commission, the European Investment Bank, the University of California at Berkeley, the University of Geneva and the University of Munich for providing useful comments.

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number of EMU-specific convergence and structural indicators which, to our knowledge, have not been tested in this context. We check robustness by applying the extreme-bounds analysis framework as suggested by Leamer (1983) and further developed by Levine and Renelt (1993) and by Sala-i-Martin (1997). Also, we divide the 25-year sample period into sub-samples in order to capture changing effects throughout the different stages of European integration. Our major findings are as follows. While many variables are significant in bivariate regressions, the extreme-bounds analysis confirms the robustness of only a few determinants. Over the whole sample period, 1980-2004, bilateral trade proves to be robust. During the pre-EMU period, 1980-1996, fiscal deficit differentials are a robust determinant. When analysing the period including EMU, 1997-2004, trade specialisation, in particular in the machinery sector, the short-term interest rate differentials and differences in stock market indices for cyclical services qualify as robust.

Section 2 provides an overview of the recent literature and presents the potential determinants of cycle correlation as well as stylized facts. Section 3 outlines the extreme-bounds analysis (EBA) and the methodology and presents the results of the EBA. Section 4 discusses the economic interpretation of the results in particular in the context of EMU.

2. What Drives Business Cycle Synchronization in the Euro Area?

This section reviews with the potential determinants of business cycle synchronization. The first sub-section both reviews the recent literature and suggests new indicators that are particularly relevant in the context of EMU. Based on these considerations, the variables used for the empirical analysis are described in the second sub-section.

Literature Review

The foremost candidate expected to influence cycle correlation is trade. In theory, however, it is unclear whether intensified bilateral trade relations result in more or in less synchronised business cycles. Models of international trade with monetary or technology innovations emphasise the cross-country spill-over of shocks and hence predict higher trade volume to be associated with more synchronised business cycles.[32] On the other hand, intensified trade relations may also lead to a higher degree of specialisation, due to the exploitation of comparative advantages. As a result, business cycles may

32 See *Imbs* (2004) for an overview.

become more asynchronous.[33] The underlying question is whether bilateral trade occurs mainly in similar or different sectors. If trade flows are predominantly intra-industry, as it is the case for most of the trade among industrialised countries, then we would expect the first effect to materialise. If bilateral trade is, or increasingly becomes, inter-industry, the second prediction may hold true. Whether an intensification of bilateral trade relatons will result in more or less synchronous business cycles can be assessed by paralleling the evolution of bilateral trade and of relative trade specialisation. Smaller cross-country differences in trade specialisation would indicate an intensification of intra-industry trade conducive to more synchronous business cycles.

Given the unclear theoretical case, the question is fundamentally an empirical one. In their seminal work on "the endogeneity of the optimum currency area criteria", Frankel and Rose (1998) estimated a single-equation model based on a large sample of developing and industrialised countries and found a strong and robust positive relationship between bilateral trade and cycle synchronization. This result is confirmed by Baxter and Kouparitsas (2004). Imbs (2004) employed a simultaneous-equations approach. He verified the overall positive impact of trade on business cycle synchronization but points out that "a sizable portion is found to actually work through intra-industry trade."[34]

The effects of economic specialisation on cycle synchronization have also been measured directly. Stockmann (1988) emphasises the importance of sectoral shocks for the business cycle since two countries will be hurt similarly by sector-specific shocks if they have economic sectors of similar nature and size. Hence, we would expect the degree of differences in sectoral specialisation to be negatively related to cycle synchronization, i.e. the more dissimilar the economies, the less correlated their cycles. Empirical studies however, find conflicting evidence regarding the robustness of this effect.[35] In the following, we consider sectoral patterns of economic specialisation across euro area countries.

Financial integration and the comovement of capital markets is the third major field of determinants. Kalemli-Ozcan et al. (2003) argue that countries with a high degree of financial integration tend to have more specialised industrial patterns and less synchronised business cycles. Evidence from the financial crises and contagion literature, however, indicates a direct, positive effect of capital flows to business cycle synchronization.[36] In addition, financial integration may lead to more synchronous cycles if new access to venture capital sources enables firms across countries to specialise similarly in

33 This point was made by *Krugman* (1992) and is known as the „Krugman Hypothesis".

34 *Imbs* (2004), p. 733.

35 While *Imbs* (2004) asserts that specialisation patterns play an independent role in cycle correlation, this notion is rejected by *Baxter* and *Kouparitsas* (2004).

36 See, for example, *Calvo* and *Reinhart* (1996) and *Claessens* et al. (2001), reviewed in *Imbs* (2004).

high-tech sectors.[37] Kose et al. (2003) point out that financial integration enhances international spillovers of macroeconomic fluctuations leading to more business cycle synchronization. Moreover, Imbs (2004) tests this direct link and finds a positive effect dominating the indirect link via specialisation dynamics. However, capital flows are not available on a bilateral basis and hence the above studies have to resort to overall measures of financial openness. In contrast to other existing studies which rely on measures on financial openness, we employ bilateral measures of actual bank flows in the context of business cycle synchronization.[38]

In addition to the above variables used in the literature, policy coordination may have a positive impact on cycle synchronization. We test a number of policy and structural indicators that are particularly relevant for the euro area. We ask whether the degree of similarity in various economic variables between two countries has influenced the bilateral synchronization of business cycles. The policy indicators include bilateral differentials in fiscal deficits, differentials in the real short-run interest rate and nominal exchange rate variations. The structural indicators capture competitiveness differentials, stock market comovements, and labour market flexibility. Finally, we add geographical distance between countries and relative country size in terms of population, in order to control for exogenous factors.

Definition of Variables

As a measure of business cycle synchronization in the euro area, we compute bilateral correlation coefficients between the cyclical part of real GDP for each pair of countries, drawing 66 pairs among the 12 euro area countries over the 1980-2004 period.[39] The cyclical parts are obtained by applying the Baxter-King band-pass filter, which Baxter and King (1995) suggested specifically in order to measure business cycle correlations.

The independent variable bilateral trade is constructed in two alternative ways. First, it is defined as the average of the sum of bilateral exports and imports, divided by the sum of total exports and imports, denoted by BTT. Second, the sum of national GDPs serves as scaling variable (BTY). The variable trade openness is calculated as the sum of total exports and imports of both countries, divided by the sum of national GDPs (TTY). We expect the bilateral trade and trade openness indicators to be positively correlated with

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37 See *Obstfeld* (1994).

38 Only *Papapioannou* (2005) explores actual bilateral flows between country pairs employing data on bank flows. *Imbs* (2006) employs bilateral survey data.

39 Annual observations for all years are available for most variables. Exceptions are trade specialisation and the index of employment protection calculated by the OECD, for which only some years are available (see following sub-section). Also, some data are not available for all years for all countries. For instance, capital flows from Greece are not available for all years, neither are bilateral trade data between Belgium and Luxembourg before 1997.

business cycle correlation. The trade specialisation indicator is measured by the cross-country difference between the average share across time of a particular sector in total exports. To obtain an overall sectoral distance measure for total exports, we add up the distances calculated for all sectors.[40] Differences in trade specialisation patterns are expected to be negatively related to business cycle correlation. Economic specialisation is defined along the same lines as trade specialisation, as the sum of the differences of sector shares in the national economies.[41] Hence we expect a negative coefficient for this variable, as for differences in trade specialisation. Bilateral capital flows are notoriously difficult to measure.[42] We use bilateral bank flows data provided by Papaioannou (2005). The source of the data is the BIS International Locational Banking Statistics. The aggregate bank flows are defined as the change in international financial claims of a bank resident in a given country vis-à-vis the banking and non-banking sectors in another country. The asset and liability flows are adjusted for exchange rate movements.[43] After converting all series in US dollars, the pair-wise series is calculated by taking the log of the average sum of bilateral asset (liability) flows between two countries.[44] The bilateral averages express a measure of financial intensity, regardless of whether flows occur in one direction or in the other. The more intensive bank flows between two countries, the stronger we expect the correlation between their business cycles to be.

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40 For instance, the share of the chemical sector in Belgium's overall exports is first averaged over the number of annual observations, then subtracted from the average chemicals share of, say Greece's total exports. This gives the economic 'distance' between the two countries for the trade in the chemical sector. Total exports of a country are divided into the ten first-digit sub-sectors of the United Nation's Standard International Trade Classification (SITC), revision 2. These sub-sectors are (i) food and live animals, (ii) beverages and tobacco, (iii) crude materials, inedible, except fuels, (iv) mineral fuels, lubricants and related materials, (v) animal and vegetable oils, fats and waxes, (vi) chemicals and related products, n.e.s., (vii) manufactured goods, (viii) machinery and transport equipment, (ix) miscellaneous manufactured articles, and (x) commodities and transactions not classified elsewhere in the SITC. The data source is the NBER World Trade Flows Database, as documented in Feenstra and *Lipsey* (2005). We calculate the average over the years 1980, 1989, and 2000.

41 National value added divides into six sub-sectors, based on the International Standard Industrial Classification (ISIC): (i) agriculture, hunting, forestry, and fishing, (ii) industry including energy, (iii) construction, (iv) wholesale and retail trade, (v) financial intermediation and real estate, and (vi) other services. Ideally we would have needed to use a more detailed decomposition of value-added in order to construct indices representing product-differentiation. A comprehensive data for more detailed sectors of the economy was unfortunately not readily available for all countries over the entire sample.

42 Existing studies of financial integration have largely focused on overall measures of financial openness, due to the unavailability of bilateral capital flows data; see *Imbs* (2004) and *Kose* et al. (2003).

43 Although similar, these two sets of series are not strictly equivalent. Asset flows from country *i* to country *j* are the assets held by banks in country *i* on all sectors in country *j*. They are not exactly the opposite of liabilities from country *j* to country *i*, since that variable represents the liabilities of banks in country *j* on all sectors in country *i*.

44 Since the dependent variable, business cycle synchronization, is by definition a ratio and all the other explanatory variables are either ratios themselves or are expressed as ratios, it is possible to compare the logarithm of financial flows to the other variables.

We consider short-term interest rate differentials, in order to determine whether differences in the monetary policy stance can be related to business cycle synchronization. In theory, countries with a similar policy stance should react in a similar way or stand at around the same point of the business cycle. We use short-term three-month money market rates deflated by consumer prices (private consumption deflator), and take the absolute value of the mean sample of pair-wise differences.[45] Nominal exchange rate fluctuations played a major role in the convergence process prior to 1999. Exchange rate volatility should be negatively correlated with business cycle synchronization. To capture the effect of variations in nominal exchange rates on business cycle synchronization, we use the standard deviations of the bilateral nominal exchange rates between countries across time, calculated via the ECU exchange rates. The standard deviations are scaled by the mean of the bilateral exchange rates over the sample period. Another convergence measure is given by the fiscal deficit differentials. Two countries with a small difference in their general government balance may exhibit more similar business cycles. We use net borrowing or net lending as a percentage of GDP at market prices as defined by the European Commission's excessive deficit procedure. The variable is constructed as the mean sample of the bilateral differences of deficit ratios, and taken as the absolute value.

To measure national competitiveness, we include the ECB National Competitiveness Indicator (NCI) for the intra-euro area group. The NCI is based on the real effective exchange rates, weighted by intra-euro area trade partners, and deflated by the HICP. Since the introduction of the euro in 1999, the NCI measures competitiveness based on relative price levels in the respective countries. As distance measure, we compute the bilateral differences of NCIs of countries and take the absolute value of the sample mean. The stock market indicator is built as the difference between stock market indices. Anderson and D'Agostino (2005) explore the role of sectoral stock market indices for business cycle fluctuations in the euro area. They find that the Datastream Total Market Index (TOTMK) and the Cyclical Services Index (CYSER)[46] are the best indicators of the business cycle. To explore this finding in the context of cycle comovement, we expect a smaller cross-country difference in the stock market indices, to be associated with more synchronised business cycles. We calculate country-pair differences in the values of these indices, scale them by national nominal GDPs and take the absolute value of the sample mean. Since the stock market indicators are expressed in terms of difference, we expect a negative relation with business cycle correlation. Labour market flexibility indicators may play a role in the process of business cycle synchronization. The more similar two countries are in terms of labour market flexibility, the more similar their adjustment to shocks might be. We employ two indicators from the OECD Labour Market Statistics. The first indicator is trade union density, measured as the percentage of organised work-

45 We test both nominal and real interest rates but do not find any sizable effects for nominal interest rates.

46 This index includes retail firms, hotel chains, media corporations and transports (such as airlines and railroads).

ers. We calculate the average over the sample and compute the bilateral differences in order to obtain a distance measure expressed in absolute value. The second indicator is the OECD index of strictness of employment protection legislation. This index ranges from 0 (no protection) to 5 (strict protection) and is given for both permanent and temporary employment. We calculate the average of the permanent and temporary employment protection indices. Since data is available only for the years 1990, 1998, and 2003, we average these values for each country before we compute the bilateral differences as the distance measure of employment protection.

Finally, we apply gravity variables that are commonly used in the literature to account for exogenous aspects. Bilateral trade flows have been well explained by the ‘gravity’ measures of geographical distance and relative size. Geographical distance is expressed in terms of distance between national capitals. Relative size is measured as the bilateral difference in population between two countries, divided by the sum of their population. The greater the distance, the smaller the expected correlation of business cycles.

A Cross-Country View of Developments in the Euro Area

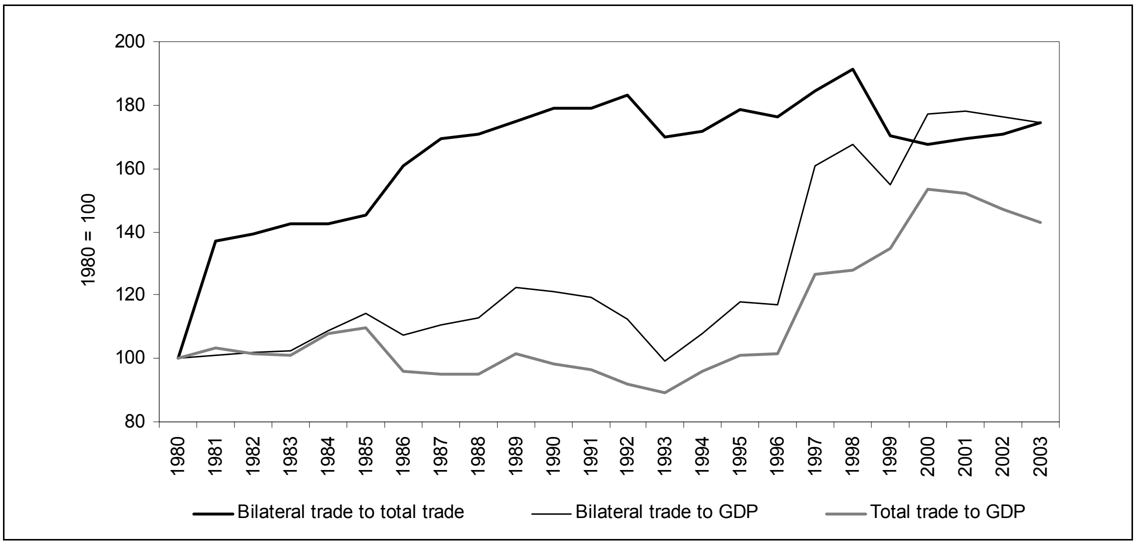
Before estimating the extreme-bounds analysis, we explore some descriptive properties of the core variables. We present rolling windows of the average correlations of the 66 country combinations in Figure 2. We choose 8-year windows corresponding to the maximum length of the business cycle in the Baxter-King filter which we applied to de-trend the real GDP series. The average correlation reached a minimum in the period 1981-1988 before increasing in the late 1980s and early 1990s. Since 1993-2000, it has remained high at around 0.7 (see Figure 1).

Inspecting the average trade ratios over time, the continued increase in bilateral trade to total trade since the early 1980s stands out (see Figure 2). However, this increase reflected partly an intensification of bilateral trade relations between euro area countries, and partly a temporary decline in the trade-to-GDP ratio with non-euro area countries. As a share of GDP, average bilateral trade inside the euro area increased only slightly between 1980 and 1996. The average total trade to GDP ratio declined somewhat during this period, suggesting that bilateral trade with non-euro area countries declined in relation to GDP. From 1997 to 2004, on average, bilateral trade between euro area countries rose relative to GDP. Total trade, including trade with non-euro area countries picked up as well relative to GDP. The consequence was a fall in the average ratio of bilateral trade between euro area countries to their total trade. In other words, the euro area countries appear to have traded more in the run-up to the single currency and since its advent, on the whole as well as relatively more with extra-EMU countries. EMU seems therefore to have been characterised by trade creation rather than by trade diversion.[47]

[47] This argument finds empirical support in *Micco* et al. (2003). For an overview, see *Baldwin* (2005).

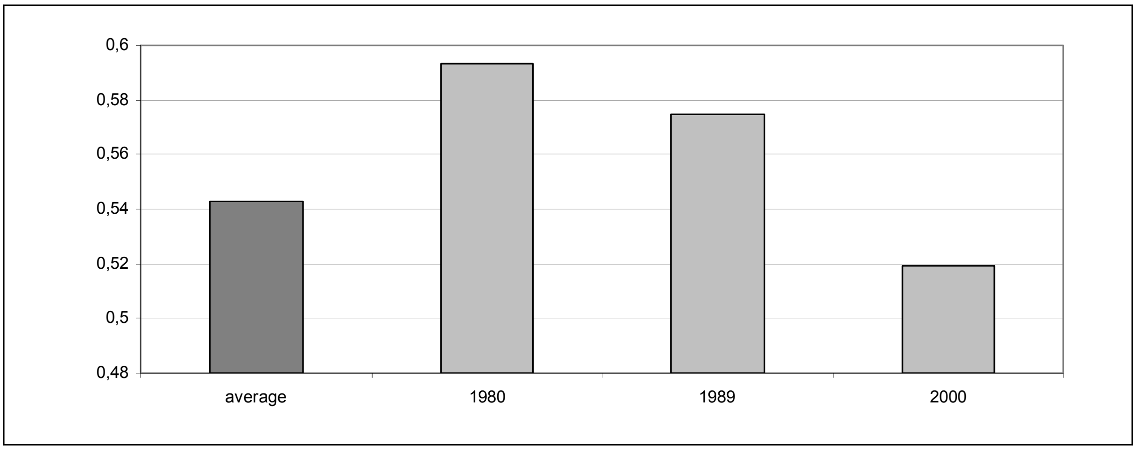
Figure 1:
8-Year Rolling Windows of of Baxter-King Filtered Real GDP, GDP Weighted and Unweighted

Figure 2:
Average Trade Volume
- Index 1990 = 100 -



Across time, euro area countries have converged in terms of trade specialisation as shown in Figure 3. From 1980 to 2000, differences in trade specialisation declined continuously. The low value of the trade specialisation indicator in 2000 indicates that euro area countries have become more similar in terms of trade structure. Combined with the above indication that EMU contributed to trade creation, this suggests that the intensification of trade relations alongside the single currency was characterised by the development of intra-industry trade, by opposition to inter-industry trade. Thus, as conjectured by Frankel and Rose (1998), the introduction of the single currency may have given a "substantial impetus for trade expansion".

