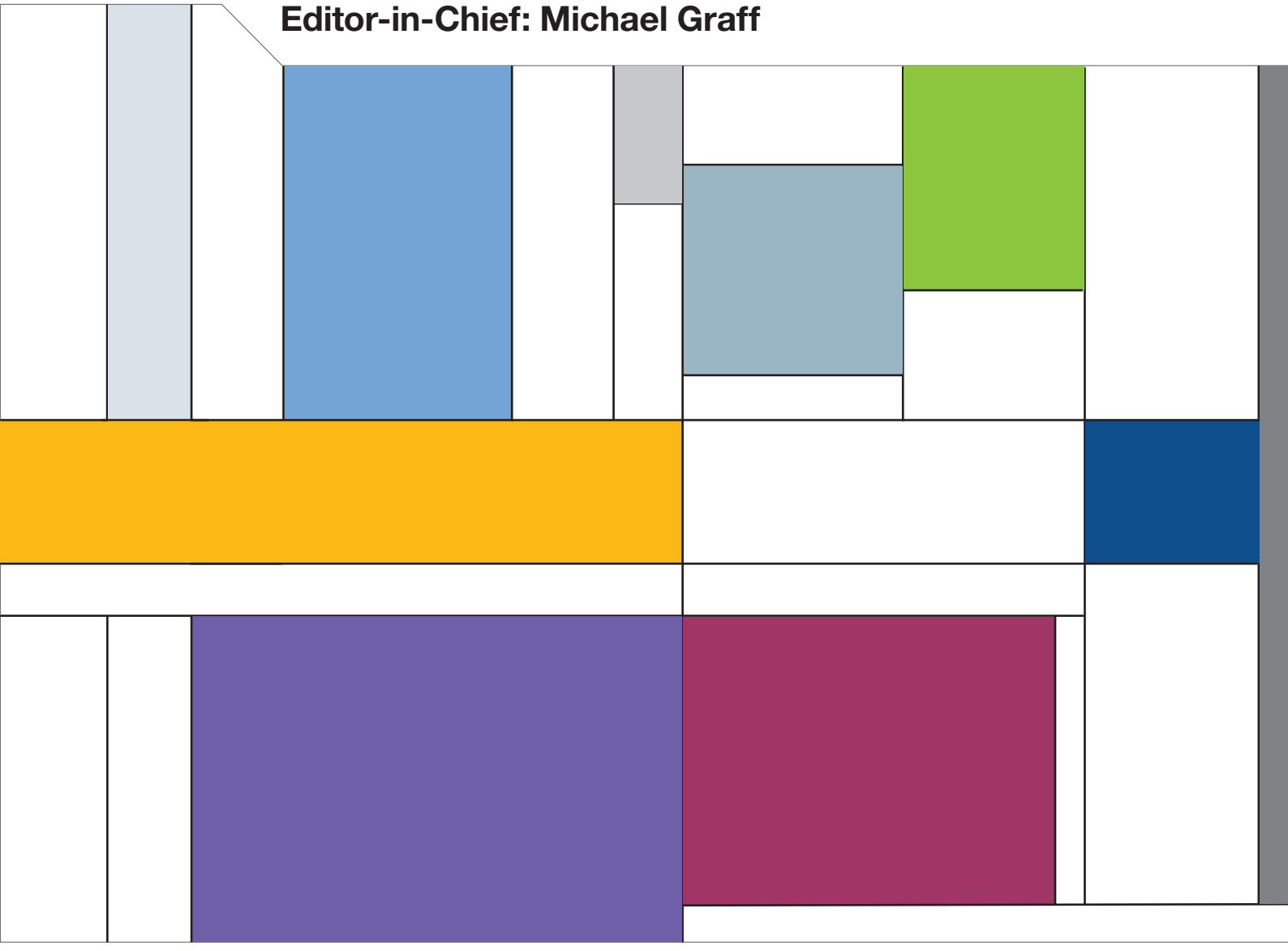
OECD Journal

# Journal of Business Cycle Measurement and Analysis

Editor-in-Chief: Michael Graff



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Volume 2012/1

OECD Journal

# Journal of Business Cycle Measurement and Analysis

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Volume 2012/1

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# Should transportation output be included as part of the coincident indicators system?

*by*
Kajal Lahiri* and Wenxiong Yao

*With the increasing importance of the service-providing sectors, information from these sectors has become essential to the understanding of contemporary business cycles. This paper explores the usefulness of the transportation services output index (TSI) as an additional coincident indicator in determining the peaks and troughs of US economy. The index represents a service sector that plays a central role in facilitating economic activities between sectors and across regions, and can be useful in monitoring the current state of the economy. We evaluate the marginal contribution of the TSI in identifying cyclical turning points in the context of four currently used NBER indicators. The TSI is found to have advantages over the composite index of coincident indicators in identifying turning points, and has been of critical importance in recent recessions.*

*JEL classification: E32, C10*

*Keywords: Transportation Services Index (TSI), business cycles, coincident indicators*

* Corresponding author: Department of Economics, University at Albany-SUNY, Albany, NY 12222, klahiri@albany.edu. This paper received the Isaac Kerstenetzky Award (Honorable mention, Best paper in the World category) at the 29th CIRET Conference, Santiago, Chile 2008. We thank Anirvan Banerji, Antony Davies, Ullrich Heilemann, Gernot Nerb, Ataman Ozyildirim, Herman Stekler, Victor Zarnowitz, two anonymous referees and Editor-in-Chief Michael Graff for helpful comments. Yongchen Zhao provided able research assistance. The research reported in this paper was supported by grants from the Bureau of Transportation Statistics, US Department of Transportation. The contents of this paper however reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein.

## 1. Introduction

Modern economies have become increasingly more service-intensive in the post-war period. For instance, over 1953-2009 in the US, the share of goods in the GDP has declined from 54% to 33% compared to an increase in the share of services from 34% to 58%. Yet among the four coincident indicators that the National Bureau of Economic Research (NBER) uses to date business cycle turning points, none specifically represents the service-providing sectors (Layton and Moore, 1989). Indicators used by dating committees in Europe and elsewhere are largely the same.

Transportation-related sectors covering goods, services and structures had been of great interest to the early NBER scholars. Dixon (1924) studied the pervasive influence of transportation on all aspects of an economy, and even proposed that regulation of the railways be a part of stabilisation policies. More interestingly, a number of transportation indicators appeared prominently among the twenty-one cyclical indicators in the original NBER list proposed by Mitchell and Burns (1938) and Moore (1950).[1] Burns and Mitchell (1946, p. 373) and Hultgren (1948, 1955) found that cyclical movements in railways coincided with the prosperities and depressions of the economy at large. Moore (1961, Volume I, pp. 48-50), based on updated data through 1958, found that railway freight carloadings, while still being coincident at troughs, showed longer leads at peaks after the 1937-1938 recession. This observation, which Moore attributed to the declining trend of rail traffic, marked the failure of railway freight movements as a roughly coincident indicator of the aggregate economy. Further efforts to study the role of transportation in monitoring modern business cycles were hindered largely due to the discontinuation of many of the monthly transportation indicators in the 1950s.[2] Today, with increasing global competition, inventories and sales have become more integrated, and consequently transportation has become critical for efficient business operations.[3] However, this part of the service economy is largely ignored in business cycle studies.

Transportation represents a significant part of the US economy. Using different definitions of the scope of the transportation industry would yield different measures of its importance, varying anywhere from 3.09% (Transportation GDP) to 16.50% (Transportation-driven GDP), see Han and Fang (2000). More importantly, transportation plays a vital role in facilitating economic activity between sectors and across regions. Ghosh and Wolf (1997), in examining the importance of geographic and sector shocks in the US business cycles, find that transport (and/or motor vehicles) is one of the few sectors that is highly correlated with intra-state and intra-sector shocks, and is crucial in the propagation of business cycles. Thus, a measure of transportation activities can potentially be very useful in monitoring the current state of general economic activity.

In a project sponsored by US Bureau of Transportation Statistics (BTS), we have developed a monthly experimental index to measure the aggregate output of the transportation sector. This transportation services output index (TSI) utilises eight series on freight and passenger movements by airlines, rail, waterborne, trucking, transit and

pipelines (NAICS codes 481-486) covering around 90% of total for-hire transportation during 1980-2000. TSI is a chained Fisher-ideal index, and is methodologically similar to the Industrial Production (IP) index, see Lahiri *et al.* (2004a, 2006) for details.[4] Lahiri and Yao (2004b) also find that the strong cyclical movements observed in the TSI appear to be well synchronised with the NBER-defined recessions and growth slowdowns of the US economy. TSI can give early signals to the onset of economic recessions while being contemporaneous to economic recoveries. Thus given its key role, TSI can be an additional coincident indicator in dating business cycle turning points in a timely fashion.[5]

The paper is organised into three sections. After the Introduction, Section 2 reviews the historical NBER chronology of US cycles since 1973 with the inclusion of transportation. Section 3, which contains the main methodological contribution of the paper, constructs various composite coincident indexes (CCI) with different combination of the four currently used coincident indicators and TSI. Three alternative methods are employed for this purpose: NBER non-parametric method, dynamic factor model (Stock and Watson 1989), and dynamic factor model with Markov regime switching (Kim and Nelson 1998). For each of these models, we use appropriate scoring methods to evaluate the relative performance of the five indicators in dating economic turning points. The last section summarises the main conclusions of the paper.

## 2. TSI and current four coincident indicators

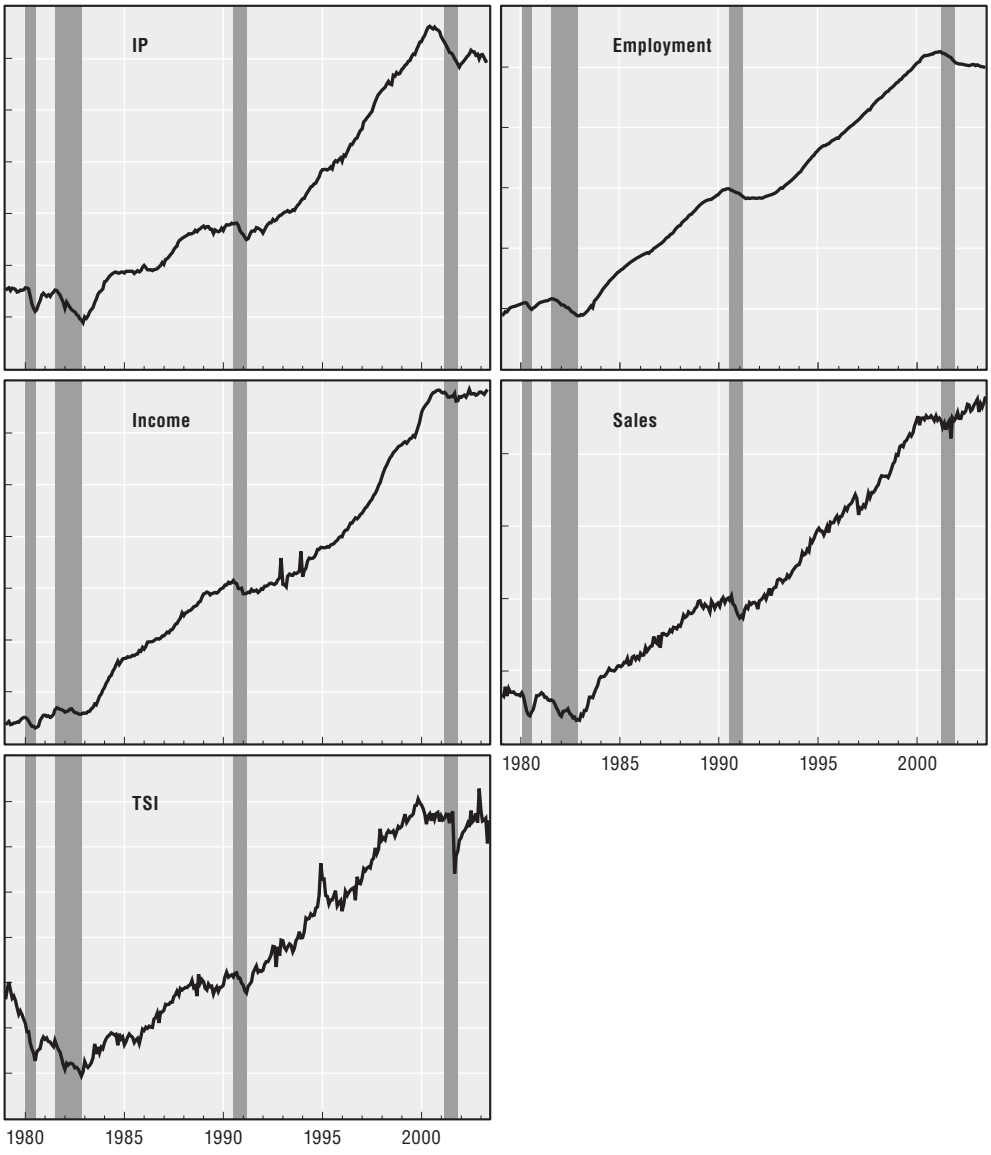
### *2.1. History of NBER coincident indicators*

In 1938, Wesley Mitchell and Arthur Burns selected a set of twenty-one indicators from among several hundred time series under the NBER project. After the World War II, Geoffrey Moore took over the job and published a new list of indicators in 1950. They are classified into three groups: leading (8), roughly coincident (8) and lagging (5) indicators, according to six selection criteria, see Lahiri and Moore (1991). These indicators, like industrial production and inventory investment, typically cover those sectors and processes that are sensitive to market conditions (Zarnowitz, 1975; 1977; 1992). The coincident indicators are used to define the current state of the economy. Among the four currently used coincident indicators, all employees of nonfarm industries (EMP) and personal income less transfer payments (INC) are comprehensive indicators with broad coverage. The other two, industrial production (IP) and, manufacturing and trade sales (Sales) measure the performance of individual sectors, namely manufacturing and trade sectors.[6] Thus, none of the current four indicators represents the service sectors of the economy. The newly constructed TSI can be the fifth coincident indicator representing a service sector that has a pervasive connection with different sectors and regions of the economy. The seasonally adjusted data of these five indicators are depicted in Figure 1.[7] They all seem to be well synchronised with NBER recessions (shaded areas). But cycles in TSI, as with IP, are very deep and clear with two extra turns capturing the stand-alone slowdowns in 1984 and 1995. This suggests that transportation output is sensitive to changes in market conditions, and thus can serve as a quality indicator such as IP.

### *2.2. Spider charts for historical business and growth cycles*

We examine the historic record of these five coincident indicators using the spider charts for six recessions and two cyclical slowdowns since 1973.[8] TSI is available from January 1979, but its value can be examined during the recession of 1973-75 using its largest component, the trucking tonnage index. To compare the timing of each indicator

Figure 1. **Proposed TSI and four current coincident indicators of US economy**



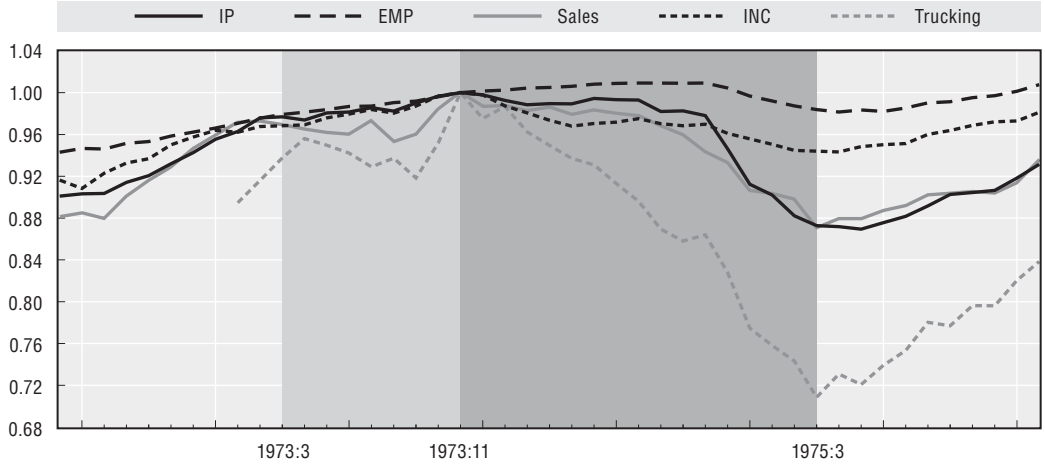

relative to NBER's chronology, the NBER dating algorithm described in Bry and Boschan (1971), namely the BB algorithm, is employed to identify the turning points via peak and trough dating. The NBER procedure for determining the reference cycle requires visually identifying clusters of turning points of all series and minimising the distance between the turning points in each cluster (Boehm and Moore, 1984).[9] In reality, many discretional considerations are involved. For instance, considerations in dating peaks could be different from those in dating troughs. This is because turning points in four current coincident indicators are more diverse at peaks than at troughs, which actually makes the decisions on peaks more difficult to make. Historically, NBER-defined peaks of the US economy coincided with the peaks of at least one of two broad indicators, EMP or INC, regardless of the other two. There was consensus among the four coincident indicators at all troughs except for the 2000 recession.

We have prepared eight spider charts, one for each of the six recessions and two growth slowdowns. They are plotted in Figures 2a through 2h, where the darker shaded areas represent NBER recessions and lightly shaded areas represent NBER-defined growth slowdowns preceding or following full-fledged recessions. See Zarnowitz (1992, Chapter 7) and Zarnowitz and Ozyildirim (2006) for discussions on growth cycles, and Gordon (1980), Zarnowitz (1992, Chapter 3), McNees (1992) and Temin (1998) for excellent commentaries on the chronology of American business cycles in historical perspective.

### *2.2.1. Recession of 1973:11-1975:3*

The 1973-75 recession produced an unprecedented dip in economic activity in the post-war period. Many studies have discussed the characteristics and causes of this recession. There is no doubt that the cause of this cycle was the quadrupling of oil price by the Organization of the Petroleum Exporting Countries (OPEC). This oil shock was clearly evident at the time and has been the object of countless studies since then (Temin, 1998). McNees (1992) and Lahiri and Wang (1994) argued that after 1967, inflation continued to intensify and the economy was struck by an oil embargo and large increases in energy costs following the outbreak of the Yom Kippur War on 6 October 1973. However, many commentators at the time and later argued that the Federal Reserve System (Fed) was excessively aggressive in its attempt to limit the resulting inflation (Gordon, 1980; Zarnowitz, 1992). The federal funds rate was maintained above 10% from April through October of 1973, the month before the start of the recession. This was recognised as a slowdown beginning in March 1973 followed by a recession beginning November 1973. As Figure 2a shows, a substantial decline had occurred in Sales in February through August of 1973 while only the deceleration of growth rates was reflected in IP, EMP, and INC. Following the monetary tightening, IP, Sales, and INC began a severe and long-lasting decline in November, which was defined as the peak of the economy-wide recession. EMP responded sluggishly with an 11-month lag following this peak.

Figure 2a. **Spider chart during recession of 1973:11 to 1975:3**




According to Romer and Romer (1994), the Fed was quick to discern the onset of recession around February 1974, but was slow to realise its severity. It was not until the October 14, 1974 Federal Open Market Committee (FOMC) meeting that the Fed

acknowledged that there would be an extended decline in real activity. Beginning in September however, the FOMC began to ease their policy significantly resulting in a dramatic decline of the federal funds rate. The summary of actions by the Board of Governors of the Federal Reserve System in September through November explicitly states the use of the discount rate and open market operation to combat recession. These anti-recessionary policies continued into the first quarter of 1975, which was dated as the end of the recession. At the trough, Sales and INC reached consensus in March 1975 while EMP and IP began their recoveries one or two months later.

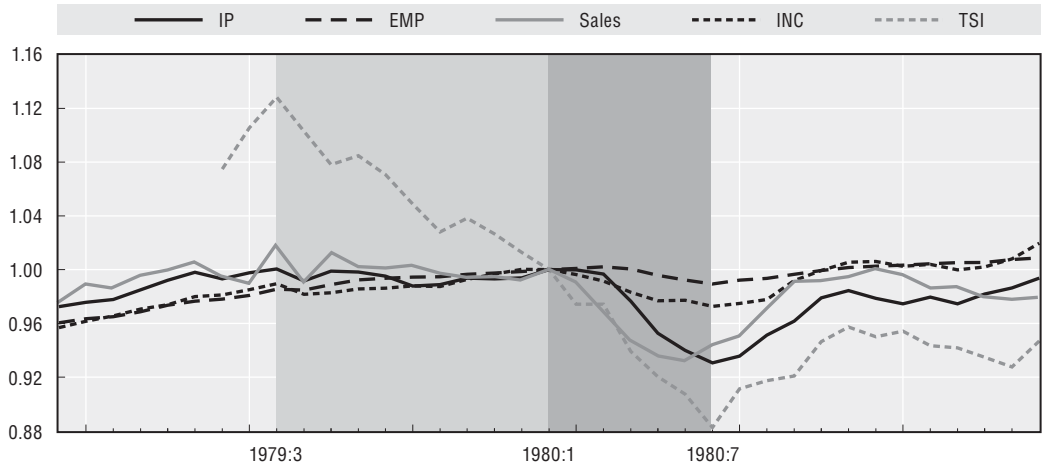
The 1973-1975 recession can be divided into two fairly distinctive phases: November 1973 to September 1974 and October 1974 to March 1975. During the first phase, EMP actually continued to grow and IP only declined slightly (McNees, 1992; Lahiri and Wang, 1994). Thus, this period was identified not as a genuine recession. It was only during the second phase of the recession that real economic activity actually decreased sharply. This distinction coincides with the timing of monetary policies.

Trucking tonnage has become available since January 1973 and thus can be used as a proxy for TSI. Like Sales in this period, trucking activity also experienced a temporary real decline in April 1973 following the monetary tightening, which corresponded to the slowdown preceding that recession. Then a much more severe decline occurred in the trucking industry exactly during the month when IP, Sales and INC began their decline in November 1973. The decline in trucking activity was much deeper than any of the others during this recession, and its turning points are exactly concurrent with the economic peak and trough. From the peak to the trough, trucking tonnage decreased by 30%. Part of the reason is that the recession was a result of the oil shocks, which actually affected the trucking industry from both the supply and demand sides. Like two other sector measures (IP, Sales), trucking tonnage is also very sensitive to monetary policy and market changes. However the cyclical behaviour of trucking tonnage is more correlated with Sales, the realisation of which involves delivery.

### *2.2.2. Recession of 1980:1-1980:7*

The first recession in early 1980s is by far the smallest downturn classified as a cycle. It is a precursor of the larger cycle in 1981. Although no separate cause for it is noted in the literature, it is possibly a result of the oil shock. There was a sudden dramatic surge in the spot price of oil in 1979 when the revolution in Iran disrupted the world oil market, which raised the price from USD 14.85 to USD 32.50 per barrel by January 1980. Driven by high energy costs, the annual inflation rate rose to 18% during 1979 and 1980. To combat this high inflation, the Fed kept the federal funds rate constantly above 10% with large increases in March and April of 1979. From August 1979 to January 1980, the Fed raised the rate again from 9% to 19%, a record-breaking high. Following these increases, both IP and Sales (see Figure 2b) began their real declines in March 1979, corresponding to the growth slowdown defined by the NBER. This shock was reflected in EMP and INC with only somewhat slight decline and decelerations until the beginning of recession in January 1980. The peak of the recession coincided with that of INC while EMP peaked two months later. The labour market had already stagnated in late 1970s and early 1980s, and hence EMP did not aid in identifying the peak of this cycle. According to Romer and Romer (1994), at every meeting of the FOMC from July 1979 through the summer of 1980, the Fed believed that a recession was either under way or was imminent. Concern about inflation and money growth however, prevented policy-makers from moving to lower interest rates

Figure 2b. **Spider chart during recession of 1980:1 to 1980:7**




until the spring of 1980. Then from the third quarter of 1980, the combination of weak money growth and unfavourable news about real GDP pushed the FOMC to lower the federal funds rate sharply, which actually brought all four coincident indicators to the end of this cycle around July 1980.

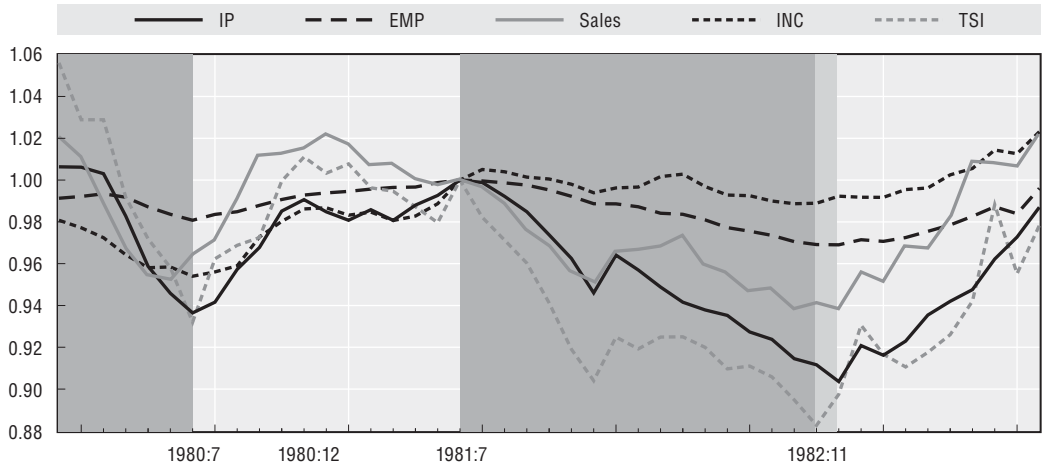
TSI is available during the recession of 1980:1 to 1980:7. Like trucking tonnage in the previous recession, cycles in TSI (see Figure 2b) are always very sharp and clear. TSI is also very sensitive to policy and market condition changes, even more so than IP and Sales. In response to oil price shocks and hyperinflation, TSI began to decline in March 1979 at the same time as IP and Sales, and continued until the end of the recession with a clear downtrend. While recoveries of both IP and Sales from the slowdown were interrupted by the monetary tightening in early 1980, nothing had affected the continuing downturn of TSI. Therefore, this indicator gave the sharpest signal for the start of the slowdown and recovery from the recession in this episode.

### *2.2.3. Recession of 1981:7-1982:11*

The recession starting in July 1981 is attributed to additional reasons besides the oil crisis, in part due to Paul Volcker, who was appointed as the Chairman of the Fed by President Carter. Monetary policy in early 1980s was a departure from Fed policy during the 1970s and was fiercely contractionary as an effort to reduce the double-digit inflation. The average federal funds rate in 1980 through July 1981 was 15.5%. Figure 2c reveals that Sales and TSI started to exhibit real declines from December 1980, and continued until the end of recession in November 1982. IP and INC only dropped slightly around December 1980, subsequently recovering from April that year until January 1981, and then falling again into recession. The peak of the recession was defined based on peaks in IP and INC, while EMP peaked one month later. TSI, IP, and Sales recorded surges in their corresponding economic activities in January 1982, corresponding to Fed's action of lowering the federal funds rate.

Following the recession, major declines in interest rates occurred in the fourth quarter of 1981, and in the third and fourth quarters of 1982. The declines in late 1981 were a response both to weak money growth and to the recession. Partly due to Fed stimuli, all coincident indicators finally reached their bottom and began to recover around

Figure 2c. **Spider chart during recession of 1981:7 to 1982:11**



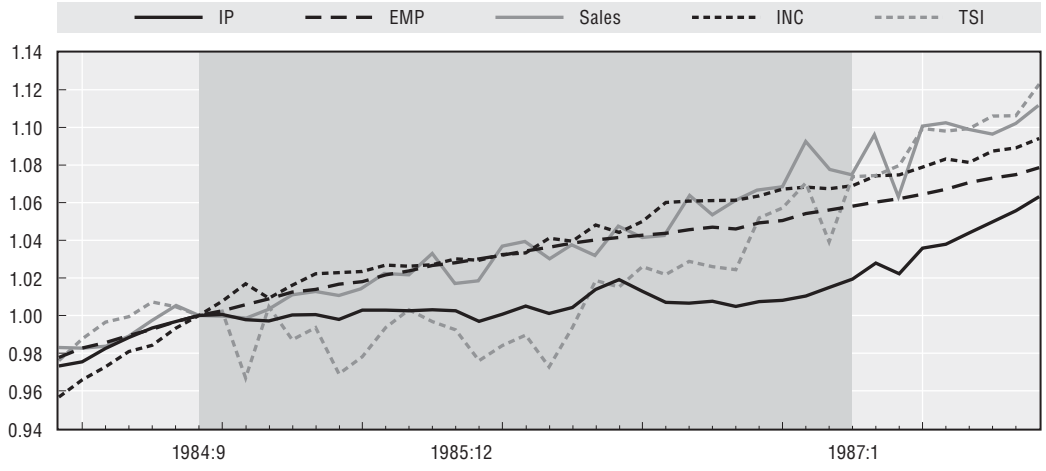

November 1982. The trough of the recession was coincident with that of INC and Sales (also TSI) while EMP and IP recovered a month later.

### *2.2.4. Slowdown of 1984:9-1987:1*

From the recession of 1982 to that of 1990, there was actually one stand-alone slowdown that lasted for 2.5 years. Since growth cycles are less well known as compared to classical business cycles, there has been not much work studying them.[10] We value them simply because recessions are usually preceded by slowdowns, which may or may not develop into recessions due to a number of reasons including concerns and discretionary policies of the Federal Reserve. But due to the sensitive nature of cyclical indicators, many usually detect signs of slowdown right from the beginning.

The slowdown beginning in 1984 was more prominent in IP and TSI than in the rest of the coincident indicators, as depicted in Figure 2d. IP, as the measure of manufacturing output, had stagnated through the period from September 1984 to January 1987 while TSI, the measure of transportation output, began to slow down two months earlier and ended

Figure 2d. **Spider chart during slowdown of 1984:9 to 1987:1**

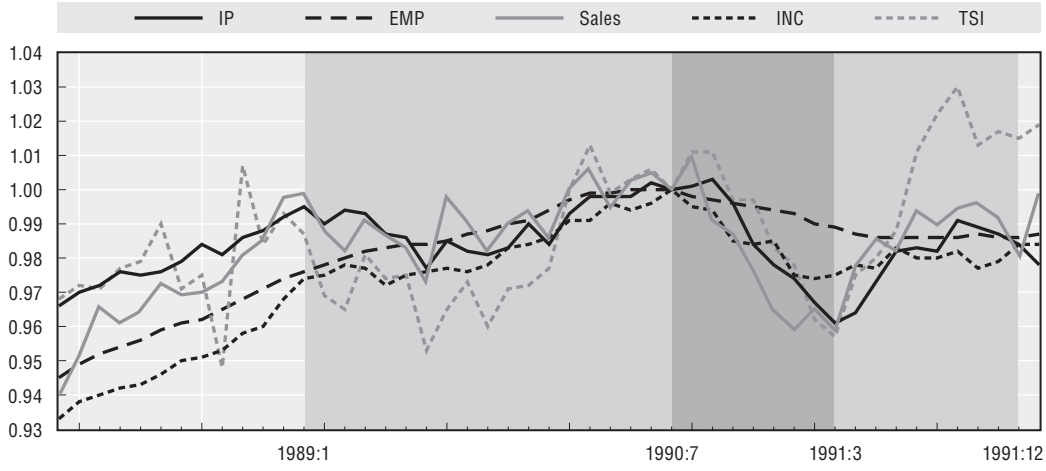


its stagnation in December 1985, about 13 months prior to IP. The cycle in the latter is also clearer with larger amplitude. FOMC actually raised the federal funds rate a few times from early 1983 through the third and fourth quarter of 1984. Slowdowns in IP and TSI could be responses to this monetary tightening.

