World, Country, and Sector Factors In International Business Cycles*

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Abstract

Do sector-specific factors common to all countries play an important role in explaining business cycle co-movement? We address this question by analyzing international co-movements of value added (VA) growth in a multi-sector dynamic factor model. The model contains a World factor, country-specific factors, sector-specific factors, and idiosyncratic components. We estimate the model using Bayesian methods for 30 disaggregated sectors in the G7 economies for the 1974-2004 period. Our findings show that although there is a substantial role for sector-specific factors, fluctuations are dominated by country-factors. Contrary to previous studies, the World factor appears to play a minimal role. This is because, when using aggregate data, the world factor captures both the factor common to all countries and industries and the factor common to the same industry across countries. We then examine how these factors evolved as globalization deepened over the past two decades. Overall, our results suggest that, contrary to the convergence hypothesis, business cycles at a disaggregate level have not, on average, become more synchronized at the international level.

Keywords: *dynamic factors, disaggregated business cycles, international co-movement.*
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1 Introduction

We examine the dynamics of business cycle co-movements over time across sectors and countries to provide an empirical characterization of common business cycle linkages at a disaggregate level among the G7 countries. Our analysis addresses several important questions. First, what are the main factors driving international business cycles at the sector level in different countries? Second, how have these factors evolved as globalization deepened over the past two decades? Third, are changes in the importance of these factors from the pre-globalization to the globalization periods accounted for by changes in sector-level co-movement or the result of structural change?

We address these questions by estimating common components for Value Added (VA) growth for 30 sectors of the G7 countries for the period covering 1974 to 2004. We employ a Bayesian dynamic latent factor model that contains: i) a world factor, which is common to all industries[1] in all countries; ii) an industry (-specific) factor, common to the same industry across all countries; iii) a country factor, common to all industries within the same country and, finally, iv) an idiosyncratic component specific to each industry time series.

This allows us to extend the empirical research on business cycle co-movements in several directions. Firstly, there are relatively few papers examining the importance of industry-specific factors for international business cycles and, to our knowledge, no study has so far analyzed these types of shocks using a Bayesian approach to multiple dynamic factor models. This approach allows us to work with a large number of cross-sectional units and factors. Moreover, following Kose et al. (2008), this model enables us to capture not only the contemporaneous spillovers of shocks but also the dynamic propagation of business cycles in a flexible manner, without a priori restrictions on the direction of these spillovers or the structure of the propagation mechanism. Secondly, we make use of a detailed level of disaggregation that also includes all major sectors in the economies considered.[2] The level of disaggregation is important as more aggregated data may hide the role of industry-specific shocks, especially if industries have similar production structures as argued by Imbs (2004). Therefore, the inclusion of industry-specific factors may have important consequences for the role of other more commonly studied factors, such as the world factor. Third, our data span covers the period of globalization characterized by increased trade and financial integration. This enables us to estimate the model for two sub-samples characterizing the pre-

[1] We use the term "industries" to refer to disaggregated sectors, as our data include sub-sectors from agriculture and mining, manufacturing, services and construction.

[2] Norrbin and Schlagenhauf (1996), for instance, consider 7 sub-sectors belonging to mining and industry only.

globalization and the globalization periods and therefore, to analyze the sources of changes in business cycle co-movement at a disaggregate level.

Our results provide a rich body of evidence about the role and evolution of common business cycles at the disaggregate level. They indicate that the country factor explains the largest proportion of the variance of VA growth for most of the G7 countries[3], while the industry-specific factor is the second most important source for the majority of the countries considered. The world factor seems to play a minimal role in accounting for movements in industrial VA growth. The introduction of sector-specific factors appears to reduce the relevance of the world factor when compared to previous studies. We cannot, however, conclude against the existence of a "world business cycle", as argued by Kose et al. (2003, 2008) and Kose et al. (2008). Our results indicate that a good part of business cycle co-movement across countries may be driven by common sector-specific factors combined with similar production structures. When using aggregate data, the world factor could be capturing not only the dynamic factor common to all countries but also the dynamic factor common to the same industry across countries. If the proportion of the variance explained by world and industry factors is added up, our results would support the prominence of "international" over "country-specific" factors.

During the pre-globalization period (1974-1988) we find support for an international business cycle at a disaggregate level for most countries. However, during the globalization period, we find support for the prominence of international factors only for two countries. Only France and the UK show evidence in favor of the business cycle convergence hypothesis. On average, thus, we do not find robust support for the hypothesis that disaggregate business cycles have become more synchronized at the international level. When looking at the variance decomposition by industry from the pre-globalization to the globalization periods, a small majority of industries (18 out of 30) display business cycle divergence. This indicates that the international factor has become less important than the country factor in driving cyclical fluctuations in the G7 countries. Overall, there is no distinct pattern between industries that are intensive in internationally traded goods and those that are not. Finally, changes in the variance decomposition from the pre-globalization to the globalization periods seem to be largely accounted for by changes in the importance of factors within industries, rather than changes in the structural composition of the economies considered.

There is a large body of theoretical and empirical literature related to our study. Economic theory provides only nuanced guidance about the impact of increased international

[3] Excluding the idiosyncratic factor which, as expected, dominates for most of the industries considered.

linkages on output co-movement across countries. For example, Frankel and Rose (1998) unveiled the empirical regularity that higher bilateral trade between country pairs is associated with more correlated business cycles, placing trade at the heart of international business cycles transmission. On the other hand, economic theory suggests that if trade increases specialization and if industry-specific shocks are dominant, the degree of output co-movement should fall with increased trade integration. In addition, financial linkages could also lead to a higher degree of business cycle synchronization via the wealth effects of external shocks. Recently, however, Kalemni-Ozcan et al. (2012) document that, during non-crisis times, banking linkages and output synchronization display a negative relationship.[4]

A number of empirical studies have also examined the impact of trade and financial linkages on international business cycles. For instance, Baxter and Kouparitsas (2005) argue that the most important channel explaining business cycle co-movements is international trade. Imbs (2004), however, is a proponent of the "common shock" view and argues that countries commove because their shocks are correlated. In particular, given that individual industries are subject to common shocks, two countries with similar production structures will be subject to greater business cycle co-movements[5].

Other studies employ dynamic factor models to quantify the importance of common factors to explain business cycle synchronization. Gregory et al. (1997) decomposed aggregate output, consumption, and investment for the G7 countries into a world and a country-specific factor. They show that both factors are statistically significant and quantitatively important for the common fluctuations across macroeconomic aggregates. Kose et al. (2003) examined the common dynamic properties of output, consumption, and investment across countries, regions, and the world for the 1960-1992 period for a 60-country panel using a Bayesian approach to model dynamic factors.[6] Their results show that while

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[4] They also document that, during crisis periods, the correlation between banking integration and co-movement becomes positive. That is, financial globalization results in less synchronized economic activity when productivity shocks are the main source of fluctuations; the opposite occurs when credit/financial shocks are the dominant source. Moreover, Kalemni-Ozcan et al. (2009), using a proprietary database on banks' international exposure, show that higher financial globalization leads to less synchronized business cycles among country-pairs.

[5] Other important studies examining the impact of trade and financial linkages on the nature of business cycles are Backus et al. (1995), Frankel and Rose (1998), Clark and van Wincoop (2001), Calderón et al. (2007), Burstein et al. (2008) and Giovanni and Levchenko (2010).

[6] Other important papers making use of a Bayesian approach to dynamic factors to quantify international business cycles co-movements include Crucini et al. (2011) and Kose et al. (2008).

the world factor accounts for a large fraction of fluctuations in most countries, the regional factor does not play an important role in explaining aggregate fluctuations.[7]

The international business cycles literature has emphasized the role of common country-level shocks and trade and capital market linkages in explaining business cycles co-movement. However, since Long and Plosser (1983), disaggregate business cycle models have highlighted the potential role of sectors in the transmission of shocks. Could sector-specific factors play an important role in shaping international business cycles? Relatively few papers have considered this question, especially at the international level. Exceptions are Costello (1993), and Norrbin and Schlagenhauf (1996), and Uebele (2010).[8] Norrbin and Schlagenhauf (1996) is perhaps the closest to our approach. They develop a model at an industry level by allowing a propagation of output changes between industries and across countries. They use data for nine industrialized countries disaggregated into seven sectors belonging to industry and mining. Using a dynamic factor state-space approach, they decompose industrial output fluctuations into a nation-specific, an industry-specific, a common, and an idiosyncratic component. Their analysis shows that the industry-specific shock explains only a small part of the variance of the forecast error, which is mostly explained by nation-specific shocks.

The rest of the paper is organized as follows. Next section presents the econometric methodology. Section 3 provides a description of the data. Section 4 presents and discusses the empirical results and, finally, section 6 concludes.

2 Empirical methodology

We now discuss the specification of the model and provide a brief description of the Bayesian approach to multiple dynamic factors models. The estimation method draws from Kose et al. (2003), which we adapt to our factor structure. This approach extends the single dynamic factor model of Otrok and Whiteman (1998) to a multifactor setting.[9]

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[7] This is in contrast with previous studies that argued in favour of the existence of a common European factor (see e.g., Artis et al. (1997), Bergman et al. (1998), Lumsdaine and Prasad (2003)). Kose et al. (2003) argue that regional factors found to be important in other studies are in fact proxies for a world factor.

[8] Long and Plosser (1987), Norrbin and Schlagenhauf (1988, 1990), Stockman (1988), Pesaran et al. (1993) and Foerster et al. (2011) also apply factor methods to disaggregate data but in a closed economy setting.

[9] We refer the reader to Kose et al. (2003) and Otrok and Whiteman (1998) for more details.

As mentioned in the introduction, our model contains i) a world factor, which is a factor common to all countries and industries in the system; ii) an industry factor, which is common to the same industry across countries; iii) a country factor, common to all industries within the same country, and iv) an idiosyncratic component. We observe one variable (VA growth) for 30 industries for the G7 countries plus the aggregate industrial VA growth for each of the economies from 1974 to 2004. An autoregressive process of each factor and idiosyncratic component is used to capture the dynamic relationships in the model. For simplicity and parsimony the factors and the idiosyncratic term are restricted to both follow an AR(3) process. Given that our data are annually distributed, this lag length should capture most spillovers (lagged or contemporaneous) across industries and countries.