Figure 3:
Average Trade Specialisation Index



3. Test of Robustness Extreme-Bounds Analysis

We employ the extreme-bounds analysis approach to investigate the determinants of business cycle synchronization. In this section, we introduce the econometric methodology and present the main results of the analysis of the determinants of business cycle synchronization across the euro area countries.

Methodology

In order to identify the robust determinants of business cycle synchronization, we employ the extreme-bounds analysis (EBA) as proposed by Leamer and Leonard (1981), Leamer (1983) and further developed by Levine and Renelt (1992), Levine and Zervos (1993), and Sala-i-Martin (1997) in the context of empirical growth analysis. Baxter and Kouparitsas (2004) employ an EBA estimation to explain business cycle synchronization across a large sample of developing and industrialised countries.

Estimation Framework. The framework consists in a cross-section OLS estimation, regressing business cycle synchronization on a variety of potential determinants. The testing strategy begins with estimating a baseline bivariate regression of the vector of business cycle correlation on each of the potential determinants of synchronization. Additional variables are added successively to the baseline estimate.

A necessary condition for a variable to be a meaningful determinant of business cycle correlation is that it should be first significant in a bivariate regression. The explanatory power of a given variable may however vary considerably when other determinants are included in the baseline regression. The EBA framework aims at identifying the variables whose explanatory power is not conditional on the information set. These variables are called ‘robust’.

In practice, the robustness of the potential determinants is determined by testing each candidate variable (*M*-variable) against a varying set of other conditioning variables (*Z*-variables). A variable is considered ‘robust’ to the model specification if its coefficient remains significant when varying the information set. Otherwise it is considered ‘fragile’. The regression framework can be written as:[48]

(1) $$Y = \beta_i I + \beta_m M + \beta_z Z + u,$$

where Y denotes a vector of coefficients of bilateral business cycle correlations. The *M*-variable is the candidate variable of interest which is tested for robustness. This robustness test is conducted by including a varying set of conditioning or control variables, Z, and checking the β_m coefficients’ sensitivity to alterations in Z. For each *M*-variable, we first run a baseline regression without any *Z*-variables, then successively include one, two, and three *Z*-variables in every possible combination.[49] The *I*-variable, on the other hand, controls for initial conditions that are exogenous. The ‘gravity variables’, geographical distance and relative population size, may fall into that group. We also run alternative set-ups with and without the *I*-variables.

For every *M*-variable under consideration, the EBA identifies the ‘extreme bounds’ by constructing the highest and lowest values of confidence intervals of the estimated β_m coefficients. In other words, the extreme upper bound (EUB) is equal to the maximum estimated β_m, plus two times its standard error, $\text{EUB} = \beta_m^{\max} + 2\sigma(\beta_m^{\max})$, the extreme lower bound (ELB) is the minimum estimated β_m, minus two times its standard error, $\text{EUB} = \beta_m^{\max} - 2\sigma(\beta_m^{\max})$. The *M*-variable is then regarded as robust, if the EUB and the ELB exhibit the same sign and if all estimated β_m coefficients are significant.

In the estimates we carried out, there were some cases when the extreme upper (lower) bound changed sign around zero when adding (subtracting) two standard deviations to the maximum (minimum) β_m coefficient. All other β_m coefficients came out significant and were of the same sign. In these cases we considered that the variable was ‘quasi-robust’ when the value of the upper (lower) bound was less than 5% the maximum (minimum) coefficient.

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48 This equation is the equation first used by *Levine* and *Renelt* (1992) and derived from the statistical theory expounded in *Leamer* and *Leonard* (1981).

49 This strategy follows *Levine* and *Zervos* (1993).

Levine and Renelt's decision rule has indeed been criticised as very restrictive. In fact, Sala-i-Martin (1997) argues that running a sufficiently large number of regressions increases the probability of reaching a non-robust result. He states that "this amounts to saying that if one finds a single regression for which the sign of the coefficient β_m changes or becomes insignificant, then the variable is not robust."[50] Instead of either rejecting or accepting 'robustness' of variables, he suggests to assign a certain 'level of confidence' to each *M*-variable by investigating the share of significant β_m coefficients. Hence, an *M*-variable with a share of significant coefficients of 95% may be distinguished to an *M*-variable with only 50% of significant β_m coefficients. In the results tables, we therefore not only state the robust/fragile result but also indicate the share of insignificant coefficients.[51]

Information Set. The dependent variable is a vector of bilateral pairs containing the 66 correlation coefficients between the cyclical part of real GDP for the 12 euro area countries. The candidate explanatory variables are drawn from the set of potential determinants presented in Section 2. They include: bilateral trade, trade openness, trade patterns, economic patterns, bilateral bank flows, real short-term interest rate differentials, nominal exchange rate fluctuations, fiscal deficit differentials, national competitiveness indicators, differences in stock market indices, labour market flexibility indicators, and gravity variables.

Among this set of indicators, we select four main categories of *M*-variables of interest which we think should be key determinants of the business cycle as indicated in the literature review (Sub-section 2.1). These variables are: bilateral trade and openness to trade; trade specialisation; economic specialisation; bilateral bank flows. Regarding the group of *Z*-variables, we conducted a pre-selection similar to the selection process used by Levine and Zervos (1993), in order to avoid including series that may overlap with the *M*-variable under review. Pre-selection allows minimising multicollinearity problems between the explanatory variables which might be a drawback of the EBA analysis. For instance, a similar trade specialisation between two countries could result in an intensification of bilateral trade. The similarity of economic structures may also be reflected in the similarity of trade patterns. Last, strong trade relations may contribute to intensify the flow of credits between two countries. In addition, we test successively for different alternative measures of the *M*-variables (Sub-section 3.2). The robustness of the *M*-variables was tested by estimating multivariate regressions where all possible combinations of 1 to 3 explanatory variables, drawn from a pool of six *Z*-variables and one *I*-variable, were added successively to the bivariate regression.

50 *Sala-i-Martin* (1997), p. 178.

51 We state the share of outliers for the cases in which at least the bivariate estimation coefficient is significant.

The core group of control *Z*-variables which may be related to the business cycle includes: bilateral exchange rate volatility (SD_NERE), differences in fiscal deficits (DEFDIFF), differences in national price competitiveness (NCIDIFF), differences in the performance of stock markets (TOTMKDIFF for the overall market index; alternatively CYSERDIFF for cyclical services), differences in trade union membership (TUDDIFF).[52] The *Z*-variables may also turn out to be potentially important explanatory variables and have also been identified, directly or indirectly, as key determinants of business cycle synchronization.

To the group of initial *Z*-variables, we added the gravity variables which we first considered as *I*-variables, and which represent external non-economic factors. However, systematically including geographical distance (GEODIST) in all equations created partial correlation problems because several explanatory variables are closely related to geographical distance, bilateral trade in the first place. As in Baxter and Kouparitsas (2004), we treated geographical distance as a 'not-always' included variable. Including or not differences in population size (POPDIFF) as an *I*-variable did not have any impact on the EBA results. Robustness tests were conducted also for the variables which we designated ex-ante as *Z*-variables and *I*-variables. In order to ensure the comparability of results, the additional explanatory variables were always drawn from the same pool of explanatory variables,[53] as for the *M*-variables.

Samples. In the following sub-sections, for each group of possible explanatory variables, we present the bivariate relations with business cycle and discuss the EBA results. The robustness of the variables is tested for the full sample from 1980 to 2004. It is of particular interest to know whether the determinants of business cycle correlation have changed since the implementation of a common monetary policy. We therefore conducted tests for two sub-periods. The first period runs from 1980 to 1996; the second period – including the run-up to and the advent of EMU – starts in 1997 and ends in 2004.[54]

Since the analysis is a cross-section analysis, across countries and for one point in time, the sample size for the estimates is always the same whatever the number of years in the period of estimation, and corresponds to the 66 country pairs. Since the series entering

52 Possibly because of the scarcity of data, the employment protection indicator (EPADIFF) was not significant in the bivariate regression and for that reason, was not used in the multivariate regressions.

53 BTT, TOTMKDIFF, IRSCDIFF, NCIDIFF, DEFDIFF, SD_NERE, TUDIFFF and GEODIST.

54 While the single monetary policy came into force in 1999, several of the convergence criteria for eligibility to the common currency were evaluated over a period of two years prior to the launch of the single currency. The exchange rate in particular ought to have fluctuated inside the normal fluctuation margins of ERM for at least two years. Empirical studies have confirmed 1997 as the start of the convergence process towards monetary union. In addition, the definite timetable for the implementation gained credibility after the agreement on the Stability and Growth Pact in June 1997. See *Frankel* (2005) who considers June 1997 as the 'breakpoint in perceptions'; according to Goldman Sachs estimations, the probability of EMU taking place in 1999 shot up above 75%.

the regressions are calculated in terms of averages, the cross-country observations might be more dispersed when calculated over a shorter period of time than when calculated over a period of several years. This is not however the case: the standard deviations of the series scaled by their means are not always higher in the two sub-samples than in the full sample, and in the last sub-sample than the first one.

Regarding parameter uncertainty, the standard errors of the coefficients tend to increase in the 1997-2004 sample which could lead to more frequent rejection of robustness. However, there is no automatic link between the size of standard errors and the acceptance or rejection of robustness. The ‘robustness’ of the explanatory variable is accepted also in the cases where the standard error of the explanatory variable’s coefficient increases considerably in the second sample.

Results for the Core Explanatory Variables

The three measures of trade are considered successively. For these variables we expect a positive coefficient: the more intensive trade between two countries (or the more open to trade), the higher the trade variable, and the more synchronous the business cycles. Business cycle correlation increases with the intensification of bilateral trade, both relative to total trade and to GDP.[55] Through bilateral trade, spill-over effects appear to affect simultaneously business cycles in two countries regardless of their relative openness to trade.

The bivariate regression of business cycle correlation on the ratio of bilateral trade to total trade (BTT) reveals a positive-sloping trend. With a *t*-statistic of 3.9, the point estimate is significant at the 5% level. The goodness of fit amounts to 0.2 which appears acceptable for a bivariate regression. In the EBA, over the full sample, BTT comes out clearly as robust. The results are reported for the two variables without geographical distance.[56] For BTT, without geographical distance, the lower and upper bounds of all estimates range from 0.1 to 3.1. The β_m coefficients range between 1.0 and 2.1, and are all significant at the 5% level. Although the lower bound drops to 0.123, the associated equation has a fairly good explanatory power. Indeed, the associated R^2 reaches 0.4 and is twice as large as for the upper bound and as in the bivariate case.

Turning to the sub-samples, for the 1980-96 period, BTT remain robust determinants of business cycle correlation. The range for the extreme bounds tends to be larger than for the full sample, due to larger standard errors. Nevertheless, the range for the actual β_m coefficients is smaller, indicating that the power of bilateral trade to explain business

55 We focus here on the ratio of bilateral trade to total trade. The results for the bilateral trade to GDP and total trade to GDP ratios are available upon request.

56 In that particular case, geographical distance may create multicollinearity problems if included among the regressors. Geographical distance is indeed a strong determinant of bilateral trade itself.

cycle synchronization is less conditioned by other variables than in the full sample. However the explanatory power of bilateral trade ratios for the 1980-1996 period is very low (the R^2s are around 0.1), indicating that bilateral trade explained only a small part of business cycle correlation.

While bilateral trade appears to have been a key element in the synchronization of business cycles before monetary union, its explanatory power has decreased since then. For both ratios of bilateral trade to total trade and to GDP, over the 1997-2004 period, the lower bound turns clearly negative as the minimum β_m becomes insignificant in particular when the fiscal deficit differential are added as explanatory *Z*-variable. However, the upper bounds increase markedly. In the bivariate case and when only difference in trade union membership is added to the equation, the maximum β_m coefficients increase to 4.1 for BTT over the 1997-2004 period, while in the 1980-2006 the maximum coefficient on bilateral trade was only half that value.

Table 1:
Bilateral Trade to Total Trade Ratio

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Robust	Bivariate		2.065	0.524	3.94	0.18		
	High	3.112	2.055	0.528	3.89	0.17	TUDDIFF	100%
	Low	0.123	0.956	0.416	2.30	0.40	TOTMKDIFF, NCIDIFF, DEFDIFF	
1980-1996								
Robust	Bivariate		1.872	0.582	3.22	0.12		
	High	3.349	2.082	0.634	3.29	0.11	SD_NERE, TUDDIFF	100%
	Low	0.301	1.369	0.534	2.56	0.13	TOTMKDIFF, NCIDIFF, TUDDIFF	
1997-2004								
Fragile	Bivariate		4.092	1.456	2.81	0.10		
	High	7.269	4.121	1.574	2.62	0.09	TUDDIFF	46.3%
	Low	−2.660	−0.830	0.915	−0.91	0.32	TOTMKDIFF, DEFDIFF, GEODIST	

Regarding ***trade specialisation*** (TRADEPAT), the expected negative relation to cycle correlation is confirmed. In other words, the more similar the trade structures of two countries, the higher is cycle correlation. The *t*-statistics amounts to −3.1, respectively and the R^2 is fairly large (0.2) for a bivariate regression. However, over the full sample, trade specialisation fails to qualify as robust in the EBA, albeit by a small margin. All the coefficients have the right expected negative sign and are significant at the 10% level but the upper bound turns positive in the case of the maximum coefficient (−0.2). The minimum coefficient (−0.4) is reached in the bivariate case and in the case with one *Z*-variable (difference in trade union membership). Noticeably, bilateral exchange rate volatility when introduced in the estimate, seems to reduce sensibly the explanatory power of trade specialisation. Over the 1980-1996 period, trade specialisation fails to qualify as robust. Even in the bivariate regression, the coefficient on trade specialisation remains insignificant. The upper bound which, in estimates for the full sample, was sensitive to changes in the information set becomes even more clearly insignificant when the national competitiveness indicator is included as a control variable. By contrast, trade specialisation becomes clearly robust in the 1997-2004 sample. The maximum and minimum β_m coefficients are all significant at the 5% level, ranging from −0.5 to −1.5 with fairly large R^2s (0.6 and 0.4, respectively).

Table 2:
Trade Specialisation Indicator

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant coefficients
1980-2004								
Fragile	Bivariate		−0.433	0.140	−3.10	0.19		
	High	0.032	−0.169	0.101	−1.68	0.38	IRSCDIFF, NCIDIFF, SD_NERE	100%
	Low	−0.715	−0.437	0.139	−3.14	0.20	TUDDIFF	
1980-1996								
Fragile	Bivariate		−0.237	0.157	−1.50	0.04		
	High	0.219	−0.074	0.146	−0.51	0.10	NCIDIFF, GEODIST	n.a.
	Low	−0.586	−0.246	0.170	−1.45	0.02	SD_NERE	
1997-2004								
Robust	Bivariate		−1.233	0.293	−4.21	0.35		
	High	−0.022	−0.469	0.224	−2.10	0.58	IRSCDIFF, DEFDIFF, GEODIST	100%
	Low	−2.055	−1.491	0.282	−5.28	0.40	NCIDIFF, TUDDIFF	

We conducted robustness tests for some of the main trade sub-sectors in order to find out if key driving sectors could be identified. We checked for trade differentiation in mineral fuels (CD_FUEL), machinery and transport equipment (CD_MACH), other manufacturing products (CD_MANU) and chemicals (CD_CHEM). These products were selected for their greater sensitivity to fluctuations in the business cycle. None of these four trade components comes out as robust over the full sample[57] but, with all the coefficients significant at the 10% level, trade in machinery and equipment comes close

57 Detailed results for the sub sectors are available upon request.

to it. Over the first sub-sample, from 1980 to 1996, the components of trade specialisation are often even not significant in the bivariate regression and do not qualify as robust. Over the second sub-sample, from 1997 to 2005, trade differentiation fails again to qualify as robust in all the sectors tested, with however the notable exception of machinery and equipment. Most of the impact of trade specialisation therefore appears to occur through trade in machinery and equipment. This category of product is indeed widely considered as a leading indicator of the business cycle, and a substantial part of intra-industry trade between euro area countries occurs in that sector.

Trade specialisation in machinery and equipment (CD_MACH) appears to have been a key driver of the impact of trade structures on business cycle synchronization since EMU. In 1997-2004, most of the impact of trade specialisation on business cycle synchronization seems to have come from machinery and transport equipment. For that sector, the results are even more significant than for total trade, Importantly, the R^2s are very large, in particular in the case of the upper bound (0.8), including three *Z*-variables (the real interest rate differentials, the competitiveness indicator, and differences in fiscal deficits).

The ***economic specialisation*** indicator (ECOPAT) is negatively related to cycle correlation. Although the *t*-statistics on the coefficient is significant at the 5% level, the R^2 of the regression (0.05) is not meaningful. This suggests that an overall similarity in the relative shares of broad economic sectors provide little information to explain business cycle correlation. Indeed, in the EBA analysis, economic specialisation fails to reach the robustness status with the extreme bounds ranging from 0.3 to −1.0. The upper bound becomes insignificant and of the wrong sign when the total stock market index, the fiscal deficit differentials and bilateral exchange rate volatility are included as control variables.

As for trade specialisation, we also analysed the robustness of some of the components of economic specialisation: industry (CD_IND), construction (CD_CNT), wholesale and retail trade (CD_TRA), financial intermediation (CD_FIN).[58] Out of the five sectors, only the differences between the share of industrial sectors (CD_IND) comes out as significant, regardless of the combination of *Z*-variables included in the equation. In the full sample, from 1980 to 2004, all the β_m coefficients are significant at the 5% level and negative, ranging from −1.2 to −2.2. Nevertheless, in the case of industrial differences, the upper bound turned to the wrong positive sign by a very small margin (less than 5% of the absolute value of the extreme coefficients), when using interest rates deflated by consumer prices. When using differentials of interest rates deflated by the GDP deflator, they remained clearly negative. By comparison using either deflator did not make any difference to the results in the case of the other variables that were tested for robustness.

58 Detailed results for the subsectors are available upon request.

Turning to the 1980-1996 sub-sample, economic specialisation fails again to qualify as robust but both the relative shares of industrial sectors (CD_IND) and the relative shares of financial sectors (CD_FIN) come close to robustness.[59] The relative importance of financial specialisation in explaining business cycle synchronization over the first sub-sample may reflect the impact on economic activity of the liberalisation, development and internationalisation of financial services during that period. Over the 1997-2004 period, neither overall economic specialisation nor any of its components comes out as robust.