### *2.2.5. Recession of 1990:7-1991:3*

The 1990 recession was due to a fall in consumption even though economists have debated whether the fall was exogenous (Temin, 1998; Blanchard, 1993; Hall, 1993; Hansen and Prescott, 1993). It is true that real consumption had declined in the fourth quarter of 1990 and the first quarter of 1991, but signs of a slowdown had appeared long before in 1989. McNees (1992) argued that this recession was the natural result when a "soft landing" was not achieved after a long lasting boom. In Figure 2e, it can be seen that IP and Sales started to decline from January 1989, began a recovery in July of that year, and were finally hit by consumption shocks in the third quarter of 1990. TSI had a similar experience, but it peaked three months earlier than both IP and Sales at the start of slowdown. It also had been recovering since July 1989 until the economic recession began. For the other two indicators, a mild slowdown occurred to INC in early 1989 while nothing significantly affected EMP until the beginning of the recession.

Figure 2e. **Spider chart during recession of 1990:7 to 1991:3**



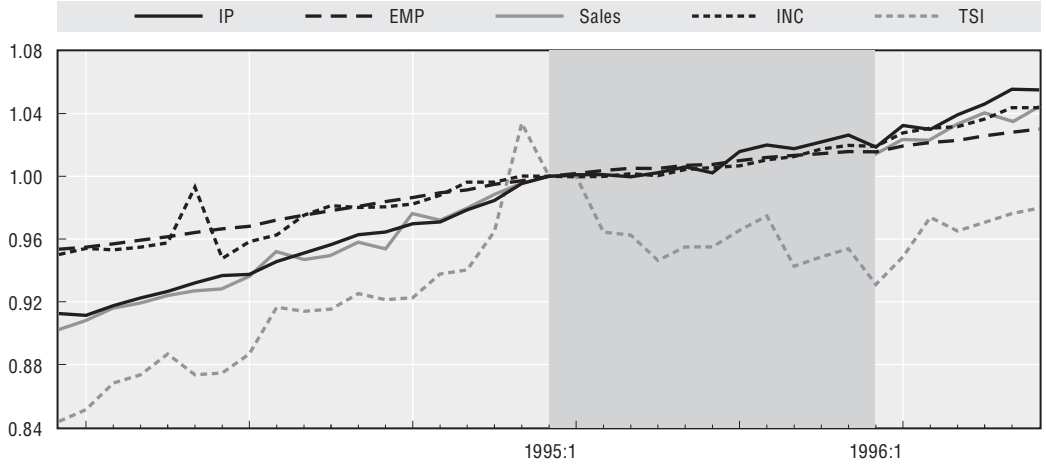

According to Romer and Romer (1994), immediately after what is now known as the peak of the recession (July 1990), the FOMC expected sustained but subdued growth in economic activity for the next several quarters. However, the Fed was fairly slow to realise that a recession was actually under way during the third quarter of 1990 and so was slow to take effective measures. Not until November 1990 did the FOMC decide for some immediate easing of severe conditions. The federal funds rate was lowered in early 1989 and additional reductions were not made until November 1990. In the four months following the Fed's move, IP, Sales and TSI all reached their trough and started moving upward. This was also defined as the trough of the economy. INC peaked slightly earlier than the economic trough while EMP was totally out of sync, recovering 10 months after the overall trough.

Immediately following the recession, the economy did not experience a strong recovery like those in 1980s or earlier. Instead, all the series except TSI underwent slowdowns until December 1991 or even later. Therefore, the recession of 1990 and the one we will discuss next were both preceded and followed by fairly long slowdowns. This new characteristic of recessions can be described as double-dip. The first phase corresponds to a slowdown and the second corresponds to a real recession. This newly observed feature has made TSI even more useful in dating peaks and troughs in a timely fashion because the onset of the slowdowns and the start of economic recovery are all well captured by TSI (Lahiri and Yao, 2004b). A similar characteristic is also found in IP and Sales. Recall one of the reasons for the so-called "great moderation" in the United States: as service-providing sectors have become increasingly more important and the supply chain management, and monetary policies more fine-tuned, the US economy has witnessed more stability since the mid-1980s. Various factors have made recessions shorter and less severe. But as we see, the reduced part of a typical recession has possibly been counted as part of the growth slowdowns, which can only be reflected in these highly sensitive sector measures such as IP, Sales and TSI, rather than the broad measures. As Figures 2e and 2g reveal, although the durations of recessions have been short, the durations of recessions and their neighbouring growth cycles have not. Thus, in the future, we may have to rely on sector indicators to identify turning points, particularly at the troughs.

### *2.2.6. Slowdown of 1995:1-1996:1*

Between the recession of 1990 and that of 2001 is a long-lasting boom. In the middle, there is also a stand-alone slowdown that did not culminate into a full-fledged recession. In Figure 2f, we see that IP, Sales and INC exhibited signs of deceleration over the period of 1995:1 to 1996:1. Declines in IP and INC were lesser than that in Sales. However, transportation experienced a severe sector-wide slump during 1994:12 to 1996:1 with a drop of 11% – about its average decline during recessions and worse than the 1990 recession (6%). Thus, TSI also gave a signal for an economy-wide slowdown. This decline followed a series of small increments in the federal funds rate since November 1993. Consequently, declines in TSI, IP and Sales could have been responses to this monetary tightening.

Figure 2f. **Spider chart during slowdown of 1995:1 to 1996:1**

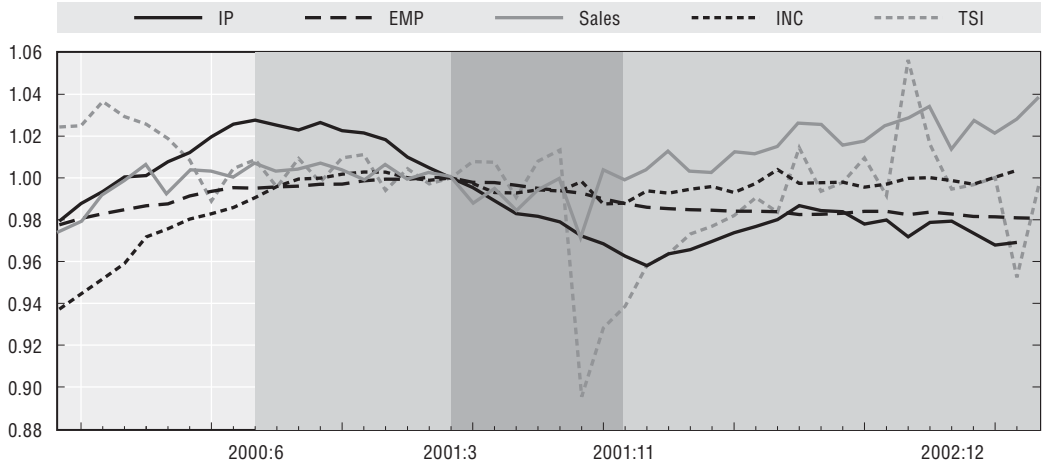


### *2.2.7. Recession of 2001:3-2001:11*

In the 1990s, the US economy experienced the longest expansion in its history. Cautious of possible "irrational exuberance", the FOMC raised the federal funds rate beginning in June 1999. This was the first credit tightening in more than two years. The rise continued until November that year when TSI began to decline. The effects on IP and Sales were a little bit slower. IP began its real decline in June 2000, while Sales showed signs of stagnation from January through December 2000 – its peak occurring in January 2000. Declines in IP, TSI and Sales corresponded to the economic slowdown beginning in June 2000. Like in the previous recession, TSI also exhibited a double-dip recession. The first phase was in the period 1999:11 to 2000:4 when this sector began recovering, and the second was from 2000:11 to 2001:9, which still gave an early signal for the economic peak four months ahead. If we combine the two phases, TSI would have issued a signal for the recession with a lead-time of 11 months.

The peak of this cycle was defined as that of EMP, while INC peaked three months earlier. Since then the federal funds rate was lowered below 2%. A special event during this recession was the September 11 terrorist attacks (9/11) which had a profound effect on TSI (dropped by 12%) but only marginal effects on Sales and other series (see Figure 2g). This marked September 2001 as the trough for TSI.[11] However the trough of this overall cycle was defined at somewhere between those of Sales, INC and IP, but closer to INC. Like in the recession of 1990, EMP did not recover till the third quarter of 2003, about two years after the general economic turnaround.

Figure 2g. **Spider chart during recession of 2001:3 to 2001:11**

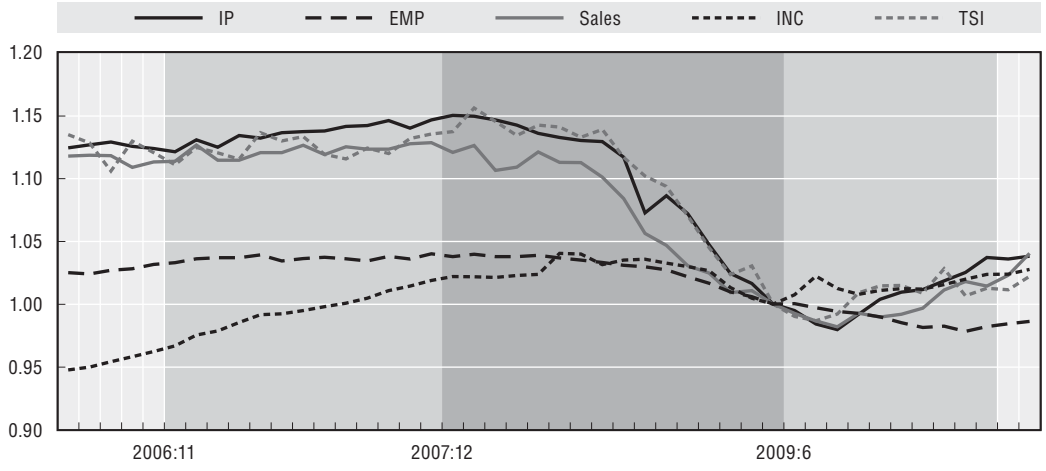



### *2.2.8. Recession of 2007:12-2009:6*

The bankruptcy of Lehman Brothers in September 2008 precipitated what in retrospect, is likely to be judged to be the most virulent global recession ever. Whereas the causes of the current recession are being debated, it is widely believed that the housing downturn which started in 2006, is a primary cause of the broader economic malaise. The fall of housing prices from its peak levels cut deeply into home building and home purchases. This also caused a sharp rise in mortgage foreclosures for which institutions that had exposure to mortgage securities took great losses to the tune of over

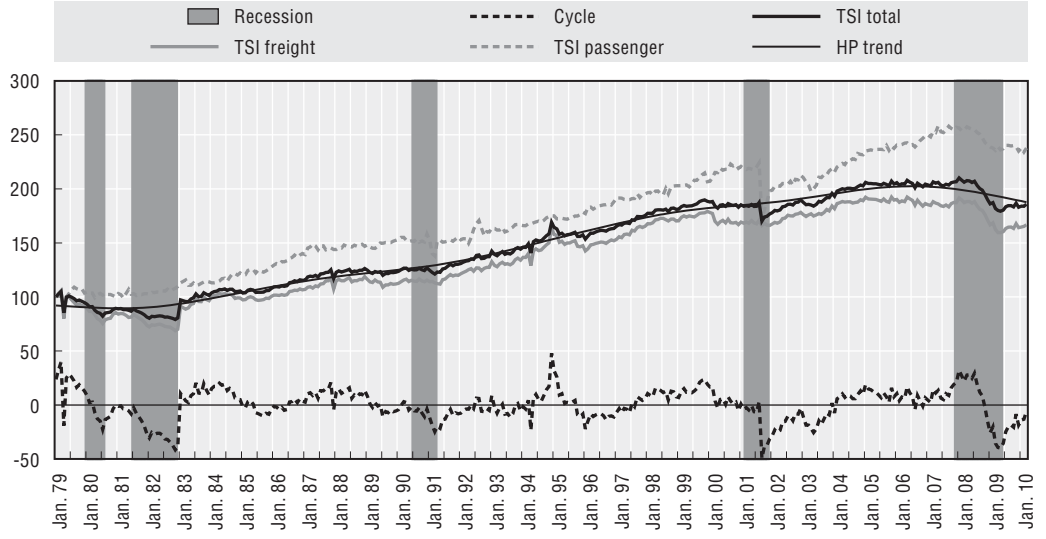
USD 400 billon. In July 2008, oil prices peaked at USD 147 a barrel and a gallon of gasoline was more than USD 4 across most of the US. In addition, US monetary policy contributed to the recession by excessive money creation. Figure 2h reveals that, compared to EMP and INC, sector indices like IP, Sales and TSI again issued very clear signals for a peak around December 2007.

Figure 2h. **Spider chart during recession of 2007:12 to 2009:06**




The same indicators together with INC suggested a trough of the cycle around June 2009 – thus the current recession would last over 16 months. In Figure 3, we have plotted TSI and its freight and passenger components from 1979:1 until 2010:3. The deviation of TSI from its HP trend is also depicted. We clearly see that during the last recession that began in December 2007, TSI has been almost coincident with the peak and the trough. The role of TSI as a faithful coincident indicator both at the peak and the trough is again established.

Figure 3. **TSI total, its components and growth cycle, Jan. 1979-March 2010**



The above episodic analysis of eight recessions and slowdowns in the US suggests that during every recession and growth slowdown, TSI, IP and Sales have been very sensitive to economic and policy shocks. All recessions since 1973 have been preceded by a fairly long slowdowns.[12] Cycles in these three individual indicators correspond to both slowdowns and recessions. Sometimes these cycles made distinctions between growth slowdowns and recessions with a two-phase cycle; otherwise, they had a complete cycle right from the onset of slowdown. During recessions of 1990 and 2001, TSI had displayed a double-dip feature, where its first phase gave clear signals for a slowdown while the second high corresponded to the next phase of the economic recession. During the latest peak of 2007 recession, TSI again signalled the onset of the recession as did IP and Sales. During this recession, the signals from personal income and employment were less clear. Thus, we can conclude that TSI always gives early and clear signals for economic recessions.

The timing of these five coincident indicators relative to the NBER chronology is reported in Table 1. At the troughs of last few recessions, recovery of EMP appears very weak, lagging behind the other measures of the overall economy, which is partly due to improved productivity since the mid-1980s. This eliminates EMP as a useful indicator in identifying economic troughs. The missing role of labour data can be made up by the TSI, whose recoveries could have always started at the same time as economic recoveries had the event of 9/11 not occurred. Nevertheless, TSI's dating power for US economic troughs is better than that of any of the four currently used coincident indicators. At peaks, TSI tends to always peak earlier, by seven months on the average. Unlike IP or Sales, which may lead, lag or coincide with economic peaks, TSI consistently leads the onset of economic recessions. Given that the NBER committee places special importance on the two broad indicators (EMP and/or INC) to identify the peak of US economy, TSI as a sector indicator can be very useful in correctly dating peaks when combined with these two broad indicators. Moreover, transportation output represents an important service sector that relates to various stages of fabrication. Adding TSI as additional coincident indicator can broaden the representation of the current NBER dating system and add additional discriminatory power.

Table 1. **Timing of five coincident indicators relative to NBER chronology**

| NBER-defined recessions | IP | | EMP | | Sales | | INC | | Median of these four | | TSI | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P | T | P | T | P | T | P | T | P | T | P | T |
| Nov. 73-March 75 | 0 | 2 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Jan. 80-July 80 | –10 | 0 | 2 | 0 | –10 | –1 | 0 | 0 | –5 | 0 | –10 | 0 |
| July 81-Nov. 82 | 0 | 0 | 0 | 0 | –6 | 0 | 1 | –1 | 0 | 0 | –7 | 0 |
| July 90-March 91 | 2 | 0 | –1 | 10 | 1 | 0 | 0 | –2 | 0.5 | 4 | –4 | 0 |
| March 01-Nov. 01 | –6 | 1 | 0 | 8 | –9 | –2 | –4 | –1 | –5 | 0 | –16 | –2 |
| Mean | –2.7 | 0.4 | 1.7 | 2.6 | –4.1 | –0.6 | –0.3 | –0.9 | –1.7 | 0.5 | –7.4 | –0.4 |
| Median | –2.0 | 0.0 | 0.0 | 0.0 | –3.0 | 0.0 | 0.0 | –1.0 | –1.0 | 0.0 | –7.0 | 0.0 |
| St Dev | 4.1 | 0.8 | 3.1 | 4.4 | 4.3 | 0.8 | 1.7 | 0.9 | 2.3 | 1.6 | 6.1 | 0.9 |
| All 4 indicators | w/o TSI | | w/ TSI | | | | | | | | | |
| Mean | –1.4 | 0.4 | –2.6 | 0.2 | | | | | | | | |
| Median | –1.3 | –0.3 | –2.4 | –0.2 | | | | | | | | |
| St Dev | 3.3 | 1.7 | 3.9 | 1.6 | | | | | | | | |
| Extra turns | | | | | | | | | | | 5/84 | 10/85 |
| | | | | | | | | | | | 12/94 | 1/96 |

## 3. CCIs with TSI

The NBER methodology of business cycles, inherited from Burns and Mitchell (1946), has two key features: comovement and regime switch (Diebold and Rudebusch, 1996). Extracting the comovement among coincident indicators leads to the creation of CCI. We consider three different methods to construct CCI: a non-parametric method of the NBER (Conference Board, 2001) and two parametric methods based on a single-index dynamic factor model (Stock and Watson, 1989), and a similar dynamic factor model with regime switching (Kim and Nelson, 1998). We name the CCI obtained from these three methods NBER index, SW index and KN index respectively.

### *3.1. NBER index*

The NBER index is created by assigning fixed standardisation factors as weights to the growth rate of each component and taking the average. Four steps are involved.

1. Month-to-month changes for each component of an indicator $X_{it}$ (i = 1, 2, 3, .., k; t = 1, 2, 3, .., T) are computed using the symmetric percentage change formula:

   $\delta X_{it} = 200 * (X_{it} - X_{it-1})/(X_{it} + X_{it-1})$.

2. The month-to-month changes are adjusted to equalise the volatility of each component using the standardisation factors. The standardisation factor for each component ($r_i$) is the inverse of standard deviation of the indicator over sample period, then normalised to sum = 1, i.e., $r_i = w_i^{-1}/\Sigma_j (w_j^{-1})$ and $m_{it} = r_i * \delta X_{it}$.

3. The level of the index is computed using the symmetric per cent change formula: first, the change of the composite index, $s_t$, is the average of adjusted month-to-month changes across all individual components for each t (i.e., $s_t = \bar{m}_t$ where $\bar{m}_t = (1/k)\Sigma_i m_{it}$); second, to get back to the level of the index, the first month's value is $I_1 = (200 + s_1)/(200 - s_1)$ and $I_t = I_{t-1} * (200 + s_t)/(200 - s_t)$ for t = 2, 3, .., T.

4. The index is re-based to be 100 in 1996.

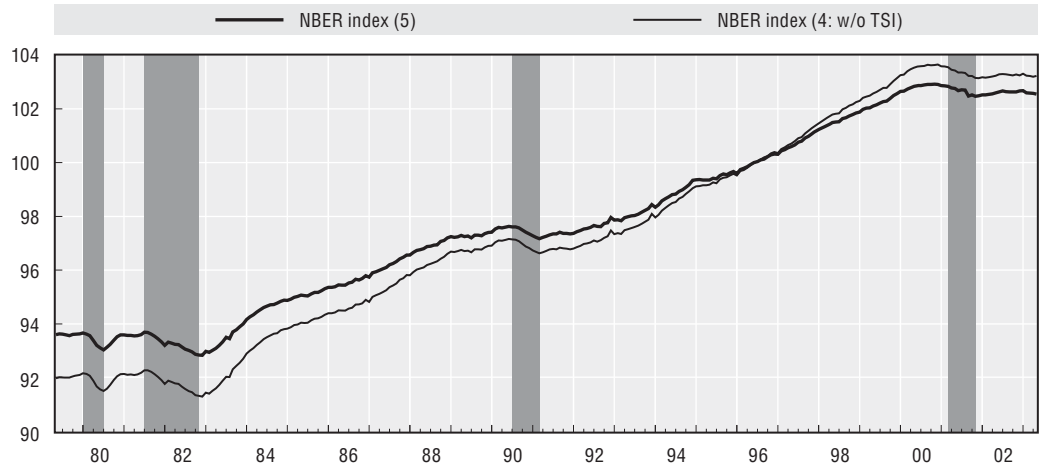
By using the inverse of the standard deviation as a weight, the contribution of the change in each series to the final index is well-balanced. The factors for constructing an NBER index from all five indicators are reported in Table 2. Besides this index, denoted as NBER index (5), four alternative indexes are achieved by excluding, individually, one indicator from the composite at a time. This results in a total of six NBER indexes. Among them, NBER index (4: w/o TSI) is constructed from four currently used coincident indicators, thus should be identical to the CCI currently maintained by the Conference Board. To keep a clear distinction between indexes, we only plot this index against NBER index (5) in Figure 4. Their cyclical movements are largely identical with only subtle

Table 2. **Standardisation factors for NBER Index**

| Components of CCI | Standardisation factors |
|---|---|
| IP | 0.159 |
| EMP | 0.532 |
| INC | 0.155 |
| Sales | 0.101 |
| TSI | 0.054 |

*Note:* The factors are defined as the inverse of standard deviations.

Figure 4. **NBER indices with and without TSI**




differences in their slopes. Note that the two indexes cross at 1996; since both have base 1996 = 100, it means that the composite NBER index with TSI is located uniformly a few points higher than the original NBER index (without TSI), but has the same cyclical characteristics.

To compare the performance of these six indexes to nowcast business cycles, their turning points are identified using the BB algorithm. The timing of these turning points relative to the NBER chronology is then reported in Table 3. Historically, all CCIs have the same turning points as the NBER chronology except that NBER index (4: w/o EMP) that shows a peak ten months earlier than that in NBER chronology for the 1980 recession. For the business cycle peak of March 2001, three indexes peaked in November 2000, two in December 2000 and one in October 2000, but none in March 2001. They also suggest a trough around November 2001 as defined by the NBER committee. All the indexes also signalled a new peak around December 2002.

We also computed Pearson's bellwether index of concordance based on a contingency table to measure the concurrence of turning points of each of these six NBER indices with NBER chronology:

$$\hat{I} = \frac{1}{T}\{\sum_{t=1}^{T} S_{xt}S_{yt} + \sum_{t=1}^{T}(1-S_{xt})(1-S_{yt})\} \quad (1)$$

where the state variables (0 for recession and 1 for recovery) are defined for two binary series *x* (a particular NBER composite index) and *y* (the NBER chronology) using the BB algorithm. Thus, $S_{yt} = 1$ if period *t* is a recovery period according to the NBER chronology (0 if recession), and $S_{xt} = 1$ if a particular NBER composite index in the same period *t* also belongs to a recovery period (0 if recession). The concordance index in equation (1) ranges between 0~1, see Harding and Pagan (2002). These values are reported in the last row of Table 3. Taking the NBER index (5) as the benchmark, the difference between $\hat{I}$ for other NBER indexes and $\hat{I} = 0.979$ for NBER index (5) shows the marginal contribution of the omitted variables to the composite five indicators CCI. Interestingly, INC and Sales have small negative contributions in correctly dating peaks and troughs of US economy, and thus the dating performance would improve without them. EMP has the largest contribution among the group of coincident indicators. However, partly because of the

Table 3. **Timing of NBER indexes (CCI) relative to NBER chronology**

| NBER-defined recessions | Five coincident indicators excluding | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | None[1] | | TSI | | IP | | EMP | | Sales | | INC | |
| | P | T | P | T | P | T | P | T | P | T | P | T |
| Jan. 80-July 80 | 0 | 0 | 0 | 0 | 0 | 0 | –10 | 0 | 0 | 0 | 0 | 0 |
| July 81-Nov. 82 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| July 90-March 91 | –1 | 0 | –1 | 0 | –1 | 0 | 1 | 0 | –1 | 0 | –1 | 0 |
| March 01-Nov. 01 | –4 | 0 | –3 | –1 | –3 | –2 | –5 | –2 | –4 | 0 | –4 | 1 |
| Detected new peak | Jan. 03 | | Jan. 03 | | Dec. 02 | | Dec. 02 | | Dec. 02 | | Jan. 03 | |
| Mean | –1.3 | 0.3 | –1.0 | 0.0 | –1.0 | –0.5 | –3.5 | –0.3 | –1.3 | 0.0 | –1.3 | 0.5 |
| Median | –0.5 | 0.0 | –0.5 | 0.0 | –0.5 | 0.0 | –2.5 | 0.0 | –0.5 | 0.0 | –0.5 | 0.5 |
| St Dev | 1.9 | 0.5 | 1.4 | 0.8 | 1.4 | 1.0 | 5.1 | 1.3 | 1.9 | 0.0 | 1.9 | 0.6 |
| Concordance w/NBER chronology | 0.979 | | 0.979 | | 0.979 | | 0.935 | | 0.986 | | 0.983 | |

1. CCI from five coincident indicators.

relatively few turning points in our sample, and also because the index value with the four original indicators is already very close to one (0.979), the marginal contribution of TSI cannot be properly discerned by looking at the concordance index in this case.

### *3.2. Stock-Watson index*

An alternative to the NBER index is the use of modern time-series techniques to develop dynamic factor models with regime switching (Kim-Nelson) or without regime switching (Stock-Watson). The resulting single indexes would represent the underlying state of its constituent time series. Thus dating turning points could be based on the probabilities of the recessionary regime implied by the regime switching models.

Defining $Y_{it}$ as the logarithm of the coincident indicators $X_{it}$, their individual growth rates are posited to be explained by an unobserved common factor $\Delta C_t$, interpreted as growth in CCI, and some idiosyncratic dynamics.This defines the measurement equation for each component:

$$\Delta Y_{it} = \gamma_i \Delta C_t + e_{it}, \tag{2}$$

where $\Delta Y$ is the simple first difference (*i.e.*, $Y_{it} - Y_{it-1}$) of the indicator $Y_{it}$ times 100. In the state-space representation, $\Delta C_t$ itself is to be estimated. In the transition equations, both the index $\Delta C_t$ and $e_{it}$ are processes with AR representations driven by noise terms $w_t$ and $\varepsilon_{it}$ respectively.

$$\Phi\,(L)\,(\Delta C_t - \mu_{st} - \delta) = w_t, \tag{3}$$

$$\psi\,(L)\,e_{it} = \varepsilon_{it}, \tag{4}$$

where L denotes the lag operator, $\delta$ is an intercept parameter, $\Phi\,(L)$ is a scalar lag polynomial, and $\psi\,(L)$ is a lag polynomial matrix. The two noise terms $w_t$ and $\varepsilon_{it}$ are assumed to be independent of each other. The equations (2)~(4) with regime specific means $\mu_{st} = 0$ define the Stock-Watson model; the state variable that we estimate from the model is the SW index. Our model specification is identical to original Stock-Watson model where three lags of state variables are used for the employment variable to account for its lagging nature, while no lag is used for newly added TSI. Like the NBER index, we estimate six SW indexes using different combinations of five coincident indicators. The estimation results are reported in Table 4, where the index estimated from all five indicators can be

Table 4. **Estimates of SW model with five coincident indicators**

| SW models | | Five coincident (IP, EMP, INC, Sales and TSI) indicators excluding | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | None | | TSI | | IP | | INC | | Sales | | EMP | |
| Parameters | | coef | s.e. | coef | s.e. | coef | s.e. | coef | s.e. | coef | s.e. | coef | s.e. |
| | $\phi_1$ | 0.43 | (0.09) | 0.45 | (0.10) | 0.74 | (0.29) | 0.35 | (0.09) | 0.50 | (0.11) | 0.37 | (0.09) |
| | $\phi_2$ | 0.22 | (0.09) | 0.23 | (0.09) | 0.00 | (0.26) | 0.24 | (0.08) | 0.18 | (0.10) | 0.27 | (0.08) |
| IP | $\gamma_1$ | 0.65 | (0.06) | 0.60 | (0.06) | – | – | 0.71 | (0.06) | 0.60 | (0.06) | 0.68 | (0.06) |
| | $\varphi_{11}$ | –0.21 | (0.09) | –0.19 | (0.09) | – | – | –0.18 | (0.12) | –0.23 | (0.09) | –0.07 | (0.11) |
| | $\varphi_{12}$ | –0.01 | (0.01) | –0.01 | (0.01) | – | – | –0.01 | (0.01) | –0.01 | (0.01) | 0.00 | (0.00) |
| | $\sigma_1^2$ | 0.32 | (0.05) | 0.37 | (0.05) | – | – | 0.29 | (0.06) | 0.36 | (0.06) | 0.33 | (0.06) |
| INC | $\gamma_2$ | 0.28 | (0.04) | 0.27 | (0.03) | 0.24 | (0.05) | – | – | 0.27 | (0.03) | 0.28 | (0.03) |
| | $\varphi_{21}$ | –0.03 | (0.05) | –0.04 | (0.05) | –0.08 | (0.06) | – | – | –0.04 | (0.05) | –0.03 | (0.05) |
| | $\varphi_{22}$ | 0.03 | (0.05) | 0.02 | (0.04) | 0.01 | (0.05) | – | – | 0.02 | (0.04) | 0.04 | (0.04) |
| | $\sigma_2^2$ | 0.28 | (0.03) | 0.27 | (0.03) | 0.23 | (0.03) | – | – | 0.27 | (0.03) | 0.28 | (0.03) |
| Sales | $\gamma_3$ | 0.34 | (0.04) | 0.31 | (0.04) | 0.25 | (0.06) | 0.37 | (0.05) | – | – | 0.37 | (0.05) |
| | $\varphi_{31}$ | –0.40 | (0.06) | –0.40 | (0.06) | –0.43 | (0.07) | –0.39 | (0.06) | – | – | –0.41 | (0.06) |
| | $\varphi_{32}$ | –0.04 | (0.01) | –0.04 | (0.01) | –0.05 | (0.01) | –0.04 | (0.01) | – | – | –0.04 | (0.01) |
| | $\sigma_3^2$ | 0.66 | (0.06) | 0.70 | (0.06) | 0.68 | (0.07) | 0.64 | (0.06) | – | – | 0.64 | (0.06) |
| EMP | $\gamma_4$ | 0.42 | (0.04) | 0.45 | (0.04) | 0.38 | (0.05) | 0.39 | (0.04) | 0.45 | (0.05) | – | – |
| | $\gamma_{41}$ | 0.07 | (0.05) | 0.04 | (0.05) | –0.07 | (0.10) | 0.13 | (0.04) | 0.02 | (0.05) | – | – |
| | $\gamma_{42}$ | 0.00 | (0.07) | –0.01 | (0.04) | 0.07 | (0.06) | –0.02 | (0.04) | –0.02 | (0.04) | – | – |
| | $\gamma_{43}$ | 0.15 | (0.04) | 0.15 | (0.04) | 0.20 | (0.04) | 0.17 | (0.04) | 0.14 | (0.04) | – | – |
| | $\varphi_{41}$ | 0.28 | (0.05) | 0.27 | (0.05) | 0.21 | (0.10) | 0.29 | (0.05) | 0.27 | (0.05) | – | – |
| | $\varphi_{42}$ | 0.44 | (0.07) | 0.46 | (0.07) | 0.33 | (0.11) | 0.45 | (0.06) | 0.49 | (0.07) | – | – |
| | $\sigma_4^2$ | 0.19 | (0.03) | 0.16 | (0.03) | 0.20 | (0.03) | 0.20 | (0.03) | 0.16 | (0.03) | – | – |
| TSI | $\gamma_5$ | 0.28 | (0.04) | – | – | 0.18 | (0.05) | 0.29 | (0.04) | 0.23 | (0.04) | 0.28 | (0.04) |
| | $\varphi_{51}$ | –0.36 | (0.06) | – | – | –0.36 | (0.06) | –0.40 | (0.06) | –0.38 | (0.06) | –0.41 | (0.06) |
| | $\varphi_{52}$ | –0.03 | (0.01) | – | – | –0.03 | (0.01) | –0.04 | (0.01) | –0.04 | (0.01) | –0.04 | (0.01) |
| | $\sigma_5^2$ | 0.61 | (0.06) | – | – | 0.64 | (0.07) | 0.62 | (0.05) | 0.64 | (0.06) | 0.60 | (0.06) |
| Log L | | 312.12 | | 223.25 | | 269.94 | | 289.26 | | 223.02 | | 337.57 | |

considered as an unrestricted model while others are restricted models. Thus, likelihood ratio tests can be employed to test the validity of these restrictions for removing one indicator at a time. All the restrictions that the coefficients of removed variable are zero are rejected at the 5% level.[13] In Table 4, coefficient estimates are very similar across different models. The estimated SW index with five indicators and that with four coincident indicators are plotted in Figure 5. They are almost identical to each other and their turning points are also very close.