Consider a panel of industrial VA growth rate series, $Y_{i,j,t}$, where the subscript i indexes the industry, with $i = 1,\ldots,I$, j indexes the country, with $j = 1,\ldots,J$, and $t = 1,\ldots,T$ indexes time, so that $Y_{i,j,t}$ is the growth rate of industrial VA of industry i in country j at time t. We assume that $Y_{i,j,t}$ can be described by the following dynamic factor model:

$$Y_{i,j,t} = \beta^{w}_{i,j} F^{w}_{t} + \beta^{s}_{i,j} F^{s}_{i,t} + \beta^{c}_{i,j} F^{c}_{j,t} + \varepsilon_{i,j,t}\ , \tag{1}$$

where F^w represents the world factor, F^s denotes the industry-specific factor, and F^c corresponds to the country-specific factor. Coefficients β^w, β^s, and β^c are the factor loadings on the world, industry-, and country-specific factors, respectively. Finally, $\varepsilon_{i,j,t}$ is the error term and is assumed to be uncorrelated cross-sectionally at all leads and lags, but can be serially correlated. The error term, $\varepsilon_{i,j,t}$, follows an autoregressive process of order p (3 in our case):

$$\varepsilon_{i.j.t} = \sum_{i=1}^{p} p_{i,j} \varepsilon_{i,j,t-i} + e_{i,j,t} \tag{2}$$

where $e_{i,j,t}$ are distributed as $N(0, \sigma^2_{i,j})$. The three unobserved factors F^w, F^s, and F^c are also assumed to follow an AR(3) process:

$$F^k_t = \sum_{l=1}^{p} p^k_t F^k_{t-l} + v^k_t \tag{3}$$

where $k = \{w, s, c\}$ and v^k_t are $N(0, \sigma^2_k)$. Finally, the innovations, $e_{i,j,t}$ and v^k_t, are mutually orthogonal across all equations in the system.

The model set out by equations (1) to (3) suffers from rotational indeterminacy and there are two related identification problems. The signs and the scales of the factors and their loadings are not separately identified. To overcome the identification issue of the signs, we require one of the factor loadings to be positive for each of the factors. In particular, the factor loading for the world factor is required to be positive for the aggregate industrial VA growth rate series of the first country in the dataset; the industry factors are restricted to load positively for all industries of the first country in the dataset; and, finally, the factor loadings for the country factors have to be positive for the aggregate variable of each country. Scales can be identified by assuming that each σ_k^2 is a constant.

We make use of the Bayesian approach with Gibbs sampling to estimate the model described by equations (1) to (3). Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method for approximating joint and marginal distributions by sampling from conditional distributions.[10] Using a MCMC procedure, we can generate random samples for the unknown parameters and the unobserved factors from the joint posterior distribution. This is feasible in this study as the full set of conditional distributions is known. That is, parameters given data and factors, and factors given data and parameters. More precisely, in our case, the algorithm can be summarized by the following steps:

1. Conditional on a draw for F^w, F^s, and F^c, we simulate the AR coefficients and the variance of the shocks to equations (2) and (3).
2. Conditional on a draw of F^w, F^s, and F^c, we draw the factor loadings β^w, β^s, and β^c.
3. Simulate F^w, F^s, and F^c conditional on all other parameters above.

The sample produced is the realisation of one step of the Markov-Chain. This process is then repeated generating at each step drawings for the regression parameters and the factors. More technical details about the estimation of the model can be found in Kose et al. (2003).

Our methodology does not allow us to identify the structural shocks driving these factors. Nevertheless, based on economic theory, a number of possible interpretations of these factors can be suggested. More precisely, the world factor could be capturing global demand and supply shocks, such as commodity price shocks, and common co-ordinated policy shocks. The country factors could be capturing country-specific macro-shocks affecting all sectors, such as changes in taxes; independent monetary policy shocks; and regulatory changes to labour markets. The sectoral factors could be capturing industry-specific demand and cost shocks, which could be technology related or arising terms of trade shocks.

There are alternative approaches to estimating dynamic factor models such as the EM algorithm combined with hill climbing techniques. However, in our case, these methods are not feasible given the dimension of our dataset (7 countries *(J=7)*, 31 industries *(I=31)*, 217 VA growth rate series *(IJ=217)*, and 39 factors *(K= 39)*). An effective estimation procedure to extract factors is the approximate factor model of Stock and Watson (1989) and Forni and Reichlin (1998). However, as argued by Kose et al. (2008), those models cannot be used when we aim to categorize some factors as belonging to a specific country by imposing zero restrictions on some factor loadings. In other words, given that in our study a country factor is identified by restricting the industrial output growth rate series of all industries in all

[10] For more technical details on Gibbs sampling see Chibb and Greenberg (1996) and Geweke (1996).

countries, except the one we are interested on, to have zero factor loadings on the country under examination, this type of approach is not suitable. The Bayesian approach exploiting Gibbs sampling techniques overcomes both issues.

To describe our results, we employ variance decompositions measuring the relative contributions of the different factors to the variance of VA fluctuations for each individual industry. Using previous notations, the variance of $Y_{i,j,t}$, with orthogonal factors is given by:

$$\mathrm{var}(Y_{i,j,t}) = (\beta^{w}_{i,j})^2 \,\mathrm{var}(F^{w}_{t}) + (\beta^{s}_{i,j})^2 \,\mathrm{var}(F^{s}_{i,t}) + (\beta^{c}_{i,j})^2 \,\mathrm{var}(F^{c}_{j,t}) + \mathrm{var}(\varepsilon_{i,j,t}) \tag{4}$$

Then, we can decompose the variance of each industrial VA growth rate series, $Y_{i,j,t}$, into the fraction due to each of the three factors. In particular, the fraction of fluctuations due to factor $f = w,\ s,\ c$ is computed as follows:

$$\frac{(\beta^{f}_{i,j})^2 \,\mathrm{var}(F^{f})}{\mathrm{var}(Y_{i,j,t})} \tag{5}$$

We obtain measures of equation (4) and (5) at each step of the Markov-Chain.

Given the number of industries in our sample, we condense the results for expositional ease in two different ways: first, we aggregate $\mathrm{var}(Y_{i,j,t})$ into an aggregate forecast error over industries and, second, over countries. We thus obtain the relative importance of the factors from both a country and an industry perspective. In particular, we build a $(J \times I)$ matrix of VA weights W_J. The variance matrix is then reduced to $\boldsymbol{J}$ country variance decompositions by multiplying (4) times $W_J^{'}$. To aggregate by industry, we construct a $(I \times J)$ country-weights matrix using real VA data in US dollars. The variance matrix is reduced to $\boldsymbol{I}$ industry variance decompositions by multiplying (4) times $W_I^{'}$.

3 Data Description

Our data come from the 2009 release of the EU Klems Growth and Productivity Accounts[11] which covers 32 industries up to 2007 for a variety of OECD countries. The EU Klems database has two main advantages. First, it covers not only manufacturing, but also services, construction, and agriculture. Second, it has been carefully harmonised improving on data quality.[12]

[11] See O'Mahony and Timmer (2009) and the web link at: http://www.euklems.net/

[12] For an analysis on the advantages of the EU Klems dataset, see Koszerek et al. (2007).

We select our data based on availability. We make use of 30 industries and we also estimate the aggregate of the 30 industries for each of the G7 countries up to 2004. Data were missing for the remaining two industries, namely Extra-territorial organizations and Bodies, and Private households with employed persons[13]; and not all countries datasets were spanning the period up to 2007. Our data cover all of the economy, including Agriculture, Hunting, Forestry and Fishing; Mining and Quarrying; Total Manufacturing; Electricity, Gas and Water Supply; Construction; Wholesale and Retail Trade; Hotels and Restaurants; Transport and Storage and Communication; Financial Intermediation; Real Estate, Renting and Business Activities; Public Administration and Defense; Education; Health and Social Work; Other Community, Social and Personal Services. All those sectors have the same level of disaggregation. Whenever data were available, those sectors were further disaggregated. Appendix A provides the list of the "industries" used.

We use VA data for 31 industries, including the aggregate of the 30 industries for each of the G7 countries and the data set spans the 1974-2004 period. Each series was log first-differenced and demeaned. Thus, we use M = 1 series per country, I = 31 industries for J = 7 countries, with T = 31 time series observations for each. For the models estimated for the pre-globalization and the globalization periods, T = 15 and T = 16, respectively. The sample split point for the pre-globalization and globalization periods, however, was changed up to 2 years either side of that breakpoint and the results remained very similar.

As previously mentioned, both the idiosyncratic term and the factors follow an AR(3) process. The prior on all the factor loadings is *N(0, 1)*, while the one for the autoregressive polynomial parameters is *N(0, Σ)*, where $\Sigma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}$. We experimented with either tighter or looser priors for both the factors and the autoregressive parameters, but the results remained qualitatively unchanged. The prior on the innovation variances in the observable equations is Inverted Gamma (6, 0.001), which is quite diffuse, as in Kose et al. (2003).

Finally, following Kose et al. (2008), since we are not sampling from the posterior itself as the elements of the Markov chain are converging to drawings from the posterior, it is important to monitor the convergence of the chain. Apart from starting the chain from different initial values, as mentioned above, we also used chains of different lengths ranging from 5,000 to 22,000. The results were essentially the same for any chosen chain length. The analysis presented in the next section is based on 22,000 Gibbs sampling replications, from

[13] For a correspondence between the industry numbers, EU Klems codes, and the actual industry names, see Appendix A.

which the first 2,000 are discarded as burn-in. Therefore, the results are from the remaining 20,000 iterations.