Table 3:
Trade Specialisation in Machinery and Equipment

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Fragile	Bivariate		−0.720	0.289	−2.50	0.11		
	High	0.061	−0.446	0.253	−1.76	0.40	IRSCDIFF, NCIDIFF, SD_NERE	100%
	Low	−1.516	−0.956	0.280	−3.42	0.25	TOTMKDIFF, TUDDIFF	
1980-1996								
Fragile	Bivariate		−0.276	0.337	−0.82	−0.00		
	High	0.457	−0.119	0.288	−0.41	0.09	NCIDIFF	n.a.
	Low	−1.383	−0.514	0.434	−1.18	0.09	TOTMKDIFF, SD_NERE, GEODIST	
1997-2004								
Robust	Bivariate		−3.590	0.536	−6.70	0.60		
	High	−0.566	−1.427	0.431	−3.31	0.78	IRSCDIFF, NCIDIFF, DEFDIFF	100%
	Low	−4.680	−3.680	0.500	−7.36	0.61	TUDDIFF	

The measure of ***financial integration***, log-bilateral flows of bank assets (LBFA), is positively related to cycle correlation and significant at the 1% level with an R^2 of 0.2. This suggests that, on a bivariate basis, higher financial openness (estimated by bilateral bank flows), is associated with higher correlation of the business cycles. However, over the full sample, bilateral bank asset flows fail to qualify as a robust determinant of business cycle synchronization, whether or not geographical distance is included in the group of *Z*-variables. Although most β_m coefficients are positive and significant at the 5% or 1% level, the coefficients of the equations including the national competitiveness indicator or real interest rate differentials as control variables are insignificant. Turning to the sub-samples, asset flows do not qualify as robust in either case but are more significant in the second period. From 1997 to 2004, bilateral asset flows are close to becoming a 'robust' determinant of business cycle correlation, whereas from 1980 to 1996 none of the coefficients are significant and most of them have the wrong sign. The series representing bilateral flows of bank liabilities broadly follow the series of the asset flows and are not explicitly reported; they never appeared as robust.

59 Construction also appears as robust but with the unexpected sign.

Table 4:
Economic Specialisation Indicator

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant coefficients
1980-2004								
Fragile	Bivariate		−0.499	0.191	−2.61	0.05		
	High	0.274	−0.145	0.209	−0.69	0.26	TOTMKDIFF, DEFDIFF, SD_NERE SDSD_NERE	81.0%
	Low	−0.980	−0.604	0.188	−3.22	0.07	TUDDIFF	
1980-1996								
Fragile	Bivariate		−0.612	0.305	−2.01	0.05		
	High	0.194	−0.412	0.303	−1.36	0.13	TOTMKDIFF, NCIDIFF, DEFDIFF	77.8%
	Low	−1.429	−0.902	0.264	−3.42	0.16	NCIDIFF, SD_NERE, GEODIST	
1997-2004								
Fragile	Bivariate		−0.473	0.419	−1.13	0.00		
	High	1.058	0.370	0.344	1.07	0.53	TOTMKDIFF, IRSCDIFF, DEFDIFF	n.a.
	Low	−1.284	−0.497	0.393	−1.27	−0.01	TUDDIFF	

Results for the Policy Indicators

The relation between ***real short-term interest rates*** differentials (IRSCDIFF) and business cycle correlation is negative. The coefficient is significant at the 10% level but the R^2 (0.03) is far too small for the bivariate regression to be meaningful at all. In the full-sample EBA, real short-term interest rate differentials do not appear as robust. When negative as expected, the β_m coefficients are far from the significance level and the R^2s of the equations are close to zero. When interest rate differentials turn out as significant, they have unfortunately the wrong positive sign. The same characteristics apply to the 1980-1996 period as for the full sample. More interesting is the fact that real interest rate differentials clearly appear robust when used as a variable of interest in the second period from 1997 to 2004. The result is also robust to the choice of the pool of *Z*-variables. The coefficients are significant at the 1% level and the R^2 very large, ranging from 0.6 to 0.7 in the multivariate regressions. The actual coefficients vary between −0.3 and −0.6, which corresponds to extreme bounds of −0.2 and −0.8.[60] Since the preparation for and the implementation of monetary union, business cycle synchronization and real interest-rate differentials have become more closely related.

The relation between ***nominal bilateral exchange rate fluctuations*** (SD_NERE) and the correlation of business cycles appears negative, according to which a lower standard deviation in the bilateral nominal exchange rates is associated with a higher degree in business cycle comovement. The *t*-statistic of −2.80 indicates statistical significance and the R^2 of 0.10 is in the medium range when compared to the other bivariate regressions.

60 The pool of *Z*-variables include: BTT, TOTMKDIFF, NCIDIF, DEFDIFF, TUDIFF AND GEODIST.

In the full sample and over the 1980-1996 period, nominal exchange rate fluctuations do not qualify as a robust determinant of business cycle synchronization.[61] Nearly all β_m coefficients are negative but many are not significant. Exchange rate volatility does not qualify as robust possibly because the national price competitiveness indicator is also included in the regressions.

Table 5:
Bilateral Flows of Bank Assets

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant coefficients
1980-2004								
Fragile	Bivariate		0.038	0.011	3.39	0.16		
	High	0.060	0.039	0.010	3.87	0.13	IRSCDIFF, SD_NERE	69.8%
	Low	−0.023	0.005	0.014	0.36	0.34	IRSCDIFF, NCIDIFF, DEFDIFF	
1980-1996								
Fragile	Bivariate		0.025	0.019	1.33	0.02		
	High	0.088	0.031	0.028	1.10	−0.03	SD_NERE, TUDDIFF, GEODIST	n.a.
	Low	−0.101	−0.042	0.030	−1.40	0.21	TOTMKDIFF, NCIDIFF, SD_NERE	
1997-2004								
Fragile	Bivariate		0.025	0.010	2.50	0.12		
	High	0.050	0.028	0.011	2.52	0.12	IRSCDIFF, NCIDIFF	22.0%
	Low	−0.020	0.000	0.010	0.01	0.31	IRSCDIFF, DEFDIFF, GEODIST	

The national price competitiveness indicator encompasses multilateral exchange rate variations which may duplicate some of the information contained in bilateral exchange rate variations.

The effects of similar ***fiscal policies*** is estimated through the bilateral differentials in fiscal budget deficits as shares of GDP (DEFDIFF). The negative sign on the fiscal indicator indicates that the more similar the fiscal policy stance, the more synchronized business cycles are. With a *t*-statistic of −5.2 and an R^2 of 0.2, the relation proves significant. In the case of fiscal deficits, however, we may face a particularly strong case of reverse causation: not only may similar fiscal policies lead to more synchronous cycles but common positions in the business cycle are likely to induce similar fiscal policy responses as well. In the EBA, over the full sample, the fiscal policy indicator appears robustly related to business cycle synchronization, with extreme bounds ranging from −0.8 to −4.2.[62] All the *t*-statistics are significant at the 1% level. Over the 1980-1996 period, the fiscal policy indicator comes very close to qualify as robust.

61 The pool of *Z*-variables include: BTT, TOTMKDIFF, NCIDIFF, DEFDIFF, IRSCDIFF, TUDIFF.

62 The pool of *Z*-variables include: BTT, TOTMKDIFF, IRSCDIFF, NCIDIFF, SD_NERE, TUDIFF AND GEODIST.

Table 6:
Real Short-term Interest Rates Differentials

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Fragile	Bivariate		−0.049	0.028	−1.73	0.03		
	High	0.175	0.109	0.033	3.27	0.34	TOTMKDIFF, NCIDIFF, SD_NERE	7.3%
	Low	−0.107	−0.050	0.028	−1.77	0.03	TUDDIFF	
1980-1996								
Fragile	Bivariate		−0.008	0.018	−0.45	−0.01		
	High	0.115	0.058	0.028	2.05	0.06	NCIDIFF, TUDDIFF	n.a.
	Low	−0.077	−0.022	0.027	−0.80	0.05	DEFDIFF, SD_NERE	
1997-2004								
Robust	Bivariate		−0.417	0.079	−5.28	0.50		
	High	−0.177	−0.328	0.076	−4.33	0.58	TOTMKDIFF, DEFDIFF, GEODIST	100%
	Low	−0.753	−0.596	0.079	−7.59	0.69	NCIDIFF, TUDDIFF	

All the β_m coefficients are negative and significant at or close to the 5% level but the upper bound becomes positive. The upper bound becomes positive by a small margin.

However, a close investigation of the residuals showed that the Germany-Finland pair acted as an outlier in the equation corresponding to the upper bound.[63] This outlier can be easily explained by the shock created by the collapse of the Soviet system in Europe. In Western Europe, Germany and Finland were the countries most affected by that event but the shock had a diverging impact on the two economies. Over the 1980-1996 period, the dummy for Germany-Finland is significant in all the equations. In addition, the extreme bounds of the fiscal deficit indicator keep the right sign, remaining clearly negative.[64]

The apparent decline in the power of fiscal deficit differentials to explain business cycle differentials since 1997-1999 might be related to the Stability and Growth Pact. Since the implementation of the Pact, fiscal policy has become less pro-actively used as a policy instrument to fine tune economic growth. Compared with the 1980-1996 period, fiscal deficits may have become more determined by the business cycle and have become less a causing variable of the business cycle. In order to test that hypothesis, we

63 The residual for Germany-Finland was 3.9 times the standard deviation of the residuals of the equation.

64 As expected, given the timing of the external shock, the Germany-Finland dummy has not significant impact on the results for the full sample and for the second sample. Over the 1997-2004 period, the fiscal policy indicator fails to qualify as rocant.

conducted tests on the robustness of business cycle correlation as a determinant of fiscal deficit differentials over the 1997-2004 period (Table 9).

Table 7:
Bilateral Exchange Rate Fluctuations

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Fragile	Bivariate		−0.301	0.107	−2.80	0.10		
	High	0.289	0.048	0.120	0.40	0.28	NCIDIFF, TUDDIFF, GEODIST	36.5%
	Low	−0.668	−0.404	0.132	−3.07	0.16	TOTMKDIFF, IRSCDIFF, TUDDIFF	
1980-1996								
Fragile	Bivariate		0.006	0.091	0.07	−0.02		
	High	0.115	0.058	0.028	2.05	0.06	NCIDIFF, TUDDIFF	n.a.
	Low	−0.077	−0.022	0.027	−0.80	0.05	TOTMKDIFF, TUDDIFF	

Table 8:
Fiscal Policy Differential

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Robust	Bivariate		−3.046	0.581	−5.24	0.21		
	High	−0.794	−1.859	0.532	−3.49	0.43	BTT, IRSCDIFF, NCIDIFF	100%
	Low	−4.166	−3.020	0.573	−5.27	0.20	TUDDIFF	
1980-1996								
Quasi-robust	Bivariate		−1.784	0.573	−3.11	0.07		
	High	0.049	−1.186	0.618	−1.92	0.13	TOTMKDIFF, IRSCDIFF, NCIDIFF	98.4%
	Low	−2.940	−1.807	0.567	−3.19	0.03	IRSCDIFF, SD_NERE, TUDDIFF	
1997-2004								
Fragile	Bivariate		−7.801	2.056	−3.80	0.12		
	High	0.776	−2.490	1.633	−1.52	0.54	BTT, IRSCDIFF, TUDDIFF	97.6%
	Low	−14.67	−8.610	3.031	−2.84	0.11	NCIDIFF, TUDDIFF	

Table 9:
Business Cycle Correlation as a Determinant of Fiscal Deficit Differentials (1997-2004)

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1997-2004								
Fragile	Bivariate		−0.017	0.004	−4.56	0.12		
	High	0.004	−0.008	0.006	−1.36	0.31	BTT, IRSCDIFF, TUDDIFF	95%
	Low	−0.046	−0.029	0.009	−3.33	0.21	TOTMKDIFF; IRSCDIFF; NCIDIFF	

Although robustness was rejected, it was so by a very small margin, suggesting that reverse causation from business cycle correlation to fiscal deficit differential became stronger in the 1997-2004 period. Hence EMU member states' ability to use fiscal policy as an active policy instrument to fine tune or to smooth out the impact of the cycle has indeed become limited by the Stability and Growth Pact.

Results for the Structural Indicators

The ECB's ***National competitiveness indicator*** (NCI) is based on real effective exchange rates, weighted by intra-euro area trade shares. The lower the differences in national competitiveness, the larger is the degree of cycle correlation. The more similar countries are in terms of relative price competitiveness, the more comparable will be their ability to adjust to international shocks. With a *t*-statistic of −4.8, the relation is highly significant. In addition, the R^2 of 0.3 is the highest of all bivariate regressions in this section.

In the multi-regression estimates, excluding geographical distance, national price competitiveness differentials comes out as significant. All coefficients are negative and significant with the extreme bounds ranging from −0.03 to −4.8. When geographical distance was included, NCIDIFF failed to qualify as robust by a small margin. Nevertheless, all the β_m coefficients were significant and negative. The upper extreme bound coefficient turned slightly positive but remained close to zero when the control *Z*-variables included geographical distance. In the sub-samples, including or not geographical distance, the competitiveness indicator clearly fails to qualify as robust. In the first sample from 1980 to 1996, the reason why competitiveness differentials fail to qualify as robust is unclear. Including or not exchange rate volatility in the set of control *Z*-variables does not affect sensibly the results. The reason why NCIDIFF does not qualify as robust may be due to its weak own explanatory power as indicated by the fairly low *t*-statistics in the bivariate regression. In the second sample, competitiveness differentials are not even significant in the bivariate regression.

The difference between ***stock markets*** performance is negatively related to business cycle synchronization. However, only the cyclical service indicator appears to be significantly correlated to business cycle correlation, with an R^2 of 0.2 and a coefficient significant at the 1% level. The total market indicator does not have a significant coefficient and the R^2 is too small to be meaningful. The relative stock market performance in the sector of cyclical services (CYSERDIFF) is clearly significant over the 1980-2004 and 1997-2004 periods.

Over the full sample, CYSERDIFF comes clearly out as robustly related to business cycle correlation(see table). All the β_m coefficients are significant at the 1% level. The extreme bounds range from −0.001 to −0.012, with R^2s of 0.4 and 0.2, respectively. By contrast, differences between national total stock market indices does not appear related at all to business cycle correlation, neither in the full sample nor in the sub-samples. In the first sample period from 1980 to 1996, the cyclical service indicator does not qualify as robust but in the second sample from 1997 to 2004, it clearly appears robust with all β_m coefficients significant at the 5% level.[65]

Table 10:
National Competitiveness Indicator

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Robust	Bivariate		−2.214	0.461	−4.80	0.26		
	High	−0.031	−1.410	0.690	−2.04	0.38	BTT, SD_NERE, GEODIST	100%
	Low	−4.777	−3.435	0.671	−5.12	0.30	IRSCDIFF, TUDDIFF	
1980-1996								
Fragile	Bivariate		−0.736	0.409	−1.80	0.04		
	High	0.532	−0.241	0.387	−0.62	0.14	BTT, DEFDIFF, TUDDIFF	53.7%
	Low	−3.159	−1.781	0.68	−2.58	0.60	IRSCDIFF, SD_NERE, TUDDIF	
1997-2004								
Fragile	Bivariate		−1.139	3.038	−0.37	−0.01		
	High	17.89	13.791	2.047	6.74	0.70	TOTMKDIFF IRSCDIFF	n.a.
	Low	−6.979	−1.190	2.894	−0.41	−0.03	TUDDIFF	

In theory, more similarities in the flexibility of ***labour markets*** should help an economy to adjust to asymmetric shocks and hence lead to more synchronous cycles even in the presence of idiosyncratic shocks.

However, labour market flexibility is difficult to measure. We apply two alternative indicators, trade union density and the employment protection index and use the bilateral differences (TUDDIFF and EPADIFF, respectively) to measure the degree of similarity across countries. High values indicate that labour market institutions differ markedly from one country to another while low values indicate similar labour market institutions. Although the coefficients exhibit the expected negative sign, neither of them is statistically significant. The trade union density differential's *t*-statistic is −0.7, the corresponding value for the employment protection index differential is −0.7. The R^2s are around zero. In the multi-variate regressions we focus on the trade union density differential due to the scarcity of data for the EPA indicator (only three years are available from 1990 to 2003). In none of the estimates and sub-samples, the trade union differential qualifies as robust.

65 *Anderson* and *d'Agostino* (2005) find that the stock market index of cyclical services is the best indicator of the euro area business cycle.

Table 11:
Stock Market Index of Cyclical Services

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Robust	Bivariate		−0.008	0.002	−4.70	0.19		
	High	−0.001	−0.004	0.001	−2.78	0.40	BTT, DEFDIFF, GEODIST	100%
	Low	−0.012	−0.008	0.002	−4.97	0.21	TUDDIFF	
1980-1996								
Fragile	Bivariate		−0.006	0.004	−1.45	0.00		
	High	0.007	0.001	0.003	0.38	0.14	BTT, NCIDIFF, DEFDIFF	n.a.
	Low	−0.015	−0.007	0.004	−2.02	0.08	IRSCDIFF, NCIDIFF, SD_NERE	
1997-2004								
Robust	Bivariate		−0.023	0.004	−5.57	0.53		
	High	−0.000	−0.009	0.005	−2.03	0.76	IRSCDIFF, NCIDIFF, DEFDIFF	100%
	Low	−0.032	−0.023	0.004	−5.72	0.54	NCIDIFF, TUDDIFF	

Gravity variables have been used extensively in the empirical trade literature to account for exogenous factors. Traditionally, geographical distance and relative size are the core gravity measures. In the case of geographical distance, the case is surprisingly clear. The closer countries are located next to each other, the more synchronous are their business cycles. With a t-statistic of −5.2 and an R^2 of 0.3, the bivariate relation exhibits strong significance and a fair goodness of fit. We would not have expected such a clear result, given the relatively small distances and low transport costs in Europe. The second gravity variable, relative population size, is not significant; the t-statistic is only −0.4. Neither is the goodness of fit satisfactory, with an R^2 around zero.[66] Surprisingly, in the EBA geographical distance appears robust in the period from 1997 to 2004 but not in the previous period and not in the full sample.[67] The difference of result between the different samples may have reflected a partial correlation problem between geographical distance and the ratio of bilateral trade to total trade.[68]

66 Detailed results for the gravity variables are available upon request.

67 The pool of *Z*-variables include: BTT, TOTMKDIFF, NCIDIFF, DEFDIFF, IRSCDIFF, SD_NERE AND TUDIFF.

68 Indeed, the pool of *Z*-variables we drew from to test the robustness of geographical distance also includes the ratio of bilateral trade to total trade which emerged as a robust determinant of business cycle correlation in the full sample and in the first sub-sample but not in the second one. Bilateral trade is also strongly related to geographical distance. However, tests conducted by replacing bilateral trade with economic specialisation in the pool of *Z*-variables, did not support that assumption. Although economic specialisation is not at all correlated to geographical distance, the latter came out again as nearly robust in the last sample, whereas for the 1980-2004 and 1980-1996 periods the rejection of robustness was clear-cut.

Table 12:
Labour Market Flexibility Index

Result	Est.	Bound	Coeff.	Std error	t-Stat.	R^2 adj.	Z control variables	Significant Coeff.
1980-2004								
Fragile	Bivariate		−0.122	0.171	−0.71	−0.01		
	High	0.372	0.077	0.148	0.52	0.34	IRSCDIFF, NCIDIFF, GEODIST	n.a.
	Low	−0.646	−0.323	0.162	−2.00	0.16	TOTMKDIFF, IRSCDIFF, SD_NERE	
1980-1996								
Fragile	Bivariate		−0.037	0.192	−0.19	−0.01		
	High	0.583	0.168	0.207	0.81	0.05	NCIDIFF, SD_NERE, GEODIST	n.a.
	Low	−0.499	−0.128	0.186	−0.69	0.03	TOTMKDIFF, IRSCDIFF	
1997-2004								
Fragile	Bivariate		−0.008	0.334	−0.02	−0.02		
	High	1.282	0.500	0.391	1.28	0.34	NCIDIFF, DEFDIFF, GEODIST	n.a.
	Low	−0.783	−0.434	0.175	−2.48	0.52	TOTMKDIFF, IRSCDIFF	

4. Summary and Economic Interpretation of Results

What Are The Robust Determinants of Cycle Correlation?