### 3.3. *Kim-Nelson index*

Adding regime switching to the Stock-Watson model forms the Kim-Nelson model.[14] The transitions of different regimes ($\mu_{st}$), incorporated into (3), are governed by a Markov process:

$$\mu_{st} = \mu_0 + \mu_1 S_t,\ S_t = \{0, 1\},\ \mu_1 > 0, \tag{5}$$

$$Prob\ (S_t = 1 \mid S_{t-1} = 1) = p,\ Prob\ (S_t = 0 \mid S_{t-1} = 0) = q, \tag{6}$$

This model can be estimated using Gibbs-sampling. To implement the Kim-Nelson model, we used priors from the estimated Stock-Watson model. Priors for regime switching parameters were obtained from sample information of the NBER index. The final specification and parameter estimates from Kim-Nelson models are reported in Table 5.

Figure 5. **SW indices with and without TSI**

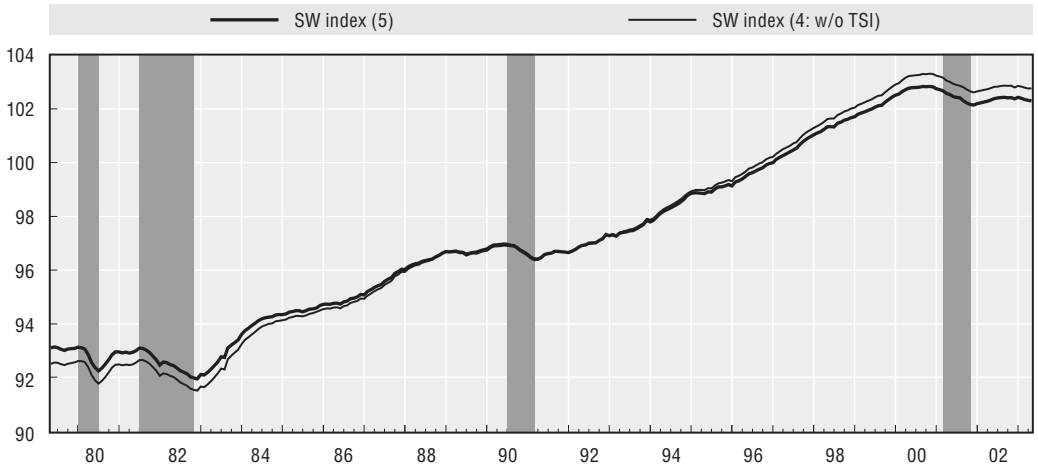
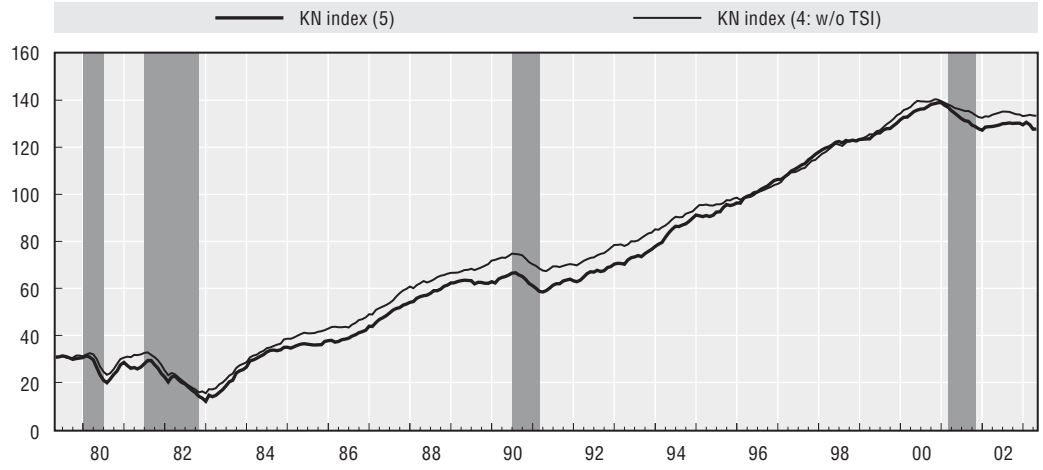



Table 5. **Estimates of KN model with five coincident indicators**

| KN model | | Five coincident (IP, EMP, INC, Sales and TSI) indicators excluding | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | None | | TSI | | IP | | INC | | Sales | | EMP | |
| Parameters | | coef | s.e. | coef | s.e. | coef | s.e. | coef | s.e. | coef | s.e. | coef | s.e. |
| | $\phi_1$ | 0.33 | (0.15) | 0.46 | (0.19) | 0.31 | (0.27) | 0.26 | (0.13) | 0.50 | (0.19) | 0.37 | (0.18) |
| | $\phi_2$ | 0.12 | (0.08) | 0.10 | (0.09) | 0.03 | (0.09) | 0.12 | (0.08) | 0.07 | (0.09) | 0.12 | (0.10) |
| IP | $\gamma_1$ | 0.58 | (0.06) | 0.56 | (0.06) | – | – | 0.60 | (0.06) | 0.54 | (0.06) | 0.61 | (0.08) |
| | $\varphi_{11}$ | –0.09 | (0.09) | –0.09 | (0.09) | – | – | –0.07 | (0.09) | –0.11 | (0.08) | –0.05 | (0.09) |
| | $\varphi_{12}$ | 0.02 | (0.08) | 0.05 | (0.08) | – | – | 0.03 | (0.08) | 0.06 | (0.08) | 0.01 | (0.08) |
| | $\sigma_1^2$ | 0.32 | (0.06) | 0.37 | (0.07) | – | – | 0.29 | (0.06) | 0.39 | (0.07) | 0.32 | (0.08) |
| INC | $\gamma_2$ | 0.26 | (0.04) | 0.26 | (0.04) | 0.26 | (0.05) | – | – | 0.25 | (0.04) | 0.26 | (0.04) |
| | $\varphi_{21}$ | –0.37 | (0.06) | –0.38 | (0.06) | –0.35 | (0.07) | – | – | –0.37 | (0.06) | –0.36 | (0.06) |
| | $\varphi_{22}$ | –0.08 | (0.06) | –0.08 | (0.06) | –0.05 | (0.06) | – | – | –0.08 | (0.06) | –0.07 | (0.06) |
| | $\sigma_2^2$ | 0.79 | (0.07) | 0.78 | (0.07) | 0.78 | (0.07) | – | – | 0.78 | (0.07) | 0.80 | (0.07) |
| Sales | $\gamma_3$ | 0.31 | (0.04) | 0.28 | (0.04) | 0.29 | (0.06) | 0.31 | (0.04) | – | – | 0.33 | (0.05) |
| | $\varphi_{31}$ | –0.36 | (0.06) | –0.36 | (0.07) | –0.36 | (0.07) | –0.35 | (0.07) | – | – | –0.36 | (0.07) |
| | $\varphi_{32}$ | –0.13 | (0.06) | –0.12 | (0.06) | –0.11 | (0.07) | –0.12 | (0.06) | – | – | –0.13 | (0.06) |
| | $\sigma_3^2$ | 0.66 | (0.06) | 0.68 | (0.06) | 0.67 | (0.07) | 0.65 | (0.06) | – | – | 0.64 | (0.06) |
| EMP | $\gamma_4$ | 0.26 | (0.04) | 0.38 | (0.05) | 0.34 | (0.07) | 0.33 | (0.04) | 0.39 | (0.05) | – | – |
| | $\gamma_{41}$ | 0.07 | (0.04) | 0.05 | (0.05) | 0.05 | (0.06) | 0.08 | (0.04) | 0.03 | (0.05) | – | – |
| | $\gamma_{42}$ | 0.09 | (0.04) | 0.09 | (0.05) | 0.10 | (0.05) | 0.09 | (0.04) | 0.10 | (0.05) | – | – |
| | $\gamma_{43}$ | 0.11 | (0.04) | 0.12 | (0.04) | 0.12 | (0.04) | 0.11 | (0.04) | 0.10 | (0.04) | – | – |
| | $\varphi_{41}$ | –0.38 | (0.06) | 0.05 | (0.08) | 0.10 | (0.10) | 0.11 | (0.07) | 0.05 | (0.08) | – | – |
| | $\varphi_{42}$ | –0.08 | (0.06) | 0.30 | (0.08) | 0.30 | (0.09) | 0.36 | (0.06) | 0.30 | (0.08) | – | – |
| | $\sigma_4^2$ | 0.72 | (0.07) | 0.34 | (0.04) | 0.37 | (0.06) | 0.37 | (0.04) | 0.34 | (0.04) | – | – |
| TSI | $\gamma_5$ | 0.26 | (0.04) | – | – | 0.24 | (0.06) | 0.26 | (0.04) | 0.22 | (0.04) | 0.28 | (0.04) |
| | $\varphi_{51}$ | –0.38 | (0.06) | – | – | –0.35 | (0.07) | –0.38 | (0.06) | –0.36 | (0.06) | –0.40 | (0.06) |
| | $\varphi_{52}$ | –0.08 | (0.06) | – | – | –0.06 | (0.07) | –0.09 | (0.06) | –0.08 | (0.06) | –0.09 | (0.06) |
| | $\sigma_5^2$ | 0.72 | (0.07) | – | – | 0.74 | (0.08) | 0.71 | (0.06) | 0.76 | (0.07) | 0.71 | (0.06) |
| | $\mu_0$ | –1.82 | (0.80) | –1.15 | (0.97) | –1.44 | (0.87) | –1.95 | (0.73) | –1.30 | (1.04) | –1.37 | (0.98) |
| | $\mu_1$ | 2.17 | (0.83) | 1.53 | (1.05) | 1.95 | (0.94) | 2.30 | (0.78) | 1.64 | (1.10) | 1.81 | (1.00) |
| | $P_{00}$ | 0.83 | (0.15) | 0.83 | (0.21) | 0.88 | (0.14) | 0.82 | (0.14) | 0.83 | (0.19) | 0.80 | (0.20) |
| | $P_{11}$ | 0.96 | (0.07) | 0.88 | (0.21) | 0.93 | (0.16) | 0.94 | (0.16) | 0.93 | (0.15) | 0.89 | (0.19) |
| | $\delta$ | 0.51 | (0.06) | 0.61 | (0.10) | 0.55 | (0.21) | 0.44 | (0.05) | 0.62 | (0.11) | 0.41 | (0.05) |
| | $\mu_0+\mu_1$ | 0.35 | (0.25) | 0.38 | (0.53) | 0.50 | (0.51) | 0.35 | (0.18) | 0.34 | (0.45) | 0.43 | (0.66) |
| QPS | | 0.09 | | 0.17 | | 0.15 | | 0.10 | | 0.14 | | 0.14 | |

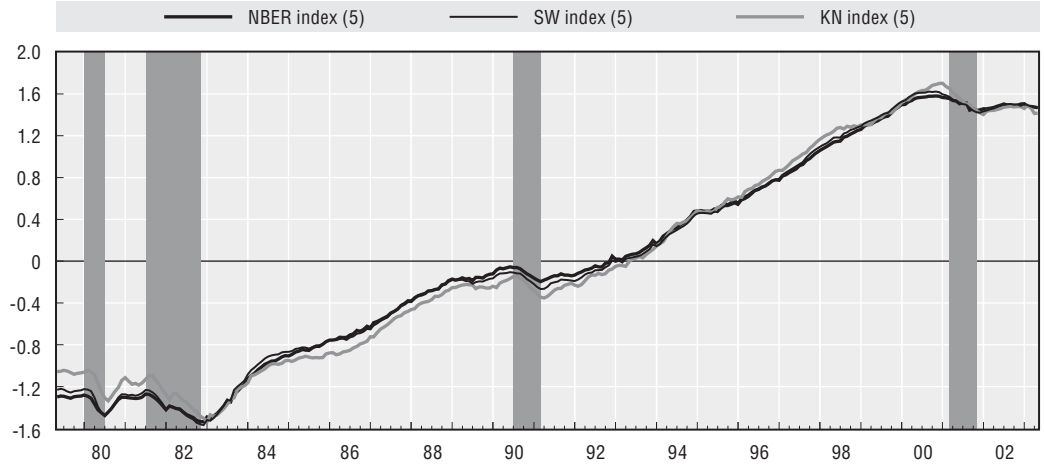
From the table, all the models distinguish between two clear-cut regimes of positive and negative growth rates. The coefficient estimates are also very similar across different model specifications. The estimated two of the six KN indexes are plotted in Figure 6. Both indexes capture the double-dip feature shared by the three sector measures (IP, Sales and TSI), as well as mild slowdowns in 1985 and 1995. All the indexes suggest that the economic peak for the 2000 recession occurred at the end of 2000, but they largely disagree on the date of the trough.

Figure 6. **KN indices with and without TSI**




The coefficient estimates of Stock-Watson and Kim-Nelson models with the same covariate specifications are close except that the sum of the AR coefficients for the state variable in the Stock-Watson model is significantly higher, implying more state dependence in the resulting index. This difference is complemented by the much larger role that employment plays in the Kim-Nelson model. Both these two types of indexes estimated from all five indicators are plotted against the NBER index in Figure 7. Compared to Kim-Nelson, the Stock-Watson index agrees more closely with the NBER index

Figure 7. **Three CCIs based on five coincident indicators**

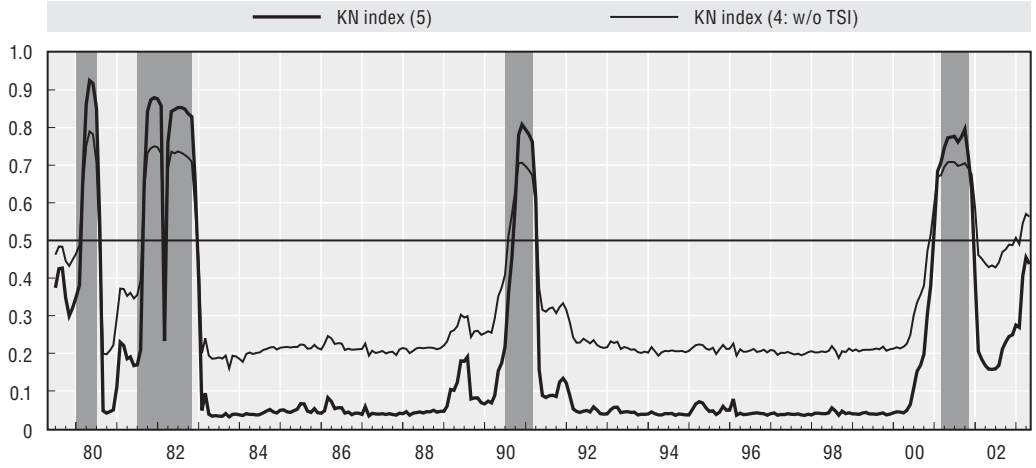



*Note:* The scale for three indexes has been normalised.

throughout the period. Despite differences in their model formulations and in minor details, their cyclical movements appear to be very similar to one another and are synchronised well with the NBER-defined recessions for the economy (the shaded areas). These results are similar to those in Kim and Nelson's original paper.

As a by-product, the Kim-Nelson model generates the posterior probability that the economy is in recession, as plotted in Figure 8. These probabilities, inferred from the model, feature a real-time and nonparametric dating algorithm. In facilitating the dating, we draw the 0.5 probability line in the figure. The first month going above (below) 0.5 probability line is defined as a peak (trough). The resulting chronology would be very similar to that from using the non-parametric NBER index. The recession probabilities in Figure 8 also suggests that the 2000 recession started a little bit earlier and ended a little bit later as compared to the NBER chronology of March 2001 and November 2001.

Figure 8. **Recession probabilities implied from Kim-Nelson models**




To compare the performances of each KN index to different combinations among the five coincident indicators, we also calculate the Quadratic Probability Score (QPS) (Brier, 1950) based on probabilities implied from each model. Let $P_t$ be the probability that economy is in recession estimated from the model, $R_t$ be the NBER-defined chronology (1 if recession, 0 otherwise), the QPS is given by:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2, \tag{7}$$

which ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. This is the unique proper scoring rule that is a function only of the discrepancy between realisations and assessed probabilities (see Diebold and Rudebusch, 1989). We calculate the QPS for the sample period from January 1979 to December 2002 and they are reported in the last row of Table 5. All six KN indexes have QPS lower than 0.2, which suggests that they have good performance in identifying peaks and troughs relative to the NBER chronology. Among them, KN index (5) has the highest accuracy with the lowest QPS with a value of 0.09, and the index excluding TSI has the lowest accuracy with the highest QPS with a value of 0.17. This is corroborated in Figure 8 as well where we see very clearly that the recession probabilities with TSI discriminate between a recession and a recovery much better than

those without TSI. This is because the KN index without TSI generates higher recession probabilities during expansions and smaller probabilities during recessions as compared to the KN index with TSI.

## 4. Conclusions

In this paper we examined the usefulness of the transportation services index (TSI) as an additional coincident indicator to determine the peaks and troughs of business cycles in the US economy. Transportation represents a service sector that plays an undisputed role in propagating sector or geographic shocks into the overall economy. Adding the TSI into a coincident indicators system can help a dating committee to account for several important changes that have taken place in the economy since mid-1980s such as reduced volatility in real GDP, decreased importance of industrial production, increased share of the services sector, and the failure of the employment indicator to co-move with other coincident indicators. We evaluated the marginal contribution of the TSI to the NBER business cycle dating chronology by using individual indicators as well as composite indexes. The historical consistency between TSI and NBER chronology at troughs outperforms any of the currently used coincident indicators. At peaks, TSI tends to peak seven months ahead on average. Thus, TSI, when combined with one of the two broad business cycle measures, would significantly save the time and confusion in correctly dating peaks in a timely fashion.

Following the single factor dynamic factor model for coincident indicators with regime switching, we constructed six different composite coincident indices using different combinations of these five indicators. For each such combination, we evaluated the marginal contribution of each individual indicator to the system. TSI was found to have a very significant marginal contribution in reducing the QPS score compared to the original four-indicator NBER mix. Given that the NBER and other dating committees place special importance on the two broad indicators (EMP and INC) to identify peaks, TSI as a sector indicator can be useful when used in conjunction with these two board measures. Moreover, transportation represents an important service sector that interconnects various stages of fabrication in any modern economy. Thus, including TSI as an additional coincident indicator can broaden the representation of the current business cycle dating system and add additional discriminatory power.

### *Notes*

1. The transportation indicators included by Mitchell and Burns are passenger car production, total railroad operating income, truck production and ton-miles of freight hauled by railways. The revised NBER list, by Geoffrey Moore in 1950, included railway freight carloadings as one of eight coincident indicators.
2. For more information on the history of cyclical indicators, see the NBER Macrohistory database available online (Feenberg and Miron, 1997). See also Klus *et al*. (2005).
3. Irvine and Schuh (2005) find that 40% of the reduced volatility in GDP is attributed to improved inventory investment and another 30% to reduced correlation between sectors due to more integrated supply chain management. Both factors are closely related with transportation.
4. Gordon (1992) and Bosworth (2001) have provided valuable insights into the different methodologies and data that BEA and BLS use to construct alternative annual transportation output series. A comparison suggests that these annual output measures reflect the long-term trends of TSI, and that the latter is superior in reflecting the cyclical movements in the transportation sector.

5. Since 10 March 2004 TSI has been released and updated on a monthly basis by the Bureau of Transportation Statistics, US DOT, and all reports are now available at *www.bts.gov/xml/tsi/src/index.xml*.
6. In the November 1968 issue of Business Conditions Digest (BCD), US Bureau of Economic Analysis began to produce composite indexes, where the CCI was based on five coincident indicators. In the December 1975 issue of BCD, one of them, (inverse) unemployment rate was dropped and four remained in use till today.
7. The seasonally adjusted TSI is based on its seasonally adjusted component series using Census' X12-ARIMA with adjustments for both trading day and holiday effects. The seasonally adjusted series of other four indicators are readily available.
8. In spider charts, the values of all depicted series are normalised to be one for the month defined as the peak or trough. The spider charts in our paper are defined for peaks, while the NBER Dating Committee presents charts for both peaks and troughs.
9. From specific cycles of each indicator to the final NBER chronology, very limited information has been provided by the NBER dating committee on its procedure. While dating the business cycle chronology for the Australian economy, Boehm and Moore (1984) have provided the clearest description of the NBER procedures.
10. A recent exception is Zarnowitz and Ozyildirim (2006).
11. But without this event, TSI would have reached its trough in November 2001 as well. Using a Census X12-ARIMA procedure, removal of this outlier results in a trend-cycle component of the original TSI that shows a trough in November 2001.
12. The only exception is the recession of 1981. The possibility of a prior slowdown was possibly preempted by the additional short and mild recession of 1980, as we see from Figure 2c.
13. Critical values for $\chi^2(4)$ (four coefficients are specified for IP, SALES, INC and TSI in the model) and $\chi^2(7)$ (EMP, three lags are specified in the equation [2]) are 9.5 and 14.1 respectively at the 5% level of significance.
14. Both models were estimated using computer routines described in Kim and Nelson (1998).

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# Euro area business cycles

*by*
Atılım Seymen*

*The role of global, euro area and country-specific shocks in business cycle dynamics of six euro area member countries is assessed with the aid of SVAR models. Output fluctuations are driven by global shocks to a large extent in the euro area, and no Europeanisation of business cycles due to, for example the European Monetary Union, could be established. Business cycle heterogeneity is driven mainly by (asymmetric) country-specific shocks in the euro area and not by heterogeneous responses to common, particularly global, shocks. The cyclical disparity across the member economies is found to be small relative to the size of business cycles.*

*JEL classification: E32, C32, F00*

*Keywords: European Monetary Union, international business cycles, common and country-specific shocks, structural vector autoregression*

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## 1. Introduction

Properties of business cycles in the euro area countries have been the subject of a large body of literature since the initiation of the European Monetary Union (EMU) process which led to using the euro as a common currency, currently in 16 countries. The subject is interesting not least because of the fact that common currency and common monetary policy may have, near positive impacts, adverse effects on some of the member economies when their cyclical positions are not sufficiently close to each other.[1] Since central banks optimise and set the monetary policy with respect to the business cycle of an entire zone that shares a common currency, common monetary policy may have destabilising effects on member countries, of which business cycles deviate to a large extent from the one of the entire single currency area. This is why two important concerns of the member countries' policy-makers in the pre-EMU and post-EMU periods have been the nature of the common driving forces of business cycles, as well as the extent and sources of business cycle heterogeneity in the euro area; subjects which have triggered extensive academic research. In this paper, we focus on these two issues within a structural vector autoregression (SVAR) framework.

The first question of interest in the current paper is the extent to which the business cycles of the euro area countries have been driven by common factors in the last decades. In the case of the euro area countries, one should differentiate between global and euro-area-specific common factors when dealing with this question. This is because the EMU process has been taking place concurrently with the globalisation phenomenon, and both of these processes are characterised by similar features such as a substantial increase in international capital flows and trade relative to former times, stronger financial market integration, higher mobility of labour, etc. Our SVAR framework contains both types of factors so that global (euro area) phenomena are not falsely interpreted as euro area (global) phenomena, which the literature has often ignored.[2] Yet, the issue has important policy implications. If the business cycles of the member economies are driven by global shocks to a large extent, for example, this would mean that the European Central Bank should set a monetary policy which is in line with other significant global actors such as the Federal Reserve. In this paper we employ the most widely used tool in the SVAR context, the forecast error variance decomposition (FEVD), for assessing the driving forces of output fluctuations at the so-called business cycle periodicities of 1.5 to 8 years.

Note that a dominant role of common shocks as a driving force of business cycle dynamics is necessary but not sufficient for a successfully operating currency area. In case individual member countries' business cycles respond heterogeneously to common shocks, such shocks may become a destabilising force for the member countries that are subject to a monetary policy which is not in accordance with their needs. Therefore, in addition to computing variance decompositions of output, we investigate the extent of business cycle heterogeneity in the face of common shocks in the euro area. Whether the heterogeneity patterns have changed over the course of the years after the initiation of the

EMU is another issue of concern in this context. It has been argued starting with the study of Frankel and Rose (1998) that becoming member of a monetary union leads to higher business cycle synchronicity across the member economies, that is the OCA criteria are endogenous.

The tool that is most widely used for assessing heterogeneity is the unconditional Pearson correlation co-efficient between each member country's cycle and the entire euro area cycle as well as between cycles of country pairs. Mixed findings have been reported in the literature with regard to changes in the correlation patterns over time. On the one hand, there are studies such as Artis and Zhang (1999) and Afonso and Furceri (2007) which find that correlation of business activity in the euro area increased over time. An indirect support to this assessment is the finding in Stock and Watson (2005) of the emergence of a cyclically coherent euro-area group of France, Germany and Italy within the group of the G7 countries. Inklaar and de Haan (2001) challenge, on the other hand, the findings of Artis and Zhang (1999) by using a similar data set and reporting a decline in the correlations over time. Later studies such as Massmann and Mitchell (2004), Gayer (2007) or Weyerstrass, van Aarle, Kappler, and Seymen (2011) point to various periods of divergence and convergence in business cycle synchronisation in the euro area by means of correlation analyses.[3] Thus the literature is not clear-cut as to whether the business cycle heterogeneity has decreased after the initiation of the EMU process in the euro area.

Correlation analysis requires choosing a method among many alternatives for extracting the cyclical component of macroeconomic time series. It is, however, well-known that characteristics of cycles depend heavily on the method with which they are extracted.[4] Moreover, popular filtering methods have often been subject to the critique that they produce spurious cycles.[5] Another disadvantage of employing only correlations for assessing the business cycle heterogeneity is that correlation refers only to synchronicity of cycles, while there may still be a differential between the cycles of two countries even when they are perfectly correlated. As Massmann and Mitchell (2004) emphasise, any reduction in cyclical disparity may not necessarily be accompanied by an increase in correlations. When the cycles of the euro area and a member country are not correlated at all but the discrepancy between them is very small, this would be a more favorable situation for the EMU than strongly correlated cycles with large discrepancies. Therefore in this paper we compute FEVD of output differential, that is the differential between the euro area output and the output of a member country, for periodicities of 1.5 to 8 years in order to detect the driving forces of business cycle heterogeneity.[6]

Our analysis is carried out with real quarterly GDP data and covers the period 1970Q1-2009Q4. We split our sample into two parts in order to capture changes that have occurred in the euro area business cycle dynamics over time. Changes in macroeconomic dynamics might have occurred due to the EMU and globalisation processes, as mentioned above. Moreover, the industrialised world went through a prolonged period of lower business cycle volatility, the so-called Great Moderation, starting roughly in the mid-1980s until recently.[7] While splitting the sample would help us detect changing patterns in the data, there are many potential dates at which we could split our sample as we discuss in Section 2. Yet it is cumbersome to consider all possibilities. Therefore besides carrying out estimations with discrete samples, we also report findings from 15-year rolling window samples. On one hand, this provides a robustness check of our conclusions based on discrete samples and highlights, on the other hand, issues that are harder to detect with discrete samples.

The paper is structured as follows. The next section presents the econometric methodology and discusses the data set. The estimation results from discrete sub-samples and rolling window samples are presented in Section 3. Section 4 concludes.

## 2. Empirical framework and data

The empirical framework underlying our analysis builds on a combination of two different bivariate SVAR models discussed by Giannone and Reichlin (2006). The first of these models comprises the output of the euro area and an individual member country. While Giannone and Reichlin (2006) report an important role for common euro area shocks in the member country business cycles by estimating that model, it is not possible to learn from their exercise whether the shock they label as the common euro area shock really reflects European peculiarities. The second model considered by the authors comprises the output of the US and the euro area, and hence allows distinguishing between global and euro area shocks. Yet it is not possible to judge the impact of these shocks on the individual member economies of the euro area in the latter model. In this paper, we combine the foregoing two structures so that estimating the impact of two types of international shocks, labelled global and euro area shocks in the following, as well as own country-specific shocks of the member countries within one framework becomes possible. In this section, we briefly describe the original framework of Giannone and Reichlin (2006) as well as our extension thereof. The section also includes a discussion of the data set and various model specification issues.