4 Empirical Results

4.1 Description of Factors

Figure 1 plots the world factor, which captures the common movement across all countries and all industries in the system. The tightness of the bands shows that the factor is estimated quite precisely. Major economic events appear to be reflected in the factor: the recessions in 1975 associated with the first oil price shock; the recession of the early 1980's associated with the tight monetary policies of major industrialized countries[14]; the mild recession of the early 1990's and the 2001 recession and the following recovery. Several of the peaks and troughs seem to be in line with NBER reference dates. More precisely, the world factor coincides with the peak of July 1981, and the troughs of March 1975, July 1980, November 1982, March 1991, and November 2001. Moreover, the world factor is consistent with the Great Moderation. The world factor becomes less volatile after the mid-1980's. Table 1 shows that the standard deviation of the world factor fell from 2.1% in the 1974-1984 period to 0.7% in the 1985-2004 period.[15]

Figure 2 presents a comparison of the international (world plus industry) and country factors with the evolution of aggregate VA aggregate growth for each country. The scales of the factors and VA growth are made comparable by multiplying the world, industry, and country factors by their respective median factor loadings. All panels in Figure 2 display the median of the estimated international and country factors along with aggregate VA growth.

The US international and country factors capture most of the peak and troughs of the NBER reference business cycle dates. In particular, the international factor displays the troughs of 1975, 1980, 1982, 1991, and 2001, while the country factor captures the peak of 1981 and the troughs of 1982, 1991, and 2001. Although the international and the country factor exhibit some common fluctuations, there are some notable differences in the evolution of the two factors. Overall, the US country factor seems to be lagging the international factor by one year. For example, the deep recession of 1975 is captured by the country factor in 1976 with the recovery taking place one year later. The two factors appear more coincident from 1997 onwards. Importantly, aggregate VA growth moves much more closely

[14] This recession seems to be nearly as deep as the one of 1975, which is in accordance with previous results (see Kose et al., 2003, and Kose et al., 2008).

[15] Estimated industry factor plots are presented in Appendix B.

with the international factor than the country factor. This is also reflected on the high correlation between the median of the world factor and aggregate VA growth for the US, 0.737 (see Table 2), which is by far the largest correlation among the G7 countries. Similar patterns arise for the UK, which displays the second largest correlation with the world factor (0.541) although a slightly higher correlation with the median of the country factor (0.666) (Table 3).

The Canadian country factor appears to be moving much more closely with VA growth than the international factors, which is reflected on a high correlation (0.753) between aggregate VA growth and the country factor for Canada. The correlation between the median of the world factor and aggregate VA growth is 0.471.

For France the international and country factors display negative correlation. There is also a low correlation between the world factor and aggregate VA growth (0.288). France is the country displaying the lowest correlation with the world factor.

Germany displays the third largest correlation between the median of the world factor and aggregate VA growth (0.503) after the US and the UK. The correlation with the country factor is the second lowest (0.551). It is worth noting that the peaks and troughs of the country and international factors appear to capture well the business cycle turning points identified by Artis et al (1997).

Italy also displays low correlations with the world factor and high correlation with the country factor. But this pattern is most distinct for Japan. From the mid-1970's to the early 1980's, the Japanese country factor displays an expansionary phase and then captures the deep recession of the 1990's and the stagnation that followed. Business cycles in Japan appear to be very specific to the Japanese economy. The international factors co-move very weakly with the aggregate VA growth, a pattern that is reversed for the country factor.

4.2 Variance Decomposition

4.2.1 By country

Table 4 presents the weighted variance decomposition of VA growth explained by each factor by country. It presents the median of posterior quantiles together with 33% and 66% posterior quantiles.

As expected because of the high level of disaggregation, idiosyncratic components dominate and are responsible for about 55% of the variation of industrial VA growth. That is, most of the variability of VA at the industry level is due to shocks that affect specific industries differently in different countries. Of the other three, the country factor explains the largest fraction of the fluctuations in industrial VA growth for all countries except

France and the US. For France, it is the industry factor that marginally dominates, whereas for the US it is the World factor. The percentage accounted for by the country factor in the US is the lowest. For the majority of the countries, hence, factors specific to the domestic economies explain the largest part of industrial VA growth.

The industry factors are the second most important except for the US and the UK. They explain an economically significant fraction of around 12%. Industry-specific demand and supply shocks are relatively important sources of business cycle fluctuations at a disaggregate level. This could point towards vertical and market integration as important drivers of co-movement.

Finally, it is important to note that the world factor seems to play a smaller role (<9%) in four out of seven countries (Germany, Italy and, especially, France and Japan). It remains a relatively important factor for the US and the UK. The introduction of sector-specific factors appears to reduce the relevance of the world factor when compared to previous studies.[16] In studies using aggregate variables, shocks that are industry-specific but common to all countries would then be captured by the world factor. Our results support the hypothesis that a good part of business cycle co-movement across countries may be driven by common sector-specific factors combined with similar production structures. This is in line with Imbs (2004), who argues that if countries have similar production structures then sectoral shocks will create co-movements. Long and Plosser (1983) suggested that disaggregate shocks to sectors, which are propagated across industries and nations can give rise to business cycles. Our results also provide nuanced support for the existence of disaggregate business cycles at the international level. National/domestic factors, however, dominate in most countries highlighting the potential importance of non-technology shocks in international business cycles. Nevertheless, we cannot conclude that a "world business cycle", as argued by Kose et al. (2003, 2008) and Kose et al. (2008), is no longer supported when using disaggregated data. If the proportion of the variance explained by world and industry factors is added up, our results would support the prominence of "international" over "country-specific" factors and the proportion would be similar to that found in the above mentioned studies.

4.2.2 By industry

Table 5 presents the weighted variance decomposition by industry. The idiosyncratic factor varies substantially between industries. There are, however, some important patterns

[16] Kose et al. (2003, 2008) and Kose et al. (2008) found the world factor to be the most significant source for explaining changes in macroeconomic aggregates.

to note. Clearly, we observe that the industries which are more intensive in globally traded primary commodities – such as agriculture, textiles, paper products, chemical products, machinery, and electrical and optical equipment – display strong industry-specific factors. This suggests that developments in globally integrated markets, such as commodity markets, play a significant role in causing common movements in VA growth rates across countries. Moreover, none of the heavily traded manufactured goods display a weak industry factor. As expected, less traded items - such as construction, wholesale trade and commission trade, and retail trade – display less significant industry factors than the traded goods.

Industry factors are found to be very important for about ¼ of the industries, especially within tradable sectors. Examples of these are agriculture, petroleum, metal products, textiles and chemicals. The world factor dominates for tradable goods such as manufacturing industries (industries 1 to 15). The country factor dominates for the non-tradable sectors (industries 16 to 30). Thus, there is some evidence that the industrial VA growth of certain internationally traded goods and items that are intensive in internationally traded inputs co-move significantly across countries.

Some puzzling results, however, also arise. On the one hand, the industry factor dominates for sectors such as real estate activities, education, and health care. On the other hand, it explains very little of the variations in VA growth of some highly traded goods and goods that are intensive in internationally traded inputs (e.g. food, beverages and tobacco, wood products, and rubber and plastic products). Common demand (preference) shocks and demographic trends could be one possible explanation for the dominance of the industry factor in those non-tradable sectors. For the highly traded goods, the world factor explains a large fraction of the fluctuations in sectoral VA growth, especially so for the rubber and plastic products. It could therefore be argued that the business cycle of those particular industries commoves strongly with the "world business cycle".

4.3 From Pre-Globalization to Globalization: The evolution of international business cycles

We now tackle the second main question of our study: How did the world, industry and country factors evolve as globalization deepened over the past two decades? We focus here on changes in the "explained" part of the variance, i.e. the part not accounted for by idiosyncratic components, in order to obtain comparable magnitudes of the relative importance of each factor. We split the sample in two periods: the pre-globalization (1974-1988) and globalization (1989-2004) periods. Admittedly, the sample split point is arbitrary. However, it is driven by the need to preserve a sufficiently long time-series components either side. As mentioned earlier, we moved the window 2 years either side, and the results remained qualitatively similar. Care, however, should be applied when attributing the results to trade and financial integration exclusively. The results can only provide an indication of whether the evolution of business cycle co-movement conforms to the prior (but not necessarily theoretically correct) view that increased integration should lead to increased co-movement.

Table 6 presents the % of the explained part of the variance decomposition by country using the median of posterior quantiles for each period and the difference between them. We also present the "international factor" as the sum of World and industry factors. In the 1974-1988 period, the international factor gives support for an international business cycle rather than a national one for all countries except the UK. The largest part of the volatility of G7 countries industrial VA growth can be attributed to international factors. These results are consistent with the ones shown in Kose et al. (2003).

For the 1989-2004 period we can see that for most of the G7 economies the country factor plays a much larger role. France is the only country for which the industry-specific factor explains most of the volatility in industrial VA growth. The world factor is only the third most important factor. International factors play now a much smaller role than in the previous sample. During this period there is only support for international factors for France and Italy.

The average contribution of the world factor has fallen for Japan and the European countries, except the UK, with the smallest fall being faced by Germany (≈3%) and the largest by Italy (≈21%). In contrast, we can see that the world factor gained importance for the US and Canada and, to a much lesser extent, for the UK. The average share of the explained variance of industrial VA growth attributed to the world factor has more than doubled during the globalization for the case of the US. These results suggest that there has been business cycle convergence for these countries. For the remaining countries, there appears to be no support for the business cycle convergence hypothesis. These results are in accordance with Kalemni-Ozcan et al. (2009), who found that higher financial globalization leads to more diverging business cycles among country-pairs. Kose et al. (2008) also found that the relative importance of the global factor fell during the globalization period.

If we focus on the contribution of "international factors", France and the UK are the only two countries showing support for the hypothesis of convergence. In the former, this is exclusively driven by the increase in the role of industry factors. Thus, industrial level business cycles coordination within countries has become stronger except in these two cases. This is especially so for Japan and Canada. On average, hence, contrary to the convergence hypothesis, we find no support for increased disaggregate business cycles synchronization.