The main results of the EBA analysis are presented in Table 13. The EBA is not a causality analysis: "[…] finding a partial correlation certainly does not imply that the variable of interest causes growth" (Levine and Renelt 1992) and the choice of the key candidate explanatory variable had to be based on economic theory. On the other hand, what the robustness analysis does is to allow to identify which variables among those identified as potential determinants of business cycle synchronization by economic theory, can effectively be proved to be 'robust' determinants. In addition, the analysis also led us to identify some variables, which although not the focus of economic theory, proved to have a relationship with business cycle synchronization and whose link with the cycle might be worth investigating in the future (such as cyclical services for instance which include transportation and tourism).

The upper panel presents the variables which were selected as potential determinants of business cycle synchronization, the so-called '*M*-variables of interest'. For these variables, economic literature indicates that they should influence business cycle synchronization. The lower panel presents variables which were used as 'control *Z*-variables'. Economic theory tells us that several of these variables should have something to do with economic growth and with the business cycle. However, the direction of the causality is far less clear than in the case of the *M*-variables. This is particularly obvious in the case of fiscal deficits and of the exchange rate where the relation works both ways, especially in the short run. This does not mean that the *Z*-variables are not determinant of the business cycle but indicates that the relationship is more likely to be bivariate than in the case of the *M*-variables.

Table 13:
Summary of Results

Variable[1]	1980-2004	1980-1996	1997-2004
M-variables: traditional determinants of business cycle synchronization			
Ratio of bilateral trade to total trade (BTT)	Robust	Robust	Fragile
Ratio of bilateral trade to GDP (BTY)	Robust	Robust	Fragile
Trade specialisation (TRADEPAT)	Fragile	Fragile	Robust
Fuels	Fragile	Fragile	Fragile
Machinery and transport equipment	Fragile	Fragile	Robust
Other manufacturing	Fragile	Fragile	Fragile
Chemicals	Fragile	Fragile	Fragile
Economic specialisation (ECOPAT)	Fragile	Fragile	Fragile
Industry	Robust	Quasi-robust	Fragile
Construction	Fragile	Robust[2]	Fragile
Wholesale and retail trade	Fragile	Fragile	Fragile
Financial intermediation	Fragile	Quasi-robust	Fragile
Bilateral flows of bank assets (LBFA)	Fragile	Fragile	Fragile
Z-variables: policy and structural indicators			
Real short-term interest rate differential (IRSCDIFF)	Fragile	Fragile	Robust
Nominal exchange rate volatility (SD_NERE)	Fragile	Fragile	--
Fiscal deficit differential (DEFDIFF)	Robust	Robust[3]	Fragile
Price competitiveness differential (NCIDIFF)	Robust	Fragile	Fragile
Stock market differential, cyclical services (CYSERDIFF)	Robust	Fragile	Robust
Trade union membership differential (TUDDIFF)	Fragile	Fragile	Fragile
Geographical distance	Fragile	Fragile	Robust

[1] As they failed to be significant in the bivariate baseline regression, we do not report the EBA results for the following variables: Trade openness (TTY), log-bilateral bank liability flows (LBFL), employment protection differential (EPADIFF), and relative population (POPDIFF). – [2] Qualifies as robust but the coefficient has the wrong (positive) expected sign. – [3] Including a dummy for the Germany-Finland country pair.

In the full sample, among the potential determinants of the business cycle, the ratios of bilateral trade to total trade and to GDP as well as the fiscal deficit differentials and the stock market differentials for cyclical services come out as robust. Economic specialisation does not qualify as robust but differences between the shares of industrial sectors in value added are close to qualify as a robust determinant of business cycle synchronization.

When considering the results for the sub-periods, the variables robustly related to business cycle synchronization from 1980 to 1996 are the ratios of bilateral trade. The relative share of financial sectors and the fiscal deficit differentials do not fully qualify for robustness but are very close to it. Over the period from 1997 to 2004, trade specialisation in particular in machinery and transport equipment, the real short-term interest rate differentials and the stock market differentials for cyclical services all appear robustly related to business cycle synchronization.

How Can The Determinants Be Interpreted in the Context of EMU?

The EBA results confirm external trade as a key determinant of business cycle synchronization in the context of the euro area. Given the theoretically unclear case of the trade effect on cycle correlation, our results support the view of Frankel and Rose (1998). They find a strongly positive effect for a wide array of countries and on these grounds postulate the "endogeneity of the optimum currency area criteria": if trade promotes the comovement of business cycles, then a common currency that fosters trade would endogenously lead to more synchronised cycles in the monetary union. Also in keeping with Rose's results (2000) and with the 'Rose effect',[69] we fail to identify a direct 'robust' relation between exchange rate volatility and business cycle correlation.

The effect of monetary union is closely related to our second major finding on the impact of trade specialisation and the degree of intra-industry trade. The positive trade effect on cycle correlation hinges on the degree of intra-industry trade, i.e. the similarity of trade specialisation patterns. The more intra-industry trade, the more likely is the positive trade effect to materialise. Empirical evidence indicates an increased degree of intra-industry trade over time across euro area countries, even though the very broad economic structures have not converged. The EBA analyses show that similar trade specialisation emerges as a robust determinant of cycle correlation in the 1997-2004 period. Taken together, these findings support Frankel and Rose's prediction that EMU would lead to trade expansion and to the development of intra-industry trade (rather than to greater trade specialisation) which in turn would "result in more highly correlated business cycles". The transmission of industry-shocks via intra-trade seems to be concentrated in the sector of machinery and equipment: trade specialisation in machinery and equipment alone explains 61% of cycle correlation in 1997-2004.

The positive impact of stock market comovements in the cyclical service sector on cycle correlation can be interpreted, either as an indication that financial integration has been

69 „[...] entering a currency union delivers an effect that is over an order of magnitude larger than the impact of reducing exchange rate volatility from one standard deviation to zero." *Rose* (2000).

conducive to greater cycle symmetry, or point to the role of cyclical services as a vehicle for cycle synchronization. Since the relative performance of overall stock market indices does not appear to be a major determinant of business correlation, the second interpretation seems more appropriate. As trade in machinery and equipment, cyclical services are a major determinant of cycle correlation, explaining 54% of it since EMU.

The indicators for trade specialisation in machinery and equipment and for stock market differentials in cyclical services capture supply-side determinants and their variations reflect essentially industry-specific shocks. Taken together, they explain 78% of cycle correlation during the period of monetary union as indicated in Table B. A negative coefficient indicates that the more similar the countries are, the greater the business cycle synchronization.

By comparison, real interest rate differentials and geographical distance explain 59% of cycle correlation. Since the implementation of the single monetary policy, real short-term interest differentials have been driven essentially, although not only, by bilateral inflation differentials. Over the course of a business cycle, differences between real short-term interest rates across euro area countries are therefore driven primarily (though not only) by demand-side shocks.[70] All in all, since the introduction of the single currency, the coherence of business cycles appears to have been affected more by industry-specific determinants and supply-side shocks than by demand-side determinants and idiosyncratic shocks. Further research would be required on financial integration. Although the bivariate correlation between bank flows and cycle synchronization is quite strong, the EBA results remain weak, partly due to incomplete data sets. Another area of research is competitiveness differentials which would require more in-depth investigation of the interactions with the synchronization of business cycles.

70 It seems more difficult to account in economic terms for the emergence of geographical distance as a robust determinant of cycle correlation over the 1997-2004 period. Nevertheless, this probably only reflects the fact that, idiosyncratic (or asymmetric) shocks had a greater impact on the Greek economy and on its correlation with other euro area economies.

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Convergence and Synchronization of Business Cycles in the Euro Area

Christian Gayer*

1. Introduction

The conduct of a common monetary policy calls for a sufficient degree of business cycle synchronization of economies integrating in a currency union as long as adjustment mechanisms such as price flexibility and labour mobility cannot effectively offset the effects of asymmetric shocks across countries. In turn, monetary union by itself and the economic and financial integration could spur the emergence of a common area-wide business cycle. At the same time, monetary union could lead to greater cross-country specialisation and therefore less synchronization. Others have argued that constraints on monetary and fiscal policy in a monetary union could reduce the risk of asymmetric shocks that are policy-driven.[71]

The empirical evidence for the euro area so far has not been very conclusive. While Artis and Zhang (1997, 1999) find that membership of EMU, or the ERM before it, has promoted convergence between participating countries' business cycles, Inklaar and de Haan (2001) challenge this finding. Using the same data set, Massmann and Mitchell (2004) find that the euro area has alternated between convergence and divergence in the last 40 years but since the early 1990s has been converging. Several authors find the effect of currency unions on business cycle synchronization to be positive (following Rose and Engel, 2002), although this is challenged by Baxter and Kouparitsas (2005). Camacho et al. (2005) and Artis (2003, 2005) conclude that European business cycles show signs of failing to hold together.

It should be noted that the cited studies cover only few years of EMU, with the data samples typically ending in 2003 or earlier. With the euro now in place for almost ten years, this chapter revisits the issue of business cycle convergence and synchronization

* European Commission, Av. de Beaulieu/Beaulieulaan 1, 1160 Brussels, Belgium. The views expressed in this paper exclusively represent the position of the author and do not necessarily correspond to those of the European Commission. The author would like to thank A. Jonsson, N. Darnaut and P. van den Noord for valuable comments and suggestions.

71 See *Darvas, Rose* and *Szapáry* (2005). For a comprehensive discussion of how EMU is affecting business cycle synchronization in the euro area, see *Mongelli* and *Vega* (2006) and the literature references therein.

in the euro area on the basis of an extended data set and using various measures of the cycle.

Section 2 outlines the methodology and data used. Section 3 presents recent developments in the dispersion of output gaps across euro-area Member States, being a very relevant measure of convergence in a short-term macroeconomic policy perspective. However, the dispersion measure is sensitive to the scale of the output gaps, such that a trend of cyclical de-synchronization might be masked by a falling amplitude of cyclical fluctuations over time.

Therefore, Section 4 turns to measures based on cross-country correlations, which are better suited to reflect the genuine synchronization aspect of cyclical convergence. Given that the industry sector accounts for the bulk of cyclical variation of the euro-area economy, most studies are based on industrial production data, filtered by some trend adjustment method. Gayer and Weiss (2006) showed that there is a marked correspondence between results derived from filtered industrial production data and those from the European Commission's survey-based Industrial Confidence Indicators (ICI). Since they avoid a number of shortcomings of hard data at the crucial end of the data sample (in terms of timeliness, revisions and end-point problem of filtering), survey-based indicators are thus a useful complementary tool to analyse synchronization processes in real time, up to and including the most recent observations.

Artis (2003, 2005) and Baxter and Kouparitsas (2005) are examples of studies using the broader, services-dominated GDP aggregate as a measure of economic activity. The greater exposure to external shocks of the trade-intensive manufacturing sector could be a source of bias towards de-synchronization relative to measures of convergence based on broader activity series. Furthermore, due to the monthly frequency, the manufacturing data might possibly indicate some short-lived periods of divergence not present in quarterly activity series. Therefore, after looking at manufacturing-related synchronization measures, the analysis is complemented by equivalent measures derived from GDP series.

Having investigated the development of mean intra-euro-area synchronization from different angles, Section 5 turns to an analysis of country-wise synchronization developments with respect to the euro-area total, trying to identify the contribution of individual countries to the mean results.

Artis (2005) provides evidence of an emerging 'world business cycle', implying that where increased business cycle synchronization is found, it is not clear whether this is due to a specific euro-area cycle or due to globalisation. Therefore, the results are cross-checked against developments at the level of the world cycle in Section 6. Section 7 briefly discusses a number of variations of the used methodology so as to verify the robustness of the attained results. Section 8 summarises and concludes.

2. Methodology

Various methods have been proposed in the literature to investigate the issue of business cycle convergence. One possible approach is to look at the evolution of the standard deviation of euro-area countries' business cycles over time. The smaller the standard deviation in a given period, the closer the individual cycles cluster together. It is important to bear in mind that the measure is scale-dependent, i.e. for a given level of cyclical synchronization, the standard deviation will rise (fall) proportionally with a rise (fall) of the mean amplitude of the individual cycles. Given that the absolute degree of dispersion of euro-area output gaps is of great importance for the conduct of monetary policy in a monetary union, the standard deviation is a very relevant measure to gauge the degree of cyclical convergence in the area.

Due to its scale-dependency, however, it is less suited to measure the genuine synchronization dimension of business cycle convergence, i.e. whether the cycles display a common periodicity and phase, disregarding possible changes in amplitude. The coefficient of correlation between the business cycles of euro-area countries lends itself well to examine this issue. Such correlation coefficients can be computed over a series of rolling windows of a fixed length, providing a continuous track of developments over time. This approach is taken in numerous investigations of the issue of business cycle synchronization, in the euro area and elsewhere.[72] Belo (2001) demonstrates that the correlation approach provides an accurate assessment of business cycle synchronization within the euro area. It enables to draw conclusions that are consistent with a turning-point-oriented tool such as the concordance index proposed by Harding and Pagan (2002).[73]

However, the correlation measure also suffers from drawbacks. Indeed, the results can be rather sensitive to the length of the rolling window chosen, see e.g. European Commission (2006a). While longer windows tend to be more reliable since they are based on more data points, there is the danger of smoothing out important medium-term changes in synchronization. Correlations based on shorter windows tend to be more sensitive to short- and medium-term deviations and, since they can be computed closer to the end of the data sample, allow for an analysis of very recent developments. However, it can be shown that if the window is shorter than the mean length of the cycle itself, small phase shifts between otherwise identical cycles can lead to systematic, but artificial, drops in the association measure at the turning points of the cycles. Finally, the empirical evidence in European Commission (2006a) suggests that shorter windows may have some

72 A similar set-up to investigate the issue of convergence in the euro area is used, inter alia, in *Döpke* (1999), *Massmann* and *Mitchell* (2004), *Mitchell* and *Mouratidis* (2004) and *BNP* (2005).

73 The concordance index measures the fraction of time that the cycles of two countries are in the same business cycle phase.

leading properties in signalling declines in business cycle synchronization in the euro area.

We use monthly industrial production (IP) data from 1975m7 to 2007m2 for eleven euro-area countries (excluding Luxembourg and Slovenia). Quarterly GDP data is available from 1980q1 to 2007q1 for eight euro-area countries: Belgium, Germany, Greece, Spain, Finland, France, Italy, and the Netherlands. For Austria, Ireland and Portugal we carry out a partial analysis based on shorter data series. All quarterly GDP series are augmented by seven observations derived from quarterly growth forecasts for 2007 and 2008.[74] Data for the Industrial Confidence Indicator (ICI), collected in the framework of the Commission's Joint Harmonised EU Programme of Business and Consumer Surveys[75] is available from 1985m1 to 2007m4. To summarise the $n(n-1)/2$ possible bilateral correlation coefficients between the n euro-area countries, we look at the evolution of both their mean and their variance. Both unweighted and size-weighted averaging of country correlations is examined (country size is approximated by total population).[76]

A rise in mean correlation is considered as evidence of increased synchronization. However, this is not a sufficient condition as, at the same time, the variance should remain stable or decrease. If only the mean criterion was met, the distribution of correlation coefficients could still have widened, implying lower instead of higher synchronization of business cycles.[77] Therefore, to properly identify cyclical synchronization, an increase in the mean should be coupled with a simultaneous decrease in the variance of the correlation coefficients, and vice versa for de-synchronization.

Reflecting the above discussion of the impact of the window length, the mean and the variance of bivariate correlation coefficients are computed over two alternative window lengths: four and six years.[78] In the case of e.g. the quarterly GDP data, the initial four-year window covers the period 1980:1-1984:1 (1980:1-1986:1 for the six-year window);

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74 The forecasts for GDP growth are taken from the Commission's Spring 2007 forecast.

75 See *European Commission* (2006b) for a detailed description of the scope and methodology of the survey data.

76 Alternatively, GDP weighting may be considered. However, the impact of weighting turns out very small.

77 The following extreme case may illustrate the point: From a situation where each individual country displays a 50% correlation with all other countries (zero variance), the mean will remain unchanged if suddenly the group is equally divided into two subgroups with perfect intra- but zero inter-correlation. Only the increase in the variance will point to this important change in synchronization within the group.

78 Given our interest in growth cycles (deviations from trend) rather than classical cycles (absolute declines of activity), the six-year window corresponds to almost two typical recent cycles, while the shorter four-year window should still be long enough to cover at least one typical recent growth cycle. The six-year window is also used in *BNP* (2005). *Massmann, Mitchell* (2004) use one window of three and a half years and a second window of seven years, while *Massman, Mitchell* (2002) use a window length of three years.

the last window summarises business cycle association in the period 2004:4-2008:4 (or 2002:4-2008:4 for the six-year window). In order to provide an appropriate, timely impression of synchronization developments readily attributable to specific events, the correlations are centered on the midpoints of these windows in the graphical presentations below. Thus, the last midpoint of the six-year window characterises euro-area synchronization around the fourth quarter of 2005, while it is 2006q4 in the case of the shorter window.

A non-negligible problem with the hard data series is that they do not provide a measure of 'the business cycle' as such, but first have to be decomposed into trend and cycle using statistical techniques. The survey data, on the other hand, contain genuine cyclical information and thus avoid the problem of (arbitrarily) identifying the cycle from the data. For a related discussion and further advantages of survey data in analysing business cycle synchronization (timeliness, absence of revisions) see Gayer and Weiss (2006). We use a band-pass version of the Hodrick-Prescott filter to extract the business cycle-related fluctuations from the (natural logarithms of the) GDP and IP series.[79]

3. Convergence of Output Gaps in the Euro Area

The dispersion (or more technically the standard deviation) of output gaps is probably the most relevant measure of convergence in a short-term macroeconomic policy perspective. At a given point in time, the dispersion will be close to zero if all Member States display a similar output gap (in percent of potential GDP). Hence, the closer to zero the measure is, the higher is the degree of convergence of relative growth performance across countries and the more appropriate common monetary impulses are for each Member State.

Figure 1 presents the dispersion of output gaps for euro-area countries.[80] It shows that, since the early nineties, dispersion in the euro area as a whole has narrowed considerably.

79 The Hodrick-Prescott (HP) bandpass filter, stemming from the subtraction of two HP low-pass filters, extracts fluctuations with a periodicity between 6 and 32 quarters or 18 and 96 months, respectively, corresponding to the usual band of 1.5 to 8 years associated with business cycle fluctuations. As robustness checks show, our results are not qualitatively changed when the band is extended to include fluctuations of up to 12 years in duration. The HP-based bandpass filter has the advantage over the alternative Baxter-King filter of not losing 12 quarters (36 months) at the start and end of the sample. However, implicitly, it is still subject to the so-called endpoint problem of all such filters, leading to revisions of cycle estimates when new data become available at the end of the sample. For details on the HP bandpass filter, see *Artis* et al. (2003).