### *2.1. Two bivariate models*

Giannone and Reichlin (2006) investigate the business cycle relationship between the euro area and each member country using bivariate VARs. The moving average (MA) representation of the model underlying their empirical analysis is given by

$$\begin{bmatrix} y_{EA,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} \mu_{EA} \\ \mu_i \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \Phi_{11,j} & \Phi_{12,j} \\ \Phi_{21,j} & \Phi_{22,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{EA,t} \\ \varepsilon_{i,t} \end{bmatrix} \quad (1)$$

where $y_{EA,t}$ and $y_{i,t}$ stand respectively for the log real output per capita of the euro area and member country $i$ at period $t$, $\mu_{EA}$ and $\mu_i$ stand for constant terms, $\Phi_{kl,j}$ is the $(k,l)$ element of the $j^{th}$ moving average co-efficient matrix, and $\varepsilon_{EA,t}$ and $\varepsilon_{i,t}$ are defined as euro area and country-$i$ shocks, respectively. It is assumed that the covariance matrix of the shocks is an identity matrix. This implies a normalisation of the shocks' standard deviations as well as their orthogonality to each other. Hence, one additional restriction is required for the identification of the structural form (1) which Giannone and Reichlin design such that country-specific shocks can affect the euro area aggregate only after a lag of one period. This last restriction has been employed before by Stock and Watson (2005) and is motivated by the assumption that international transmission of country-specific shocks takes at least one period. In this spirit, Giannone and Reichlin limit the impact effect of a country-specific shock on the euro area output to the population share of the member country the shock stems from. Formally,

$$\Phi_0 = \begin{bmatrix} \Phi_{11,0} & p_i \Phi_{22,0} \\ \Phi_{21,0} & \Phi_{22,0} \end{bmatrix} \quad (2)$$

where $\Phi_0$ is the MA co-efficient matrix showing the impact effects of one-standard-deviation shocks, and $p^i$ is the population share of country $i$ in the euro area.[8]

In a similar model to the previous, Giannone and Reichlin (2005, 2006) also investigate the business cycle relationship between the US and the euro area. The model reads

$$\begin{bmatrix} y_{US,t} \\ y_{EA,t} \end{bmatrix} = \begin{bmatrix} \mu_{US} \\ \mu_{EA} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \Phi_{11,j} & \Phi_{12,j} \\ \Phi_{21,j} & \Phi_{22,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{US,t} \\ \varepsilon_{EA,t} \end{bmatrix} \tag{3}$$

with

$$\Phi_0 = \begin{bmatrix} \Phi_{11,0} & 0 \\ \Phi_{21,0} & \Phi_{22,0} \end{bmatrix} \tag{4}$$

so that euro area shocks are spilled over to the US after a one-period lag, while US shocks affect both the US and the euro area in the period they occur. Giannone and Reichlin motivate this type of framework with Granger causality tests (among others). In particular, the hypothesis that the log output growth of the US and the euro area do not Granger-cause the log output differential (in levels) between the US and the euro area is not rejected by the data. The hypothesis that the output differential does not Granger-cause the US output growth is also not rejected, whereas the hypothesis that the output differential does not Granger-cause the euro area output growth is rejected. Giannone and Reichlin (2005) conclude from this picture that "the euro area rate of growth adjusts itself to the US growth while the US does not respond to shocks specific to the euro area". Granger-causality tests based on our sample with quarterly data, of which results we do not report here, are also in accordance with this picture. Moreover, euro area shocks play either virtually no role or only a minor role in US output fluctuations depending on the sample according to our models.

Perez, Osborn, and Artis (2006) order the US output before the EU15 output within a similar VAR structure due to "the important role of the US in the international economy during the post-war period". Yet, the same argument could also be put forward for the euro area economy. Moreover, besides being a significant international actor in general, Europe has always been one of the most important markets for US industry and it would not be surprising that shocks originating from the euro area could also anticipate some (large) fluctuations in the US economy. Therefore ordering the euro area output before the US output in the VARs might be no less reasonable than *vice versa*. Such a structure would mean that euro area shocks impact the US economy immediately, but global shocks may impact the euro area economy first after a one-period lag. The proponents of the view that the US economy is much more flexible than the euro area economy and adjusts to shocks in general and global shocks in particular much faster might also support the foregoing ordering more than our original ordering. However our results are only partly sensitive to changing the orders of the US and euro area output (see Section 3.1.3).

### *2.2. The trivariate model*

The bivariate model in (1) does not allow us to distinguish between global and euro area shocks which may bias our results as has been argued in the introduction. There are multiple studies which suggest that a global factor as an important driver of business cycle fluctuations in many economies exists.[9] Therefore, it is useful to augment the model in (1) with the US output in the way the model in (3) suggests. That natural extension of the

previous bivariate models enables us to isolate the effects of global, euro area and country-specific shocks on each member economy. Such an extension resembles the model employed by Perez, Osborn, and Artis (2006), who work with trivariate VARs containing the first-differenced log real output of the US, EU15 (the first 15 members of the EU) and one of the G7 countries except the US and impose a Cholesky structure on this framework. The difference of our approach to the foregoing one is *i*) to consider the euro area instead of the EU15, since the euro area is a more coherent group in terms of being subject to common policy and is our subject of interest, and *ii*) to take into account the population shares of the member countries in the identification scheme in the way Giannone and Reichlin (2006) do, which is a more reasonable restriction than the zero restriction used by Perez *et al*. for the impact effect of German, French and Italian shocks on the EU15 output. Moreover Perez *et al*. do not consider smaller member economies such as Belgium, Spain and the Netherlands as we do.

The trivariate model we propose is given by

$$\begin{bmatrix} y_{US,t} \\ y_{EA,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} \mu_{US} \\ \mu_{EA} \\ \mu_{EA} \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} \Phi_{11,j} & \Phi_{12,j} & \Phi_{13,j} \\ \Phi_{21,j} & \Phi_{22,j} & \Phi_{23,j} \\ \Phi_{31,j} & \Phi_{32,j} & \Phi_{33,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{US,t} \\ \varepsilon_{EA,t} \\ \varepsilon_{i,t} \end{bmatrix} \tag{5}$$

the only difference to (1) being that the US output, the corresponding co-efficients and a US shock are now a part of the VAR as well. In this case, the impact effects of shocks on the US, the euro area and country *i* are given by

$$\Phi_0 = \begin{bmatrix} \Phi_{11,0} & 0 & 0 \\ \Phi_{21,0} & \Phi_{22,0} & p_i\Phi_{33,0} \\ \Phi_{31,0} & \Phi_{32,0} & \Phi_{33,0} \end{bmatrix} \tag{6}$$

The zero entries in the first row of $\Phi_0$ imply that euro area and country-specific shocks do not influence the US economy in the period they occur in accordance with (4).

Note that our labeling of the first shock in the model as global shock throughout the paper is a simplification.[10] Our measure of the global shock possibly reflects the idiosyncratic shocks of the US economy to a certain degree. Moreover, approximating the global economy with the US economy might be problematic for our interpretations due to the existence of other big economies such as Japan and more recently China. In order to address the latter issue at least partly, we alternatively estimate VARs where the US output is substituted by the OECD output. While emerging big economies such as China and India are not members of the OECD, the US produces only a third of the OECD output and the OECD output might represent the world economy better than the US alone. Yet our findings change only partly when we follow this alternative strategy, as we discuss in Section 3.1.3.

The motivation of our identification scheme comes from the factor-SVAR framework of Stock and Watson (2005). International shocks, such as oil price shocks, of which effects are seen in all countries immediately would be captured as a global shock affecting all three economies in a SVAR of type in (5). Moreover, a stock market shock that hits a major economy such as the US or the euro area and is spilled over to other economies within a short time, that is in less than a quarter, would also be registered as a global shock according to our definition. On the other hand, our framework implies that cross-dynamics across the member economies are only due to common, global and/or euro area, shocks

whereas spillovers of country-specific shocks do not find a place in the SVAR given by (5) and (6). Given that Stock and Watson find only a minor share of spillovers for Germany, France and Italy within the G7 group over the period 1984-2002, we would argue that our model is a good approximation in this respect.[11, 12]

### *2.3. Model specification*

Distinguishing between the impact of global and euro area shocks within one framework is one of the improvements of our approach on the framework of Giannone and Reichlin (2006). Another important difference is that we work with quarterly data (at the cost of losing some countries in the sample) as is typical in studies dealing with business cycles, while Giannone and Reichlin use annual data. Furthermore, using annual data not only hampers a business cycle analysis but also implies in terms of the given framework that spillovers of country-specific shocks to the euro area or the US as well as of euro area shocks to the US take at least one year, which is an implausibly long period. Another novelty in this paper in comparison to Giannone and Reichlin is that we carry out estimations for sub-periods in order to capture the time variation due to changes in the size of shocks as well as their transmission. Finally, dynamics of output forecast errors underlie our analysis, while Giannone and Reichlin concentrate on output level or annual growth.[13]

Stock and Watson (2005) and Perez, Osborn, and Artis (2006) as well as a long list of other studies estimate time series models in the first difference of log real output. This may however, be problematic in case the time series used in the analysis are co-integrated. Giannone and Reichlin (2006) obtain a co-integrating relationship between the output of the US and the euro area, which is valid for our data set as well according to Johansen co-integration tests. According to tests based on our trivariate framework, the rank of co-integration varies across country-specific model estimations, possibly due to the shortness of the samples at hand. Setting the co-integration rank to 0, 1 or 2 in different estimations may be inappropriate, however since the US and euro area output are common variables for all country-specific models: different co-integration ranks in different country-specific models might lead to implausible differences in the dynamics of these common variables. Hence, estimating the country-specific models in levels of log real output, as Giannone and Reichlin (2006) do, is the practice we follow.[14] Nevertheless, our results do virtually not change when a vector error correction model (VECM) with a co-integration rank of 1 or 2 underlies our structural estimation. Some results from a co-integration framework are discussed in Section 3.1.3.

Different information criteria point to different optimum lag orders across the country-specific models we estimate. Yet, the suggested lag order is most of the time 1 or 2. Setting the lag order differently across the country-specific models is inappropriate since the models share two common variables. Different lag orders could render a healthy comparison of our results difficult. The lag order is therefore uniformly set to 2 for all VARs estimated in this study which is high enough to get rid of autocorrelation in the residuals in most cases. Moreover, although some residuals show a slight autocorrelation with this lag order and as much as eight lags would be needed to alleviate the problem, our structural analysis is only partly sensitive to this issue. The consequences of setting the lag order to 4 is discussed in Section 3.1.3.

### *2.4. Data*

The empirical analysis of this study is carried out using using quarterly log real GDP data. The data set covers the period 1970Q1-2009Q4 and includes the real GDP per capita of eight countries: the US, the euro area consisting of the first 12 members plus Slovakia, Belgium (BEL), Germany (GER), Spain (ESP), France (FRA), Italy (ITA) and the Netherlands (NLD).[15] In the following, we first report results from two different sub-periods: 1970Q1-1990Q2 and 1990Q3-2009Q4. The most important reason for splitting the sample at 1990Q2 is that it corresponds to the official kick-off of the EMU process, as suggested by the so-called Delors report "Report on Economic and Monetary Union in the European Community" prepared by the Committee for the Study of Economic and Monetary Union headed by the then president Jacques Delors of the European Commission. The report foresees three stages leading to the establishment of the euro area, the first of which was started on 1 July 1990. Note that this period also coincides roughly with the collapse of the Iron Curtain and a new wave in globalisation. It is also the quarter immediately before the reunification of Germany, the country with the highest economic weight in the euro area.

We call the first sub-period the pre-EMU period and the latter period the EMU period in accordance with the foregoing description. Yet, other plausible break dates also exist. Perez, Osborn, and Artis (2006) split their sample, for example in 1979, the year of the commencement of the European Monetary System (EMS). Another candidate year is 1984, which many studies date as the start of the Great Moderation in the US. A later date might also make sense due to the fact that the EMU process got on its way in a more accelerated pace after the adoption of the Stability and Growth Pact (SGP) in 1997 or the introduction of the euro in 1999 in the first eleven member economies. However the EMU is a dynamic process that started to affect the corresponding economies possibly at the time of its announcement in the late 1980s. Furthermore, besides being also somehow arbitrary, all other aforementioned choices of sample split period would imply the length of the sub-periods be unbalanced. Therefore we do not consider these other possibilities in this paper and present instead results from 15-year rolling window estimations as an alternative for capturing changes in business cycle dynamics over time in the next section.

### *2.5. Comparison of country-specific models*

A potential drawback of our empirical approach is that six different trivariate models are estimated for measuring the same phenomenon, global and euro area shocks and their dynamic multipliers. In case these estimates differ largely from each other, the effects of common shocks on individual countries can no longer be compared consistently. Moreover, the estimated country-specific shocks must be orthogonal to each other. Non-zero correlations among them would suggest that those are not really country-specific.

We start addressing the foregoing issues by summarising the correlation among the different types of shocks from each country-specific model over the two sub-periods in Table 1. The correlation among the estimated global shocks of the country-specific models is very high in all cases, the lowest co-efficient being 0.94 in the first panel of Table 1. Moreover, global shocks of the country-specific models show a higher correlation than euro area shocks over both sub-periods, as a comparison of the first and second panels of the table points to. The euro area shocks' correlations across the country-specific models are yet still strong, most of them being above 0.8. One noticeable observation in this regard is that the estimated euro area shock of Germany's

Table 1. **Correlations of estimated shocks**

| | Global shock correlations | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Sample: 1970Q1-1990Q2 | | | | | Sample: 1990Q3-2009Q4 | | | | |
| | BEL | DEU | ESP | FRA | ITA | BEL | DEU | ESP | FRA | ITA |
| DEU | 0.99 | | | | | 0.95 | | | | |
| | (0.00) | | | | | (0.02) | | | | |
| ESP | 0.99 | 0.99 | | | | 0.95 | 0.96 | | | |
| | (0.00) | (0.01) | | | | (0.02) | (0.01) | | | |
| FRA | 0.98 | 0.98 | 0.98 | | | 0.98 | 0.96 | 0.96 | | |
| | (0.01) | (0.01) | (0.00) | | | (0.00) | (0.02) | (0.02) | | |
| ITA | 1.00 | 0.99 | 1.00 | 0.98 | | 0.99 | 0.96 | 0.95 | 0.99 | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | (0.00) | (0.02) | (0.03) | (0.00) | |
| NLD | 0.97 | 0.97 | 0.97 | 0.96 | 0.97 | 0.97 | 0.94 | 0.95 | 0.98 | 0.98 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.00) | (0.01) |
| | Euro area shock correlations | | | | | | | | | |
| | Sample: 1970Q1-1990Q2 | | | | | Sample: 1990Q3-2009Q4 | | | | |
| | BEL | DEU | ESP | FRA | ITA | BEL | DEU | ESP | FRA | ITA |
| DEU | 0.81 | | | | | 0.80 | | | | |
| | (0.04) | | | | | (0.04) | | | | |
| ESP | 0.93 | 0.82 | | | | 0.91 | 0.88 | | | |
| | (0.02) | (0.04) | | | | (0.02) | (0.03) | | | |
| FRA | 0.91 | 0.81 | 0.93 | | | 0.93 | 0.85 | 0.96 | | |
| | (0.03) | (0.04) | (0.03) | | | (0.02) | (0.04) | (0.01) | | |
| ITA | 0.88 | 0.72 | 0.84 | 0.87 | | 0.94 | 0.79 | 0.92 | 0.96 | |
| | (0.03) | (0.06) | (0.04) | (0.03) | | (0.01) | (0.04) | (0.02) | (0.01) | |
| NLD | 0.93 | 0.79 | 0.96 | 0.95 | 0.85 | 0.95 | 0.86 | 0.96 | 0.98 | 0.96 |
| | (0.02) | (0.06) | (0.01) | (0.01) | (0.03) | (0.01) | (0.03) | (0.02) | (0.01) | (0.01) |
| | Country-specific shock correlations | | | | | | | | | |
| | Sample: 1970Q1-1990Q2 | | | | | Sample: 1990Q3-2009Q4 | | | | |
| | BEL | DEU | ESP | FRA | ITA | BEL | DEU | ESP | FRA | ITA |
| DEU | –0.24 | | | | | –0.13 | | | | |
| | (0.11) | | | | | (0.12) | | | | |
| ESP | 0.08 | –0.14 | | | | –0.07 | –0.47 | | | |
| | (0.11) | (0.12) | | | | (0.12) | (0.14) | | | |
| FRA | 0.05 | –0.31 | –0.01 | | | –0.12 | –0.43 | 0.11 | | |
| | (0.12) | (0.12) | (0.13) | | | (0.12) | (0.12) | (0.11) | | |
| ITA | 0.14 | –0.24 | –0.08 | –0.11 | | 0.19 | –0.40 | –0.01 | 0.15 | |
| | (0.12) | (0.12) | (0.12) | (0.12) | | (0.13) | (0.13) | (0.12) | (0.14) | |
| NLD | 0.12 | –0.19 | –0.02 | –0.08 | –0.05 | 0.10 | 0.02 | 0.02 | –0.24 | –0.25 |
| | (0.11) | (0.13) | (0.13) | (0.12) | (0.12) | (0.12) | (0.13) | (0.14) | (0.15) | (0.13) |

*Notes:* Standard errors in parentheses; see Brockwell and Davis (1996), p. 232, and further for their computation.
*Abbreviations*: BEL: Belgium, DEU: Germany, ESP: Spain, FRA: France, ITA: Italy, NLD: the Netherlands.

country-specific model often shows a weaker correlation than the correlations across the other models' euro area shocks. Note that the country-specific shock correlations given in the bottom panel of Table 1 are usually statistically insignificant. The exceptions to this rule are the correlations related to Germany's country-specific shocks, in particular: German-Belgian, German-French, German-Italian and to a lesser extent, German-Dutch shocks in first sub-period; German-Spanish, German-French and German-Italian shocks

in the second sub-period. A slight correlation between the Dutch-French and Dutch-Italian country-specific shocks is also registered for the second sub-period.

The reading of this picture is that the empirical framework is quite successful in isolating global shocks from common or individual country euro area shocks. Country-specific shocks are asymmetric to a large extent, that is not spilled over to other countries. A word of caution regarding Germany's country-specific model is needed. Besides country-specific shocks of Germany being related to other country-specific shocks, we also find that German country-specific shocks show some moderate correlation with the euro area shocks of the other country-specific models, the correlation co-efficient ranging between 0.42 (0.37) and 0.51 (0.50) for the first (second) sub-period. Furthermore, some slight correlation between the country-specific shocks of some models and the euro area shocks of others is registered.[16] This mingling of euro area shocks and country-specific shocks across our models suggests that the weight of euro area shocks in the forecast error variance must be interpreted as a lower bound in the following.

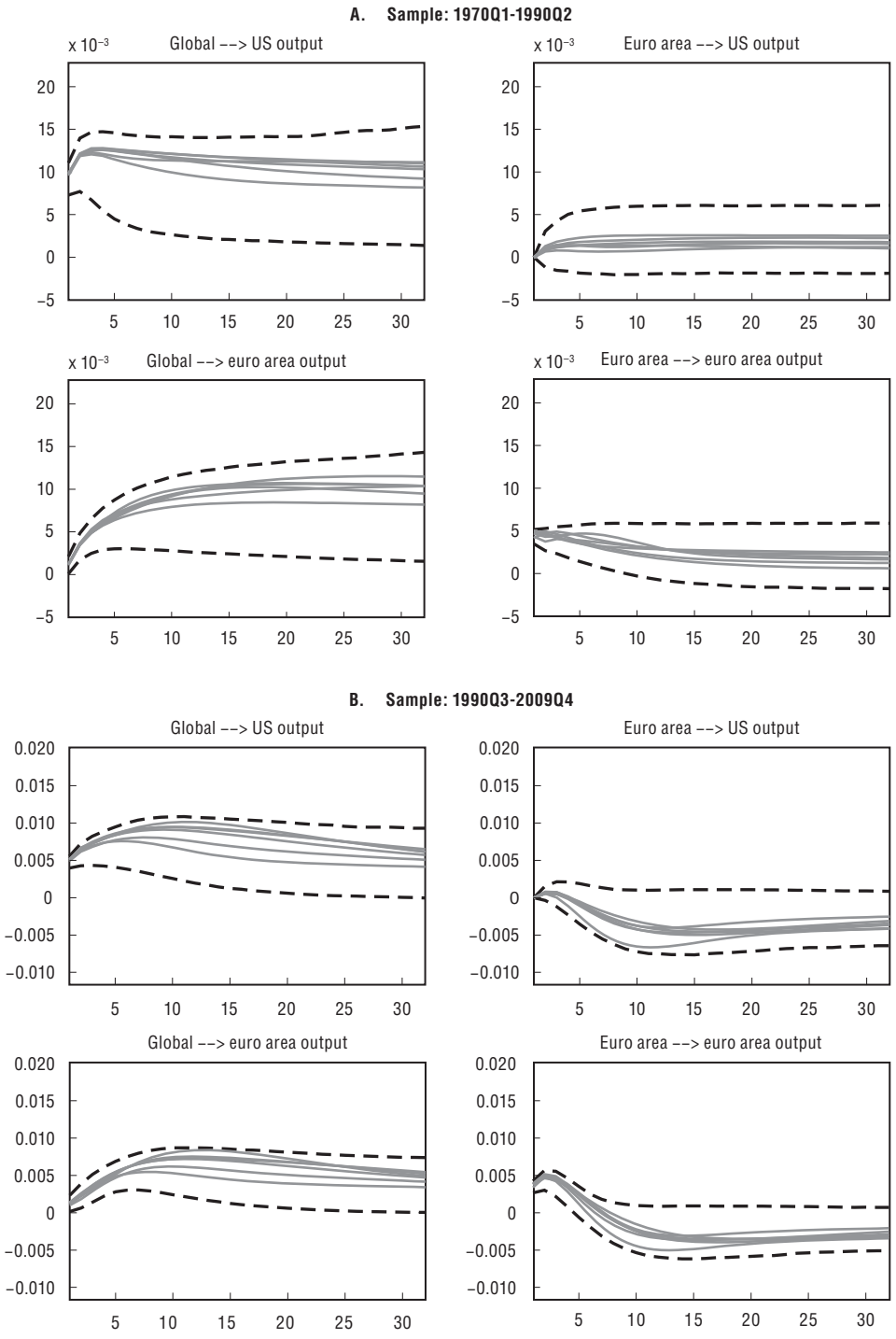
That the mingling of euro area and country-specific phenomena is most evident for Germany must not be surprising given the weight of Germany within the euro area economy. The impact of this country on the economic affairs of the euro area is even larger than its GDP weight due to, for example its strong trade ties with other member economies. The share of Germany in the total exports and imports of France was, for example 0.26, whereas the share of France in Germany's total exports and imports amounted to only 0.16 over the period 2000-2002.[17] Therefore our identification scheme imposing that Germany's country-specific shocks are spilled over to other member economies with a lag of one quarter might be only a rough approximation for Germany. This issue is addressed further in Section 3.1.3.

Another test of the validity of our empirical framework is the comparison of the response of common variables in the country-specific models to common shocks. Figure 1 illustrates the response of the US and euro area outputs to global and euro area shocks in the six trivariate models.[18] Again, in the ideal case all impulse response functions coincide. Unsurprisingly the ideal case does not hold, but the impulse response functions of both variables with respect to both shocks are quite similar across the estimates of the country-specific models. We hence conclude that our empirical framework provides a good approximation for the inspection of the questions of interest posed at the beginning.

## 3. Results

Given the asymmetric character of country-specific shocks in the euro area to a large extent, it would, on the one hand, be an impossible task for the ECB to address the needs of the member economies with a common policy if common shocks were not their main driving force. On the other hand, common shocks could become a destabilising force for the common currency area if the economic structures of the member economies differed widely, manifesting itself in differing responses of the member countries' output to common impulses. In such a case, the forecast error variance of the output differential between the entire euro area and a member economy would be attributable to common shocks. In this section we carry out analyses of the driving forces of the member country business cycles as well as the differential between the euro area output and the output of each member economy. Results are reported and discussed for both discrete and rolling samples.[19]

Figure 1. **Response of US and euro area output to common shocks in trivariate models**




*Notes:* Grey solid lines show the response in the six country-specific models. Black dashed lines show the mean of the 95% Hall confidence interval from the country-specific models.

### *3.1. Discrete sub-samples*

#### *3.1.1. Driving forces of output fluctuations*

The FEVD estimates for the business cycle periodicities are displayed in the two panels of Figure 2 corresponding to the pre-EMU and EMU periods. The graphical information is also summarised for forecast errors of horizon 4, 16 and 32 quarters with 90% Hall confidence intervals in Table 2. Two observations apply to both sub-periods. First, the forecast error variance of output of all member economies is dominated by global shocks for forecast horizons above two years. At the highest forecast horizon we consider, 32 quarters, global shock is the only one that has a significant impact on the output of the member economies in the pre-EMU period. Although that shock dominates the long run also in the EMU period, its impact is weaker than in the pre-EMU period. On the whole, euro area shocks have a significant but relatively small share in the forecast error variance of output of Spain, France, Italy and the Netherlands in the EMU period at the 32-quarters horizon. In the same period and at the same horizon, country-specific shocks have a statistically significant share only in Germany. Recall however that Germany's country-specific shocks may represent euro area phenomena to a certain extent (see Section 2.5).

The second observation that applies to both sub-periods is that country-specific shocks play a significant role in short-run fluctuations but lose their impact over the long run. The share of country-specific shocks at impact is very large for Spain, Italy and the Netherlands in the pre-EMU period, while it decreases to about 0.5 in the EMU period. Country-specific shocks play a larger role in the Spanish economy relative to other member economies for all forecast horizons in the pre-EMU period, possibly due to the political and economic change the country went through during the 1970s and 1980s. Yet the share of those shocks in Spanish output is statistically insignificant at forecast horizons longer than five years.

All in all, we obtain that the very short-run, that is shorter-than-one-year, output fluctuations are dominated by country-specific shocks, whereas global shocks are the main driving force of the long-run component of output in the euro area countries. Euro area shocks on the other hand, gain some importance in the EMU period in comparison to the pre-EMU period, particularly at longer forecast horizons, but are never the dominant driving force of output fluctuations in the six member economies we consider.

The foregoing commonalities over both sub-periods hardly imply that business cycle dynamics stayed the same over time in the member economies. Table 3 reports the change in the shares of shocks in 8-quarters- and 16-quarters-ahead forecast error variance from the pre-EMU to the EMU period. For 8-quarters-ahead forecast errors of output, a substantial increase in the share of global shocks in Belgium, Spain, the Netherlands and a more moderate increase of 12 percentage points in France is registered, whereas Germany and Italy show a strong decline of about 20%. The share of euro area shocks increases somewhat in Germany, Spain and Italy, decreases to some degree in France, stays roughly the same in the Netherlands, and shows a substantial decline of 36% in Belgium. When we turn our attention to 16-quarters-ahead forecast errors, for which the results are given in the second panel of Table 3, a strong decline in the share of global shocks for Germany and Italy as well as a moderate increase in the share of euro area shocks for Germany, Spain and Italy still applies.