One possible way for explaining these results is to recall our analysis on the evolution of the different factors shown by Figure 2. As noted earlier, there were large common disturbances during the pre-globalization period, namely the first oil price shock of the early 1970's and the recession of the early 1980's associated with the tight monetary policies of major industrialized countries. However, during the globalization period common international disturbances have become less important in explaining international business cycles fluctuations. Note that, from the mid-1980's, business cycles were found to be more idiosyncratic as the country factor was capturing the largest part of industrial VA growth recession episodes. These developments have led to a decline in the relative importance of the international factor in explaining business cycles.

Table 7 looks at the results by industry aggregates across countries. There is no particular pattern distinguishing industries that are intensive in primary traded inputs from industries that are mainly non-tradable. Within both groups, the number of industries displaying a drop in the % explained by international factors is approximately the same as the number displaying an increase. Only 12 industries support the hypothesis of convergence, while the remaining 18 decoupled from international and converged towards national business cycles. During the pre-globalization period, the world factor played a dominant role for only two industries, namely Mining and Quarrying (Industry 2) and Financial Intermediation (Industry 24). Those two industries together with many others were characterised by a declining importance of the world factor during the globalization period. In contrast, the contribution of the world factor to VA fluctuations of Education (Industry 28) and Health and Social Work (Industry 29) increased substantially from 18.99% to 46.01% and from 11.07% to 48.99%, respectively. The industry-specific factor played a dominant role for 10 industries during the pre-globalization period. In contrast, during the globalization period, it only dominated in 5 industries. Overall, there were slightly more industries facing a fall than an increase in the importance of the industry-specific factor. Interestingly, Financial Intermediation (Industry 24) showed a large increase for the industry-specific factor.

4.3.1 Decomposition analysis

Are country-level changes in the importance of factors driven by changes in the importance of factors within industries, or to changes in the structural decomposition of these economies? To answer this question we decompose changes in the variance decomposition at the country level into "within effects", "structural change effects", and an "interaction effect". The within effect, which measures changes in the industry-level correlation, shows the contribution of time **t** variance decomposition changes accounted by each factor, holding VA shares at their **t-1** values. The structural change effect is the contribution of time **t** changes in industrial VA shares, holding the variance decompositions accounted by each factor at their **t-1** values. Finally, the interaction effect displays the contribution arising from the co-movement between changes in the industry-level correlation and structural changes. We carry this analysis for all three factors (World, Industry and Country) as well as for the International factor.

Figure 3 shows the contribution of each of these effects by factor for each country. For the case of the US, for instance, the within effect is very large and contributes positively for all factors. That is, for all factors, changes in the variance decomposition for industries dominate the effect of changes in the structural composition of the economy. The interaction term contributes negatively for the world and the country factors and positively for industry and international factors. When positive, this effect shows that, on average, sectors whose variance decomposition has gained (lost) importance have also gained (lost) shares. When negative, it implies that sectors whose variance decomposition has gained (lost) importance have lost (gained) shares. Finally, the structural effect is not very important for the US.

Very similar patterns arise for the rest of the countries. The only exception is the UK for which not only the interaction term accounts for the largest proportion, but also the structural effect plays an important role. On the one hand, the structural term shows that sectors whose correlation with the world economy was low in the 70's have gained shares in the 1989-2004 period. On the other hand, the interaction effect shows that there are sectors for which the industry factor has gained (lost) importance while losing (gaining) shares during the same time period. Most industries seem to contribute towards the negative interaction effect for the industry factor.

5 Conclusions

We provide a comprehensive examination of the importance of industry-specific factors for international business cycle co-movement in VA growth at a disaggregate level. We estimate a dynamic latent factor model using a Bayesian approach considering world, country-, industry-specific and idiosyncratic factors on a dataset of 30 sectors for the G7 countries during the 1974-2004 period.

Our results provide a rich body of evidence about the role and evolution of common business cycles at the disaggregate level. First, idiosyncratic shocks specific to each industry dominate business cycles at a disaggregate level. Second, of the explained part of business cycles, the country factor explains the largest proportion of the variance while the industry-specific factor is the second most important source for the majority of the countries considered. World and industry factors, however, appear to play a dominant role for tradable sectors. Third, on average, the world factor seems to play a minimal role in accounting for movements in industrial VA growth. The introduction of sector-specific factors appears to reduce the relevance of the world factor when compared to previous studies. We cannot, however, conclude against the existence of a "world business cycle", as argued in previous studies. Our results indicate that a good part of business cycle co-movement across countries may be driven by common sector-specific factors combined with similar production structures. When using aggregate data, the world factor could be capturing not only the dynamic factor common to all countries but also the dynamic factor common to the same industry across countries. If the proportion of the variance explained by world and industry factors is added up, our results would support the prominence of "international" over "country-specific" factors.

During the pre-globalization period (1974-1988) we find support for an international business cycle at a disaggregate level for most countries. However, during the globalization period, we find support for the prominence of international factors only for two countries. Only France and the UK show evidence in favor of the business cycle convergence hypothesis. On average, thus, we do not find robust support for the hypothesis that disaggregate business cycles have become more synchronized at the international level. The prevalence of global shocks such as the two oil shocks and co-ordinated deflationary policies in the first half of the sample may be driving these results. When looking at changes in the variance decomposition by industry from the pre-globalization to the globalization period, a small majority of industries (18 out of 30) display business cycle divergence. This indicates that international factors became less important than the country factor in driving cyclical fluctuations in the G7 countries. Overall, there is no distinct pattern between industries that are intensive in internationally traded goods and those that are not. Finally, changes in the variance decomposition from the pre-globalization to the globalization periods seem to be largely accounted for by changes in the importance of factors within industries, rather than changes in the structural composition of the economies considered.