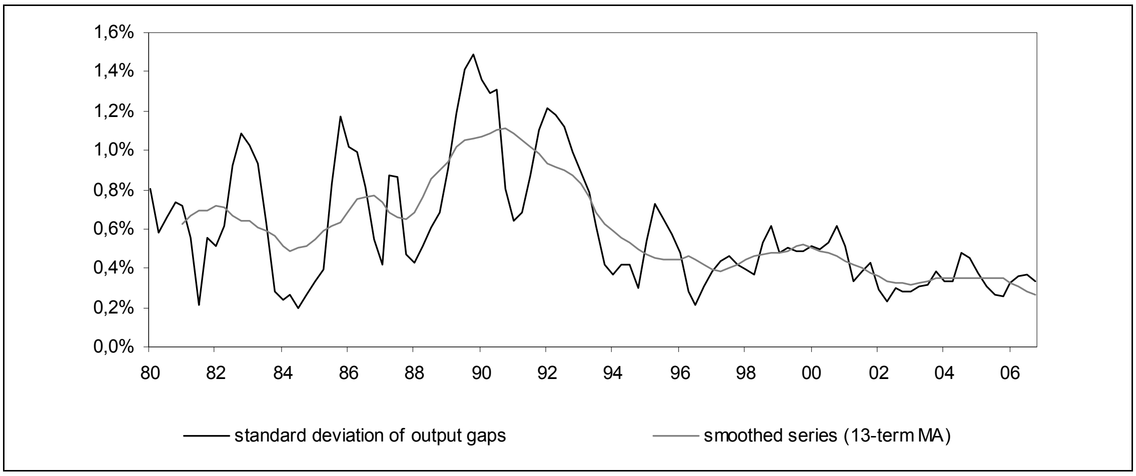
80 The output gaps were derived by subtracting the logarithm of GDP trend estimates from the logarithm of smoothed GDP series. Using HP filters with parameters set to eliminate fluctuations of less than, respectively, 8 and 1.5 years in duration, these (smoothed) output gaps are thus identical to the GDP-based business cycle estimates used for the calculation of cross-country correlations in later sections.

A mild pick-up in the dispersion of output gaps in the late nineties is followed by renewed convergence during the 2001-2003 downturn. As pointed out by European Commission (2004), the temporary phase of divergence around the 2000 boom largely reflects the overheating of the Irish and Luxembourg economies.[81] Apart from that, the analysis suggests that differences in the degree of exposure to extra-euro-area trade played a central role.

Looking at the most recent period, with the exception of a transitory pick-up in 2004, the dispersion of output gaps in the euro area has been standing at historically low levels since around 2002.

The increase in dispersion of output gaps in 2004 is more marked if the focus is on the four large euro-area Member States only (Germany, France, Italy and Spain), which together account for almost 80% of euro-area GDP. As discernible from Figure 2, the level of output dispersion between the four large Member States is overall markedly lower than that between all euro-area countries. However, after a historically high degree of convergence in late 2003, the dispersion of the four countries' output gaps can be seen to pick up sharply in 2004.

Figure 1:
Standard Deviation of Euro-area Output Gaps
- as % of Potential GDP, 1980-2006 -

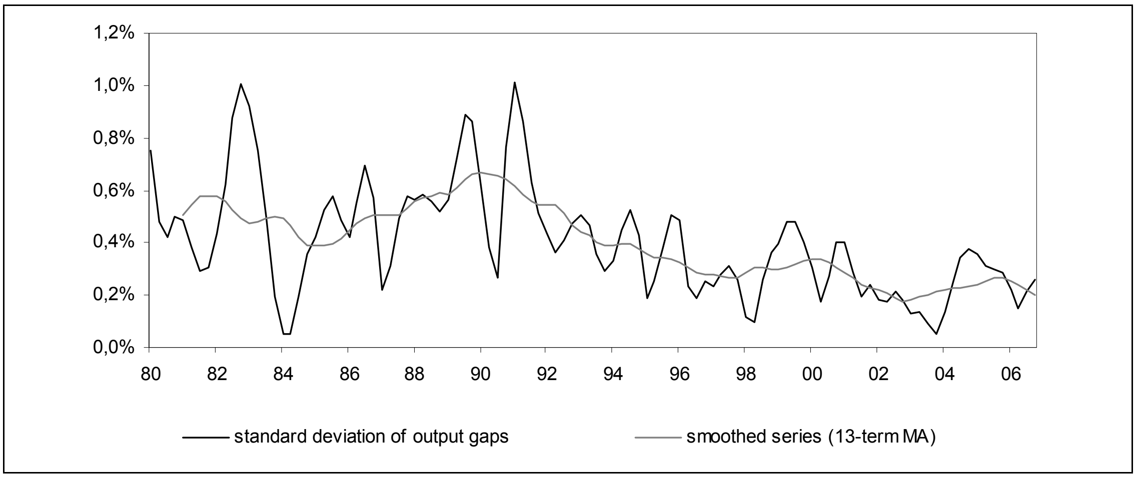


Source: Commission service.

McCarthy (2006) attributes these diverging growth performances in the early phase of the current recovery to disparities in the sources of growth across Member States, with Germany relying mainly on exports and seeing domestic demand stagnate, while domestic demand underpinned the robust performance in Spain and was the main factor sustaining growth in France.

81 Luxembourg is not included here due to a lack of quarterly data.

Figure 2:
Standard Deviation of Output Gaps of Big 4 MS
- as % of Potential GDP, 1980-2006 -



Source: Commission service.

Finally, however, with the recovery gaining momentum, the dispersion of output gaps both within the euro area and between the four large Member States can be seen to have decreased again in 2005-2006.

As mentioned previously, the observed long-term downward trend in the dispersion of output gaps since the early nineties is not necessarily due to the fact that Member States' business cycles are increasingly in phase but might rather be explained by a general decrease in the amplitude of cyclical fluctuations. Indeed, the dispersion will remain low even when national business cycles move apart, as long as output gaps do not stray too far from zero. In that case, a cyclical de-synchronization trend would be masked by the low amplitude of cyclical fluctuations. While this would not necessarily be a problem for the conduct of monetary policy in the short term, it could herald more difficult times if the forces that have led to a reduction of cyclical fluctuations wane.

Since there has been a well-documented decline in the cyclical volatility of GDP observed in most G7 and OECD countries since the 1990s (see Stock and Watson (2005) for a review of the literature),[82] it cannot be excluded that this trend indeed explains part of the prevailing low level of cyclical dispersion measured in the euro area. It is therefore necessary to complement the analysis by looking at additional indicators of cyclical synchronization.

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82 Three main alternative explanations have been advanced in the literature for this phenomenon labelled 'the Great Moderation': structural improvements in the economy, particularly better inventory management, improved macroeconomic policies, and simply 'good luck', in the form of fewer and smaller shocks to the economy. Another explanation is that of increased risk sharing, smoothing out GDP variance through capital markets, credit markets and other transfers, see e.g. *Giannone* and *Reichlin* (2006). For a recent analysis of the reduced volatility of output growth in the euro area see *European Commission* (2007).

4. Synchronization of Business Cycles in the Euro Area

Correlation Results Based on Industrial Production

The industrial sector accounts for less than one-fourth of the euro-area economy but for most of its cyclical variation. The use of industrial production data for business cycle analysis is furthermore justified by the historically strong correlation between IP and GDP data and by the fact that, in contrast to GDP data, monthly observations on IP are available on a consistent basis for the large majority of countries back to the 1960s. Using IP data for eleven euro-area countries, Figure 3 displays the unweighted and weighted mean of the 55 pair-wise country correlations, calculated over moving six-year windows. Clearly, the weighting issue does not qualitatively alter the findings.

The picture on the basis of correlations is quite different from that based on the variance of output gaps (Figure 1). Thus, the general moderation of output variance does indeed seem to hide some divergent trends in business cycle synchronization. In interpreting the graph, it might be useful to relate the developments in average correlation to the exchange rate regime or, more generally, to specific economic events. As noted by Massmann and Mitchell (2004), the period of falling correlation in the early 80s until 1986 can be characterised as a period where the EMS was rather unstable, with a number of exchange rate re-alignments taking place. At the same time, the fall in cross-country correlation could be more directly attributed to the asymmetric effects of the second oil price shock.

The marked increase in mean correlation in the later eighties occurs in a period when the EMS was relatively stable and credible, with no re-alignments taking place. The next significant decrease in correlation around 1997 coincides with the Asian emerging markets crisis, and reflects the differentiated effects the crisis had on individual euro-area countries.[83] The subsequent Stage 3 of EMU is characterised by a rather steady increase in cyclical synchronization until mid 2003, when a sudden decline in business-cycle association sets in. While the renewed rise in correlation since the late nineties may be attributable to the effects of enhanced trade and financial integration in the wake of the Internal Market programme and EMU as well as closer macroeconomic policy coordination in the euro area,[84] there is no obvious explanation for the subsequent drop in synchronization at the end of the sample. The last depicted correlation is based on the sample from 2001m2 to 2007m2 and thus characterises cyclical synchronization around 2004.

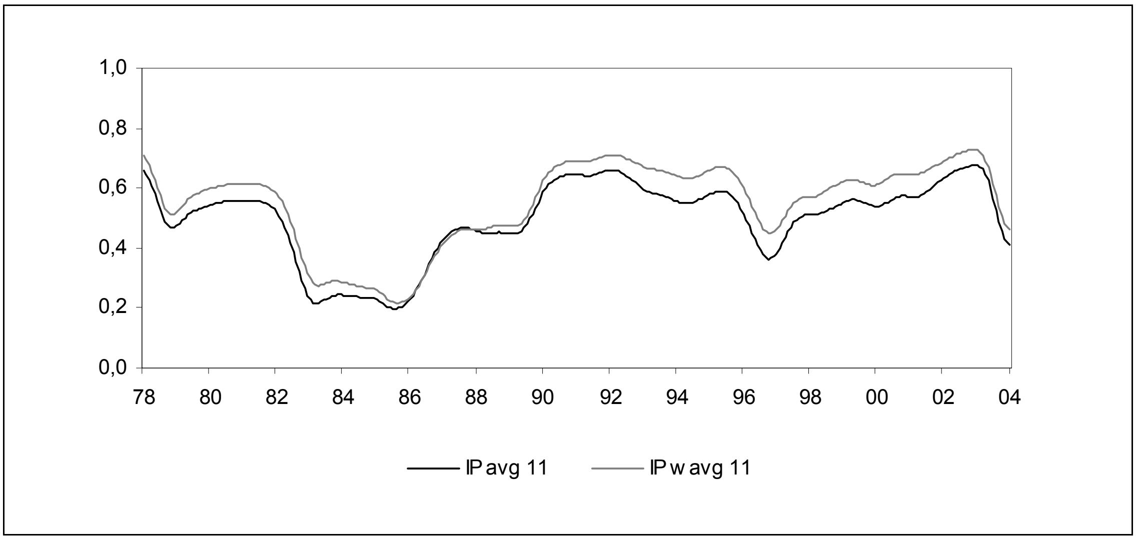
83 Furthermore, the decrease reflects the beginning of a phase of severe divergence between Greece and the rest of the euro area; see Section 5 for a country-wise analysis of synchronization developments.

84 See *European Commission* (2004) for a detailed discussion of these forces of cyclical convergence in EMU.

Before we turn to an analysis of the observed drop in correlation, Figure 4 shows the evolution of correlations computed over the shorter four-year window. While clearly more sensitive to short-run deviations (as for example the de-synchronization following German re-unification in 1990 or the dip around the ERM turmoil in 1992-1993), the graph essentially confirms the previous findings. Due to the higher sensitivity of the four-year window, the recent decline in business cycle association is signalled somewhat earlier, around late 2002.[85] The extent of this de-synchronization, as measured by the low level of mean correlation of 0.2 in late 2003 appears considerable. However, the subsequent four-year correlation windows for 2004 and early 2005 point to a rebound in euro-area synchronization from early 2004 onwards.

As to the question whether EMU has promoted business cycle synchronization in the euro area, Figures 3 and 4 suggest that the degree of cross-country correlation was slightly higher in the first half of the nineties (single market, run-up to EMU) than in the first five or six years following the introduction of the euro in 1999.[86]

Figure 3:
Mean Euro-area Correlations
- IP 6-Year Window -

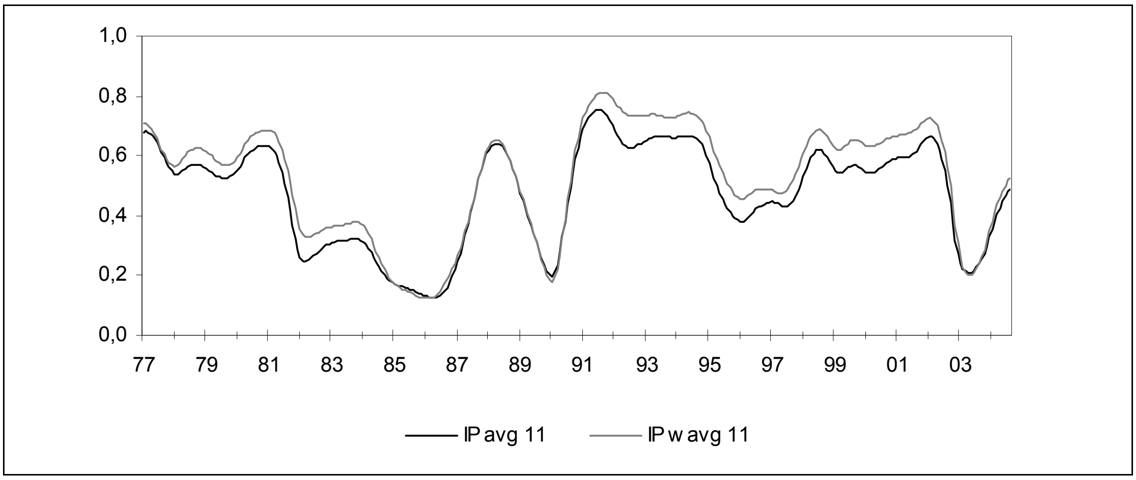


Source: Commission service.

[85] In line with the outlined characteristics of the different windows lengths, the previous declines in correlation of the early 80s and the mid 90s can also be seen to lead the corresponding declines in the curve based on the longer 6-year window.

[86] Average correlation in the period 1990-1994 is 0.61 (0.58) for the 6-year (4-year) window, while it is 0.58 (0.53) for the period 1999-2003. Clearly, these comparisons are rather sensitive to the selection and length of the benchmark period.

Figure 4:
Mean Euro-area Correlations
- IP 4-Year Window -



Source: Commission service.

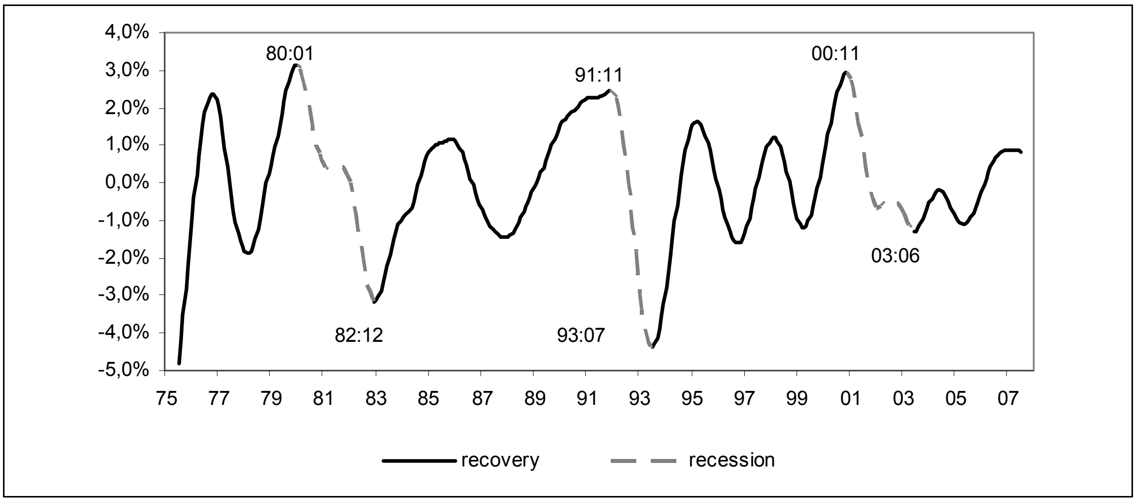
Figure 5:
Dispersion of Bivariate Correlation Coefficients
- IP, 6- and 4-Year Window –

Source: Commission services.

Figure 5 displays the evolution of the (unweighted) variance of the 55 bivariate correlation coefficients over time, using the six- and four-year windows, respectively. Across the sample, the analysis of the variance of cross-country correlations over time mirrors the above findings based on the mean. Confirming the reading of the mean correlations, the distribution of correlation coefficients has apparently narrowed since around 2000, implying higher synchronization among the eleven euro-area countries considered. However, particularly the 4-year window shows a subsequent widening of the distribution of correlations around 2002/2003. As a mirror image of Figure 4, this signal of desynchronization is then reversed at the very end of the sample, where the dispersion of country-correlations falls again.

Apart from interpreting the evolution of euro-area synchronization against the background of specific economic events, there is also a 'mechanical' approach to the interpretation of phases of falling or rising correlation, based on stylised business cycle facts.

Figure 6:
Euro-area Business Cycle Phases
- IP, 1975m7-2007m2 -



Source: Commission services.

To this end, Figure 6 displays the euro-area business cycle phases as identified by applying the previously mentioned bandpass version of the HP filter to monthly industrial production.[87] It emerges that, while euro-area business cycle recessions are typically short and steep, recovery phases tend to stretch out over a longer period and evolve in (mini-)cycles.[88] Given different adjustment speeds across countries following a recession, it is often argued that there is a general pattern of higher cyclical dispersion across countries during cyclical recoveries. Duval and Elmeskov (2006) e.g. argue that smaller and open economies are more flexible and recover faster from recession through spontaneous accommodation via endogenous changes in competitiveness and external trade. On the other hand, structural rigidities can lower the speed of adjustment to shocks. Fur-

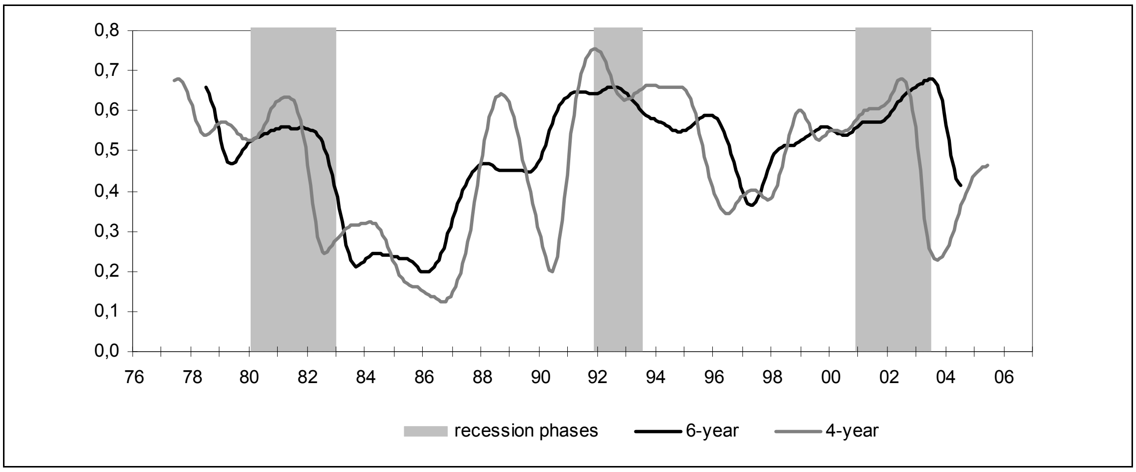
87 The resulting business cycle phases are rather robust to the use of different filtering techniques, such as the Baxter-King bandpass filter. Furthermore, using quarterly GDP instead of monthly IP data results in very similar cyclical turning points, see Section 4.2. For a comparison of different filters for the euro-area business cycle see *Artis, Marcellino* and *Proietti* (2003).