We can thus establish that euro area economies are subject to common shocks to a large extent. Furthermore, there has been a change in the dynamics of output as to its driving forces at the business cycle horizon over time. As is so often the case with VAR

Figure 2. **FEVD of output in the member economies**

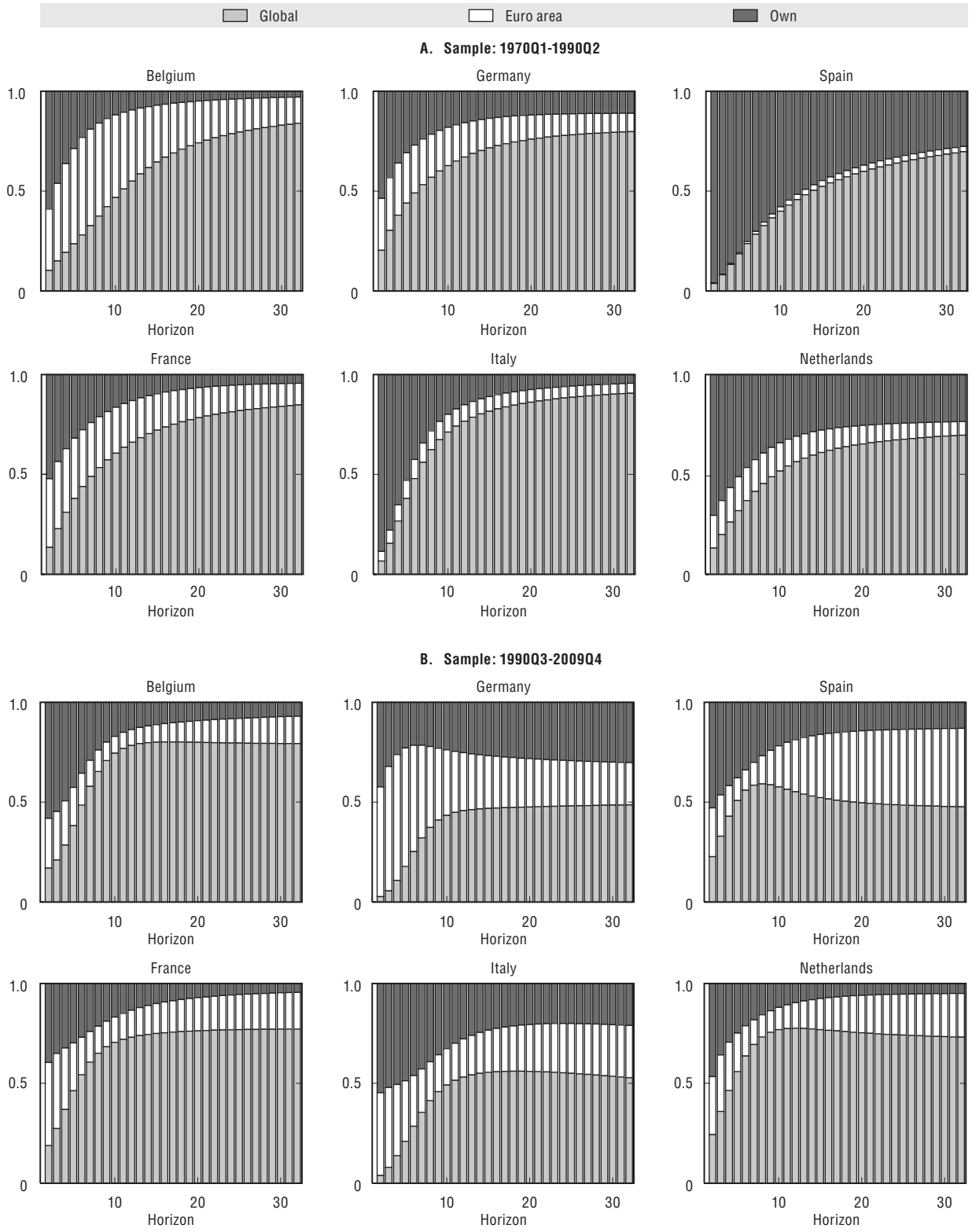


Table 2. **Forecast error variance decomposition of output**

| Horizon | BEL | DEU | ESP | FRA | ITA | NLD |
|---|---|---|---|---|---|---|
| | 1970Q1-1990Q2 | | | | | |
| | Share of global shock in the forecast error variance | | | | | |
| 4 | 0.19 | 0.38 | 0.13 | 0.31 | 0.27 | 0.26 |
| | (0.00, 0.35) | (0.17, 0.60) | (0.00, 0.24) | (0.08, 0.52) | (0.04, 0.44) | (0.05, 0.42) |
| 16 | 0.67 | 0.73 | 0.54 | 0.74 | 0.83 | 0.62 |
| | (0.48, 1.00) | (0.59, 1.00) | (0.26, 0.96) | (0.60, 1.00) | (0.76, 1.00) | (0.48, 1.00) |
| 32 | 0.84 | 0.80 | 0.70 | 0.85 | 0.91 | 0.70 |
| | (0.75, 1.00) | (0.69, 1.00) | (0.51, 1.00) | (0.77, 1.00) | (0.87, 1.00) | (0.56, 1.00) |
| | Share of euro area shock in the forecast error variance | | | | | |
| 4 | 0.45 | 0.26 | 0.00 | 0.32 | 0.08 | 0.17 |
| | (0.23, 0.68) | (0.04, 0.42) | (0.00, 0.01) | (0.09, 0.50) | (0.00, 0.15) | (0.00, 0.29) |
| 16 | 0.27 | 0.14 | 0.03 | 0.17 | 0.07 | 0.11 |
| | (0.00, 0.45) | (0.00, 0.25) | (0.00, 0.06) | (0.00, 0.31) | (0.00, 0.13) | (0.00, 0.18) |
| 32 | 0.13 | 0.09 | 0.03 | 0.11 | 0.05 | 0.07 |
| | (0.00, 0.22) | (0.00, 0.16) | (0.00, 0.05) | (0.00, 0.19) | (0.00, 0.09) | (0.00, 0.11) |
| | Share of country-specific shock in the forecast error variance | | | | | |
| 4 | 0.36 | 0.36 | 0.86 | 0.37 | 0.65 | 0.57 |
| | (0.18, 0.53) | (0.18, 0.51) | (0.77, 1.00) | (0.19, 0.55) | (0.49, 0.90) | (0.41, 0.76) |
| 16 | 0.07 | 0.13 | 0.43 | 0.09 | 0.10 | 0.27 |
| | (0.00, 0.09) | (0.00, 0.21) | (0.04, 0.72) | (0.00, 0.13) | (0.00, 0.15) | (0.03, 0.37) |
| 32 | 0.03 | 0.11 | 0.28 | 0.04 | 0.04 | 0.24 |
| | (0.00, 0.04) | (0.00, 0.19) | (0.00, 0.48) | (0.00, 0.06) | (0.00, 0.06) | (0.00, 0.36) |
| | 1990Q3-2009Q4 | | | | | |
| | Share of global shock in the forecast error variance | | | | | |
| 4 | 0.29 | 0.11 | 0.43 | 0.37 | 0.14 | 0.46 |
| | (0.03, 0.47) | (0.00, 0.18) | (0.23, 0.63) | (0.13, 0.56) | (0.00, 0.25) | (0.24, 0.65) |
| 16 | 0.80 | 0.47 | 0.52 | 0.75 | 0.56 | 0.77 |
| | (0.72, 1.00) | (0.26, 0.70) | (0.28, 0.81) | (0.63, 1.00) | (0.40, 0.87) | (0.64, 1.00) |
| 32 | 0.79 | 0.49 | 0.48 | 0.77 | 0.53 | 0.73 |
| | (0.68, 1.00) | (0.26, 0.76) | (0.20, 0.80) | (0.64, 1.00) | (0.36, 0.85) | (0.56, 1.00) |
| | Share of euro area shock in the forecast error variance | | | | | |
| 4 | 0.22 | 0.63 | 0.15 | 0.31 | 0.36 | 0.24 |
| | (0.01, 0.38) | (0.51, 0.88) | (0.01, 0.26) | (0.14, 0.48) | (0.16, 0.59) | (0.07, 0.39) |
| 16 | 0.09 | 0.26 | 0.33 | 0.15 | 0.22 | 0.16 |
| | (0.00, 0.16) | (0.02, 0.40) | (0.12, 0.59) | (0.00, 0.26) | (0.01, 0.35) | (0.00, 0.28) |
| 32 | 0.14 | 0.21 | 0.39 | 0.18 | 0.26 | 0.22 |
| | (0.00, 0.25) | (0.00, 0.34) | (0.19, 0.73) | (0.01, 0.33) | (0.07, 0.44) | (0.02, 0.41) |
| | Share of country-specific shock in the forecast error variance | | | | | |
| 4 | 0.49 | 0.26 | 0.42 | 0.32 | 0.51 | 0.29 |
| | (0.29, 0.74) | (0.09, 0.37) | (0.24, 0.59) | (0.13, 0.49) | (0.25, 0.75) | (0.17, 0.45) |
| 16 | 0.11 | 0.27 | 0.16 | 0.09 | 0.23 | 0.07 |
| | (0.00, 0.16) | (0.05, 0.44) | (0.00, 0.25) | (0.00, 0.15) | (0.00, 0.34) | (0.00, 0.11) |
| 32 | 0.07 | 0.30 | 0.13 | 0.04 | 0.21 | 0.05 |
| | (0.00, 0.11) | (0.02, 0.52) | (0.00, 0.22) | (0.00, 0.06) | (0.00, 0.32) | (0.00, 0.08) |

*Notes:* 90% Hall confidence intervals are shown in parentheses. Abbreviations: BEL: Belgium, DEU: Germany, ESP: Spain, FRA: France, ITA: Italy, NLD: the Netherlands.

Table 3. **Change in output FEVD shares of shocks in euro area countries**

| | 8-quarters-ahead forecast errors | | | | | |
|---|---|---|---|---|---|---|
| | BEL | DEU | ESP | FRA | ITA | NLD |
| Global shock | 0.28 | –0.20 | 0.26 | 0.12 | –0.21 | 0.28 |
| | (–0.03, 0.68) | (–0.63, 0.04) | (–0.01, 0.69) | (–0.26, 0.44) | (–0.63, 0.07) | (–0.02, 0.57) |
| Euro area shock | –0.36 | 0.19 | 0.12 | –0.12 | 0.10 | –0.04 |
| | (–0.71, –0.11) | (–0.01, 0.57) | (–0.02, 0.24) | (–0.36, 0.18) | (–0.09, 0.33) | (–0.22, 0.15) |
| Country shock | 0.08 | 0.01 | –0.39 | 0.00 | 0.11 | –0.24 |
| | (–0.12, 0.28) | (–0.19, 0.26) | (–0.79, –0.13) | (–0.25, 0.28) | (–0.17, 0.43) | (–0.44, –0.01) |
| | 16-quarters-ahead forecast errors | | | | | |
| | BEL | DEU | ESP | FRA | ITA | NLD |
| Global shock | 0.13 | –0.26 | –0.03 | 0.02 | –0.27 | 0.14 |
| | (–0.29, 0.49) | (–0.76, –0.03) | (–0.45, 0.41) | (–0.46, 0.31) | (–0.72, –0.00) | (–0.23, 0.47) |
| Euro area shock | –0.17 | 0.12 | 0.30 | –0.02 | 0.15 | 0.06 |
| | (–0.43, 0.21) | (–0.10, 0.52) | (0.10, 0.60) | (–0.23, 0.34) | (–0.02, 0.50) | (–0.13, 0.37) |
| Country shock | 0.04 | 0.14 | –0.27 | 0.01 | 0.12 | –0.20 |
| | (–0.17, 0.17) | (–0.09, 0.49) | (–0.77, 0.07) | (–0.28, 0.27) | (–0.16, 0.38) | (–0.51, 0.00) |

*Notes:* 90% Hall confidence intervals are shown in parentheses. Abbreviations: BEL: Belgium, DEU: Germany, ESP: Spain, FRA: France, ITA: Italy, NLD: the Netherlands.

models, the FEVD estimates exhibit a high variance, which is reflected, for example in the wide confidence bands reported in Table 3. This technical limitation prevents us from concluding that euro-area-shocks definitely emerged as a non-negligible source of business cycles in the period after 1990Q2. In Section 3.1.3 we will return to this issue again when we discuss the robustness of our conclusions.

A direct comparison of the foregoing FEVD results with the existing literature is not possible due to differences in sample periods, data frequency or empirical methodology. A tentative comparison could nevertheless provide some useful insights. Giannone and Reichlin (2006) report by means of the model given by (1) and (2) the contribution of country-specific shocks to the annual output growth forecast error at different horizons. The reported contribution for the period 1970-2006 is rather small for Belgium and France at the 5-year horizon with shares of 0.10 and 0.24, respectively. It is however, between 0.39 and 0.66 for the other four member countries in our data set at the same horizon. This barely matches our findings with respect to both of our sub-samples that the impact of country-specific shocks is rather small at such a long horizon.

As mentioned in Section 2.2 the trivariate VAR structure of Perez, Osborn, and Artis (2006) is at first sight more closely related to ours. The differences to our framework is that Perez, Osborn, and Artis use the EU15 output instead of the euro area output, estimate the VAR in first difference (which might lead to biased results due to negligence of co-integration) and impose a Cholesky decomposition. Perez *et al*. report FEVD results for EU15 as well as Germany, France and Italy corresponding to sample periods 1960Q2-1979Q4 and 1980Q1-2002Q1, among others. For both of these sub-samples, the share attributed to global shocks by their models in the FEVD of the foregoing countries' output is less than 0.13 up to a forecast horizon of 20 quarters. The EU15 shocks play, on the other hand, a much more important role in the FEVD of these countries with shares in the forecast error variance that are about 0.41, 0.55 and 0.37 for Germany, France and Italy respectively over 1980Q1-2002Q1. More strikingly however, the same share is above 0.80 for

the EU15. The latter finding is surprising since the three foregoing big member economies see much smaller contributions of EU15 shocks. This might reflect a mingling of global and euro-area-specific phenomena to some extent since EU15 includes the United Kingdom which seems to be more closely related to the US economy than the euro area economy.[20]

Finally, Stock and Watson (2005) report FEVD findings for up to a forecast horizon of 8 quarters by means of a factor-SVAR model for the G7 economies where the log real output enters the model in first difference. The authors carry out estimations for two sub-periods, 1960Q1-1983Q4 and 1984Q1-2002Q4 with quarterly data. Two significant differences to our framework are that Stock and Watson do not consider a euro-area-specific factor/shock although they establish the emergence of a cyclically coherent group of major euro area countries. The authors find that the French cycles are driven almost exclusively by global factors often with shares close to or above 0.90. In contrast, in Germany and Italy the country-specific shocks dominate the output cycles, especially over the periods 1960Q1-1983Q4 and 1984Q1-2002Q4. Spillovers of country-specific shocks is however, not found to be an important driver of cyclical fluctuations in the major euro area economies.

### *3.1.2. Heterogeneity*

After establishing that the member economies' business cycles are driven to a large extent by common sources, particularly global shocks, we now discuss the closeness of the cyclical positions generated by the common shocks. Closeness of cycles is measured by the output differential, the difference between the euro area and a member country output, forecast errors corresponding to business cycle periodicities.[21] We decompose the variance of these forecast errors for detecting their driving forces. The results for the sub-periods (Figure 3 and Table 4) point to country-specific shocks as the force driving the dynamics of output level differentials to a large extent at the business cycle horizon. In the pre-EMU period, country-specific shocks are virtually the only source of the German differential. Moreover, those shocks have FEVD shares above 0.50 at almost all forecast horizons for Spain, France and the Netherlands. As shown in the upper panel of Table 4 however, euro area shocks also exert a relatively smaller but statistically significant influence on the Spanish output differential, while being ignorable for the French and Dutch differentials. For the latter differentials, global shocks are on the other hand, of some minor but statistically significant importance, especially at longer forecast horizons. They thus resemble the behavior of the Italian differential to a large extent which is yet more weakly (strongly) driven by country-specific (global) shocks in the short (long) run than is the case for the French and Dutch differentials. Finally, country-specific and euro area shocks are both main drivers of the Belgian differential with significant FEVD shares at all horizons, whereas the contribution of the global shock to that differential is insignificant in the period before 1990Q3.

The FEVD shares of country-specific shocks exceed 0.50 for Belgium, Germany, Italy and the Netherlands in the EMU period. For all of these countries the shares of global and euro area specific shocks in the output differential forecast error variance are generally insignificant with the exceptions of Germany and Italy at longer horizons (see the lower panel of Table 4). On the other hand, both global and euro area shocks together with their country-specific shocks contribute a lot to the differentials of Spain and France. France in the EMU period is the only example in Figure 3, where euro area shocks even have a roughly equal share as the country-specific shocks in explaining the FEVD of the

Figure 3. **FEVD of output differential**

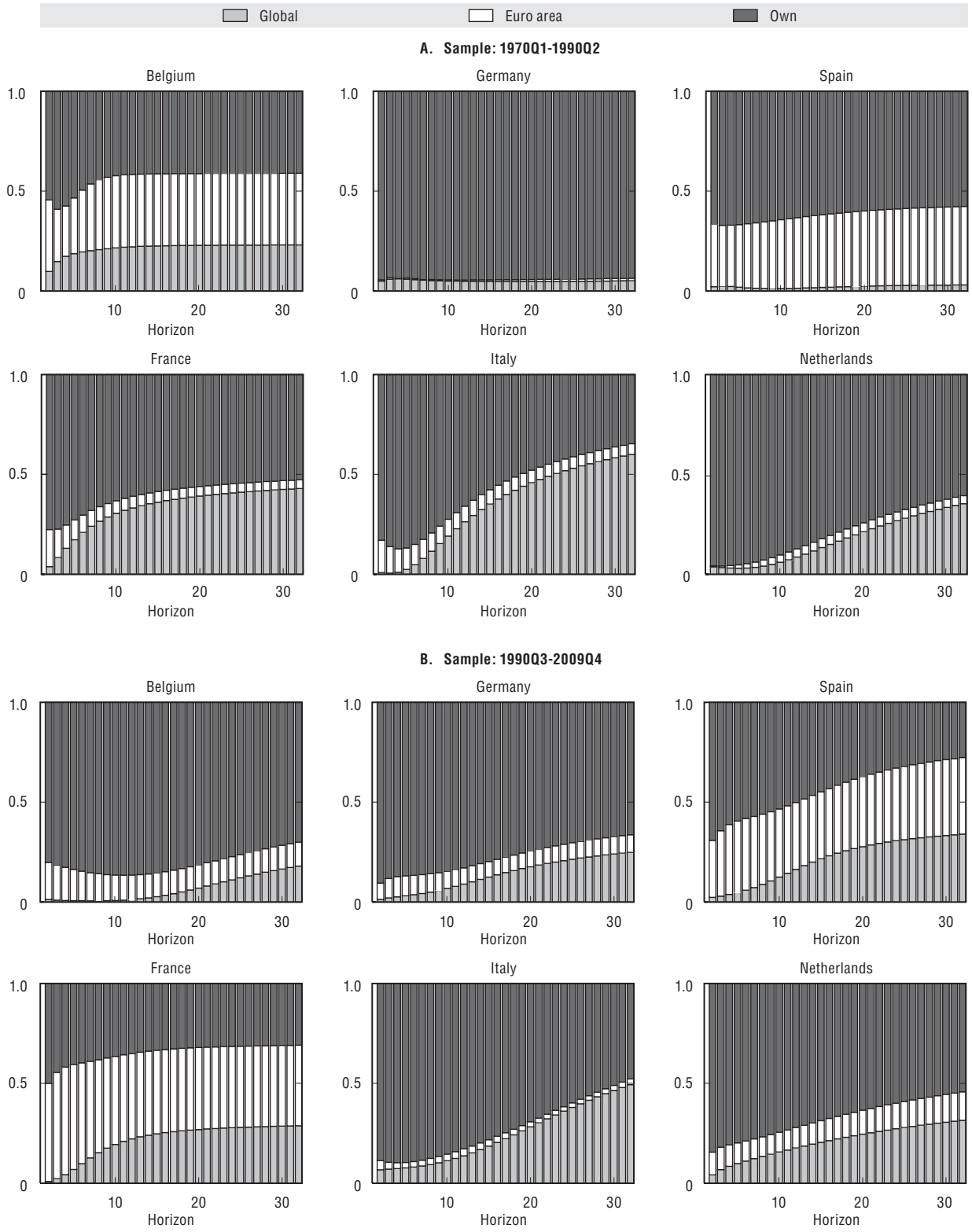


Table 4. **Forecast error variance decomposition of output differential**

| Horizon | BEL | DEU | ESP | FRA | ITA | NLD |
|---|---|---|---|---|---|---|
| | 1970Q1-1990Q2 | | | | | |
| | Share of global shock in the forecast error variance | | | | | |
| 4 | 0.17 | 0.06 | 0.02 | 0.13 | 0.01 | 0.03 |
| | (0.00, 0.32) | (0.00, 0.11) | (0.00, 0.04) | (0.00, 0.23) | (0.00, 0.01) | (0.00, 0.05) |
| 16 | 0.23 | 0.05 | 0.02 | 0.37 | 0.38 | 0.15 |
| | (0.00, 0.40) | (0.00, 0.07) | (0.00, 0.03) | (0.14, 0.68) | (0.14, 0.66) | (0.00, 0.24) |
| 32 | 0.23 | 0.05 | 0.03 | 0.43 | 0.60 | 0.35 |
| | (0.00, 0.41) | (0.00, 0.07) | (0.00, 0.04) | (0.23, 0.79) | (0.45, 1.00) | (0.13, 0.61) |
| | Share of euro area shock in the forecast error variance | | | | | |
| 4 | 0.25 | 0.01 | 0.31 | 0.12 | 0.12 | 0.01 |
| | (0.08, 0.33) | (0.00, 0.01) | (0.11, 0.51) | (0.00, 0.19) | (0.00, 0.20) | (0.00, 0.02) |
| 16 | 0.36 | 0.01 | 0.37 | 0.05 | 0.07 | 0.04 |
| | (0.19, 0.54) | (0.00, 0.01) | (0.16, 0.64) | (0.00, 0.07) | (0.00, 0.10) | (0.00, 0.08) |
| 32 | 0.36 | 0.01 | 0.39 | 0.04 | 0.05 | 0.04 |
| | (0.19, 0.53) | (0.00, 0.01) | (0.22, 0.70) | (0.00, 0.06) | (0.00, 0.08) | (0.00, 0.07) |
| | Share of country-specific shock in the forecast error variance | | | | | |
| 4 | 0.57 | 0.93 | 0.67 | 0.75 | 0.87 | 0.96 |
| | (0.42, 0.82) | (0.89, 1.00) | (0.49, 0.90) | (0.64, 1.00) | (0.81, 1.00) | (0.94, 1.00) |
| 16 | 0.41 | 0.94 | 0.61 | 0.58 | 0.55 | 0.81 |
| | (0.16, 0.60) | (0.94, 1.00) | (0.42, 0.92) | (0.34, 0.84) | (0.32, 0.81) | (0.74, 1.00) |
| 32 | 0.41 | 0.94 | 0.58 | 0.53 | 0.35 | 0.61 |
| | (0.17, 0.60) | (0.93, 1.00) | (0.37, 0.88) | (0.25, 0.76) | (0.01, 0.51) | (0.41, 0.85) |
| | 1990Q3-2009Q4 | | | | | |
| | Share of global shock in the forecast error variance | | | | | |
| 4 | 0.01 | 0.03 | 0.04 | 0.04 | 0.07 | 0.08 |
| | (0.00, 0.01) | (0.00, 0.05) | (0.00, 0.07) | (0.00, 0.08) | (0.00, 0.14) | (0.00, 0.16) |
| 16 | 0.03 | 0.14 | 0.23 | 0.25 | 0.20 | 0.21 |
| | (0.00, 0.05) | (0.00, 0.24) | (0.00, 0.43) | (0.04, 0.46) | (0.00, 0.38) | (0.00, 0.39) |
| 32 | 0.18 | 0.25 | 0.34 | 0.29 | 0.49 | 0.31 |
| | (0.00, 0.31) | (0.02, 0.46) | (0.09, 0.64) | (0.08, 0.52) | (0.25, 0.91) | (0.00, 0.59) |
| | Share of euro area shock in the forecast error variance | | | | | |
| 4 | 0.17 | 0.10 | 0.35 | 0.54 | 0.03 | 0.11 |
| | (0.00, 0.29) | (0.00, 0.19) | (0.16, 0.57) | (0.37, 0.79) | (0.00, 0.05) | (0.00, 0.20) |
| 16 | 0.12 | 0.08 | 0.34 | 0.42 | 0.03 | 0.11 |
| | (0.00, 0.19) | (0.00, 0.13) | (0.13, 0.59) | (0.18, 0.61) | (0.00, 0.05) | (0.00, 0.20) |
| 32 | 0.12 | 0.09 | 0.38 | 0.40 | 0.03 | 0.14 |
| | (0.00, 0.19) | (0.00, 0.16) | (0.18, 0.69) | (0.17, 0.60) | (0.00, 0.05) | (0.00, 0.27) |
| | Share of country-specific shock in the forecast error variance | | | | | |
| 4 | 0.83 | 0.87 | 0.61 | 0.42 | 0.90 | 0.81 |
| | (0.72, 1.00) | (0.78, 1.00) | (0.40, 0.82) | (0.24, 0.61) | (0.83, 1.00) | (0.69, 1.00) |
| 16 | 0.85 | 0.79 | 0.43 | 0.33 | 0.77 | 0.68 |
| | (0.80, 1.00) | (0.67, 1.00) | (0.05, 0.66) | (0.13, 0.49) | (0.62, 1.00) | (0.47, 1.00) |
| 32 | 0.70 | 0.66 | 0.28 | 0.31 | 0.48 | 0.54 |
| | (0.56, 1.00) | (0.44, 0.98) | (0.00, 0.44) | (0.09, 0.45) | (0.12, 0.75) | (0.22, 0.91) |

*Notes:* 90% Hall confidence intervals are shown in parentheses. Abbreviations: BEL: Belgium, DEU: Germany, ESP: Spain, FRA: France, ITA: Italy, NLD: the Netherlands.

differential. The same applies also to Spain for forecast horizons longer than roughly five years.

A striking observation from Figure 3 is that the contribution of common shocks to forecast error variance often increases with the forecast horizon. This observation applies with respect to the impact of global shocks in all countries in the EMU period. The relative importance of those shocks differs, however, across the member economies. The share ranges between 0.18 for Belgium and 0.49 for Italy at the forecast horizon of 32 quarters. This observation points to a relatively more important role of structural differences across the member economies in explaining the long-run differences. The short-term, particularly up to three years, is, however, clearly dominated by country-specific shocks with the exception of France.

The foregoing results deviate from the ones for the annual output growth differentials in Giannone and Reichlin (2006) by attributing a smaller weight to country-specific shocks in explaining the differentials. According to the model of Giannone and Reichlin, the Belgian and Spanish differentials can be totally attributed to the country-specific shocks of those countries, whereas shares of those shocks above 0.96 are observed for Germany, Italy and the Netherlands. The French differential, for which the forecast error share of country-specific shocks amounts to merely 0.66, is the only exception to this rule. It is worth noting that the analysis of Giannone and Reichlin covers the period 1970-2003 with annual data.

Note that the analysis of this subsection is not informative about the size of the differentials. When these are small, their composition is obviously less important for the policy makers. In such a case European policy makers may focus only on the size of the business cycle when shaping the policy and may neglect the decomposition. The rolling window analysis below will give information on the evolution of the size of the differentials. The foregoing discrete sample analysis only suggests that common, particularly global, shocks do not seem to be a major source of business cycle heterogeneity in the euro area.

### 3.1.3. *Robustness*

There are several issues which might influence the hitherto conclusions on the business cycle dynamics of the euro area. One concern related to the specification of the country-specific VARs is the lag order of the models. The pre-EMU period results are generally not sensitive to setting the lag order higher. A few EMU period results show on the other hand, a certain degree of sensitivity. In particular, the share of euro area shocks increases for Germany and Spain, the share of country-specific shocks increases for Spain and Italy, whereas the share of global shocks decreases for Germany, Spain and Italy when the lag order is set to four instead of two as in our baseline case. However it must also be remembered that the estimation uncertainty is considerably larger with the higher lag order, given the shortness of the sample period. There are 18 more VAR co-efficients to be estimated when two more lags are added to a trivariate VAR.

Estimating VARs in levels instead of vector error correction models (VECMs) where co-integration is handled explicitly is another concern regarding the model specification. In order to account for this possibility, we re-estimate the reduced-form country-specific models as VECMs with one co-integrating relationship between the US and euro area output. The estimation is carried out in two steps. In the first step the co-efficients of the co-integrating equation are estimated using the Johansen approach. The estimation of the

VECM is carried out in the second step, where the error correction term from the first step is treated as an exogenous variable and the remaining model co-efficients are estimated by OLS. The FEVD estimates of output, which such a VECM underlies, for the two sub-periods are given in Figure 4. These estimates are broadly in line with the basic estimates reported in Figure 2. Some differences are yet visible. The latter model estimates that the global shocks have a smaller weight in the long run fluctuations in comparison to the basic models' predictions. For example, with the exception of France, a larger role is attributed in the forecast error variance to country-specific shocks during the pre-EMU period. The EMU-period results are also qualitatively very similar across the models with and without co-integration. The most striking difference is that the model in which co-integration is explicitly taken into account attributes a larger share to global shocks and lower share to country-specific shocks for the outputs of Germany, Spain and Italy. Finally, the role played by country-specific shocks in the dynamics of output differentials is much bigger according to the co-integration model over both sub-periods of interest.

Up to now, we have labeled the first shock in the country-specific VARs as a global shock. As has already been argued in Section 2.2 however, this shock might at least partly represent country-specific shocks of the US economy which do not affect the rest of the world. Therefore, substituting the US output with the OECD output in the models might be more appropriate for detecting a global shock. Note that in such a case the impact effects of the euro area and the underlying country-*i* shocks must be limited to the GDP shares of them in the total OECD economy. Accordingly, the matrix of the contemporaneous multipliers given in equation (6) for the system with US output, should become

$$\Phi_0 = \begin{bmatrix} \Phi_{11,0} & p_{EA}\Phi_{22,0} & p_{i,OECD}\Phi_{33,0} \\ \Phi_{21,0} & \Phi_{22,0} & p_i\Phi_{33,0} \\ \Phi_{31,0} & \Phi_{32,0} & \Phi_{33,0} \end{bmatrix}$$

where $p_{EA}$ stands for the output share of the euro area within the OECD economy, and $p_{i,OECD}$ is the output share of country *i* within the OECD economy. The FEVD of output of the member economies for this system is given in Figure 5. The difference to the benchmark FEVD estimates corresponding to the pre-EMU period is small, while somewhat more important differences with respect to the EMU period are observed. In particular, the model with OECD output attributes a larger weight to country-specific shocks in Germany and Spain in the period after 1990Q3 than the basic model. Furthermore, a smaller role for euro area shocks in Germany, Spain and Italy in the latter period is also observed in comparison to the benchmark model. Findings with respect to output differentials are in general similar to the ones from the basic model.