Figures and Tables

Figure 1: World Factor

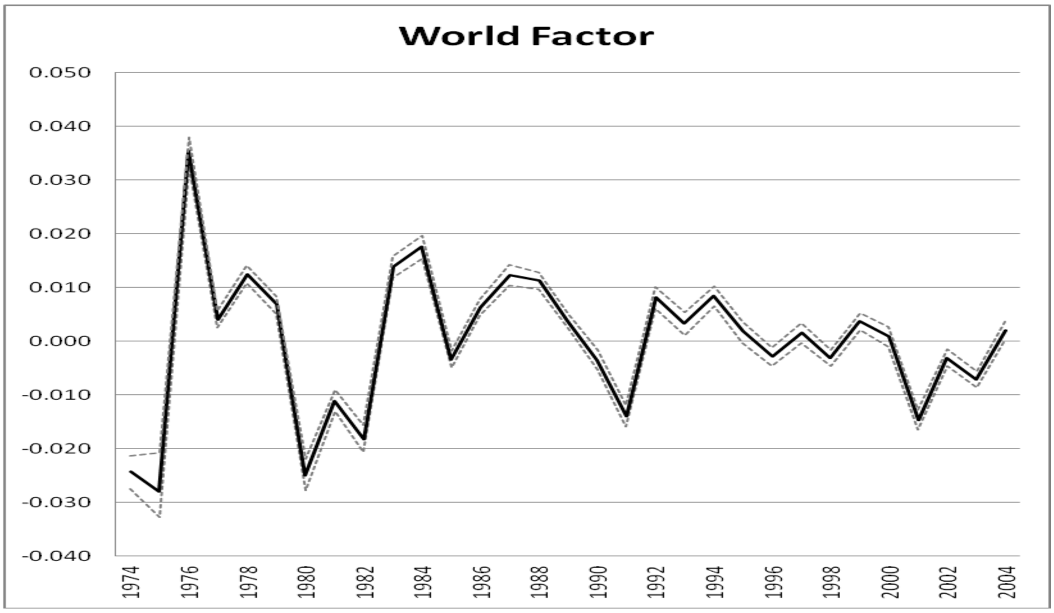
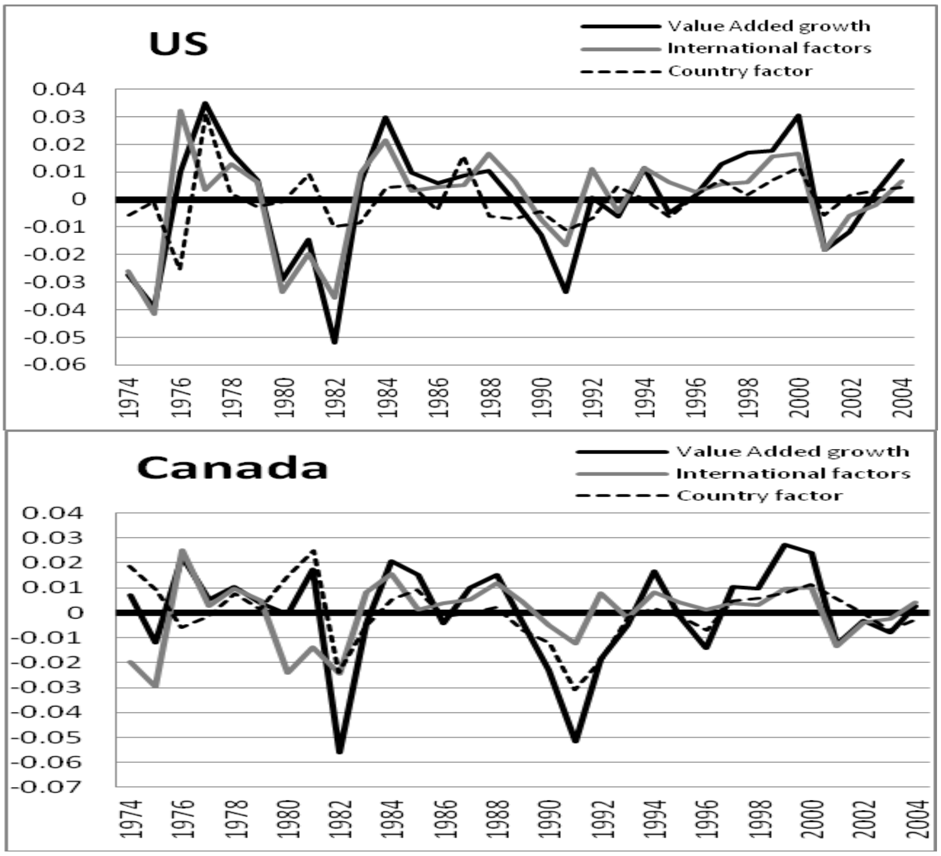
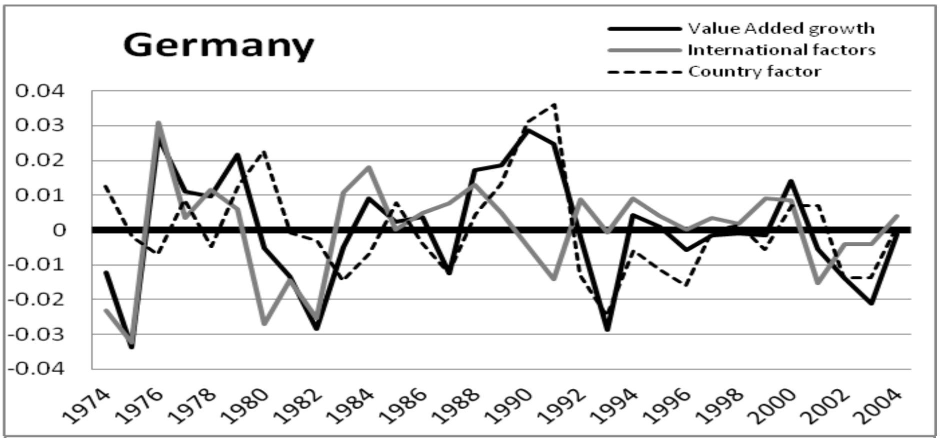
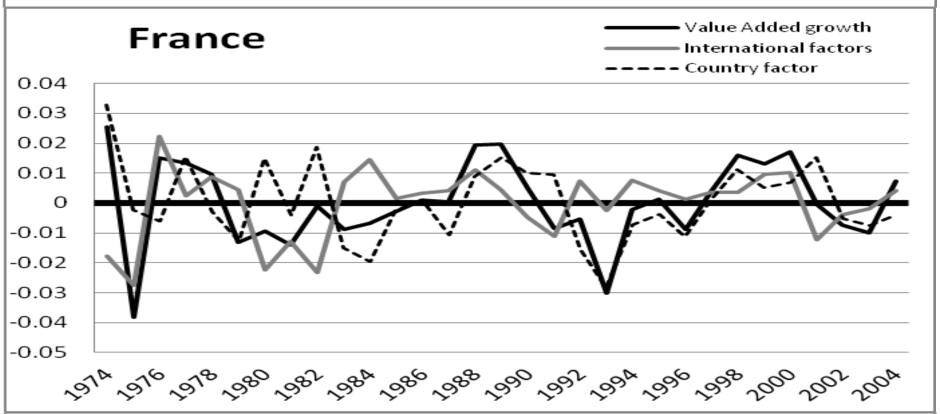
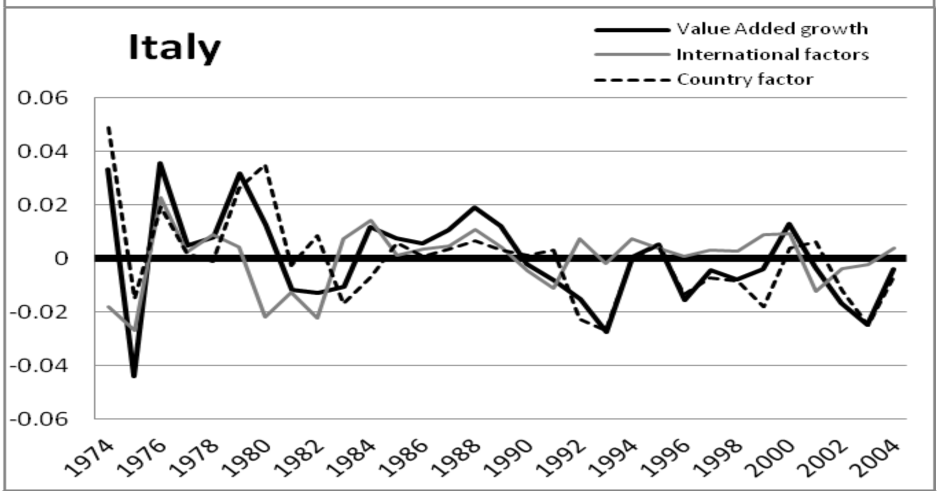


Figure 2: Country Factors




Germany
Value Added growth
International factors
Country factor
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004


France
Value Added growth
International factors
Country factor
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004


Italy
Value Added growth
International factors
Country factor
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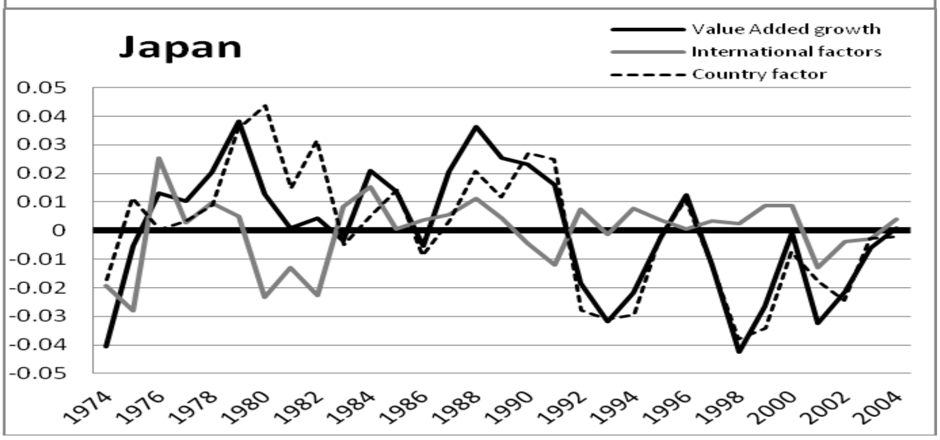
0.04
0.02
0
-0.02
-0.04
-0.06
1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004


Japan
Value Added growth
International factors
Country factor
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
1974 1976 1978 1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004

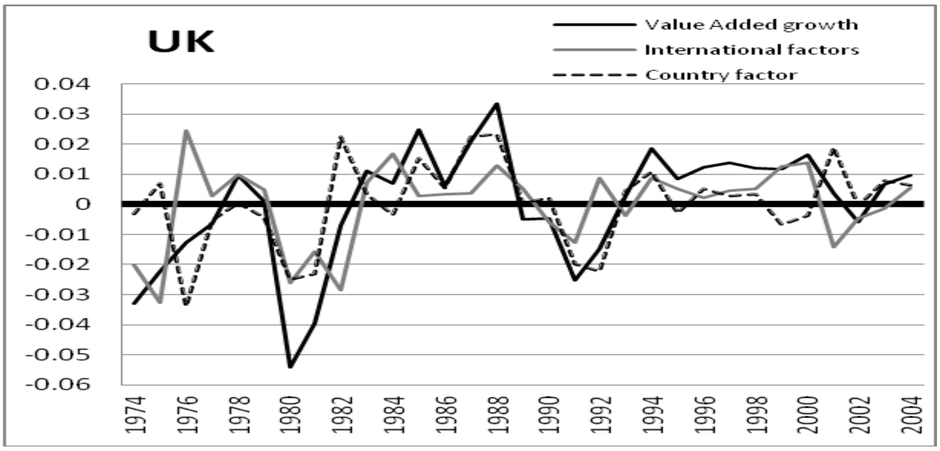


Figure 3: Variance Decomposition changes explained by within effects, structural effects and the interaction term