88 This observation is very much in line with stylised facts of the business cycle in general and with those of the euro-area cycle in particular, see e.g. *Agresti* and *Mojon* (2001).

thermore, small countries are on average found to undertake more and faster structural reforms, while slower reforms in larger countries may restrict their adjustment mechanisms, leading to persistent cyclical weakness.

Against this background, Figure 7 reconsiders the moving correlations of Figures 3 and 4 by cross-plotting them against the recession phases as identified in Figure 6. As can be seen, the three recession phases indeed seem to be characterised by a higher degree of cross-country correlation, and thus higher synchronization of business cycles. After a recession, cross-country correlations typically decline.[89]

Figure 7:
Mean Euro-area Correlation and Recession Phases
- IP Data, 11 Euro-area MS -



Source: Commission services.

Table 1 quantifies the extent of this pattern by showing the mean levels of area-wide correlation during recession and recovery phases for both the six-year and four-year windows. It emerges that mean euro-area correlation is on average 12-13 percentage points lower in recoveries than it is in recessions. In relative terms, this corresponds to a reduction of business cycle synchronization during recoveries by slightly more than 20% compared to the level during (the previous) recession. There is thus some evidence, although based on three euro-area cycles only, that the observed decline in business cycle synchronization after the latest turnaround in mid 2003 can be partly ascribed to a recurrent pattern of temporary de-synchronization during cyclical recoveries, owed to cross-country differences in the speed of adjustment to common shocks. However, given that the causes of transmission asymmetries are manifold and that other sources of cyclical divergence are likely relevant, too, such as idiosyncratic shocks or persistent inflation

89 See *Doyle* and *Faust* (2002) for analogous evidence for G7 countries.

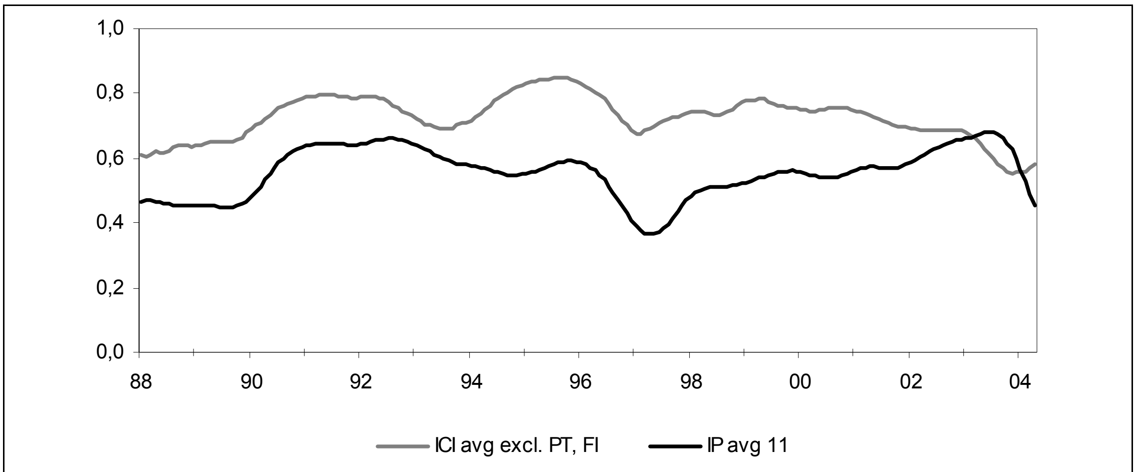
and real interest rate differentials magnifying divergences,[90] this 'mechanic' explanation of recurrent phases of de-synchronization cannot explain the full extent of the developments in cross-country correlations that we see in the graphs.

Table 1:
Mean Euro-area Business Cycle Correlation in Recoveries and Recessions

	Correlation Window	
Mean correlation	6-years	4-years
in recovery	0.47	0.44
in recession	0.59	0.57
overall	0.50	0.47

Source: Commission services.

Figure 8:
Mean Euro-area Correlations, ICI vs. IP
- 6-Year Window -



Source: Commission services.

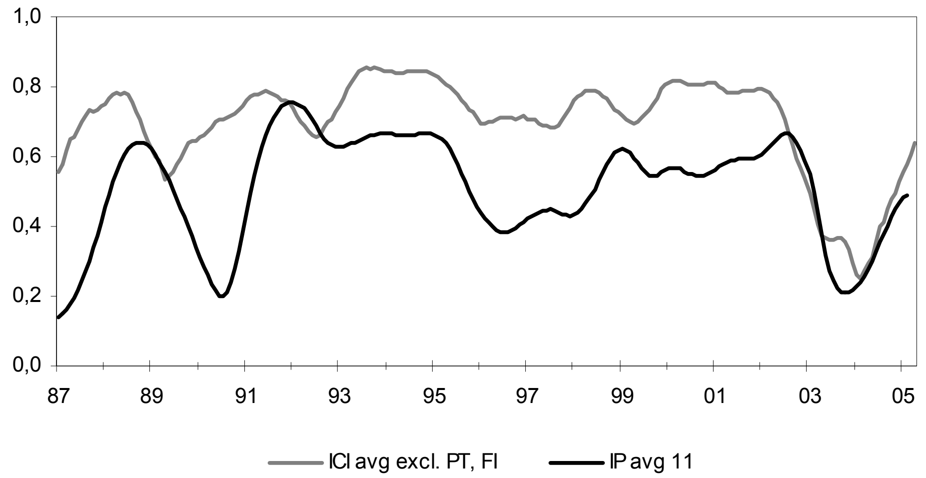
Furthermore, the degree of the decline in mean correlation according to the four-year window in late 2003 and the very fast recovery thereafter point to some peculiarities compared to the previous two post-recession phases.

In order to avoid the potential analytical problems that arise from the use of hard statistical data at the end of the data sample (due to revisions, largely arbitrary trend-cycle de-

90 *Giannone* and *Reichlin* (2006) find that remaining cyclical heterogeneity in the euro area is mainly due to small but persistent idiosyncratic shocks, whereas propagation mechanisms of common shocks are similar across Member States. For a discussion of the various sources of transmission asymmetries (such as differences in the openness to trade, importance of wealth effects, transmission of monetary impulses, degree of oil dependency) and other main sources of cyclical divergence in the euro area, see *European Commission* (2004).

composition, end-point problems and publication lags),[91] the following two graphs display the evolution of mean correlations computed from the survey-based ICI series across countries.[92] Focusing on the shorter samples available for the surveys, the results are presented along with the corresponding IP-based curves. In line with the results of Gayer and Weiss (2006), a rather close correspondence between the two measures of euro-area synchronization is evident for both window lengths. While the level of correlation is overall higher using the ICI series, all major ups and downs of the IP-based curves are matched by corresponding movements of the survey-based synchronization measure, usually with a lead of around six months.[93]

Figure 9:
Mean Euro-area Correlations, ICI vs. IP
- 4-Year Window -



Source: Commission services.

Looking at the longer window first, the evolution of the ICI-based curve, on a slight downward trend since around 2000, suggests a more marked fall in synchronization in early 2003. Thanks to the lead over the IP series and the additional two observations available at the end of the sample (no publication lag of the survey results), the aforementioned very recent recovery of synchronization is manifest in the survey-based correlations also using the 6-year window. Turning to the more sensitive 4-year window, it can be seen that, from the high level of synchronization attained after the emerging markets crisis and the early EMU period, mean correlation started to drop already in early

91 See *Gayer* and *Weiss* (2006) for a discussion of these problems.

92 At the euro-area level, the correlation between the ICI and IP growth is above 90%, while it is lower at above 60% on average across euro-area countries.

93 This is a consequence of the fact that, on average across countries, the ICI shows a corresponding leading behaviour with respect to the cyclical component of IP.

2002. As can be seen from Figure 9, the extent of this drop in correlation between 'confidence cycles' is unprecedented. It can thus not be fully explained by a mere recurrent decline of business cycle synchronization in phases of economic uncertainty.[94] However, the more recent steep recovery since 2005 clearly points to the transitory character of this apparent de-synchronization around 2003.

Correlation Results Based on GDP

This section complements the so far manufacturing-oriented analysis by a look at cyclical synchronization at the level of overall economic activity. Figure 10 displays the mean of pair-wise country correlations, calculated over moving windows of quarterly GDP data of both six-year and four-year length.95 Turning to the longer window first, the midpoint of the first six-year window refers to 1983:1. Partly based on the available Commission forecasts for GDP growth, the last window summarises business cycle association in the period 2002:4-2008:4. We can observe a marked increase in mean correlation from the mid-eighties to the early nineties and a stabilisation thereafter. After diminishing around 1997 (emerging markets crisis), synchronization increases again until 2003. From mid 2003 to late 2004, we see a rather sharp decline in business-cycle association. Since 2005, however, mean correlation has stabilised at a level around 50%. Turning to the correlations computed over the shorter four-year window, the graph, whilst obviously more responsive to short-run divergence (e.g. German reunification in 1990), corroborates the previous findings. Due to the higher sensitivity of the four-year window, the recent decline in business cycle association is signalled somewhat earlier, around 2002/2003 and appears slightly more pronounced. The mild recovery and stabilisation of business cycle synchronization thereafter (2004-2006) is also evident from the graph.

As to the crucial comparison of synchronization before and after the introduction of the euro, average correlation on the basis of GDP data appears somewhat more pronounced under Stage 3 of EMU than in the first half of the nineties,[96] in slight contrast to the earlier IP-based Figures 3 and 4.

Figure 10 also displays the recession phases since 1980, based on the turning points of the cyclical component of euro-area GDP.[97] Here again, the graph suggests a general

94 *Gayer* and *Weiss* (2006) report that this recurrent pattern of declining correlation in cyclical upswing phases and increasing correlation during downswings is less visible using qualitative ICI data compared to IP data.

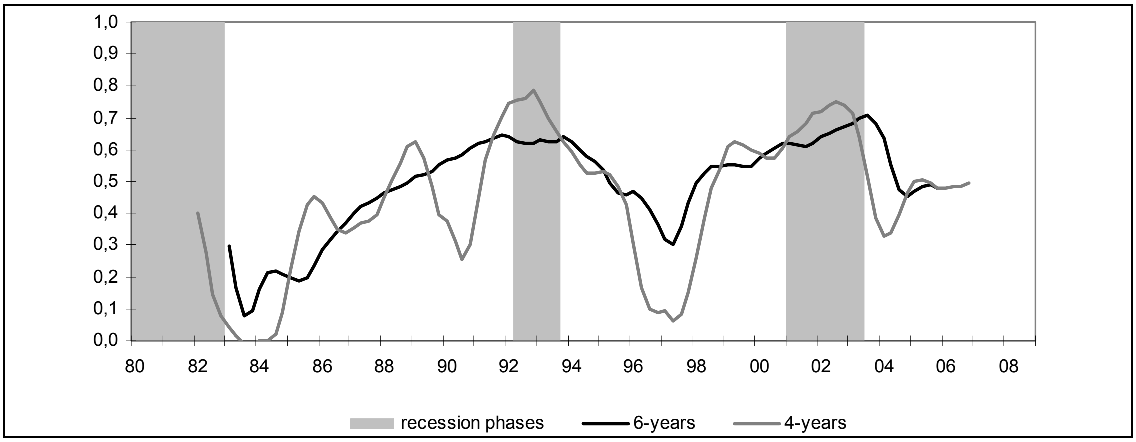
95 The graph focuses on the unweighted mean. Again, the weighting of countries does not qualitatively alter the findings.

96 Average correlation in the period 1990-1994 is 0.61 (0.58) for the 6-year (4-year) window, while it is 0.62 (0.63) for the period 1999-2003.

97 Reassuringly, the turning points of the HP-filtered quarterly GDP series (peaks in 1980:1, 1992:1 and 00:4, troughs in 1982:4, 1993:3 and 03:2) are fully congruent with those derived from the correspondingly filtered monthly IP series (Figures 6 and 7).

pattern of decreasing mean euro-area correlation just after the recession phases of the cycle have come to an end, i.e. after the trough has been passed. If this pattern remained valid also for the current business cycle, then an increase in cross-country correlations should be expected in the further course of the recovery, with laggards in cyclical adjustment catching up with faster rebounding countries.

Figure 10:
Mean Euro-area Correlations and Recession Phases
- GDP, 6- and 4-Year Window -



Source: Commission services.

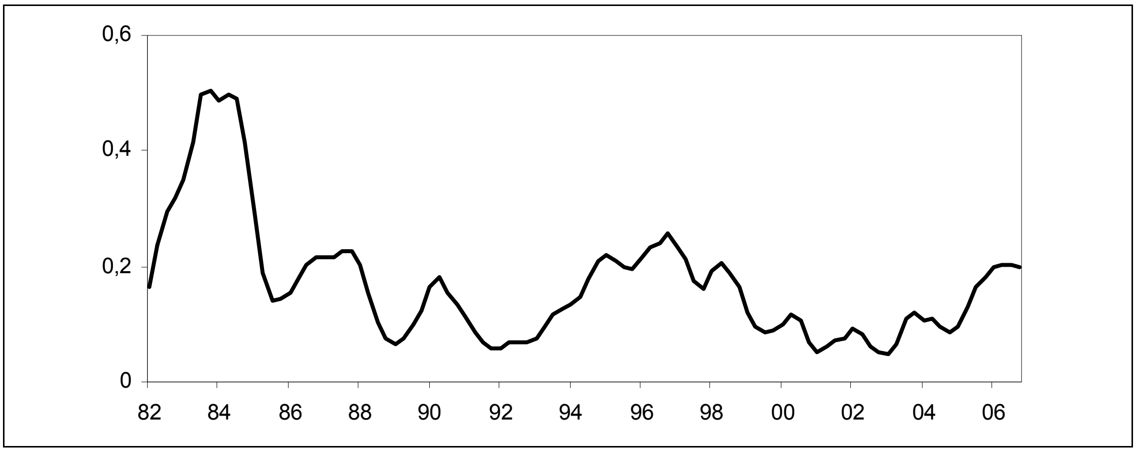
Based on the identified pattern of recurrent ups and downs in synchronization in the course of the business cycle, one may compare mean correlation in the period 1999-2006 with mean correlation in the corresponding eight-year period of the previous cycle. As discernible from Figure 10, the introduction of the euro in 1999 occurred approximately four and a half years ahead of the latest cyclical trough in 2003q2, when cycles started to diverge. The corresponding benchmark period around the previous trough in mid-1993 thus runs from 1989 to 1996. Mean correlation over that period is 0.58 (based on the six-year window), while it is marginally higher at 0.59 for the corresponding period since the introduction of the euro. On average across the business cycle, synchronization in the euro area thus appears to have stabilised at a high level.[98] Additional synchronization effects due to the introduction of the euro on top of those following from the Internal Market programme (through further market integration, the EMU's policy coordination framework and its impact on structural reforms) may still be largely forthcoming.

Figure 11 displays the evolution of the variance of bivariate correlation coefficients over time, using the four-year window. From 1997 to 2002, a decrease in the dispersion of country-to-country correlations can be observed, pointing to overall higher cyclical homogeneity among the group of countries. Since 2003, however, in line with the previous

98 See Section 6 for a comparison with countries outside the euro-area.

findings, a widening of the dispersion between country correlations is observable. Towards the very end of the sample, there is a stabilisation of the dispersion of cross-country correlations. However, the level of dispersion does not actually decline, as was the case with the IP-based four-year window correlations (Figure 5) and as could have been expected from the pick-up of mean correlation in Figure 10, if empirically a rise in mean correlation was systematically accompanied by a corresponding fall in the dispersion of correlation across countries. Apparently, the latter is not always true, such that a higher mean association can indeed mask that at the same time the differences in association between individual country pairs increase. This observation might be explained by the existence of some negative outliers, i.e. country pairs with particularly poor bivariate correlation at the end of the sample, affecting the variance more markedly than the mean of the distribution. More specifically, it could be that while there is a general trend of increasing correlation between countries' business cycles, certain countries' cycles become increasingly more different from all other countries' cycles – against the trend. This calls for a closer, country-wise analysis of correlations to see the contributions of individual countries to mean euro-area developments.

Figure 11:
Dispersion of Bivariate Correlation Coefficients
- GDP, 4-Year Window -



Source: Commission services.

5. Country Contributions

Figure 12 shows the correlations of individual euro-area Member States with the euro area aggregate, using GDP data and based on the six-year window.[99] Averaging across

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99 This approach generates largely equivalent results to calculating averages of countries' bivariate correlations with all other euro-area countries. Calculating correlations with the euro-area aggregate leads to systematically higher average correlation levels, since any given country contributes to the

these individual correlations with the euro area produces very similar curves to those presented above (Figure 10). Looking at the individual graphs, several groups of countries can be distinguished. First, there is a group comprising Germany, France, Italy, Spain and the Netherlands that have been displaying consistently high correlation with the euro area since at least 1999. Before that, the Dutch correlation curve showed a marked slump in the mid-nineties, when the country's cycle was temporarily shifted with respect to the aggregate cycle. France and Spain show signs of slightly lower synchronization since around early 2004, with the French correlation dropping from a level close to 100% to below 80%. However, for both countries, correlations appear to recover again at the very end of the sample.[100] Austria and Portugal displayed slightly lower correlation levels in the first years after the introduction of the euro. Between 2001 and 2003, both countries experienced an increasing association with the euro-area cycle, likely explicable by the very evenly spread cyclical downturn following the burst of the dotcom bubble in 2000. Both countries then experienced a temporary dip in their euro-area correlations around 2004. At the end of the sample, both countries' correlations are back to levels comparable to those recorded around 1999.

An interesting case is Greece. It shows insignificant or even negative correlation with the euro-area cycle since the mid nineties. Continuously falling since 2004, recent developments in correlation point towards counter-cyclical behaviour. As argued in European Commission (2006a), the disconnection from the rest of the euro area can partly be explained by structural features of the Greek economy, particularly its comparatively low integration in intra-area trade. Furthermore, the Greek economy has benefited in recent years from the positive stimuli of a later euro adoption and the Olympic Games in 2004.