In Section 2.5, we had pointed to some mingling between the country-specific shocks of Germany and the euro area shocks estimated via other country-specific models. Germany is often labeled as the engine of the EMU and has arguably stronger connections to the rest of the world than other euro area member countries due to its export-oriented growth strategy. Therefore, modification of our benchmark model in order to take the foregoing issues into consideration may be a useful exercise. We consider three alternative strategies: *i)* adding the German output to the benchmark country-specific models as the third variable and ordering the country variable as the fourth variable; *ii)* substituting the euro area output with the German output; and *iii)* ordering the euro area output before the US output. The specification *i)* might allow an orthogonalisation of euro area shocks from German shocks, but could lead to multicollinearity problems due to the strong relatedness

Figure 4. **FEVD of output in the member economies when the underlying reduced-form model is VECM with co-integration rank one**

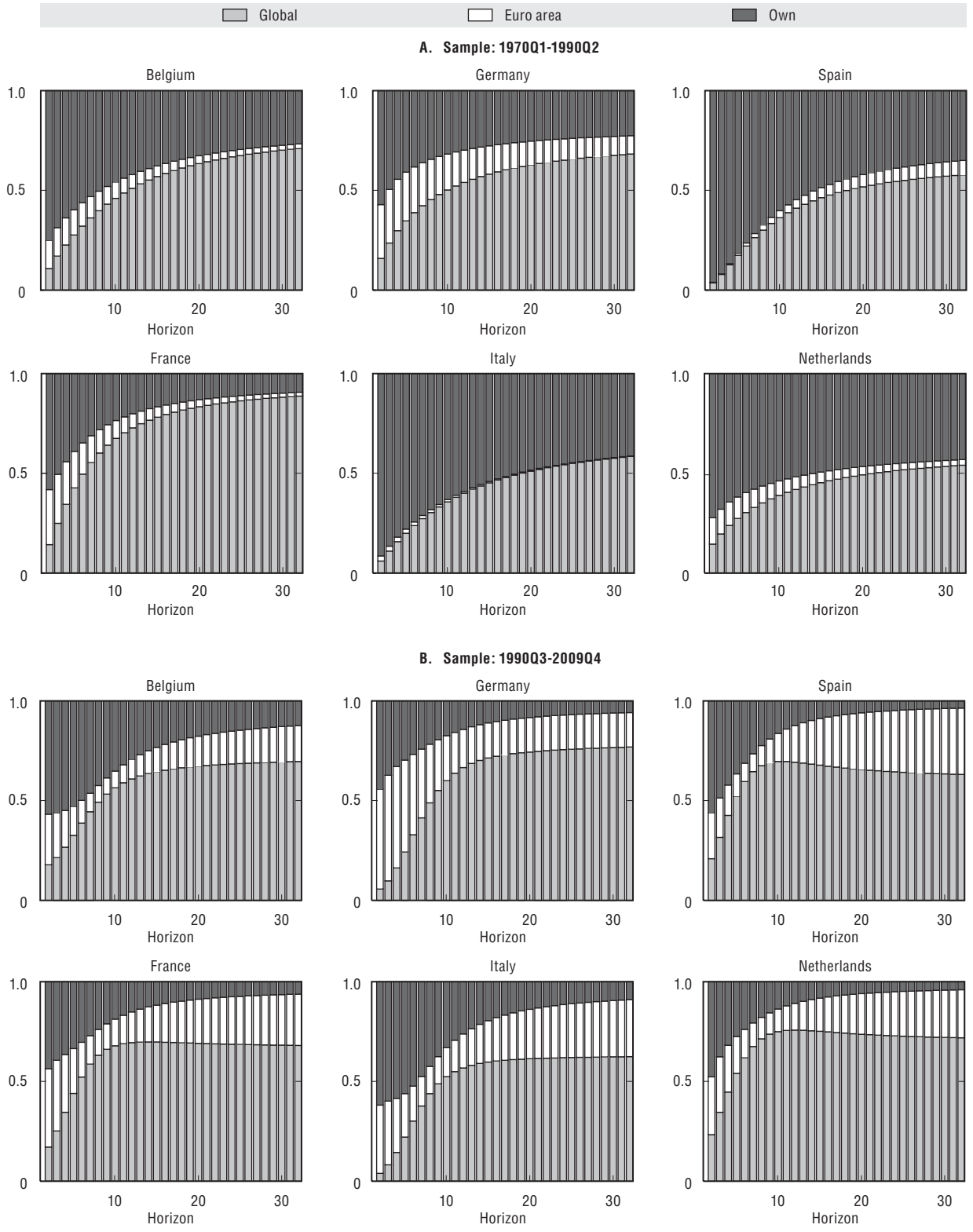
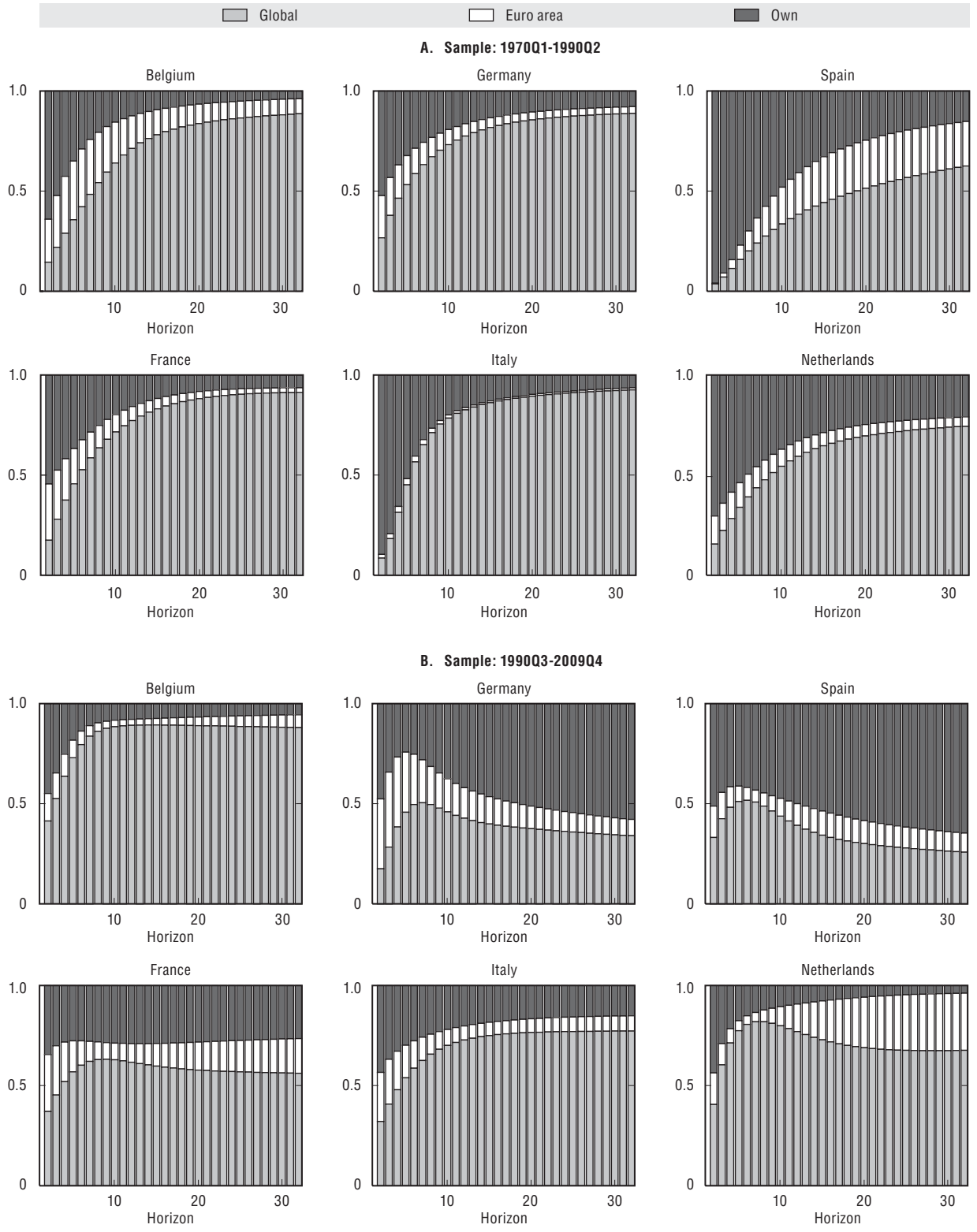


Figure 5. **FEVD of output in the member economies when the US output in the original model is substituted with the OECD output**



of the German and euro area economies. That specification leads to higher estimated shares of euro area shocks in the member country business cycles. However, the share of these shocks on the US economy is also implausibly high in the EMU period. The same finding applies also to specification *ii)* and we therefore discard specifications *i)* and *ii)* as implausible. The same critique does, on the other hand, not apply to specification *iii)* which attributes a somewhat more important role to the euro area shocks in the member country business cycles than the benchmark model.

To sum up, our hitherto findings are robust with respect to the main driving force of business cycles in the member economies in the pre-EMU period: global shocks dominate the output fluctuations. Different model specifications imply the same also for the EMU period, albeit with occasionally smaller shares of global shocks for the German, Spanish and Italian output cycles. Given the possible mingling of euro-area-specific with country-specific phenomena discussed above, we see the reported shares of euro area shocks in output forecast errors as a minimum for the member economies. The output differentials with respect to the euro area are driven, on the other hand by country-specific shocks to a large extent across almost all modifications of the benchmark model and a somewhat significant role of global shocks in the long run is also obtained.

### *3.2. Rolling regressions*

The hitherto presented results were based on the assumption of a discrete break in the data in 1990Q2. Changing the break date in the data could lead to changes in some of the results, and there are other potential break dates that could have been chosen as we already discussed in Section 2.4. We should note that our previous conclusions generally hold under other break dates. However, each euro area member country possesses its own peculiarities in addition to common features. In order to capture these peculiarities, we estimate in this section SVARs of the kind described by (5) and (6) for each member country in rolling windows of 15 years (60 quarters). Hence the estimation windows cover the periods 1970Q1-1984Q4, 1970Q2-1985Q1, and so on until the last estimation window covers the period 1995Q1-2009Q4. Note that in this way we are able to display the developments after the beginning of the Great Moderation, which is often dated to 1984 for the US. Moreover, our last estimation window corresponds roughly to the completion of the single market as foreseen by the Single European Act. It also excludes some peculiarities of the period in the early 1990s such as the German reunification and the ERM crisis (which affected Italy in particular). Figures 6 and 7 displays results from rolling window estimations, each statistic is reported at the quarter that is at the center of the corresponding estimation window.

#### *3.2.1. Driving forces of output fluctuations*

In the two panels of Figure 6, we display the level as well as the decomposition of 12-quarters-ahead forecast error variance of output in the member countries. Figure 6.A shows the level of that variance. A moderation of cyclical activity took place in all member economies in the decades prior to the recent recession according to this picture. The time variation in the forecast error variance is not one that gradually moves towards lower levels during the Great Moderation decades. Furthermore, the decline pattern varies substantially across the countries. This suggests that splitting the sample at any break date would bring certain problems with it. On the other hand, the decline pattern of output

forecast error variances is also implied by our previous discrete-sample estimations which have not been reported in this paper.

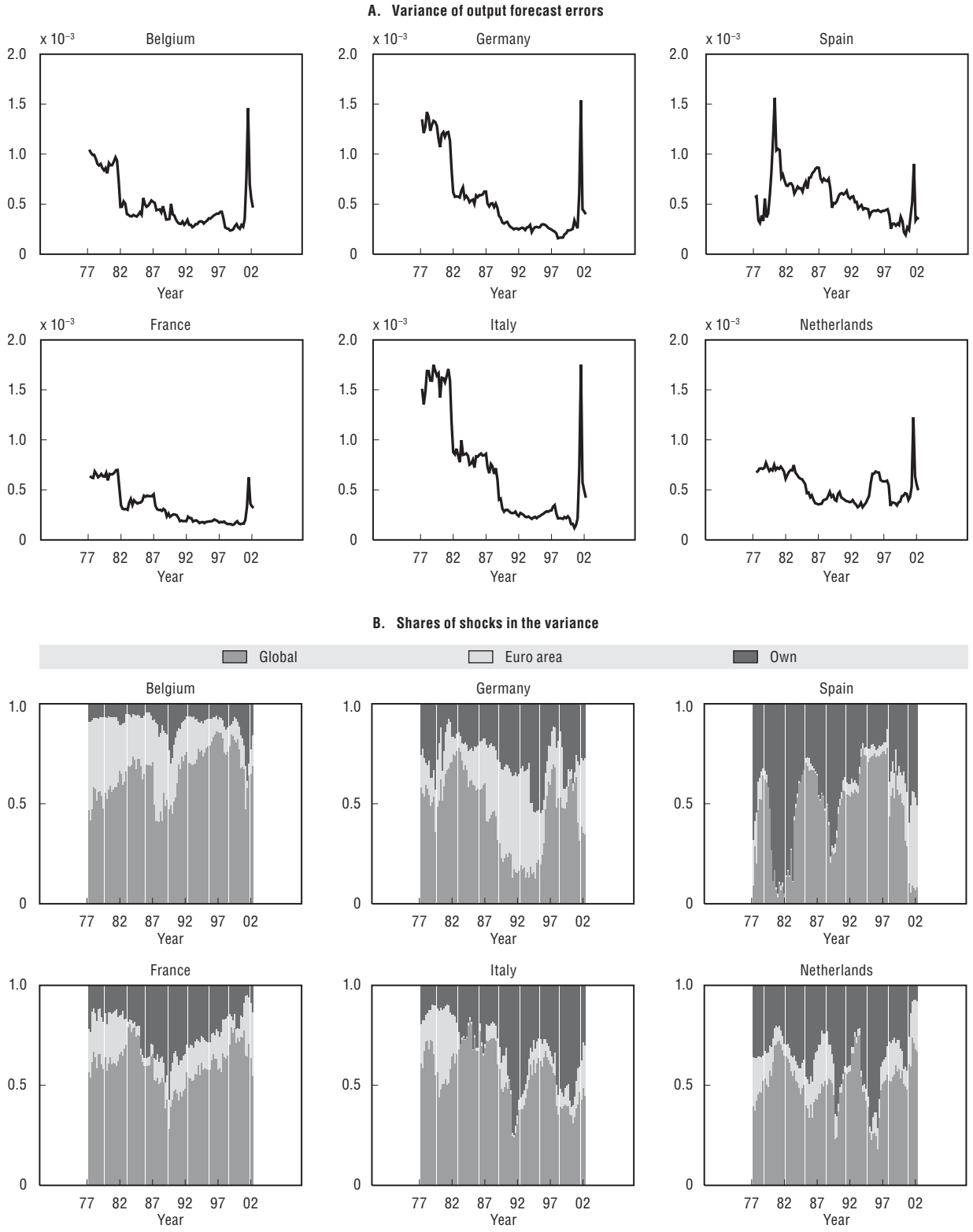
A hike in the forecast error variance occurs for all countries in the window covering the data from 1994Q2-2009Q1, which can obviously be traced back to the latest concurrent recession in the member countries. The variance declines strongly in the last three rolling windows following the hike. Whether an adjustment back to the pre-crisis levels takes place in the future, on the other hand, remains to be seen. In the last window of the current data set, 1995Q1-2009Q4, the level of 12-quarters-ahead forecast error variance is generally much closer to what it was before the recession, that is at the end of the Great Moderation period.

The shares of shocks in the 12-quarters-ahead forecast error variance (Figure 6) are roughly in line with the sub-period results given in Figure 2. Global shocks used to be the dominant driving force of output forecast error variance in the member countries in many sub-periods. One important exception to this statement is the situation in Spain until the 1990s, where country-specific shocks dominate the output forecast error volatility. This finding is indeed not so surprising given the vigorous political and structural changes the country went through in the 1970s and 1980s. Another exception is Italy in the windows around the ERM crisis of the early 1990s.

Euro area shocks are of some significant importance in Germany in the rolling windows centered roughly between 1987 and 1997, in early windows for Belgium and in later windows for Spain. The importance of those shocks has however, been limited in most cases.[22] At this point, it is in order to discuss the impact of the chosen window length on our rolling window results. There is no generally accepted criteria among macroeconomists as to the convenient window length. Perez, Osborn, and Artis (2006) set the window length, for example, to 9 years for trivariate models, Blanchard and Galí (2008) prefer a window length of 10 years for bivariate models. According to our estimations, 15 years seems to be a minimum length for reliable estimates in the trivariate case. However it becomes much harder to capture the peculiarities of each window. Lower window lengths are likely to increase the estimation uncertainty for trivariate models. When we nevertheless try out shorter rolling windows, we obtain that a larger share is attributed to euro area shocks in the 12-periods-ahead forecast error variance for many estimation windows. The general pattern is however, roughly similar to what we present in Figure 6. Not surprisingly, 12-years estimates, for example, are much closer to the original 15-years estimates than the 9-years estimates. Moreover, global shocks are still dominant in many estimation windows.

Perez, Osborn, and Artis (2006) provide 9-years rolling window estimates of FEVD for Germany, France and Italy, which differ from ours significantly. In particular, as it has already been discussed for the discrete-sample estimates, the estimates of Perez *et al*. attribute a dominant role to country-specific shocks for Germany and Italy and to EU15 shocks in many windows for France, while the shares of global shocks turn out small and not seldom negligible for the three major economies of the euro area. Almost all variation in the EU15 output is, on the other hand due to EU15 shocks, which is clearly at odds with our findings. As we have argued above, the results in Perez *et al*. might be mingling particularly global and euro-area-specific phenomena substantially.

Figure 6. **Variance decomposition of 12-quarters-ahead output forecast errors over 15-year rolling windows**



### *3.2.2. Heterogeneity*

We show the evolution of the 12-quarters-ahead forecast error variance of output differentials in Figure 7, which is analogous to Figure 6. A decline is also observed in the level of this variance in Figure 7 for all member economies. This can be interpreted as that the cyclical disparity has diminished between the euro area and individual member economies over the course of the years, although as discussed in the introduction, the literature is ambiguous as to an increase in business cycle synchronisation. Belgium and France are the countries that show smallest cyclical disparities with the euro area over many rolling windows, followed by Germany and Italy, while the disparity corresponding to the Netherlands is somewhat higher. Moreover, the evolution of the forecast error variance of the Dutch differential shows more volatility than Belgian, French, German and Italian differentials. The disparity corresponding to Spain is much larger in comparison to the other member economies in the early estimation windows, whereas it diminishes strikingly in recent windows. Finally, some increase in the disparities can be established following the recent recession, while the increase has been rather small and negligible relative to the increase in the size of the forecast error variances reported in Figure 6.

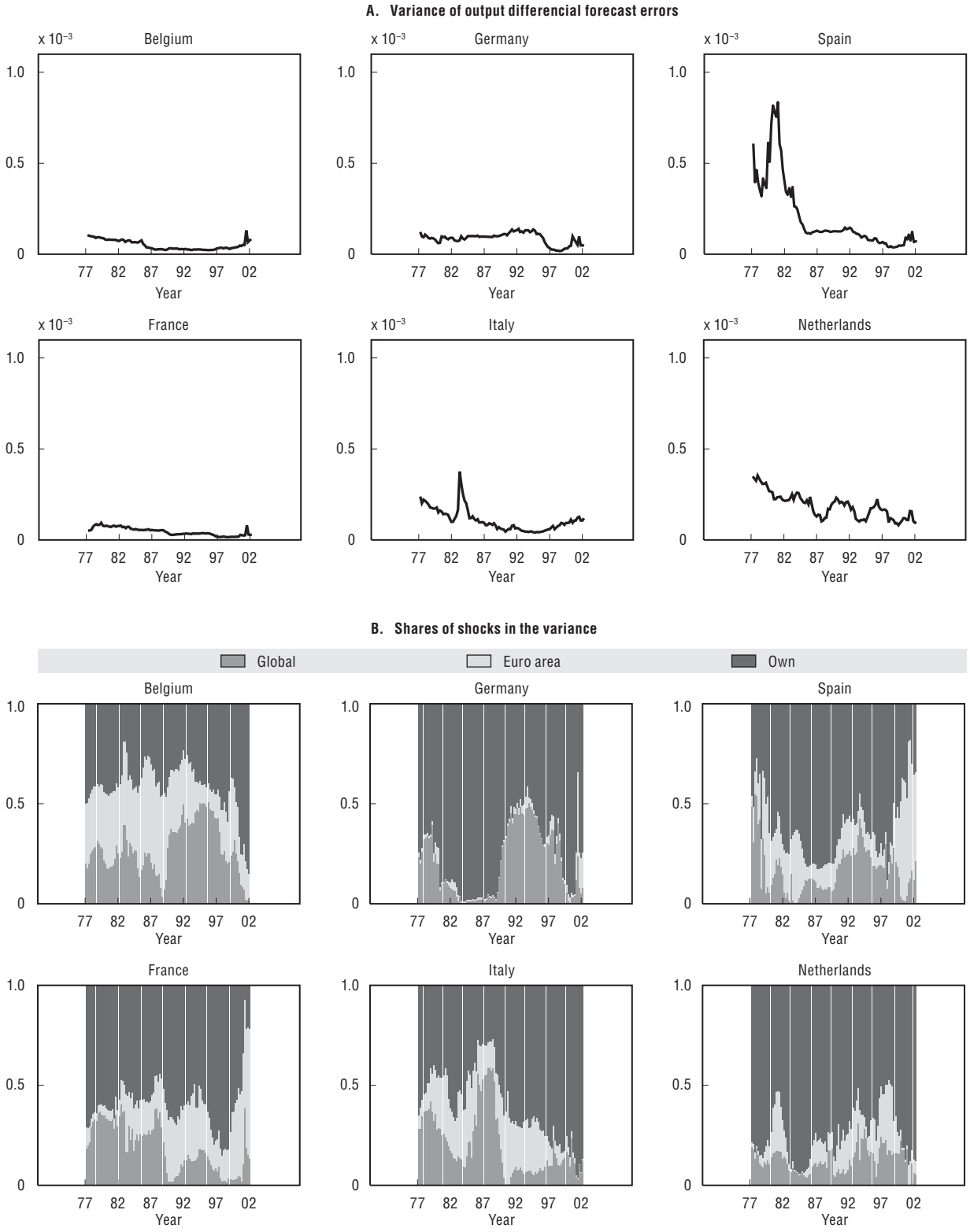
A commonality with our previous results based on discrete samples is that country-specific shocks are an important, and often the most important driving force of 12-quarters-ahead output differential forecast errors in many rolling windows, as suggested in Figure 7. This is particularly so for Germany, Spain, Italy, the Netherlands and, abstracting from the most recent periods, France. For the differential of Belgium can be established, on the other hand, that euro area shocks also played a non-negligible role in its forecast error variance at the 12-quarter horizon. Given that this country's differential used to be also one of the smallest in many estimation windows, the latter finding is probably not problematic. The impact of global shocks on the differential forecast error variance is found to be negligible in many windows.[23] To sum up, our general finding suggests that heterogeneity can to a large extent be traced back to asymmetric shocks, while common shocks lead to only moderate disparities between the cycles of the member economies and the entire euro area. When this rule does not apply as in the case of, for example Belgium and France, the cyclical disparity is rather small.

## 4. Concluding remarks

In this article, we have investigated various aspects of the business cycle dynamics in the euro area using the SVAR methodology. Given the concurrence of the globalisation and the EMU phenomena within the sample period we have covered (1970-2009), we have employed an empirical framework which contains both global and euro-area-specific shocks as potential common sources of output fluctuations in the member economies in addition to their own country-specific shocks. This aspect had been neglected in many studies which emphasised either only global or only common euro area phenomena, but did not incorporate both within one framework.

Our results have been reported for sub-samples corresponding to pre-EMU and EMU periods, defined as 1970-1990 and 1990-2009, as well as for 15-year rolling windows in order to capture time variation in business cycle dynamics of euro area member economies. We have confined our analysis to two core issues: the driving forces of member countries' business cycles and the source of business cycle heterogeneity in the euro area. We have computed forecast error variance decompositions, the most widely used tool for

Figure 7. **Variance decomposition of 12-quarters-ahead output differential forecast errors over 15-year rolling windows**



business cycle analysis in the SVAR framework, corresponding to business cycle periodicities in order to address these issues.

Our findings on the sources of business cycle fluctuations can be summarised as follows. Global shocks play an important role in the output fluctuations of the member economies, whereas common euro area shocks can be attributed only a limited importance. Country-specific shocks contribute to the forecast error variance significantly at shorter forecast horizons, with their impact decreasing at longer forecast horizons. Although discrete sub-sample as well as rolling window estimations point to time-variation and cross-country variation in the estimates, the foregoing pattern applies to most of the results presented in the paper. A number of robustness checks with respect to VAR lag order, rank of co-integration, using the US output as a proxy for the global output and the special position of Germany within the euro area confirm this view. In particular, the dominant role of global shocks in the output fluctuations over the period 1970-1990 is a robust result. While the same view can be asserted for Belgium, France and the Netherlands also with respect to the period 1990-2009, the FEVD results corresponding to Germany, Spain and Italy show some variation across the different model specifications in that period. The benchmark FEVD estimates point to a still dominant but somewhat less important role of global shocks in the latter countries than in the former ones over 1990-2009. When co-integration is explicitly taken into account however, that discrepancy disappears, that is all member economies' output fluctuations turn out to be driven by global shocks to a high degree. In the models corresponding to Germany and Spain where the US output is substituted by the OECD output on the other hand, country-specific shocks are found to have a significant impact together with global shocks at the longer horizon of the business cycle.

The findings of this paper point to a slight mingling of euro area shocks with the country-specific shocks across the estimated models, suggesting that the reported FEVD shares of euro area shocks can be seen only as a lower bound and the actual shares are possibly somewhat higher than what we have reported. This nevertheless, barely changes the conclusion that global shocks are the main driver of business cycle fluctuations in the euro area member economies. The label "global" is arguably more reasonable than "US" for the first shock of the model since most of the trade of the euro area countries occurs among each other. In 2008 the US accounted for 12% of exports and 9% of imports of the euro area according to Eurostat. Moreover, the share of exports to and imports from the European Union, of which euro area countries constitute a very large part, in the total of the exports and imports of the US has also shown a decreasing trend since the 1970s. Given the decreasing trade shares between the US and the euro area (or the EU) and that trade is known to be an important transmission channel of business cycles, the large FEVD shares of the global shock makes labeling the first shock as "global" and not "US" all the more plausible. Therefore, an effort aimed at a global monetary policy co-ordination by the ECB seems to be a sensible policy choice.

Heterogeneity, measured by the differential between the output of the entire euro area and each member economy, is largely driven by asymmetric shocks in the two discrete samples considered, while it could be traced back to euro area shocks particularly in Belgium, Spain, France and the Netherlands according to the rolling window estimates. Most strikingly, global shocks do not contribute importantly to the discrepancy between the entire-euro-area and individual-country cycles although they appear to be the main driving force of cyclical fluctuations in the member economies. This implies that global

shocks do not lead to heterogeneous responses of member countries' output at the business cycle frequencies. Given this finding and the relatively small size of the output differential forecast errors in comparison to output forecast errors, a relatively high share of euro area shocks in the FEVD of some output differentials is not a hindrance for a successful operation of the euro area.

Finally, that we do not find a significant role for shocks stemming from the euro area in business cycle dynamics of the member economies is in contrast with studies that emphasis euro-area-specific business cycles in isolation from global phenomena. As to the endogeneity of the OCA criteria, the share of common shocks, global or euro area, has not increased in recent periods where the EMU process accelerated. However, the decline in cyclical disparity of the cycles that we have reported in this paper might, at least partly be due to an endogeneity of the OCA criteria. The resolution of the issue is left to future research.

### *Notes*

1. The optimum currency area (OCA) theory sets some guidelines on the conditions that should be fulfilled by a successful monetary union. See Dellas and Tavlas (2009) for a recent review on the OCA theory.
2. Bovi (2005) emphasises the importance of comparing the degree of globalisation and Europeanisation. Kose, Otrok, and Prasad (2008) and Bayoumi and Bui (2010) consider a euro area factor in their model, but their empirical frameworks differ from ours significantly. Moreover, both studies contain results for only regions, that is the euro area, but not for individual member countries as in this study. Many studies do, on the other hand, not address the issue. Stock and Watson (2005) for example, who claim the emergence of a euro area group within the G7, do not attempt to estimate a distinct euro area factor in their factor-SVAR model. Giannone and Reichlin (2006) estimate SVARs with only a euro area shock as the common shock, excluding a global component. Such models may mix up global and euro area phenomena by construction.
3. Note that other synchronisation measures have also been proposed in the literature. Mink, Jacobs, and de Haan (2007) suggest for example, two measures of synchronicity and co-movement. The concordance index in Harding and Pagan (2002) is another example. We do not report findings from studies using these and other measures, since our general conclusion does not change: results on changes in business cycle synchronisation over time are mixed.
4. See for example, Canova (1998).
5. See for example, Harvey and Jaeger (1993) and Benati (2001).
6. Massmann and Mitchell (2004) suggest using the root mean squared difference between the euro area cycle and the cycle of each member country, while Giannone and Reichlin (2006) investigate output differentials, both in terms of level and growth rate, in a similar spirit.
7. See Stock and Watson (2005) for some references on this literature. Cabanillas and Ruscher (2008) explicitly focus on the Great Moderation in the euro area.
8. Using GDP shares instead of population shares does not have a significant impact on our conclusions.
9. This applies particularly to industrialised countries, see for example, Stock and Watson (2005) and Kose, Otrok, and Prasad (2008).
10. Giannone and Reichlin (2006) use the term worldwide shock, while Perez, Osborn, and Artis (2006) label the corresponding shock US shock.
11. See also our discussion in Section 2.5 on the correlation among the country-specific shocks.
12. See Stock and Watson (2005) for a discussion of the advantages and disadvantages of various types of empirical models for international business cycle analysis.
13. Forecast error dynamics are typically considered in the conventional SVAR literature when the interest lies in detecting the driving forces of business cycles.

14. Note that OLS estimation of co-integrated systems in levels is asymptotically consistent; see pp. 369-70 in Lütkepohl (1993).
15. The data source is the database of the *OECD Economic Outlook*, No. 87.
16. These results are not collected here in tables in order to save space.
17. See Table 2 in Bussiére, Chudik, and Sestieri (2009). The numbers for Italy, Spain and the Netherlands were 0.25/0.11, 0.33/0.13 and 0.21/0.09, respectively.
18. The Hall confidence intervals in this figure as well as in the rest of the paper are computed along the lines described in Appendix D.3 of Lütkepohl (2005).
19. The MATLAB codes and data are available from the author upon request.
20. See Stock and Watson (2005) and Bovi (2005) on the emergence of cyclically coherent English-speaking club in recent decades.
21. It is trivial to add to the model in (5) the output differential between the entire euro area and the member country *i*, which is only a linear combination of the second and third variables of the model.
22. We do not report confidence intervals in the paper in order to save space. Note that these are somewhat large as in the case of the ones reported in Section 3.1. It turns out that the share of global shocks are significant in almost all windows for all countries. One significant deviation from this rule is Germany for which we find insignificant shares in the windows centred between roughly 1988 and 1996. Estimated shares of euro area and country specific shocks are on the other hand, insignificant for most of the windows considered for all countries.
23. The general picture described here is also supported by the fact that the shares of country-specific shocks in the forecast error variance of output differentials are significant in almost all estimation windows for all countries considered, while the opposite is true with respect to global and euro area shocks. The latter are a significant driver particularly of the Belgian differential, and the share of euro area shocks are also highly significant for the Spanish and French differentials in the most recent estimation windows.

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# Report

# Measuring confidence and uncertainty during the financial crisis: Evidence from the CFS Survey

*by*
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*The CFS survey covers individual situations of banks and other companies of the financial sector. This provides a rare opportunity to analyse appraisals, expectations and forecast errors of the core sector of the recent financial crisis. Following standard ways of aggregating individual survey data, we first present and introduce the CFS survey by comparing CFS indicators of confidence and predicted confidence to Ifo and ZEW indicators. The major contribution is the analysis of several indicators of uncertainty. In addition to well-established concepts, we introduce innovative measures based on the skewness of forecast errors and on the share of "no response" replies. Results show that uncertainty indicators fit quite well with patterns of real and financial time series of the time period 2007 to 2010.*

*JEL Classification: C83, E32, G14*

*Keywords: business sentiment, financial crisis, survey indicator, uncertainty*

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## 1. Introduction

The global financial crisis of 2007-09 can be considered the most severe economic crisis since the great depression of the 1930s. Explanations for the outbreak of the crisis are causal relationships on the micro and macroeconomic level, which have been addressed for example by Issing *et al.* (2008). Although these explanations are convincing, economists agree that another factor has to be taken into account: a high degree of uncertainty about the current and future situation of the banking system and its inherent systemic risk. Financial transactions depend on trust in the business relationship and the overall financial system; high uncertainty amplifies the likelihood of runs on financial institutions.

This paper uses new German survey data from the Center for Financial Studies, Frankfurt (CFS) to measure the degree of confidence and uncertainty during the financial crisis. The innovative feature of the CFS survey compared to the well-established Ifo (Munich) and ZEW (Mannheim) surveys of Germany's economic prospects is twofold. First, the focus is on the financial sector, that is respondents of the financial sector report on their individual situation within the financial sector. This differs from the ZEW financial experts' panel and from Ifo, where respondents are interviewed regarding the economy as a whole, or about individual situations within manufacturing or service companies, respectively. Thus, typical questions regarding financial institutions, such as transaction volume, will be covered in the CFS survey and not elsewhere. A second, perhaps minor but still interesting and innovative point is the presence of a "no response" category in the CFS questionnaire. This category may help to avoid reporting biases from forced responses. In this paper we also interpret variations in the "no response" replies as an indicator of uncertainty.

The availability of survey data covering individual situations of banks and other companies of the financial sector during the financial crisis provides a unique source which allows us to analyse the core sector of the recent turmoil. Following standard methods of aggregating individual survey data, we initially present and introduce the CFS survey by comparing CFS indicators of confidence and predicted confidence to Ifo and ZEW indicators. The major contribution of this paper is the analysis of several indicators of uncertainty which are based on both the standard deviation and skewness of individual appraisals of current situations, expectations and forecast surprises (forecast errors) as well as on "no response" replies. Comparisons with real (GDP, investment) and financial data (total assets, VDAX) reveal that the CFS survey provides an added value to already existent surveys on Germany's current and future economic and financial situation.