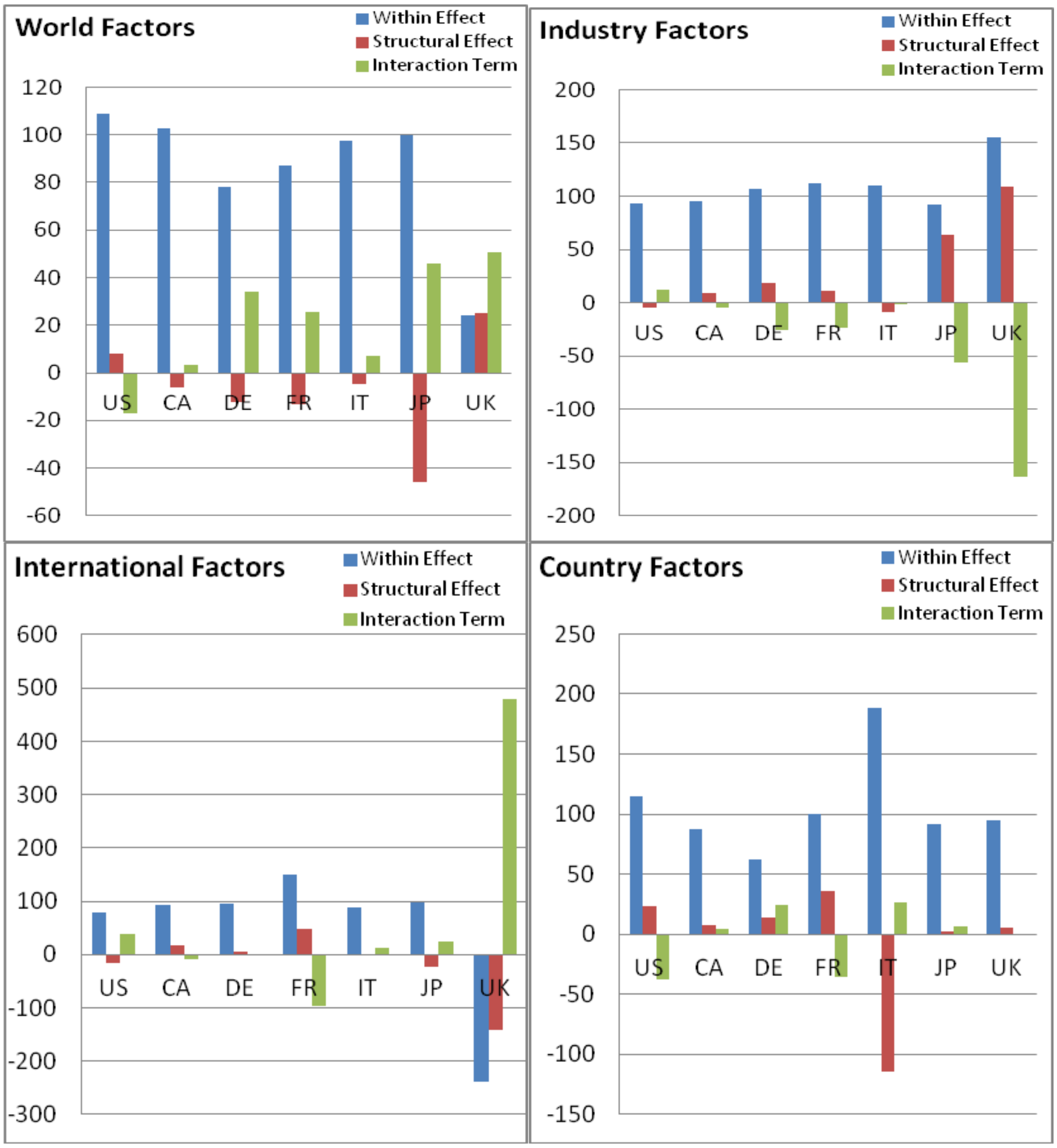


Table 1: Standard Deviation (in %) of the World Factor

	StDev
1974-1984	2.10138
1985-2004	0.73096

Table 2: Correlation between World Factor and the aggregate VA growth

	WF-Canada	**WF-Germany**	**WF-France**	**WF-Italy**	**WF-Japan**	**WF-UK**	**WF-US**
Correlation	0.470534	0.502881	0.288116	0.388082	0.293433	0.541072	0.73683

Table 3: Correlation between Country Factor and aggregate VA growth

	CF-Canada	**CF-Germany**	**CF-France**	**CF-Italy**	**CF-Japan**	**CF-UK**	**CF-US**
Correlation	0.75346	0.55126	0.59282	0.78630	0.82977	0.66648	0.46920

Table 4: Variance decomposition by country

	World			**Industry**			**Country**			**Idiosyncratic**		
	33%	***50%***	*66%*	*33%*	***50%***	*66%*	*33%*	***50%***	*66%*	*33%*	***50%***	*66%*
Canada	8.84	***10.55***	12.15	10.02	***12.98***	16.68	21.18	***23.24***	25.42	48.38	***52.02***	55.35
Germany	6.71	***7.89***	9.17	7.97	***11.31***	15.44	16.46	***18.39***	20.43	56.70	***61.02***	64.85
France	2.15	***2.85***	3.67	11.79	***16.14***	21.43	13.37	***15.41***	17.58	58.60	***63.92***	68.53
Italy	7.02	***8.47***	10.07	7.35	***10.55***	14.46	22.40	***24.30***	26.22	51.22	***55.32***	58.94
Japan	4.67	***5.83***	7.24	7.57	***10.52***	14.11	22.51	***24.36***	26.30	53.90	***57.78***	61.30
UK	13.35	***15.25***	16.94	9.66	***12.79***	16.47	15.67	***17.79***	20.21	49.32	***53.12***	56.61
US	14.21	***15.95***	17.56	7.41	***11.08***	15.71	9.73	***11.75***	14.11	54.60	***59.68***	64.02

Table 5: Variance decomposition by industry

	World			Industry			Country			Idiosyncratic		
	33%	***50%***	*66%*	*33%*	***50%***	*66%*	*33%*	***50%***	*66%*	*33%*	***50%***	*66%*
Industry 1	0.36	***0.61***	0.99	10.17	***14.04***	18.87	1.15	***1.84***	2.72	77.08	***82.12***	86.38
Industry 2	4.48	***5.70***	6.84	3.96	***7.32***	12.19	1.93	***2.60***	3.52	78.51	***83.31***	86.62
Industry 3	10.49	***11.83***	13.20	3.93	***7.44***	12.42	7.33	***9.01***	10.88	64.36	***70.01***	74.67
Industry 4	7.89	***9.34***	10.97	8.88	***12.15***	15.82	27.51	***29.94***	32.48	43.17	***47.09***	50.76
Industry 5	7.20	***8.40***	9.67	2.85	***6.75***	13.54	7.71	***9.09***	10.69	67.64	***74.27***	78.14
Industry 6	25.23	***28.18***	30.90	11.15	***15.52***	20.30	22.56	***25.28***	28.36	25.81	***30.37***	34.51
Industry 7	5.39	***6.34***	7.34	11.24	***16.01***	22.08	1.56	***2.13***	2.83	68.47	***74.70***	79.78
Industry 8	34.99	***38.39***	41.27	12.50	***16.47***	20.95	5.89	***7.56***	9.63	33.59	***37.29***	40.72
Industry 9	31.34	***34.78***	37.67	6.30	***8.66***	11.35	21.71	***24.41***	27.42	29.30	***31.90***	34.46
Industry 10	31.34	***34.87***	37.79	12.34	***14.48***	16.90	20.93	***23.54***	26.51	24.56	***26.51***	28.49
Industry 11	25.29	***28.31***	30.81	11.68	***14.59***	17.79	24.50	***27.27***	30.43	26.64	***29.29***	31.94
Industry 12	11.80	***14.38***	16.55	23.59	***26.62***	29.72	30.54	***33.49***	36.76	21.89	***24.52***	27.26
Industry 13	11.23	***13.77***	16.06	20.89	***23.96***	27.03	18.97	***21.66***	24.90	36.50	***39.41***	42.30
Industry 14	17.49	***19.77***	21.70	7.76	***9.73***	12.03	10.18	***12.15***	14.37	54.62	***57.37***	60.02
Industry 15	24.40	***27.23***	29.75	7.15	***9.30***	11.75	23.91	***26.58***	29.57	33.60	***36.18***	38.73
Industry 16	5.65	***6.81***	7.99	7.62	***10.91***	14.86	9.91	***11.58***	13.57	64.15	***68.89***	73.09
Industry 17	22.96	***24.90***	26.89	2.10	***4.33***	7.53	16.47	***18.54***	20.88	46.39	***50.06***	53.38
Industry 18	6.78	***8.05***	9.49	7.04	***10.87***	15.53	31.01	***35.28***	39.42	38.21	***43.35***	48.47
Industry 19	6.36	***7.49***	8.72	2.44	***4.87***	8.74	18.51	***20.03***	21.69	62.36	***66.17***	69.03
Industry 20	1.67	***2.39***	3.24	4.72	***7.54***	11.17	43.19	***47.11***	50.96	36.63	***40.91***	45.11
Industry 21	8.05	***9.18***	10.36	8.05	***10.96***	14.31	16.07	***18.24***	20.58	57.20	***60.62***	63.71
Industry 22	24.48	***26.98***	29.28	7.46	***9.19***	11.23	14.87	***16.46***	18.35	43.42	***46.25***	49.11
Industry 23	1.70	***2.29***	3.04	6.71	***10.24***	14.83	5.59	***6.79***	8.22	74.11	***78.97***	82.95
Industry 24	3.50	***4.51***	5.82	6.28	***13.77***	23.64	3.96	***4.82***	5.82	64.63	***75.01***	82.89
Industry 25	2.59	***3.37***	4.28	5.10	***9.22***	14.28	7.10	***8.12***	9.35	72.85	***77.90***	81.98
Industry 26	12.26	***13.97***	15.49	12.62	***16.56***	21.03	16.96	***19.11***	21.58	44.52	***49.19***	53.49
Industry 27	1.80	***2.53***	3.31	7.55	***10.09***	13.23	22.17	***25.59***	29.01	55.45	***60.42***	65.03
Industry 28	5.71	***6.76***	8.08	10.02	***13.52***	17.71	8.78	***10.67***	12.67	62.65	***66.94***	70.91
Industry 29	6.12	***7.51***	8.92	6.39	***10.24***	15.19	2.96	***3.92***	5.25	71.52	***76.42***	80.56
Industry 30	9.18	***10.73***	12.65	11.77	***15.58***	19.85	15.77	***17.52***	19.47	50.05	***54.41***	58.48
Industry 31	27.34	***30.56***	33.34	7.01	***8.63***	10.39	46.49	***49.52***	52.81	9.43	***10.66***	11.98

Table 6: Explained part of Variance Decomposition by country

	World			*Industry*			*International*			*Country*		
	1974-1988	1989-2004	**Diff**	1974-1988	1989-2004	**Diff**	1974-1988	1989-2004	**Diff**	1974-1988	1989-2004	**Diff**
Canada	10.56	16.72	**6.15**	44.52	19.88	**-24.64**	55.08	36.59	**-18.49**	44.92	63.41	**18.49**
Germany	24.43	21.44	**-2.99**	29.34	23.75	**-5.58**	53.76	45.19	**-8.57**	46.24	54.81	**8.57**
France	40.83	31.58	**-9.25**	22.13	41.31	**19.18**	62.96	72.89	**9.93**	37.04	27.11	**-9.93**
Italy	40.75	20.17	**-20.57**	21.09	36.40	**15.30**	61.84	56.57	**-5.27**	38.16	43.43	**5.27**
Japan	26.86	14.49	**-12.37**	27.45	21.50	**-5.95**	54.31	36.00	**-18.31**	45.69	64.00	**18.31**
UK	14.51	15.80	**1.29**	23.82	28.24	**4.42**	38.33	44.04	**5.71**	61.67	55.96	**-5.71**
US	10.45	23.11	**12.66**	40.82	24.78	**-16.04**	51.27	47.89	**-3.38**	48.73	52.11	**3.38**