Another particular case is Finland, where correlation with the euro area was rather low before 2000, particularly during the period of economic crisis in the early nineties. Having reached a peak level around the recessionary phase of 2002/2003, euro-area association has again fallen since then. Similarly pronounced drops in correlation around 2003/2004 can be seen for Belgium and Ireland. Both countries displayed high levels of euro-area synchronization from the late nineties (and, in the case of Belgium also before that) to 2003. While the dip seems to be pronounced but temporary in the case of Bel-

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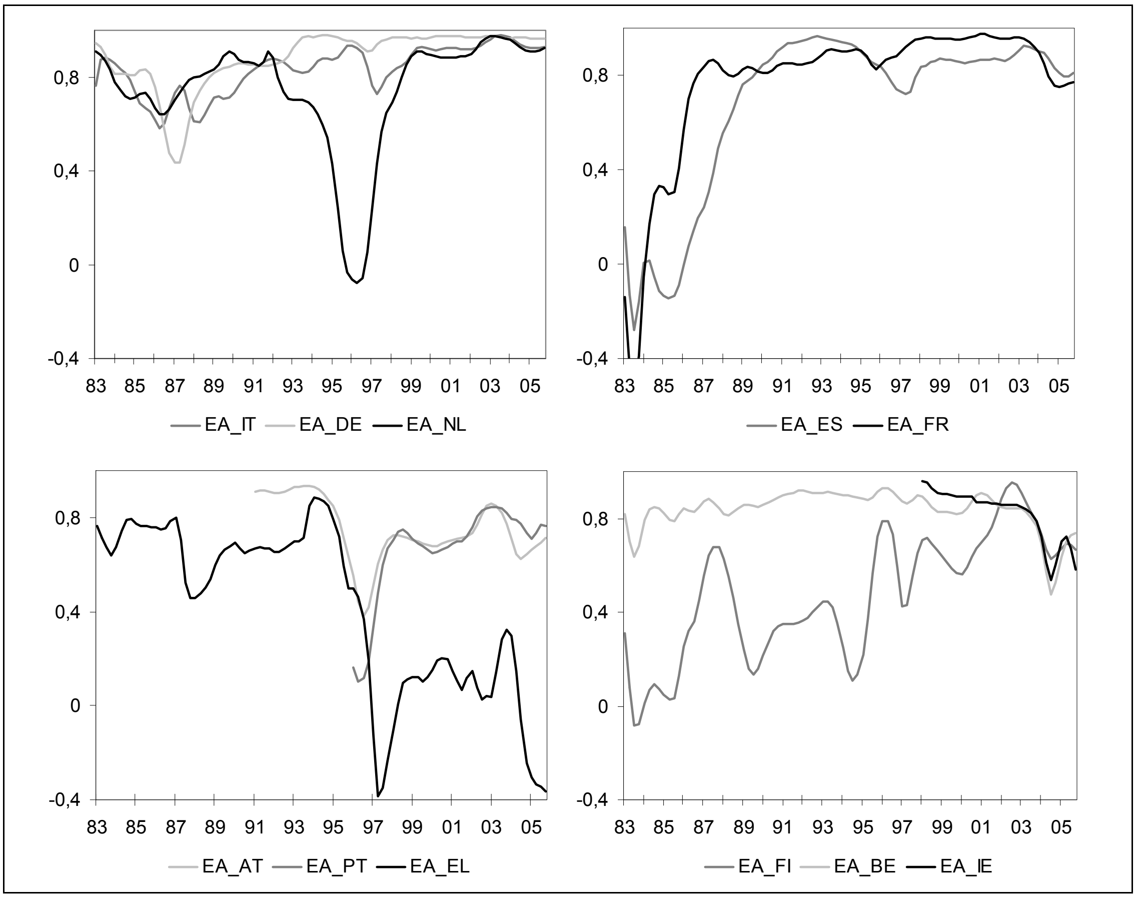
aggregate cycle itself. Obviously, average pair-wise correlations are particularly lower for the large 'core' euro-area countries Germany, France and Italy. Furthermore, contrary to the graphs in the text, a mild fall in mean correlation at the end of the sample can also be observed for Germany and Italy (and the Netherlands), if bivariate correlations are averaged. A bias arises, however, from the fact that in such an unweighted average, a marked de-synchronization of one (small) country is enough to bring down mean correlations of all other countries. Using the (explicitly weighted) euro-area cycle instead mitigates this problem. Finally, if one believes that there is a genuine 'euro-area cycle' driving individual national cycles, then this is the relevant benchmark that the country cycles should be compared to.

[100] This is confirmed by the corresponding calculations based on the four-year window.

gium, the apparent de-synchronization of the Irish cycle does not (yet) show clear signs of reversal. The four-year window results largely corroborate the above findings. The assessment of individual country developments in terms of synchronization with the euro-area aggregate is partly different when based on IP instead of GDP series (Figure 13). Here, the Netherlands appear to contribute to the overall fall in correlation already since around 2001, which is not visible in Figure 12.

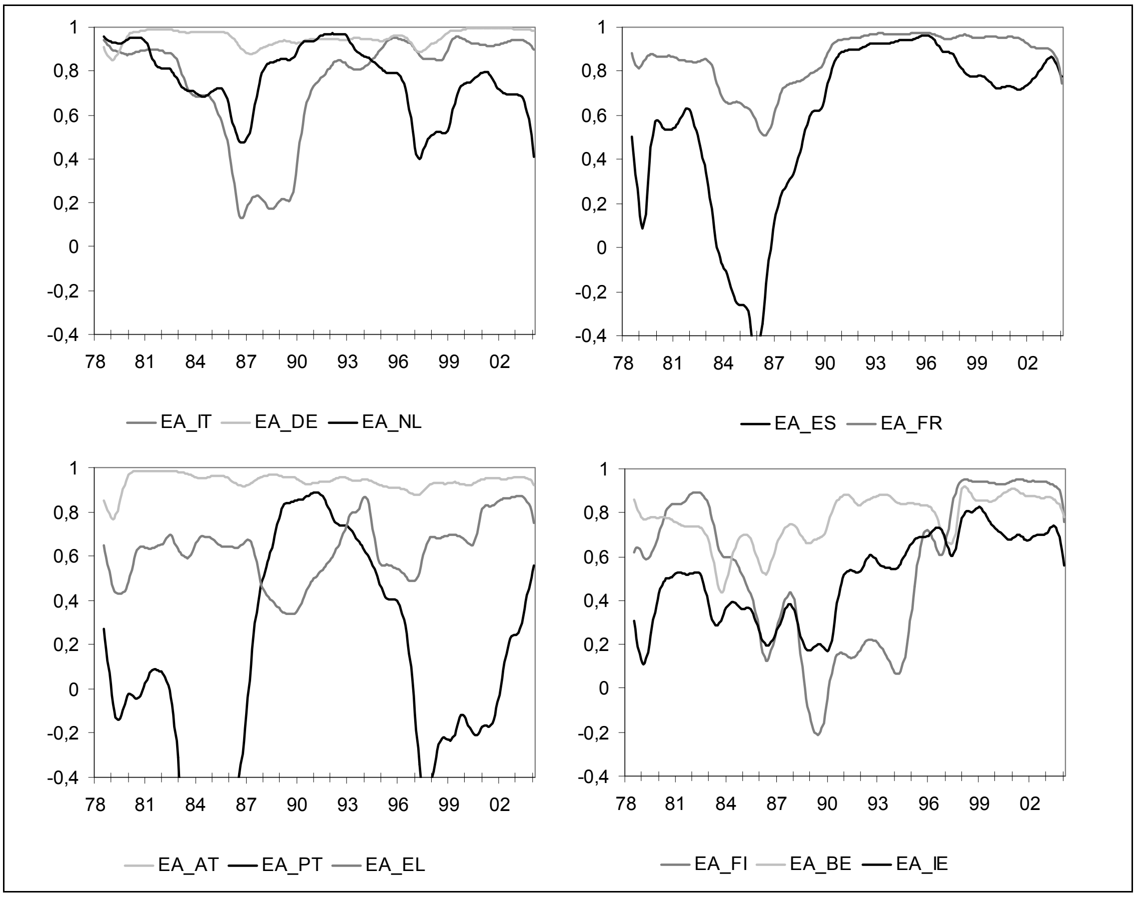
Figure 12:
Correlation of Individual MS with Euro-area Aggregate
- GDP, 6-Year Window -



Source: Commission services.

However, the picture is rather coherent for Germany, Italy, France and Spain, with the latter two countries showing slight signs of decreasing adherence to the euro-area cycle at the end of the sample. For Spain, a somewhat more severe and rather protracted phase of de-synchronization from the euro-area IP cycle can be seen between 2000 and 2002 already. A look at the underlying cyclical developments shows that Spanish industrial production peaked two quarters before the euro-area aggregate in 2000 and reached the latest trough more than one year in advance in early 2002, when industrial activity in the euro area remained subdued for almost another year.[101]

Figure 13:
Correlations of Individual MS with Euro-area Aggregate
- IP, 6-Year Window -



Source: Commission services.

The curves in Figure 13 for Portugal and Greece differ from those of Figure 12. On the basis of IP cycles, Portugal shows a severe fall in euro-area correlation in the early and mid-nineties, followed by a steep and unbroken recovery from 2001 onwards. The correlation of the Greek cycle with the euro area, on the other hand, appears much closer than on the basis of GDP data. Displaying a step-wise upward trend towards the correlation level of the four large euro-area countries between the mid nineties and 2003, the curve indicates a decline in euro-area synchronization only very recently. As for Austria, the results are again broadly coherent with those based on GDP for Belgium, Ireland and

101 For a brief discussion of the impact of the real interest rate channel on de-synchronization in Spain, see *European Commission* (2006a).

Finland, with the latter two countries showing more pronounced signs of a recent weakening in euro-area synchronization.

As to the short-term tendency, reflecting the pick-up in mean euro-area correlation at the very end of the sample in Figure 4, the correlations of IP cycles calculated over four-year windows point to a rebound in synchronization for the majority of countries where a decrease around 2003 is discernible from the graphs displaying the six-year window results. All in all, the observed decline in mean correlation in the euro area around 2003 seems to be due to a relatively widespread de-synchronization at the level of individual countries. Apart from countries such as Greece, Finland and Ireland, there is evidence of rather distinct drops in correlation even for 'core' countries such as France and Belgium. Using IP data, also the Dutch cycle shows signs of de-linkage from the euro aggregate. Importantly, however, the drop in synchronization in 2003 appears to be of a temporary nature overall. Greece, Finland and Ireland are the only countries, for which the GDP-based synchronization measure does not show a rebound at the end of the sample (Figure 12).

As to the mean level of business cycle correlation since the introduction of the euro in 1999, the GDP data points to a particularly low level of cyclical adherence to the rest of the zone for Greece, while on the basis of IP data the level is particularly low for Portugal. Importantly, however, in the latter case the data point to a strong upward trend in euro-area synchronization since 2001.

Figure 14 takes a final look at individual country developments, now based on survey data, corresponding to the mean results shown in Figure 8. It emerges that, apart from Greece, mainly Spain, Portugal and Ireland[102] are displaying significant drops in correlation with the euro-area confidence indicator (ICI) towards the end of the sample. Among the countries with usually high and stable correlation, presented in the upper panel of the graph, France can be seen to experience a transitory dip in euro-area correlation lately, in line with previous observations. Furthermore, the observation of a slowly descending trend in mean ICI correlation already since 2000 (Figure 8) appears mainly attributable to corresponding developments in Greece and Spain. While the development of the Greek curve is very much in line with the slump in the GDP-based correlations, the contribution of the Spanish ICI to the de-synchronization of industrialists' confidence in the euro area around 2003 is much more pronounced than suggested by the preceding correlation results using hard data.

Summarising the analysis of individual country developments, the picture of a relatively widespread but temporary de-synchronization of cyclical forces across the euro area emerges, spurred by peculiar developments in some countries such as Greece. Despite some signs of transitory de-synchronization in the case of France and Spain, the larger countries seem to continue to stick reasonably well together.

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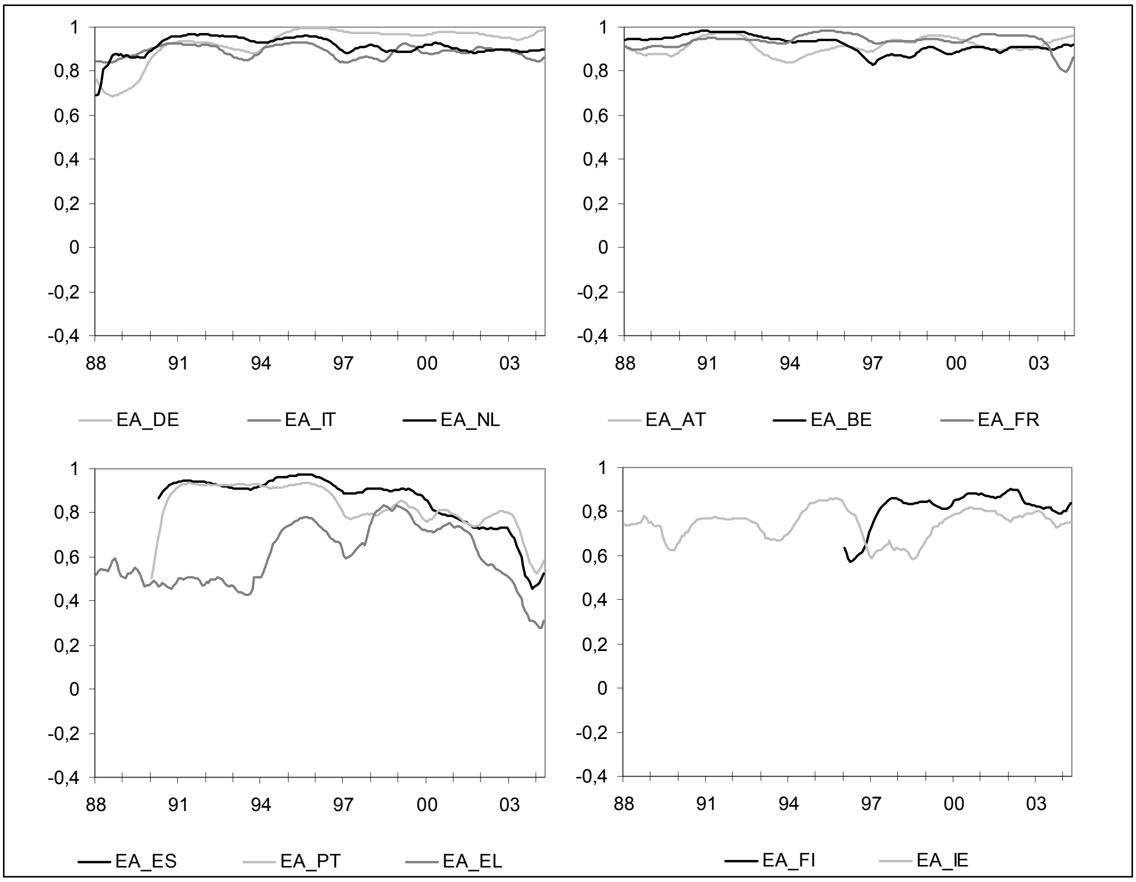
102 The decrease in correlation for Ireland is much more pronounced when the four-year window is used.

Figure 14:
Correlations of Indiviudal MS with Euro-area Aggregate
- ICI, 6-Year Window -



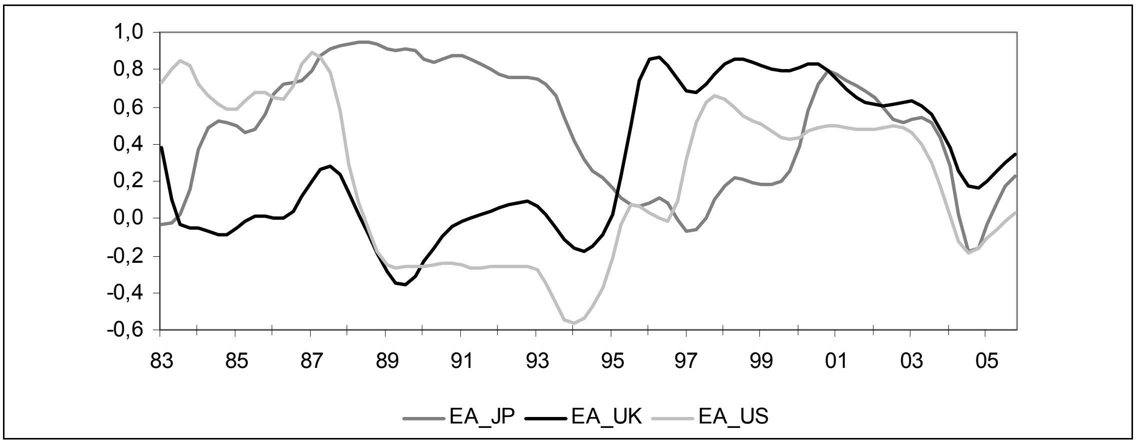
Source: Commission services.

6. International Environment

OECD countries have experienced a strong convergence in business cycles over the past few years on the back of rising trade and financial integration as well as forceful common shocks. Correspondingly, Artis (2005) finds evidence of an emerging 'world business cycle', implying that where increased business cycle synchronization in the euro area is found, it is not clear whether this is due to area-specific forces or global trends. Similarly, the finding of a recent dip in business cycle synchronization within the euro area has to be checked against possible parallel developments at the world level. For this reason, we repeat the analysis for some important non-euro-area countries.

Figure 15 displays the moving correlations of the UK, the US and Japan with the euro-area aggregate. The effects of the emerging markets crisis are clearly visible in the temporary decoupling of the Japanese cycle from that of the euro-area. While high levels of correlation around the early 2000s suggest a period of close euro-area-world synchronization until very recently, the business cycles of all three external economies appear to simultaneously decouple from the euro-area cycle since early 2003, followed by a rebound in synchronization in 2004/2005.

Figure 15:
Correlations of UK, US and JP with the Euro-area
- 6-Year Window -



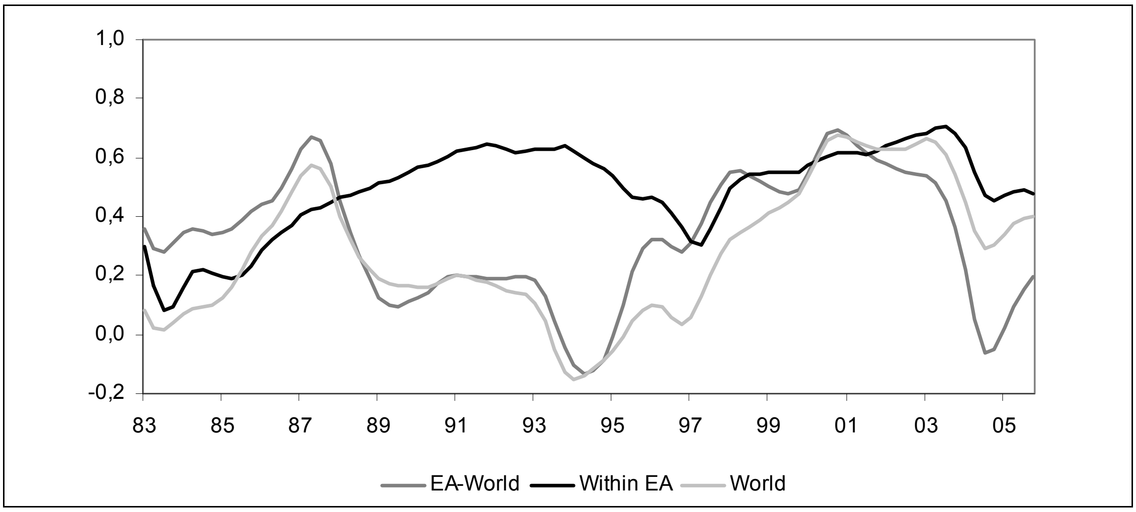
Source: Commission services.