The paper is organised as follows: Section 2 gives a description of CFS data and provides comparisons with well-known reference time series; Section 3 presents measures of uncertainty and compares them to real and financial data; and, Section 4 concludes.

## 2. CFS survey-based indicators: Construction and description

The Ifo Business Climate Index and the ZEW Indicator of Economic Sentiment are the two most popular German sentiment indices. Both possess a long tradition and can claim to have an impact on markets as changes in the indices regularly transform into subsequent security price changes (see Entorf, Gross, and Steiner, 2009). The CFS survey complements existing indicators as it focuses on the financial sector in Germany, while the Ifo Business Climate Index addresses firms in manufacturing, construction, wholesaling and retailing. The ZEW Indicator of Economic Sentiment addresses financial experts. Although the survey samples could partially overlap, the aim of the ZEW index is for respondents to report on the perspective of macroeconomic figures in global markets (*e.g.* inflation, interest and exchange rates, commodities prices and equity markets), rather than on their own business. The major and innovative contribution of the CFS survey is to explicitly measure the business sentiment of the financial sector in Germany at the firm level and to exploit heterogeneity in firm responses. This paper is the first to analyse such financial sector data.

The CFS requires each entity's respondent to be in a leading executive position. This top-level approach is to ensure that the participant's overview suffices to assess their current business situation and to make meaningful forecasts. The survey form contains questions about the participant's views on four different business parameters: transaction volume, profits, employment and investment in product, and process innovations.[1] The answers to the questions may be given qualitatively as "positive", "neutral", "negative" or "no response" and a reply is requested for both the elapsed and forthcoming quarters. The CFS index explicitly allows the "no response" option in order to circumvent a response bias. We exploit the "no response" option to generate a new uncertainty measure (see Section 3.2 of this paper). The survey is carried out quarterly, at the beginning of January, April, July and October. Hence the timing is always at the junction of two quarters and yields a response for the elapsed quarter which the CFS labels "Performance", as well as a forecast for the forthcoming quarter, "Prediction". A survey wave period is seven working days and the results of the surveys are published within a time frame of ten working days after the end of the survey period. At the time of carrying out the estimations underlying this paper, the survey was repeated in 14 waves and the time range of the quarterly data is from January 2007 until April 2010 yielding a total of 2 922 answers and an average of 209 responses per wave.[2]

The raw dataset of the CFS survey responses are anonymised and throughout this paper we use this data to create several measures and relate them to the financial crisis. We first compute indicators of confidence as a time series of balances of equally weighted positive and negative answers. More formally, these indicators are based on individual qualitative responses of survey participants which are coded as:

$$C_i = \begin{cases} 1 & \text{if respondent is positive (about current/future situation)} \\ 0 & \text{if respondent is neutral (about current/future situation)} \\ -1 & \text{if respondent is negative (about current/future situation)} \\ \text{na} & \text{if no certain answer } (i.e. \text{ " + ", "=" or " − ") given} \end{cases} \quad (1)$$

At the aggregate level, like many CIRET survey institutes such as Ifo (Munich) and ZEW (Mannheim) in Germany, so-called balances are calculated as the difference between the

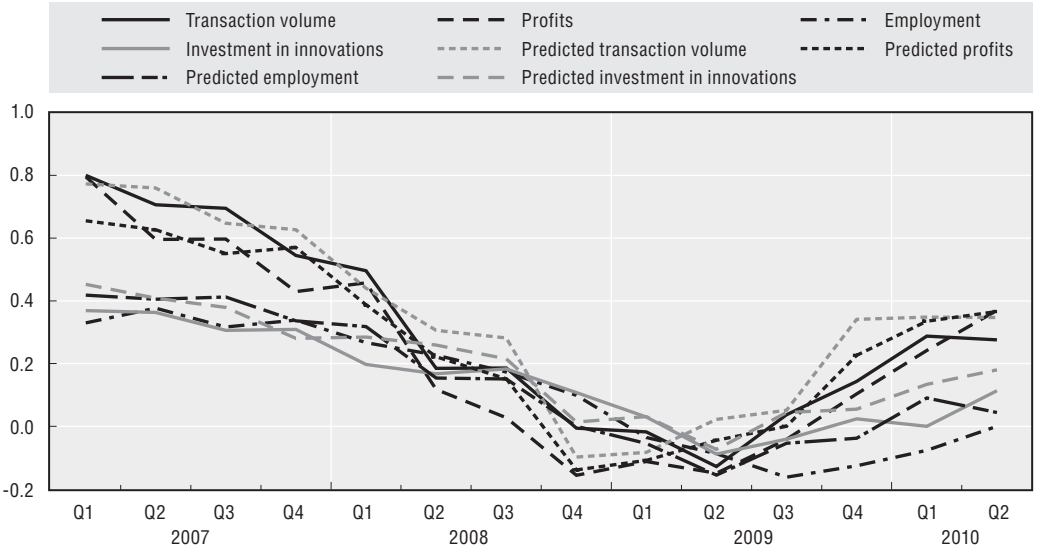
shares of positive and negative answers in the sample (*i.e.* by ignoring respondents who are uncertain about their answers):

$$\overline{C} = \frac{1}{N}\sum_{i=1}^{N} C_i = P^+ - P^- \qquad (2)$$

where $P^+ = \frac{C^+}{N}$ share of positive answers in the sample (with *N* being the number of valid +, = and – responses; $P^-$ is defined analogously). Ifo uses the same concept for surveying the current ("Geschäftslagebeurteilung") and expected economic situation ("Geschäftslageerwartung"), also ZEW economic forecasts ("ZEW – Konjunkturerwartungen") are based on the balance of positive and negative replies. Using the notion of "*confidence*" (following Bachmann *et al.*, 2010) we believe that changing levels of $\overline{C}$ represent varying confidence levels of transaction volume, profits, employment, and investment in product and process innovations.

We distinguish between the appraisal of the current (performance) *confidence* and the (expected) *predicted performance* during the forthcoming quarter. Figure 1 shows that *confidence* is U-shaped over the sample period for all of the four categories. At the beginning of the survey, in January 2007, the time series show the highest values followed by an erosion of confidence for several waves. We find the minima of confidence levels between October 2008 and April 2009, a time period which many consider the climax of the financial crisis, while from the second half of 2009 confidence figures start increasing again.

Figure 1. **Presentation of confidence and predicted confidence indicators**




We start describing time series characteristics by comparing the behaviour of CFS confidence relative to ZEW and Ifo indices, as all three indices are based on balances of positive and negative replies, and all sources report aggregate survey information on current and future economic situations. Table 1 gives an impression of the strength of inter-relationships by looking at extreme values of cross-correlation functions and corresponding correlation co-efficients. Two groups of clustered variables can be identified. The first group consists of Ifo climate and CFS confidence indicators related to transaction volume and profits. Also predicted confidence of transaction volume and profits belong to

this group. All five group members have neither lead nor lag compared to other members of the same group. At the same time all variables of this first group have a lead of one quarter over employment confidence, all but Ifo climate lead one quarter over ZEW economic situation, and all but both transaction volume variables have a lead over investment confidence. Thus, a second group, comprising ZEW economic situation, investment confidence and employment confidence, is somewhat lagging behind. The only remaining indicator, the ZEW economic forecast (ZEW economic sentiment), can be considered an outlier. Looking at the cross-correlation evidence since 2007, it has a lead of at least two quarters and even more over all other indicators, but higher leads come at the cost of much lower correlation.

Table 1. **Maximal cross correlation of $r(X_t, Y_{t-\tau})$ and corresponding lag $\tau$ (of $X$ behind $Y$)**

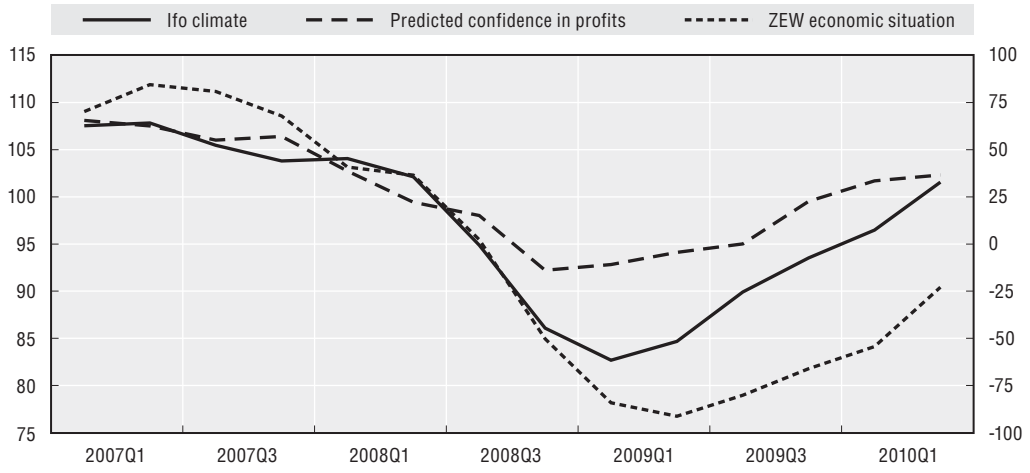
| $X_t \backslash Y_{t-\tau}$ | | Confidence | | | | Pred. conf. | | Ifo | ZEW |
|---|---|---|---|---|---|---|---|---|---|
| | | Trans. vol. | Profits | Employ. | Invest. | Trans. vol. | Profits | climate | situation |
| Confidence | Profits | 0.98 | | | | | | | |
| | | (0) | | | | | | | |
| | Employment | 0.90 | 0.86 | | | | | | |
| | | (+1) | (+1) | | | | | | |
| | Investments | 0.90 | 0.83 | 0.95 | | | | | |
| | | (0) | (+1) | (0) | | | | | |
| Predicted confidence | Trans. vol. | 0.96 | 0.95 | 0.85 | 0.83 | | | | |
| | | (0) | (0) | (–1) | (0) | | | | |
| | Profits | 0.96 | 0.97 | 0.85 | 0.82 | 0.99 | | | |
| | | (0) | (0) | (–1) | (–1) | (0) | | | |
| Ifo | Climate | 0.92 | 0.93 | 0.86 | 0.85 | 0.94 | 0.95 | | |
| | | (0) | (0) | (–1) | (–1) | (0) | (0) | | |
| ZEW | Situation | 0.92 | 0.92 | 0.96 | 0.96 | 0.90 | 0.91 | 0.91 | |
| | | (+1) | (+1) | (0) | (0) | (+1) | (+1) | (0) | |
| | Forecast | 0.46 | 0.54 | 0.51 | 0.47 | 0.48 | 0.55 | 0.57 | 0.48 |
| | | (–3) | (–3) | (–5) | (–5) | (–3) | (–2) | (–3) | (–4) |

*Notes: i)* Maxima of cross-correlation functions and corresponding leads and lags of reported time series. Read, for example: "ZEW economic situation has a lag of +1 behind 'confidence in profits'; the corresponding correlation co-efficient at lag +1 is 0.92". *ii)* The sample period is 2007Q1 to 2010Q2. *iii)* Quarterly data of Ifo and ZEW are obtained by averaging original monthly data. *iv)* Trans. vol. = Transaction volume.

Summarising the results from cross-correlations, Ifo climate and CFS indicators related to transaction volume and profits all share similar leading indicator business cycle patterns. However some indirect inference reveals that both CFS transaction volume and profits might have a small lead over the Ifo climate index. Its cross-correlation function with the ZEW economic situation has its maximum at lag = 0, whereas both CFS indicators have a lead of one quarter over the ZEW indicator. Moreover, the "transaction volume" (confidence) and "profits" (confidence as well as prediction) both indeed have a lead of one quarter over the Ifo climate index when we repeat the cross-correlation analysis using first differences (see Table A.3).

Figure 2 gives a visual impression of the time series behaviour of the predicted CFS confidence indicator of profits (balances) in comparison to the Ifo climate index and the ZEW economic situation indicator (balances). The graph is in line with results from Table 1 and confirms the promising performance of "expected profits" compared to the well acknowledged Ifo and ZEW indicators. All time series indicate an excellent economic

Figure 2. **Comparison of survey-based indicators**




*Note:* Left scale: Ifo index value; right scale: ZEW index value; CFS confidence is rescaled to [-100, 100]
*Source:* Ifo Institute for Economic Research (Ifo), Centre for European Economic Research (ZEW), Center for Financial Studies (CFS).

situation in 2007, a lasting downswing starting in the first half of the year 2008 and a recovery in 2009. However the exact timing of the turning point ranges between the fourth quarter of 2008 and the second quarter of 2009. In October 2008, the earliest indication of an upswing is observed for the CFS indicator which is supposed to cover future profits in the finance sector. Surprisingly in contrast to the other indicators representing the general economic situation, "predicted confidence in profits" moved only slightly into negative territory. This pattern confirms that the financial sector itself seems to be less affected by the financial crisis than other sectors such as manufacturing or services. The next time series showing an upturn is Ifo climate (based on the geometric mean of appraisals and expectations, that is by averaging early and coinciding indicators), finally followed by the ZEW survey indicator, representing the prevailing economic situation of considered survey periods (ZEW economic situation). The comparison of Figure 2 to Table 1 reveals that leads or lags, as far as these are identifiable from nave cross-correlation analysis, do not necessarily fit leads or lags at crucial turning points of the business cycle. However additional comparisons of the lead-lag structure based on first differences and further indirect consistency checks, provide us with a more reliable, though tentative, overall picture.

Summing up, CFS indicators offer an interesting source of information concerning the general economic situation and the financial sector in particular. Descriptive cross-correlations and visual inspections show a strong correlation with well-established indicators such as the Ifo climate index or the ZEW economic situation. Future experience with the CFS is required in order to learn more about the particularities and special features of the CFS data. The evidence in this paper reveals that CFS confidence indicators do behave in a familiar fashion as demonstrated in other well-acknowledged indicators.

## 3. Measuring uncertainty during the financial crisis

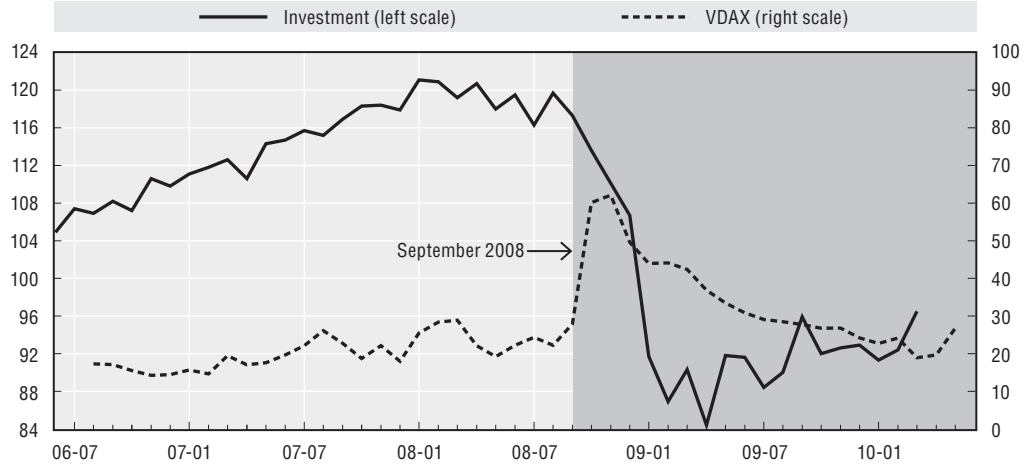
### *3.1. Motivation and methods*

Uncertainty is considered an important factor of economic recessions.[3] Bloom (2009) argues from a real business cycle model that firms postpone hiring and investment

decisions when the future is highly uncertain because adjustment to optimal capital and labor inputs is costly and would need to be revised (perhaps more than once) when future demand would not meet future capacities. Thus, to avoid expensive sunk costs from excess capacity or from hiring and firing labour, it makes sense to wait for more certain expectations of the future economy before final decisions will be made.

Bloom (2009) measured uncertainty by making use of a stock market volatility index. Bachmann *et al.* (2010), replicating Bloom (2009) using US data and employing Bloom's measure of uncertainty, found that only in the 1975, 1980 and 1991 recessions (out of 15 NBER recessions) was volatility high at the beginning of a recession and never prior to a recession. Chugh (2009) and Popescu and Smets (2009) also cast some doubt on the claim in Bloom (2009) that stock market uncertainty shocks can be considered as general predictors for all recessions.

Figure 3. **Stock market volatility and investment in Germany**




*Notes:* Left scale: German investment index of manufacturers (adjusted for price differences, base year 2005 = 100); right scale: implied volatility of the DAX (VDAX).

*Source:* Deutsche Börse, Statistisches Bundesamt: Genesis Datenbank.

Analysing the recent past of the German economy (Figure 3) cannot confirm a clear negative correlation between stock market volatility (measured by VDAX) and investment. However, we do observe a clear decline of investment after the Lehman crisis in September 2008, whereas volatility sharply rose during October/November 2008. The drop of investment activities started in October 2008, *i.e.* within the same month of the rapid rise of stock market volatility, but the most dramatic change occurred during December 2008 and January 2009, *i.e.* three months later when the investment index plummeted from 107.1 to 79.5.

In our subsequent empirical analysis (Section 3.2), we use CFS survey data to construct alternative measures of uncertainty and all indices are based on the individual qualitative responses of survey participants. As described in more detail in Section 2 of this paper, individual responses are aggregated as balances $\overline{C}$, which we interpret as indicators of confidence. The first measure of uncertainty used in this paper is the standard deviation $S_c$ of responses $C_i$ which, after employing $S_C^2 = \overline{C^2} - \overline{C}^2$, is calculated as

$$S_C = \sqrt{P^+ + P^- - (P^+ - P^-)^2} \tag{3}$$

$S_c$ covers "uncertainty" among survey respondents about the prevailing economic situation (this measure is also used by Bachmann *et al.*, 2010). When applied to the current situation of respondents, $S_c$ measures the degree of heterogeneity of companies during the current economic situation. This is different from the dispersion of "uncertain" future "plans and expectations" (in the sense of Nerlove, 1983) which can be quantified using survey questions about forthcoming time periods (the CFS survey asks for investment and hiring decisions three months ahead).

The second and third measures of uncertainty we are going to implement are based on what (Nerlove, 1983) referred to as "surprises". These are forecast errors or non-fulfillment of plans. For each quarter $t$ we have a look at the realisation (assessment of the current situation) and at the forecast made for $t$ in period $t-1$. Following Nerlove (1983), we quantify the surprise of the forecast error (FE) as shown in Table 2, again not taking companies with uncertain answers into account at this stage.[4]

Table 2. **Definition of the forecast error (FE): Potential outcomes**

| | "Increase" in $t$ | "Unchanged" in $t$ | "Decrease" in $t$ |
|---|---|---|---|
| Expected "Increase" for $t$ in $t-1$ | 0 | –1 | –1 |
| Expected "Unchanged" for $t$ in $t-1$ | 1 | 0 | –1 |
| Expected "Decrease" for $t$ in $t-1$ | 1 | 1 | 0 |

Using FE we compute mean, standard deviation and skewness across all firms (given we have valid data in $t-1$ and $t$) for each period. Standard deviation, $S_{FE}$, and skewness, $Sk_{FE}$, represent the second and third measure of uncertainty used in the empirical study.

$$S_{FE} = \sqrt{FE^+ + FE^- - (FE^+ - FE^-)^2} \tag{4}$$

$$Sk_{FE} = \frac{(FE^+ - FE^-)(1 - 3S_{FE}^2 - (FE^+ - FE^-)^2)}{S_{FE}^3} \tag{5}$$

Taking the skewness in addition to the standard deviation allows us to draw some additional conclusions about the asymmetry of positive and negative surprises (whereas the standard deviation weighs positive deviations from the mean equal to negative deviations such that no further information about the reasons of measured uncertainty can be obtained).

Unlike other survey data on business expectations, the CFS survey does not force respondents to fill in "+", = or "–". Participants are offered a no response category if they are uncertain about their assessment or expectation.[5] Thus, the share of no response answers represents a straightforward motivation of the fourth measure of uncertainty. It is simply defined as follows:

$$P^U = \frac{1}{N^*} \sum_{i=1}^{N^*} na_i \tag{6}$$

Where $na_i = 1$ if respondent $i$ had "no response" in two subsequent periods $t$ and $t-1$ ($na_i = 0$ otherwise), and $N^*$ being the number of valid responses in two subsequent waves of the CFS survey. Here, two subsequent periods are employed in order to capture systematic response behaviour and to exclude casual participation.

### *3.2. Results*

In this sub-section we compare four indicators of uncertainty which have been introduced in Section 3.1. These indicators are applied as follows:

*a)* Standard deviation $S_c$ of individual survey responses regarding current and future confidence in terms of transaction volume and profits.

*b)* Standard deviation of errors ("surprises") of forecasting/planning in terms of transaction volume and profits of the current period, when the prediction was made three months ago, $S_{FE}$.

*c)* Skewness of errors ("surprises") of forecasting/planning transaction volume and profits of the current period, when the prediction was made three months ago, $Sk_{FE}$.

*d)* Share of "no response" replies in terms of transaction volume and profits, $P^U$.

We compare CFS survey data to GDP, investment and total assets which we use as reference time series of the real economic activity. Moreover, in order to learn how CFS survey-based measures of uncertainty relate to the standard stock market measure of uncertainty, we add the German market volatility index (VDAX) to the list of variables under comparison.

Table 3 shows results of a cross-correlation analysis. To avoid spurious results arising from trending data, the time series of investment, GDP and total assets are used as quarterly (quarter-on-quarter) growth rates. VDAX has no evident long-run trend such that we employ the original time series. The same holds for the CFS uncertainty measures introduced above.[6] All extreme values of estimated cross-correlation functions have the expected signs: *a)* High heterogeneity/uncertainty about current/future economic situations at the micro level is associated with low rates of aggregate economic

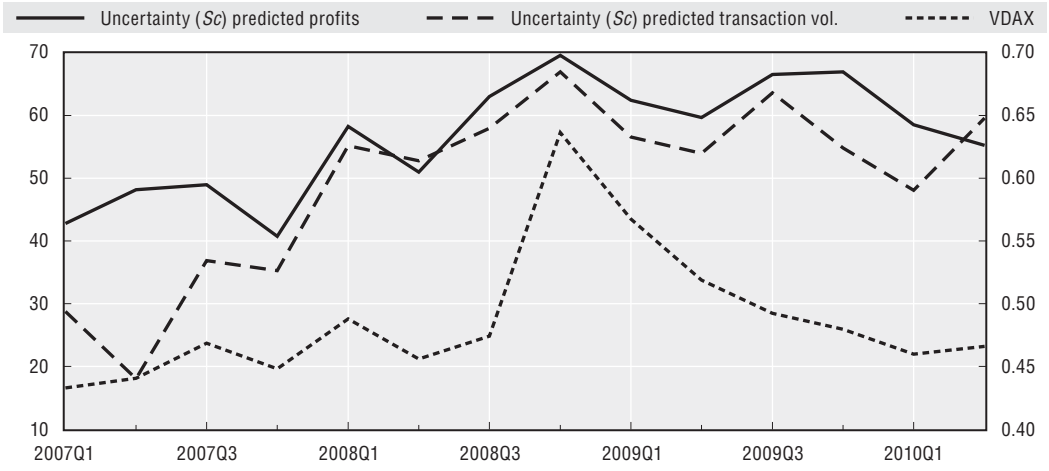
Table 3. **Cross-correlation functions $r(X_t,Y_{t-\tau})$: performance of survey-based indicators**

| $X_t \backslash Y_{t-\tau}$ | Investment | GDP | Total assets | VDAX |
|---|---|---|---|---|
| $S_c$-transaction volume | –0.52 | –0.50 | –0.63 | 0.64 |
| (growth rates) | (0) | (0) | (0) | (+1) |
| $S_c$-profits | –0.42 | –0.38 | –0.59 | 0.49 |
| (growth rates) | (0) | (0) | (0) | (0) |
| $S_c$-predicted transaction volume | –0.52 | –0.59 | –0.49 | 0.63 |
| (growth rates) | (–1) | (–1) | (–2) | (0) |
| $S_c$-predicted profits | –0.50 | –0.62 | –0.55 | 0.69 |
| (growth rates) | (–1) | (–1) | (–2) | (0) |
| $S_{FE}$-transaction volume | –0.23 | –0.25 | –0.41 | 0.41 |
| (growth rates) | (–1) | (–1) | (–4) | (–3) |
| $S_{FE}$-profits | –0.60 | –0.41 | –0.16 | 0.70 |
| (growth rates) | (+4) | (–3) | (+2) | (+5) |
| $Sk_{FE}$-transaction volume | –0.31 | –0.34 | –0.50 | 0.37 |
| (growth rates) | (0) | (0) | (–1) | (+1) |
| $Sk_{FE}$-profits | –0.43 | –0.52 | –0.56 | 0.56 |
| (growth rates) | (0) | (0) | (–1) | (+1) |

*Notes: i)* Maxima of cross-correlation functions $r(X_t,Y_{t-\tau})$ and corresponding lags $\tau$(of X behind Y) of reported time series. Read, for example: "$S_C$ – predicted profits has a lag of –1 (*i.e.* a lead of +1) with respect to quarterly (q.o.q.) GDP growth rates; the corresponding correlation co-efficient at lag –1 (lead +1) is –0.62". *ii)* Sample period: 2007Q1 to 2010Q2. *iii)* Quarterly data on investment and VDAX are obtained by averaging original monthly data.

performance, and *b)* survey-based indicators of uncertainty are positively correlated with stock market volatility, VDAX, *i.e.* the standard measure of uncertainty used in the literature (see for example, Bloom, 2009). As regards investment, Table 3 reveals that uncertainty measures based on the standard deviation of individual confidence responses $S_c$, of predicted profits as well as of predicted transaction volumes have a lead of one quarter over investment growth, whereas $S_c$ related to the current situation does not show any clear lead or lag. Results on GDP, total assets and VDAX also confirm that $S_c$ of predicted transaction volume and predicted profits deliver the highest correlation with actual economic data (see rows 3 and 4 of Table 3). The overall lead of both indicators is one quarter on GDP, even two quarters ahead of total assets. VDAX and "$S_c$ of predicted transaction volume" as well as VDAX and "$S_c$ of predicted profits" show closely related and co-inciding patterns, as can be seen from the high correlation co-efficients with zero lead or lag (Table 3). Figure 4 provides some additional graphical impression. Compared to $S_c$, standard deviation and skewness of forecast errors show weak correlations with reference time series or unreasonably high leads or lags. The only exception is $Sk_{FE}$ – *profits* which is negatively correlated with total assets (–0.56, lead = one quarter) and positively correlated with VDAX (+0.56, lag = one quarter).

Figure 4. **Uncertainty and VDAX**

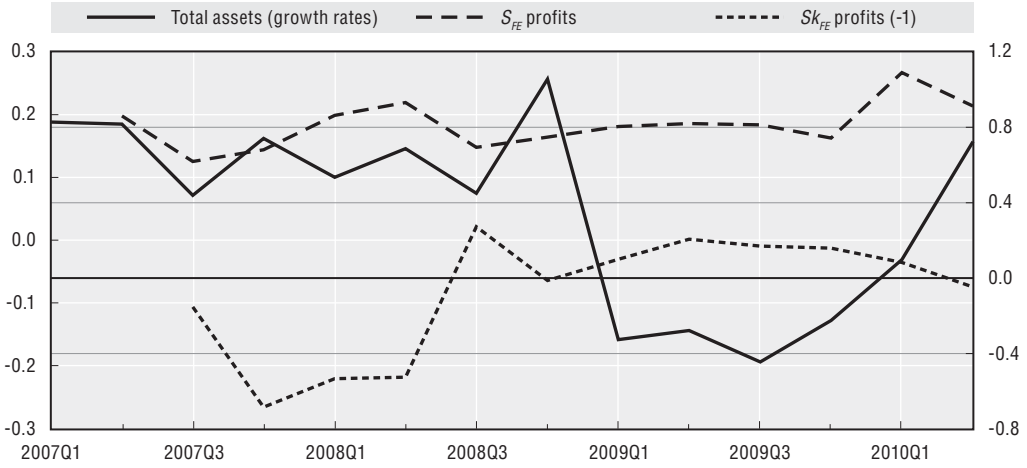



*Notes:* Left scale: implied volatility of the DAX (VDAX); right scale: $S_c$ uncertainty indicators.
*Source:* Deutsche Börse, Center for Financial Studies (CFS).

Figure 5 reveals that skewness, *i.e.* $Sk_{FE}$, might indeed entail some complementary information in addition to the standard deviation, *i.e.* $S_{FE}$. The skewness indicator (displayed in period t + 1) is clearly negative until the second quarter of 2008, indicating that there have been more negative than positive surprises throughout the pre-Lehman time period. In 2009 after having realised the surprisingly well performing economy, the picture changed as the sign of the skewness indicator turned positive. Some final reversal can be observed for the 2nd quarter 2010, when the Greece crisis led to some negative shocks.

In contrast to other business surveys, CFS questionnaires offer "no response" categories for those participants who deliberately decide not to respond to given survey categories. Given that such behaviour represents "uncertainty" about the exact current or future situation, it seems quite natural to interpret the share of "no response" respondents

Figure 5. **Growth of total assets, standard deviation and skewness of forecast errors in profits**




*Notes:* Left scale: quarterly growth rates of bank total assets; right scale: one-quarter lag of $Sk_{FE}$ and $S_{FE}$ uncertainty indicators.