Table 7: Explained part of Variance Decomposition by industry

	World			*Industry*			*International*			*Country*		
	1974-1988	1989-2004	**Diff**	1974-1988	1989-2004	**Diff**	1974-1988	1989-2004	**Diff**	1974-1988	1989-2004	**Diff**
Industry 1	31.44	7.35	**-24.09**	49.64	76.82	27.18	81.09	84.17	3.08	18.91	15.83	**-3.08**
Industry 2	36.01	34.60	**-1.41**	28.71	58.75	30.04	64.72	93.35	28.64	35.28	6.65	**-28.64**
Industry 3	26.62	27.61	1.00	33.78	34.38	0.61	60.39	62.00	1.60	39.61	38.00	**-1.60**
Industry 4	27.83	22.85	**-4.98**	19.73	16.90	**-2.83**	47.57	39.76	**-7.81**	52.43	60.24	7.81
Industry 5	25.91	15.57	**-10.33**	44.44	33.07	**-11.36**	70.34	48.64	**-21.70**	29.66	51.36	21.70
Industry 6	11.71	6.22	**-5.49**	39.39	26.85	**-12.54**	51.10	33.07	**-18.03**	48.90	66.93	18.03
Industry 7	11.01	15.30	4.29	67.77	12.62	**-55.16**	78.78	27.92	**-50.87**	21.22	72.08	50.87
Industry 8	9.99	9.64	**-0.36**	46.86	35.98	**-10.88**	56.86	45.62	**-11.24**	43.14	54.38	11.24
Industry 9	13.88	24.97	11.09	27.97	14.63	**-13.35**	41.86	39.59	**-2.26**	58.14	60.41	2.26
Industry 10	3.21	4.65	1.44	19.45	15.80	**-3.66**	22.66	20.45	**-2.22**	77.34	79.55	2.22
Industry 11	5.64	12.68	7.05	16.87	25.70	8.83	22.50	38.38	15.88	77.50	61.62	**-15.88**
Industry 12	24.54	18.31	**-6.23**	21.28	37.45	16.17	45.82	55.77	9.94	54.18	44.23	**-9.94**
Industry 13	41.56	6.02	**-35.55**	10.88	32.77	21.89	52.44	38.79	**-13.65**	47.56	61.21	13.65
Industry 14	16.34	29.62	13.29	15.66	41.21	25.55	32.00	70.83	38.83	68.00	29.17	**-38.83**
Industry 15	7.45	7.49	0.04	22.12	17.27	**-4.85**	29.58	24.76	**-4.81**	70.42	75.24	4.81
Industry 16	35.88	15.93	**-19.95**	41.56	41.53	**-0.03**	77.44	57.46	**-19.98**	22.56	42.54	19.98
Industry 17	24.54	16.94	**-7.59**	23.25	9.91	**-13.34**	47.79	26.85	**-20.93**	52.21	73.15	20.93
Industry 18	23.55	26.35	2.80	23.91	25.56	1.65	47.46	51.91	4.46	52.54	48.09	**-4.46**
Industry 19	18.95	14.06	**-4.90**	20.64	16.37	**-4.27**	39.59	30.43	**-9.16**	60.41	69.57	9.16
Industry 20	16.22	5.03	**-11.20**	10.98	25.09	14.11	27.20	30.12	2.91	72.80	69.88	**-2.91**
Industry 21	19.80	15.51	**-4.29**	14.36	19.71	5.35	34.16	35.22	1.06	65.84	64.78	**-1.06**
Industry 22	32.08	18.21	**-13.87**	12.09	23.17	11.07	44.17	41.38	**-2.79**	55.83	58.62	2.79
Industry 23	25.13	39.23	14.09	52.74	48.25	**-4.49**	77.87	87.48	9.60	22.13	12.52	**-9.60**
Industry 24	38.69	14.49	**-24.20**	28.26	42.92	14.66	66.95	57.42	**-9.54**	33.05	42.58	9.54
Industry 25	18.76	21.44	2.68	60.35	18.90	**-41.45**	79.11	40.33	**-38.78**	20.89	59.67	38.78
Industry 26	18.97	18.68	**-0.29**	40.70	13.53	**-27.17**	59.67	32.21	**-27.46**	40.33	67.79	27.46
Industry 27	12.39	30.29	17.90	24.67	24.83	0.16	37.06	55.12	18.06	62.94	44.88	**-18.06**
Industry 28	18.99	46.01	27.02	52.86	43.03	**-9.82**	71.84	89.04	17.20	28.16	10.96	**-17.20**
Industry 29	11.07	48.99	37.91	79.36	33.00	**-46.36**	90.44	81.99	**-8.45**	9.56	18.01	8.45
Industry 30	30.95	22.64	**-8.30**	25.73	16.26	**-9.47**	56.67	38.90	**-17.77**	43.33	61.10	17.77
Industry 31	13.39	8.57	**-4.82**	8.15	7.51	**-0.64**	21.54	16.08	**-5.46**	78.46	83.92	5.46

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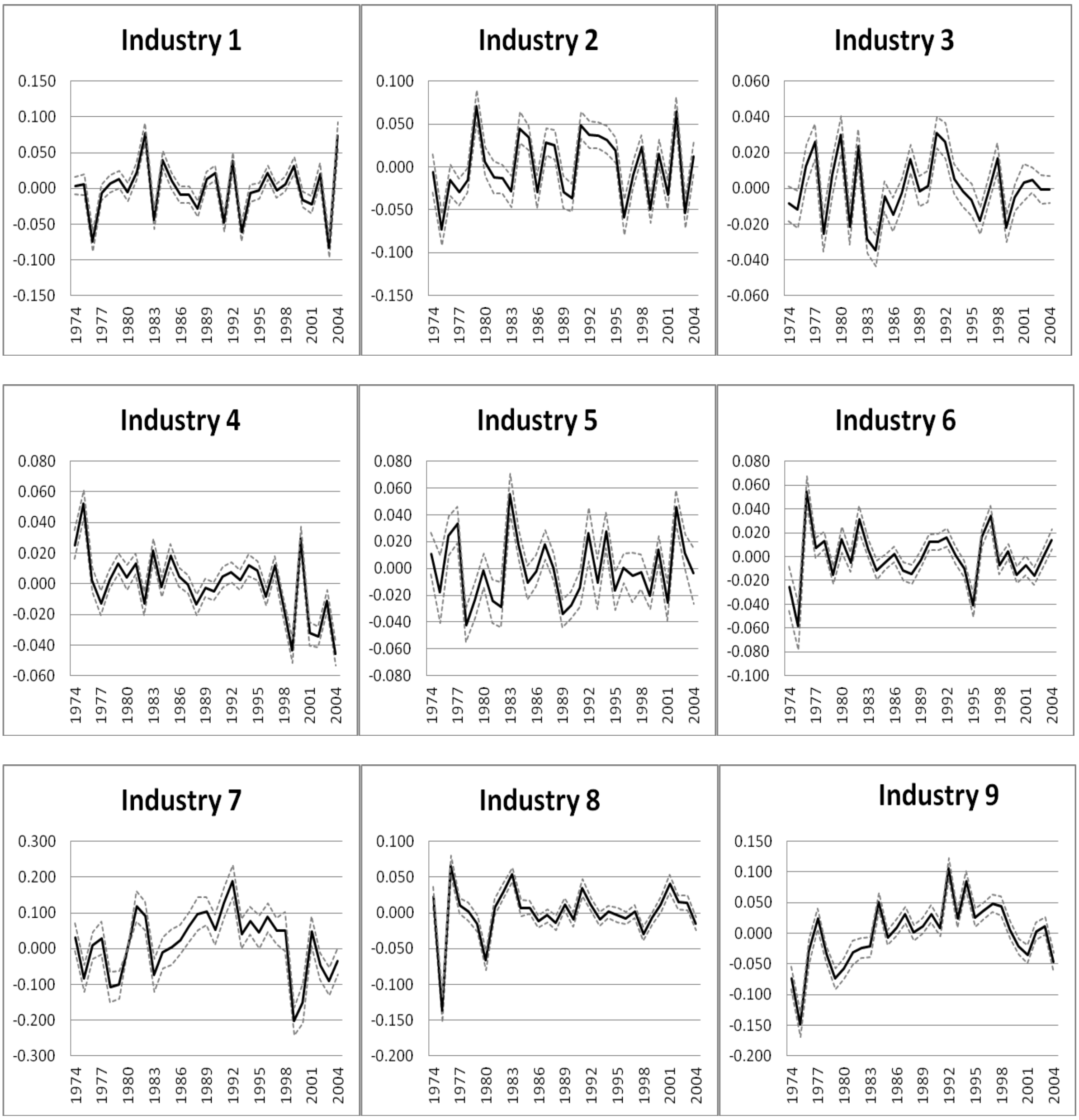
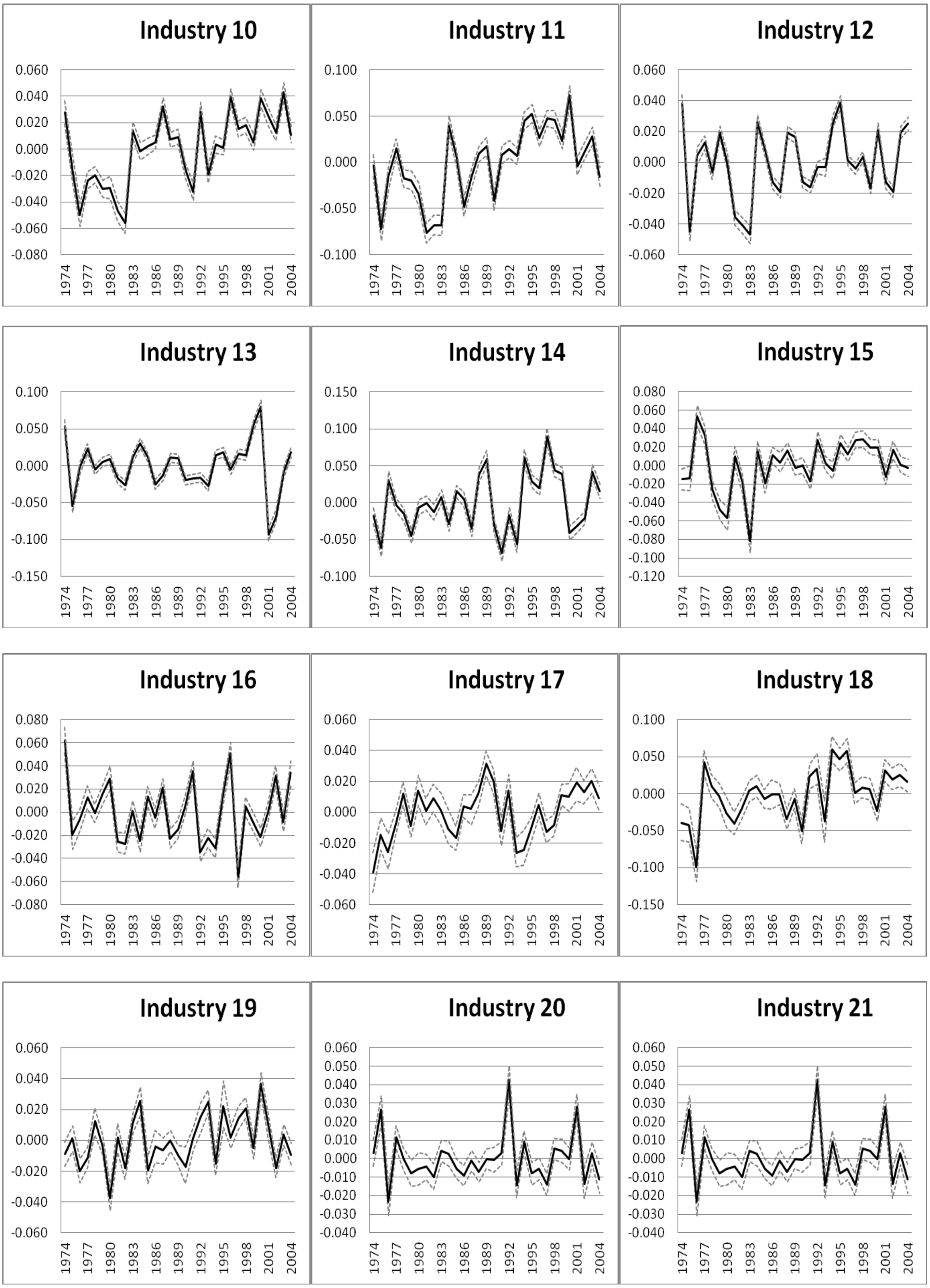
Appendix A: List of Industries