Figure 16 displays the mean of the six pair-wise correlations between the euro area, the UK, the US and Japan, serving as a measure of worldwide synchronization of cycles (World). It also displays the mean of the three correlation series from Figure 21 as a measure of mean correlation between the euro area on the one hand and important outside countries on the other (EA-World). Finally, the graph also recalls the mean of the intra-euro-area correlations (Within-EA), known from Figure 10.

The gap between the World and EA-World curves on the one hand and the Within-EA curve on the other hand over the 10-year period from the late eighties to the late nineties clearly points to a euro-area specific process of cyclical synchronization during that time. As suggested by Mélitz (2004) and Kalemli-Ozcan et al. (2004) this increase in the symmetry of business cycles in the euro area during the 1990s might reflect the closer economic and financial integration and policy coordination in the run-up to, and early stages of, EMU. This result would thus support the predictions of the endogenous Optimum Currency Area (OCA) hypothesis due to Rose (2000 and 2004) and Frankel and Rose (1997).

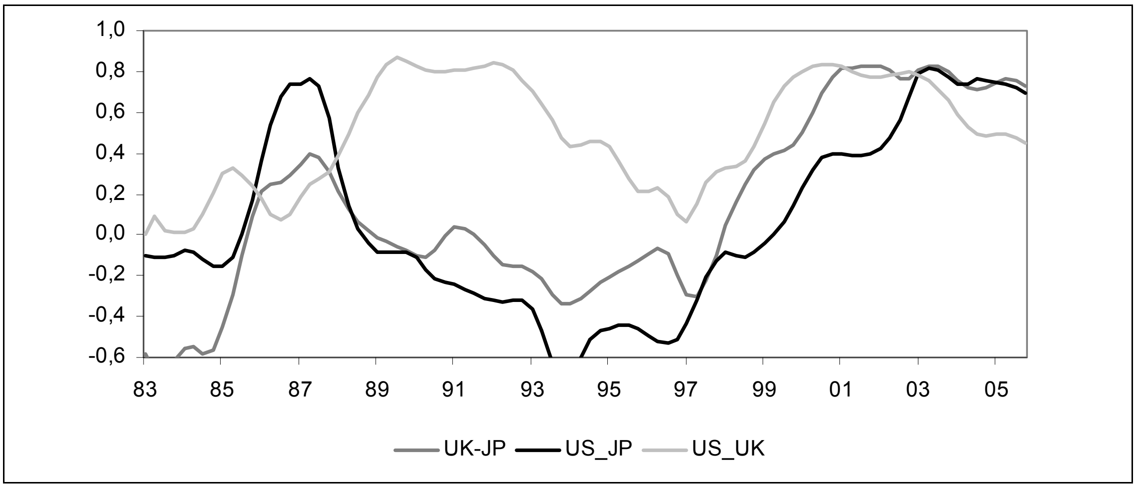
At the same time, the rapid convergence of world cycles since the mid-nineties and the ensuing high level of world-cycle synchronization attained since 2000 suggest that synchronization within the euro area might have benefited from synchronization tendencies at the world level, driven by forceful common shocks such as the universal IT boom of the late nineties and the ensuing dotcom bust and 9/11 terror attacks. Between 1997 and 2002, business cycle association was as high on average between the euro area and the US, UK and Japan as it was within the euro area.

Figure 16:
Mean Correlation: Euro-area-World vs. World vs. within-Euro-area
- 6-Year Window -



Source: Commission services.

Figure 17:
Correlations between the UK, the US and JP
- 6-Year Window -



Source: Commission services.

The ensuing parallel decline of both intra-euro-area and euro-area-world correlation since 2003 shows that the temporary de-coupling of business cycles between euro-area Member States is accompanied by a parallel phase of de-coupling of the eurozone aggregate from the rest of the world. However, the latter de-synchronization appears far more pronounced, with mean euro-area-world correlation temporarily falling to below zero and remaining in insignificant territory until the end of the sample (Figure 16, EA-World). At the same time, Figure 17 shows that business cycle synchronization between the US, the UK and Japan has remained at high levels overall, with the partial exception of the pair US-UK, showing milder downward tendencies since 2003. These latter developments mirror the well-known differences in economic performance between the euro area and its major economic counterparts over the past few years. While the euro area saw actual output growth above potential for the first time in 2006 after a prolonged period of sluggishness in 2003-2005, the US economy experienced three years of rapid expansion and only moved to a growth path below trend in the second quarter of 2006. The UK had reached potential growth already in 2003 and grew clearly above potential in 2004. Japanese growth was also clearly above potential in 2004, and close to potential in 2005.

The dent in the measure of world-cycle synchronization in Figure 16 (World) is thus obviously due to a particular pattern of the euro-area cycle, while the other big economies' cycles appear to remain reasonably closely aligned.

The observation of a transitory decline in synchronization of euro-area Member States' business cycles thus has to be partly qualified by a much more pronounced decline in synchronization between the area and the rest of the world. The implied relative closeness of cycles within the monetary union points to a sustained distinct euro-area business cycle affiliation.

Together with the finding that the observed dip in euro-area synchronization is partly attributable to a recurrent pattern of transitory de-linking in early recovery phases of the cycle, the analysis provides continuous evidence of a distinct euro-area business cycle. The observed temporary divergence within the monetary union around 2003 is much less pronounced than between the union and important outside countries. Coming back to the question whether increased synchronization in the euro area might be a mere by-product of globalisation, the empirical evidence is not supportive. During the 10-year period from the late eighties to the late nineties, synchronization within the euro area was clearly ahead of that on the world level. While world-cycle synchronization rose steeply from the mid-nineties to match euro-area synchronization around 1999, the recent experience shows that euro-area cycles hold together relatively more closely than cycles on the world level.

7. Robustness of Results

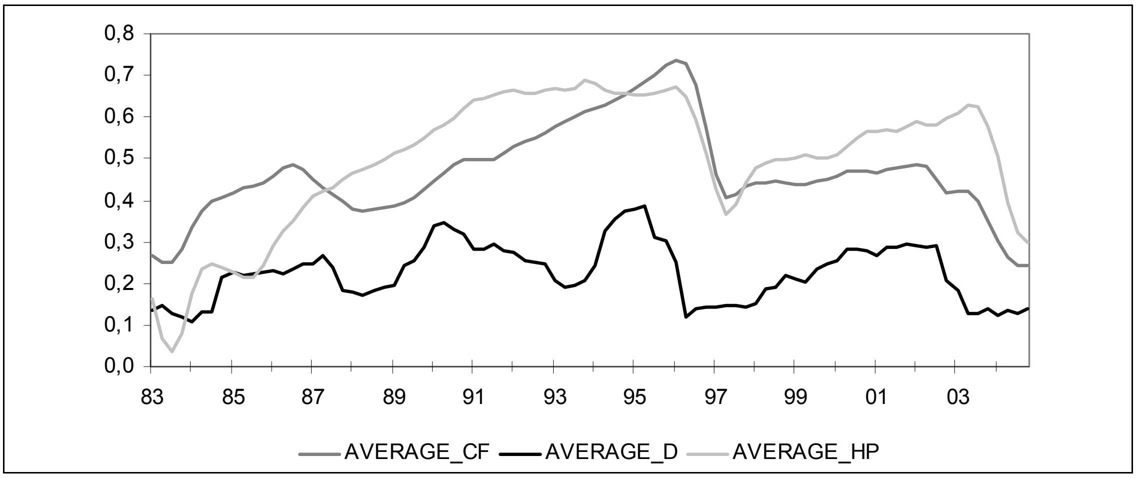
Several variations of the described methodology were used to check the robustness of the results. First, since its is well-known that different trend-cycle decompositions can lead to different properties of the estimated business cycle,[103] two alternatives to the use of HP filters were applied to distil the cyclical fluctuations from the GDP series: a genuine band-pass filter derived by Christiano/Fitzgerald (CF, 1999)[104] and the calculation of growth rates as the differences of the logarithm of GDP. The development of average

103 See e.g. *Canova* (1998).

104 The CF-filter is an asymmetric variant of the well-known Baxter-King filter, having the advantage that it can be computed up to the ends of the sample, albeit at the risk of introducing a phase shift.

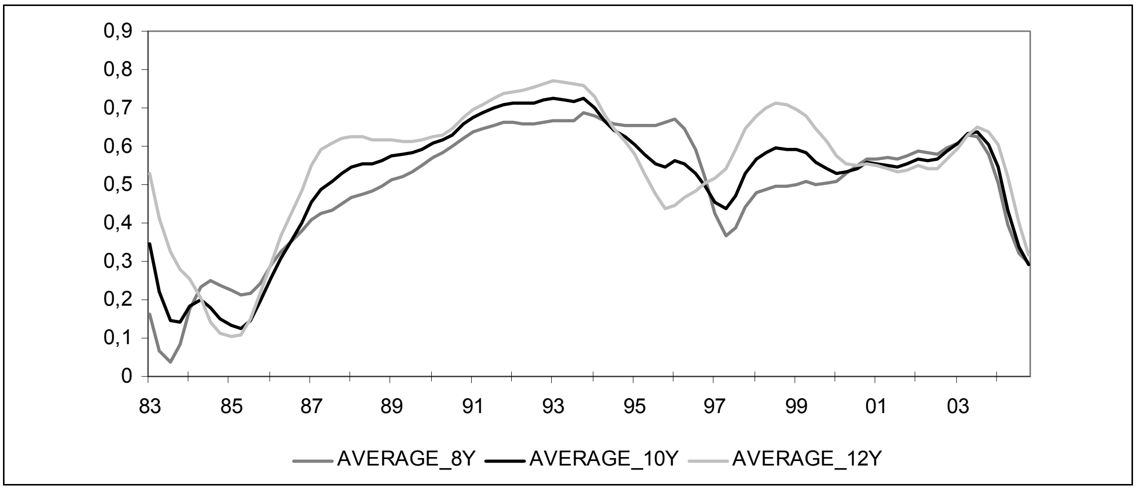
correlation between the euro-area countries considered is qualitatively unaffected compared to e.g. Figure 10: a peak in mean within-euro-area correlation in the mid-nineties is followed by a temporary trough in 1996/1997 and a subsequent recovery until the early 2000s. However, in case of both the CF-filtered series and the growth rates, the subsequent decline in correlation sets in somewhat earlier, i.e. in mid-2002 (Figure 18).

Figure 18:
Mean Euro-area Correlation Using Different Business Cycle Estimates
- GDP, 6-Year Window -



Source: Commission services.

Figure 19:
Mean Euro-area Correlation Using Different Business Cycle Lengths
- GDP, 6-Year Window -

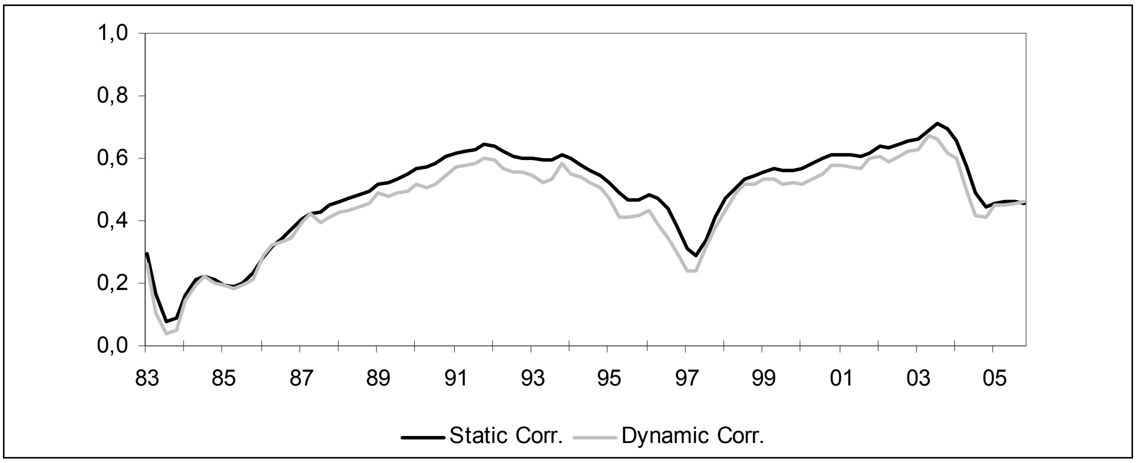


Source: Commission services.

Second, the definition of the maximum duration of business cycles was altered from 8 years to 10 and 12 years in the calculation of the band-pass filter. As before, the main message from the moving correlations is not affected (Figure 19).

Lastly, an alternative measure of association, based on estimation in the frequency domain, was used instead of the static correlation coefficients. The mean across euro-area countries of these so-called dynamic correlations,[105] computed over rolling windows as before, is depicted in Figure 20. As can be seen, the picture is again unchanged in qualitative terms.

Figure 20:
Mean Euro-area Correlation: Static vs. Dynamic
- GDP, 6-Year Window -



Source: Commission services.

8. Summary and Conclusions

This paper revisits the issue of euro-area business cycle convergence and synchronization on the basis of a data sample covering more than eight years of EMU experience and using various measures of the business cycle.

The introductory analysis of convergence of output gaps across Member States shows that the absolute dispersion of growth in the euro area has narrowed considerably since the early nineties and, with the exception of a transitory pick-up mainly between the four

105 See *Croux* et al. (2001) for details on the concept of dynamic correlation. The basic idea is to measure the co-movement of two series over a specified frequency band. Since analysis in the frequency domain requires stationarity of the series, they were de-trended using a HP filter. The measure is used e.g. in *Bulligan* (2005) and *Camacho* et al. (2005) to investigate the issue of convergence in the euro area. We also computed the concordance index proposed by *Harding* and *Pagan* (2002), which evaluates the fraction of time the cycles of two countries spend in the same phase. It gives further support to the robustness of the results.

large Member States in 2004, has been standing at historically low levels since around 2002.

However, the observed downward trend in the dispersion of output gaps is not necessarily due to the fact that Member States' business cycles are increasingly in-phase. It might simply be due to a general decrease in the amplitude of cyclical fluctuations. Therefore, a trend of cyclical de-synchronization might be masked by the low amplitude of cyclical fluctuations.

The remainder of the analysis uses correlation-based measures of synchronization, which are unaffected by changes in amplitudes. The level of synchronization of euro-area business cycles since the introduction of the euro is found to be overall high, though not higher than in the first half of the nineties, i.e. before the worldwide fall in business cycle affiliation in the wake of the 1997 emerging markets crisis.

Around 2003, however, the level of cross-country synchronization in the euro area experienced a quite abrupt decrease. This picture is shared between several measures of the business cycle (based on IP, GDP and survey data).

Moving correlations computed over windows of four years, though possibly subject to some short-lived changes, indicate a rebound and partial recovery of cross-country association from around 2004 onwards. Again, this picture is shared across several indicators and confirmed for most of them using a smoother six-year correlation window. The observed dip in synchronization thus appears to be a transitory phenomenon.

Looking at the track history of business cycle synchronization in the euro area, there is some evidence of a recurrent pattern of falling business cycle synchronization in the recovery phases of the cycle, which could account for the observed temporary decrease in mean intra-euro-area correlation. The start of the recent decrease in correlation coincides with the latest cyclical trough in mid-2003.

In line mainly with the results based on the shorter correlation window, this pattern would call for a (further) recovery of synchronization in the further course of the current business cycle.

On the country level, the analysis points to a rather widespread de-synchronization between Member States around 2003, with even core countries showing temporary signs of disassociation. However, this general tendency is aggravated by some particularly poorly synchronised countries like Greece and Finland. The very recent renewed upward trend of business cycle association is confirmed for almost all countries.

Cross-checking the results against developments outside the currency union, we find that business cycle synchronization within the euro area was distinctly higher than world-cycle synchronization in the ten-year period prior to the introduction of the euro. The finding of a recent (temporary) fall in synchronization within the euro area is shared by corresponding developments at the level of the world cycle. This observation is, however, mainly due to the contribution of the euro area itself, i.e. it reflects a de-linkage of the area as a whole from its trading partners.

While synchronization between the euro area and its main economic counterparts was as high as within the area between 1997 and 2002, the recent temporary de-synchronization is much more pronounced between the area on the one hand and the US, UK and Japan on the other than within the monetary union. This may be interpreted as a relative gain in business cycle affiliation within the currency zone compared to affiliation with outside countries and world-cycle affiliation over the past few years. Together with the finding that the observed dip in euro-area synchronization is partly attributable to a recurrent pattern of transitory de-linking in early recovery phases, the results are evidence of the continuous existence of a distinct euro-area business cycle. At the same time, evidence for a further increase in synchronization since the introduction of the euro is sparse at present. Additional synchronization effects due to the monetary union may still be largely forthcoming.

The present analysis focuses on the pure synchronization aspect of convergence, i.e. on the degree that cycles move in phase. This explains why the observed temporary decline in synchronization around 2003 does not coincide with a significant increase in the dispersion of output gaps across countries. Remaining differences in cyclical amplitudes, though found to be small in historical terms, might point to the need for further structural reforms in countries with still subdued response to the improved business cycle conditions. This should also help to narrow the distribution of adjustment speed across countries in phases of economic uncertainty in the future.

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Contributors

Ivana Bátarová, Comenius University, Bratislava, Slovakia

Uwe Böwer, European Commission, Brussels, Belgium

Gerhard Fenz, Oesterreichische Nationalbank, Vienna, Austria

Jarko Fidrmuc, LMU München, Munich, Germany

Christian Gayer, European Commission, Brussels, Belgium

Catherine Guillemineau, National Institute of Economic and Social Research, London, United Kingdom

Claude Hillinger, LMU München, Munich, Germany

Oliver Holtemöller, Halle Institute for Economic Research, Halle, Germany

Andrew Hughes-Hallett, George Mason University and CEPR, Fairfax, United States

Eva Köberl, ETH Zurich and KOF Swiss Economic Institute, Zurich, Switzerland

Iikka Korhonen, Bank of Finland, Helsinki, Finland

Christian Müller, Zurich University of Applied Sciences and KOF Swiss Economic Institute, Zurich, Switzerland

Jörg Rahn, Marcard, Stein & Co., Hamburg, Germany

Christian Richter, Kingston University, London, United Kingdom, and INFER

Torsten Schmidt, Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI), Essen, Germany

Martin Schneider, Oesterreichische Nationalbank, Vienna, Austria

Michael H. Stierle, European Commission, Brussels, Belgium

Institut für Wirtschaftsforschung Halle – IWH

Hausanschrift: Delitzscher Straße 118, 06116 Halle (Saale)
Postanschrift: Postfach 16 02 07, 06038 Halle (Saale)
Telefon: (03 45) 77 53 - 60, Telefax: (03 45) 77 53 820

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