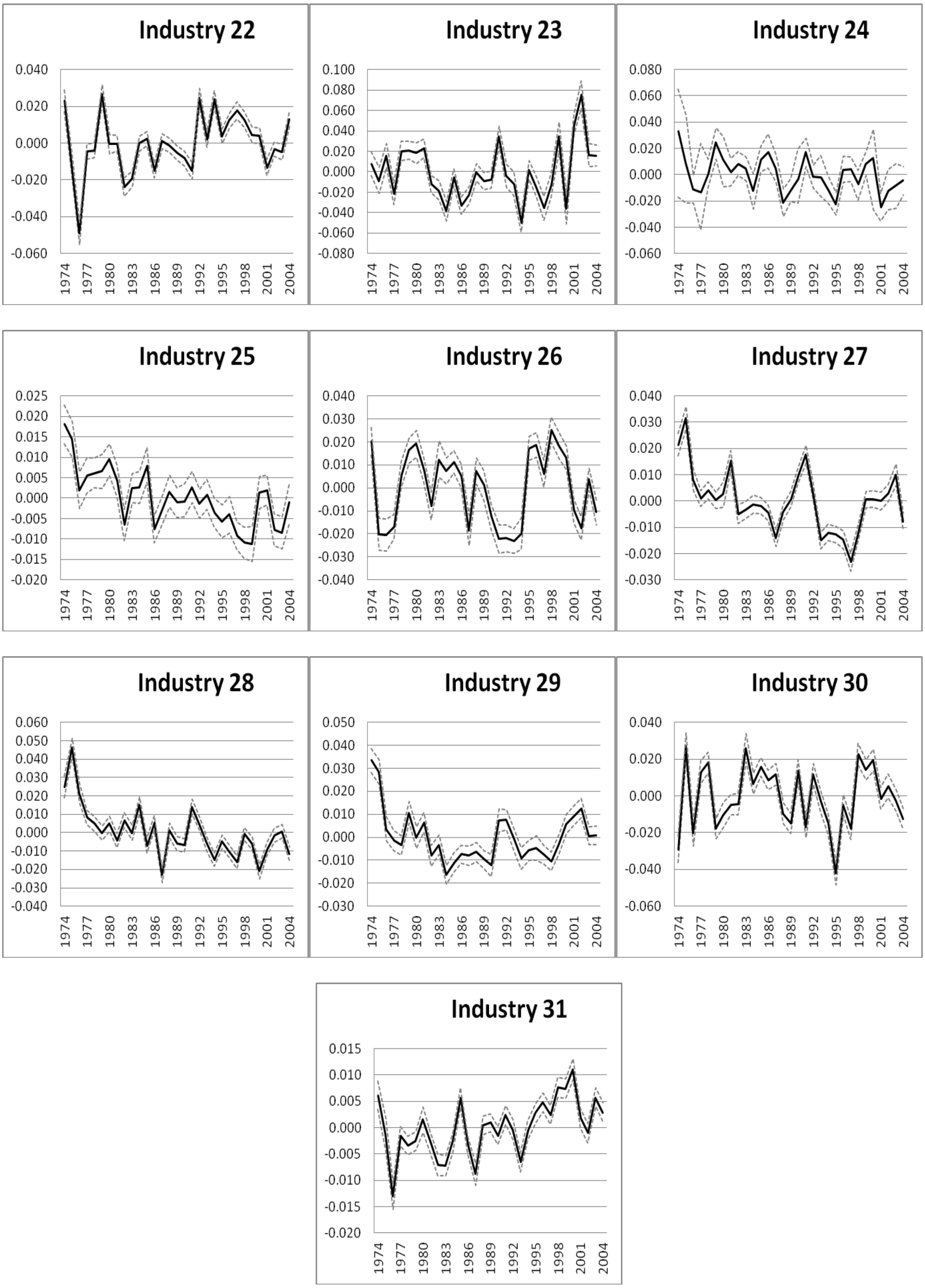
Industry Number	EUKlems Code	Industry
1	AtB	AGRICULTURE, HUNTING, FORESTRY AND FISHING
2	C	MINING AND QUARRYING
3	15t16	FOOD PRODUCTS, BEVERAGES AND TOBACCO
4	17t19	TEXTILES, TEXTILE PRODUCTS, LEATHER AND FOOTWEAR
5	20	WOOD AND PRODUCTS OF WOOD AND CORK
6	21t22	PULP, PAPER, PAPER PRODUCTS, PRINTING AND PUBLISHING
7	23	Coke, refined petroleum products and nuclear fuel
8	24	Chemicals and chemical products
9	25	Rubber and plastics products
10	26	OTHER NON-METALLIC MINERAL PRODUCTS
11	27t28	BASIC METALS AND FABRICATED METAL PRODUCTS
12	29	MACHINERY, NEC
13	30t33	ELECTRICAL AND OPTICAL EQUIPMENT
14	34t35	TRANSPORT EQUIPMENT
15	36t37	MANUFACTURING NEC; RECYCLING
16	E	ELECTRICITY, GAS AND WATER SUPPLY
17	F	CONSTRUCTION
18	50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
19	51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
20	52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
21	H	HOTELS AND RESTAURANTS
22	60t63	TRANSPORT AND STORAGE
23	64	POST AND TELECOMMUNICATIONS
24	J	FINANCIAL INTERMEDIATION
25	70	Real estate activities
26	71t74	Renting of m&eq and other business activities
27	L	PUBLIC ADMIN AND DEFENCE; COMPULSORY SOCIAL SECURITY
28	M	EDUCATION
29	N	HEALTH AND SOCIAL WORK
30	O	OTHER COMMUNITY, SOCIAL AND PERSONAL SERVICES
31	---	Aggregate

Appendix B: Industry Factors

Figure 3: Industry Factors based on Value Added growth rate series




Industry 10
0.060 0.040 0.020 0.000 -0.020 -0.040 -0.060 -0.080
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 11
0.100 0.050 0.000 -0.050 -0.100
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 12
0.060 0.040 0.020 0.000 -0.020 -0.040 -0.060
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 13
0.100 0.050 0.000 -0.050 -0.100 -0.150
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 14
0.150 0.100 0.050 0.000 -0.050 -0.100
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 15
0.080 0.060 0.040 0.020 0.000 -0.020 -0.040 -0.060 -0.080 -0.100 -0.120
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 16
0.080 0.060 0.040 0.020 0.000 -0.020 -0.040 -0.060 -0.080
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 17
0.060 0.040 0.020 0.000 -0.020 -0.040 -0.060
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 18
0.100 0.050 0.000 -0.050 -0.100 -0.150
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 19
0.060 0.040 0.020 0.000 -0.020 -0.040 -0.060
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 20
0.060 0.050 0.040 0.030 0.020 0.010 0.000 -0.010 -0.020 -0.030 -0.040
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004
Industry 21
0.060 0.050 0.040 0.030 0.020 0.010 0.000 -0.010 -0.020 -0.030 -0.040
1974 1977 1980 1983 1986 1989 1992 1995 1998 2001 2004


Industry 22
Industry 23
Industry 24
Industry 25
Industry 26
Industry 27
Industry 28
Industry 29
Industry 30
Industry 31