*Source:* Deutsche Bundesbank, Center for Financial Studies (CFS).

as independent indicators of uncertainty. Table 4 presents the results of some cross-correlation analysis based on "no response" shares. As the variance from the strong downward trends of the first six quarters would dominate the correlation analysis and cause misleading lead-lag patterns, all times series but VDAX enter the analysis as quarter-on-quarter growth rates. All signs are as expected. The highest correlation with all included "real world" time series has the "no response" share of predicted profits. Moreover, it has a lead of one quarter over investment and GDP, it is two quarters ahead of total assets, and even one quarter ahead of VDAX. The two-quarter lead over total assets is illustrated in Figure 6. For expository reasons, the sign of the "no response" growth rate is turned negative and the lead is exposed by displaying "no response" realisations of period $t$ in period $(t + 2)$. After doing so, we observe a highly co-inciding time series behaviour

Table 4. **Cross correlation functions $r(X_t, Y_{t-\tau})$: performance of "no response" shares**

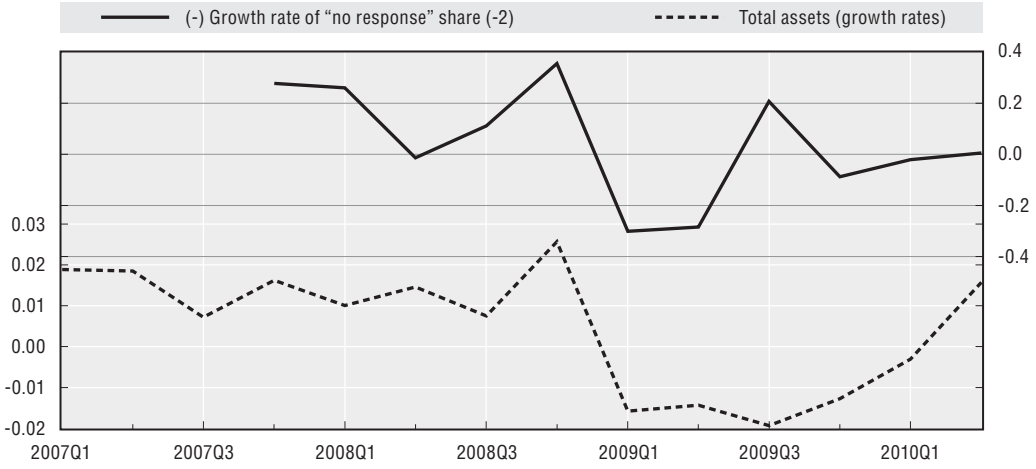
| $X_t \backslash Y_{t-\tau}$ | Investment | GDP | Total assets | VDAX |
|---|---|---|---|---|
| $P^U$-transaction volume | –0.61 | –0.60 | –0.47 | 0.42 |
| (growth rates) | (+1) | (+1) | (–2) | (+1) |
| $P^U$-profits | –0.39 | –0.35 | –0.34 | 0.39 |
| (growth rates) | (–1) | (–1) | (+1) | (0) |
| $P^U$-predicted transaction volume | –0.38 | –0.37 | –0.56 | 0.52 |
| (growth rates) | (–1) | (–2) | (–2) | (–1) |
| $P^U$-predicted profits | –0.60 | –0.61 | –0.59 | 0.67 |
| (growth rates) | (–1) | (–1) | (–2) | (–1) |

*Notes:* i) Maxima of cross-correlation functions $r(X_t, Y_{t-\tau})$ and corresponding lags $\tau$(of $X$ behind $Y$) of reported time series. Read, for example: "the quarterly growth rate of the share of 'no response' replies regarding the prediction of profits, $P^U$, has a lag of –1 (*i.e.* a lead of +1) with respect to quarterly GDP growth rates; the corresponding correlation co-efficient at lag –1 is –0.61". ii) Sample period: 2007Q1 to 2010Q2. iii) Quarterly data on investment and VDAX are obtained by averaging original monthly data.

during the period 2008Q3 until 2009Q2. Disregarding the outlier of GDP growth in 2009Q3, both time series share the same upward trend until 2010Q2.

Of course, given the short time series we have, it might be too early to consider reported coinciding patterns as evidence of highly reliable (leading) indicators of the financial sector or even the economy as a whole. However, the reported results represent some interesting and promising observations that should be focused on in future research and analysed after forthcoming waves of the CFS survey.

Figure 6. **Share of "no response" replies of profit prediction as leading indicator of total assets**




*Notes:* Left scale: quarterly growth rates of bank total assets; right scale: negative values of quarterly growth rates of $P^U$ on profit predictions, displayed in quarter (t + 2).

*Source:* Deutsche Bundesbank, Center for Financial Studies (CFS).

## 4. Conclusion

A high degree of uncertainty about the current and future situation of the banking system and its inherent systemic risk is considered as one of the main reasons for the recent financial crisis. Many authors, see in particular Bloom (2009), argue that uncertainty and wait-and-see behaviour cause recessions because firms refrain from committing themselves to costly investment and hiring decisions. Thus, measuring uncertainty might help to better understand the reasons driving the recent turmoil and should improve the forecasting of future recessions. In this paper, we present and use new German survey data from the Center for Financial Studies, Frankfurt (CFS) to construct indicators of confidence and uncertainty.

The most important innovative feature of the CFS survey compared to well-established Ifo (Munich) and ZEW (Mannheim) surveys of Germany's economic prospects is the focus on the financial sector, *i.e.* respondents of the financial sector report on their individual situation within the financial sector. This gives a unique opportunity to analyse the core sector of the recent turmoil during the time period of financial instability. Following standard methods of aggregating individual survey data, we first present and introduce the CFS survey and compare CFS indicators of confidence and predicted confidence to Ifo and ZEW indicators. The major methodological contribution is the analysis of several indicators of uncertainty. In addition to well established concepts, we introduce new measures of uncertainty based on the skewness of forecast errors and on

the share of "no response" replies. Results show that uncertainty indicators fit quite well with patterns of real and financial time series of the time period 2007 to 2010.

So far, CFS survey data are only available for a relatively short time period. However results presented in this paper show a promising performance for measures of confidence and uncertainty such that future waves of the CFS survey will provide researchers, professional financial analysts and economic forecasters with some sensitive indicators of transaction volume, profits and other indicators of the current and future situation of the financial sector.

### *Notes*

1. The original wording used in the questionnaire (in German language) refers to "Geschäftsvolumen", "Ertragssituation", "Mitarbeiterzahl" and "Investitionssumme in Produkt- oder Prozessinnovationen". For the design of the questionnaire, see Table A.2.
2. The complete list of the survey's participants is provided in Table A.1.
3. To avoid confusion, here "uncertainty" does not necessarily imply uncertainty in the sense of mathematical statistics, where dealing with uncertainty means knowledge of statistical regularities such as distribution parameters or population moments. Thus, contrary to statistical uncertainty, "uncertainty" does not allow calculation of mathematical expectations.
4. Note that extreme surprises (such as a realisation of –1 after an expectation of +1) are not defined as –2 or +2, but rather as –1 and +1. This has the disadvantage that extreme surprises are not treated differently from simple surprises, but it has the advantage that FE has just three potential outcomes and that summing up squared and cubic terms for obtaining second and third moments is not highly sensitive to few outliers.
5. Of course, likewise participants might be unwilling to respond because they do not want to share any private information with others. Moreover, changes in "no response" behaviour might indicate uncertainty changes.
6. Alternative calculations using first differences of CFS uncertainty measures have resulted in randomly located extreme values of the cross-correlation functions at unreasonably high leads or lags. Signs, too, vary in a non-systematic way.

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# *Annex*

Table A.1. **List of CFS survey participants**

| Group | Branch/Wave | 2007 | | | | 2008 | | | | 2009 | | | | 2010 | | Total | Avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | | |
| 1 | Asset Management | 4 | 11 | 16 | 16 | 17 | 14 | 17 | 9 | 12 | 9 | 13 | 13 | 12 | 11 | 174 | 12 |
| | Bank | 35 | 59 | 60 | 66 | 66 | 62 | 40 | 49 | 71 | 67 | 58 | 59 | 56 | 57 | 805 | 58 |
| | Brokerage | 2 | 7 | 6 | 6 | 9 | 7 | 6 | 5 | 8 | 8 | 7 | 5 | 5 | 6 | 87 | 6 |
| | Exchange | 3 | 4 | 5 | 6 | 5 | 4 | 6 | 5 | 6 | 3 | 3 | 5 | 3 | 4 | 62 | 4 |
| | Insurance | 8 | 7 | 8 | 11 | 14 | 13 | 12 | 11 | 11 | 10 | 12 | 10 | 11 | 10 | 148 | 11 |
| | Investment Bank | 6 | 7 | 11 | 13 | 10 | 10 | 6 | 5 | 8 | 5 | 5 | 5 | 6 | 6 | 103 | 7 |
| | VC and PE | 0 | 3 | 5 | 12 | 10 | 10 | 9 | 8 | 9 | 8 | 7 | 9 | 8 | 8 | 106 | 8 |
| 2 | Accounting and Tax | 7 | 7 | 10 | 14 | 13 | 14 | 12 | 10 | 16 | 14 | 12 | 12 | 14 | 16 | 171 | 12 |
| | Advisory | 8 | 29 | 36 | 35 | 32 | 28 | 24 | 24 | 28 | 21 | 23 | 26 | 27 | 25 | 366 | 26 |
| | Financial Service | 0 | 7 | 10 | 12 | 8 | 10 | 8 | 7 | 10 | 8 | 9 | 9 | 11 | 9 | 118 | 8 |
| | Lawyer | 9 | 15 | 17 | 21 | 20 | 22 | 17 | 15 | 21 | 17 | 22 | 18 | 18 | 17 | 249 | 18 |
| | Media | 4 | 11 | 11 | 14 | 13 | 14 | 12 | 10 | 10 | 11 | 10 | 7 | 9 | 8 | 144 | 10 |
| | Rating Agency | 1 | 3 | 2 | 4 | 4 | 3 | 1 | 3 | 2 | 0 | 1 | 1 | 0 | 0 | 25 | 2 |
| | Wealth Management | 4 | 6 | 8 | 13 | 8 | 9 | 8 | 8 | 11 | 7 | 9 | 7 | 7 | 7 | 112 | 8 |
| 3 | Academic Institution | 0 | 1 | 2 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 3 | 2 | 2 | 3 | 24 | 2 |
| | Interest Group | 3 | 9 | 12 | 10 | 12 | 9 | 10 | 6 | 6 | 7 | 7 | 4 | 7 | 7 | 109 | 8 |
| | Supervisory | 4 | 4 | 4 | 4 | 4 | 4 | 3 | 3 | 4 | 3 | 3 | 4 | 4 | 3 | 51 | 4 |
| 4 | Non-financial Service | 3 | 6 | 6 | 6 | 5 | 2 | 1 | 1 | 2 | 3 | 3 | 4 | 2 | 3 | 47 | 3 |
| | Real Estate | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 21 | 2 |
| | Total | 103 | 198 | 231 | 266 | 254 | 239 | 194 | 181 | 238 | 205 | 208 | 201 | 203 | 201 | 2,922 | 209 |

Table A.2. **Survey questionnaire**

| Business climate | The firm's observed dynamics in the 1st quarter of 2011 | | | | The firm's forecasted dynamics for the 2nd quarter of 2011 | | | |
|---|---|---|---|---|---|---|---|---|
| | Positive | Neutral | Negative | No response | Positive | Neutral | Negative | No response |
| Transaction volume | o | o | o | o | o | o | o | o |
| Profits | o | o | o | o | o | o | o | o |
| Employment | o | o | o | o | o | o | o | o |
| Investment in product and process innovations | o | o | o | o | o | o | o | o |

*Note:* Example questionnaire in April 2011.
*Source:* Center for Financial Studies (CFS).

Table A.3. **Maximal cross correlation of $r(\Delta X_t, \Delta Y_{t-\tau})$, and corresponding lag $\tau$ (of $\Delta X$ behind $\Delta Y$)**

| $X_t \backslash Y_{t-\tau}$ | | Confidence | | | | Pred. conf. | | Ifo climate | ZEW situation |
|---|---|---|---|---|---|---|---|---|---|
| | | Trans. vol. | Profits | Employ. | Invest. | Trans. vol. | Profits | | |
| Confidence | Profits | 0.89 | | | | | | | |
| | | (0) | | | | | | | |
| | Employment | 0.73 | 0.66 | | | | | | |
| | | (+1) | (+1) | | | | | | |
| | Investments | 0.39 | 0.47 | 0.63 | | | | | |
| | | (0) | (+2) | (0) | | | | | |
| Predicted confidence | Trans.vol. | 0.54 | 0.51 | 0.55 | 0.76 | | | | |
| | | (0) | (0) | (–2) | (–2) | | | | |
| | Profits | 0.66 | 0.64 | 0.62 | 0.71 | 0.95 | | | |
| | | (0) | (0) | (–1) | (–2) | (0) | | | |
| Ifo | Climate | 0.56 | 0.67 | 0.68 | 0.61 | 0.63 | 0.70 | | |
| | | (+1) | (+1) | (–2) | (–1) | (0) | (+1) | | |
| ZEW | Situation | 0.62 | 0.67 | 0.74 | 0.65 | 0.60 | 0.68 | 0.87 | |
| | | (+1) | (+1) | (0) | (0) | (+2) | (+2) | (0) | |
| | Forecast | 0.68 | 0.70 | 0.64 | 0.55 | 0.63 | 0.74 | 0.62 | 0.68 |
| | | (–2) | (–3) | (–4) | (–2) | (–2) | (–2) | (–3) | (–4) |

*Notes: i)* Maxima of cross-correlation functions and corresponding leads and lags of the first differences of the reported time series. Read, for example: "The first difference of the ZEW economic situation has a lag of +1 behind the first difference of 'confidence in profits'; the corresponding correlation co-efficient at lag +1 is 0.67". *ii)* The sample period is 2007Q2 to 2010Q2. *iii)* Quarterly data of Ifo and ZEW are obtained by averaging original monthly data. *iv)* Trans. vol. = Transaction volume.

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# An analysis of the embedded frequency content of macroeconomic indicators and their counterparts using the Hilbert-Huang transform

*by*
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*Many indicators of business and growth cycles have been constructed by both private and public agencies and are now in use as monitoring devices of economic conditions and for forecasting purposes. As these indicators are largely composite constructs using other economic data, their frequency composition is likely different to that of the variables that they are used as for indicators.*

*In this paper, we use the Hilbert-Huang transform which comprises empirical mode decomposition (EMD) and the Hilbert spectrum in order to analyse the frequency content of comparable OECD confidence indicators, and national sentiment indicators for industrial production and consumption. We then compare these with the frequency content of both industrial production and real consumption growth data. The Hilbert-Huang methodology first uses an iterative process (EMD) to identify the embedded frequencies within a time series and then the changing nature of these embedded frequencies (IMFs) can be analysed by estimating the instantaneous frequency (using the Hilbert spectrum). This methodology has several advantages over conventional spectral analysis: it handles non-stationary and non-linear processes, and it can cope with short data series.*

*The aim of this paper is to decompose both indicator and actual economic variables to evaluate* i) *whether the number of IMFs are equivalent in both indicators and actual variables, and* ii) *to see which frequencies are accounted for in indicators, and which frequencies are not.*

*Key Words: economic growth, Hilbert-Huang transform, empirical mode decomposition, frequency domain, economic indicators, OECD.*

*JEL Classification: C63, E21, E32.*

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## 1. Introduction

Cyclical indicators aim to condense the information about economic activity by capturing the cyclical patterns in economic variables into one-dimensional variables that are tractable and possibly available prior to release of economic variables. In their book Burns and Mitchell (1946) introduce a system to measure cyclical fluctuations in economic activity developed by the National Bureau of Economic Research (NBER). Since then, such regularly collected information is now an integral part of the measurement *ex-post* of business cycles or to anticipate *ex-ante* cyclical fluctuations in economic activity. Thus, the indicators of business cycles (see for example Kydland and Prescott, 1990) and growth cycles (see for example Zarnowitz and Ozyildirim, 2002) are routinely used as monitoring devices in the analysis of macroeconomic conditions and forecasting in many countries.

A number of public and private institutions have developed cyclical indicators. The Organisation for Economic Co-operation and Development (OECD) has developed a comprehensive system of internationally comparable cyclical indicators. The data surveyed with harmonised business tendency surveys is used with data published by national agencies in construction of the OECD composite leading indicators. Through a standardisation procedure, both the business and the consumer confidence indicator data are made comparable between countries. The European Central Bank (2001) has dissected the information content of the composite indicators of the euro area and how closely indicators follow the cyclical pattern of the euro area reference series. As composite indicators are summary indicators, we might not only be interested in the cyclical behaviour of the aggregate series, but we might also be interested in determining what frequencies are at work in the indicators as well as the relevant macroeconomic variables, so that potential lead/lag relations between frequencies of particular interest can be identified.

In this empirical paper, we dissect the information content of the OECD standardised confidence indicators along with some national sentiment indicators and economic variables for the euro area, Japan and the US. To do this we employ the Hilbert-Huang transform (HHT) of Huang *et al.* (1998). The first step is to extract the embedded frequencies of indicators and economic variables using empirical mode decomposition (EMD). Secondly, we analyse the embedded frequencies by using a Hilbert spectrum. As emphasised by Wu and Huang (2004), we use a recently developed variation of EMD that corrects some recognised problems associated with EMD. Finally, we evaluate the frequencies in the economic variables that are or are not being captured by the indicators.

The rest of the paper is organised as follows: Section 2 introduces the cyclical indicators and describes the data: Section 3 outlines the empirical method to be used; Section 4 presents the empirical results; and, Section 5 offers some conclusions.

## 2. Data

### *2.1. Cyclical indicators*

The timeliness and extensive geographical breakdown of economic data provides a vast amount of information available to today's economic policymaker. As is often the case in statistical work, extensive economic data is reduced and summarised by computing a smaller number of derived measures that try to incorporate what is relevant and informative or even accidental in the cyclical behaviour of economic activity. The indicators of cyclical behaviour in economic activity, that is cyclical indicators, are classified by the Conference Board (2001) into three categories of leading, coincident, and lagging based on the timing of their movements. Coincident indicators are series that define the business cycle by measuring aggregate economic activity and leading indicators are series that tend to shift direction in advance of the business cycle, while in contrast, lagging indicators tend to change direction after the coincident series.

Burns and Mitchell (1946) document the measures of cyclical behaviour developed in the 1930s by the National Bureau of Economic Research (NBER). The leading economic indicator approach has been applied to measure business cycles ever since. While the literature on business cycle theory attempts to explain recurrent fluctuations, the empirical leading indicator approach is criticised for lack of constituent economic theory. With regard to criteria of an economic nature, Koopmans (1947) notes that the constituent series of cyclical indicators are chosen mainly on empirical grounds, rather than on the basis of economic theory.

It is desirable to properly assess the current and in particular, future economic activity for effective economic policy-making. For these purposes, business opinion is surveyed with so-called business tendency surveys of company managers concerning the current situation of their business and about their plans and expectations for the near future. In collaboration with the European Commission, the Organisation for Economic Co-operation and Development (OECD) has developed a system of harmonised business tendency surveys. The economic data published by national agencies is used together with OECD harmonised business tendency survey data in order to construct the OECD composite leading indicators (CLIs) for both OECD member and non-member economies. The system of OECD (2008) leading indicators is based on the growth cycle approach, which measures deviations from the long-term trend, whereas the leading indicator approach is based on repetitive but non-periodic fluctuations in economic activity.

The OECD released new cyclical indicators in December 2006 (OECD, 2006). These new standardised indicators enhance the existing product range in the OECD CLIs by providing both comparability between countries and the likelihood of fewer revisions. OECD CLIs are constructed to predict cycles in a reference series chosen as a proxy measure for the aggregate economy. The CLIs are released by the OECD on a monthly basis, and given their timeliness, are appropriate to model short-term movements in economic variables. However, short-term movements should be interpreted with caution because local volatility and revisions that are a natural part of the calculation procedure can obscure the main patterns in economic activity.

The new set of OECD standardised cyclical indicators includes both Business Confidence Indicators (BCIs) and Consumer Confidence Indicators (CCIs). These new cyclical indicators are in addition to the existing CLIs, also published by the OECD. The BCIs are presumed to anticipate reference series with shorter and more stable lead times than the CLIs, and to date they appear to be subject to less revision than the CLIs.

The business confidence indicators are supposed to capture the cyclical patterns in real-economic activity. Usually the volume of industrial production or real gross domestic product (GDP) would be used as reference series for these indicators. Mourougane and Roma (2002) find confidence indicators useful in forecasting real GDP growth rates in the short run in a number of European countries. Industrial production data is also often used as a proxy measure for real GDP. While real GDP is a more comprehensive variable for analysing economy-wide fluctuations, industrial production data has the advantage of being available on a monthly rather than a quarterly basis.

An article by the European Central Bank (2001) dissects the information content of composite indicators of the euro area business cycle and the analysis suggests that composite indicators may with hindsight, have followed developments broadly similar to those of the business cycle as measured by both industrial production and real GDP growth. However, the relationship between composite indicators and the business cycle may not be very stable over time, which hampers the interpretation of the latest readings of such indicators. For example, Japanese survey forecasts of industrial production were found to be biased and inconsistent with rational expectations in comparison with the US by Aggarwal and Mohanty (2000). Furthermore, Fukuda and Onodera (2001) point out that several research institutes in Japan made serious errors in forecasting business cycles and prolonged recessions in the 1990s.

Consumer confidence indicators are presumed to capture cyclical patterns in household consumption behaviour. Andersen and Nielsen (2003) note that the consumer confidence indicator is often taken as an indicator of the development in consumer spending, but in general it is not so clear which economic variable, if any, consumer confidence indicators describe. There is little agreement over the value of consumer confidence indicators for forecasting consumer spending over what is already captured by economic fundamentals. Consumer confidence indicators may potentially be used to point to future behaviour, since households are asked also about their future expectations of the economic activity. It is however, ambitious to think that the indicator can describe not only the current, but also future economic development.

Few papers have investigated the usefulness of consumer confidence in modelling consumer spending (see for example Ludvigson, 2004). Carroll *et al.* (1994) and Bram and Ludvigson (1998) report the predictive information content of lagged values of consumer confidence for US consumer spending. For Japan, Utaka (2003) finds that consumer confidence has only a short-term effect on fluctuations in economic activity. Other studies found in Chopin and Darrat (2000), examine the value of consumer attitudes for forecasting economic performance, but fail to produce a consensus about the value of attitudes from consumer measures for forecasting consumer behaviour. For example, Garner (1991) finds the consumer confidence indicator published by the University of Michigan an unreliable predictor of consumer spending.

For evaluation and proper use of an indicator, it is crucial to know how leading indicators are constructed and moreover how composite leading indicators are constructed. Furthermore, in the context of economic policymaking, composite indicators, by construction, hide the driving factors behind current and short-term changes in economic activity. Nevertheless, it is clear that many of the components of these indicators may work at different frequencies, so that compiling composites might lead to internal frequency mismatches.

### *2.2. Data description*

For our data set, we use a range of economic indicators for the euro area, Japan and the US. Both the national sentiment indicators and the OECD standardised confidence indicators are used. The national indicators are also used by the OECD in its construction of leading indicators so there will be some overlap here. In the frequency domain, we study the comparable OECD confidence indicators and the nationally published sentiment indicators alike. The series used for each country are given in Table 1. The data is seasonally adjusted and the economic variables used as reference series are measured in real terms for each country.

Table 1. **Description of indicators and economic variables**

| | Euro area | Japan | US |
|---|---|---|---|
| Business tendency survey | Harmonised EU Business Tendency Survey Indicator[1] | Short-term Economic Survey of Enterprises in Japan (TANKAN)[3], quarterly. | Monthly Manufacturing Report on Business |
| *Source*: | European Commission, OECD | Bank of Japan, OECD | The Institute for Supply Management |
| Consumer opinion survey | Harmonised EU Consumer Opinion Survey Indicator[1] | The Consumer Behavior Survey | University of Michigan Consumer Sentiment Index |
| *Source*: | European Commission | Economic and Social Research Institute, Cabinet Office | University of Michigan |
| Business confidence indicator | Standardised Business Confidence Indicator[1] | Standardised Business Confidence Indicator | Standardised Business Confidence Indicator |
| *Source*: | OECD | OECD | OECD |
| Consumer confidence indicator | Standardised Consumer Confidence Indicator[1] | Standardised Consumer Confidence Indicator | Standardised Consumer Confidence Indicator |
| *Source*: | OECD | OECD | OECD |
| Industrial production | Volume Index of Production[2] | Indices of Industrial Production | INDPRO, Industrial Production Index |
| *Source*: | Eurostat | Ministry of Economy, Trade and Industry | Board of Governors of the Federal Reserve System |
| Consumption | Private Final Consumption Expenditure[2] | Final Consumption Expenditure | Final Consumption Expenditure |
| *Source*: | Eurostat | Economic and Social Research Institute, Cabinet Office, IMF, OECD | Bureau of Economic Analysis |

1. Euro area, 12 EMU countries up to 2006. 13 EMU countries, including Slovenia since 2007.
2. Euro area, 12 EMU countries up to 1989, 13 EMU countries including Slovenia since 1990.
3. Interpolated to monthly series by the OECD.

We follow the OECD (1998) and European Commission (2007) in defining industrial production for manufacturing (henceforth referred to as industrial production), which is defined as a reference series for OECD business composite indicator construction. Both the industrial production data and the business confidence data are published on a monthly basis (except for Japan where we use the monthly series interpolated by the OECD). More information on the data used by the OECD is available in OECD (2006).

We define private final consumption expenditure in GDP including non-profit institutions serving households (henceforth referred to as consumption) as the reference for consumer confidence. Since the data for consumption is available on a quarterly basis, we aggregate the consumer confidence indicator series from a monthly into a quarterly series. The indicator value in a quarter is calculated as the average of the monthly observations in that quarter for the consumer confidence indicator.

The data set covers the period up to the end of 2007 with the start of the sample period varying from country to country depending on availability of the data. More specifically, the industrial production data for the US starts in 1950, for Japan in 1978 and in 1990 for the euro area. The consumption data for the US, Japan and the euro area all start in 1973. In the short-term, the growth of economic variables against confidence indicators is obtained by taking month-on-month growth rates for industrial production and quarter-on-quarter rates for consumption. This most accurately corresponds to the measurement of the indicators, as they are constructed to measure changes in economic activity or spending rather than the absolute levels. Figure 1 plots both the monthly industrial production and the quarterly consumption series with one period growth as measured by the log-change for the euro area, Japan and the US. The corresponding OECD standardised confidence indicators are plotted in Figure 2.

## 3. The Hilbert-Huang Transform

### *3.1. Frequency domain analysis: a brief synopsis*

In terms of the investigation of time series, there are only two basic approaches – analysis in the time domain and analysis in the frequency domain. While most economists are familiar with time-domain techniques, most of the techniques employed in frequency domain analysis have been developed outside the domain of economics, but nonetheless are widely applied in the physical sciences and medical fields.

For most economists frequency domain analysis is synonymous with spectral analysis. Although spectral analysis has quite a long history in economics, beginning with research in the 1920s alongside the original work done on the business cycle, most economists are only familiar with the oft-cited article by Granger (1966). While there have been regular contributions in applied economics using spectral methods,[2] there has been relatively little research done using more recently-developed frequency domain techniques[3] up until recently despite that there has been a raft of new developments in frequency domain analysis over the last 20 years.

Spectral analysis (which was originally invented by the mathematician Fourier in 1811 to solve the problem of how heat dissipates in a metal plate) essentially decomposes a periodic function into a sum of simple oscillating functions, namely sines and cosines. Applying a Fourier transform to a time series decomposes the time series by convolving sine and cosine functions to the series in order to represent the oscillations present in the series and subsequently estimate these frequencies. Any linear combination of sines and cosines that is used to represent the original time series is known as a Fourier series.

In mathematical terms, spectral analysis can be defined quite simply as the sum of an infinite series of harmonic functions:

$$f(x) = a_0 + \sum_{n=1}^{\infty}(a_n \cos(nx) + b_n \sin(nx)) \quad (1)$$

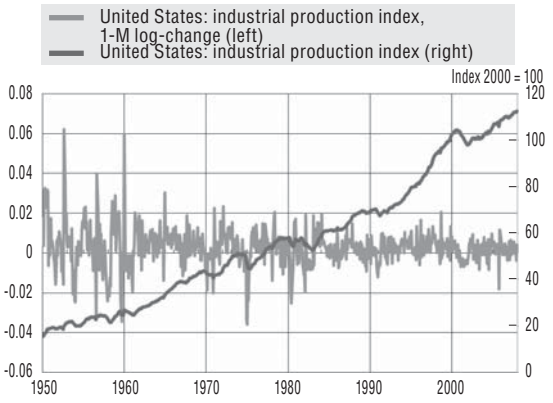
where,

$$a_n = \frac{1}{\pi}\int_{-\pi}^{+\pi} f(x)\cos(nx)dx \quad (2)$$

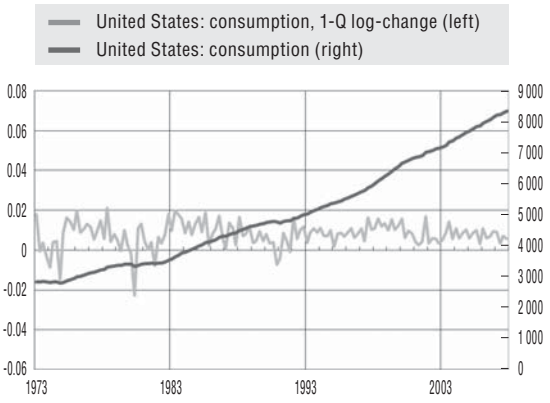
and,

$$b_n = \frac{1}{\pi}\int_{-\pi}^{+\pi} f(x)\sin(nx)dx \quad (3)$$

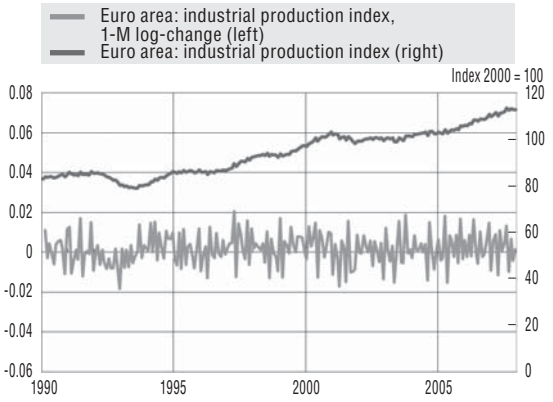
Figure 1. **Industrial Production monthly and consumption quarterly with growth rates as measured by log-change**



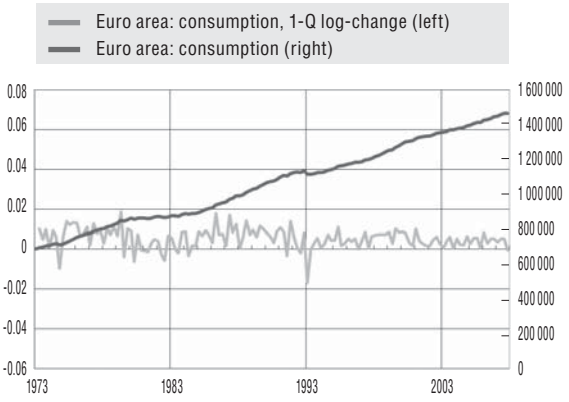

*Source:* Board of Governors of the Federal Reserve System.



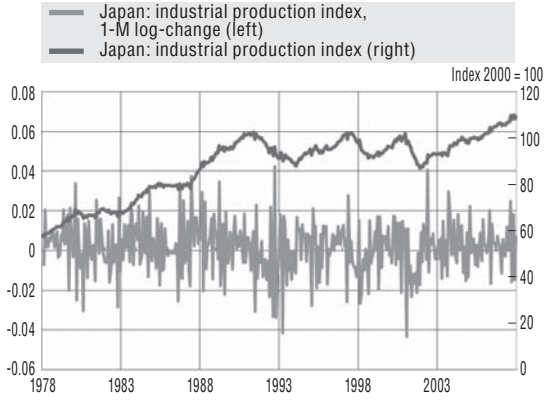

*Source:* Bureau of Economic Analysis.



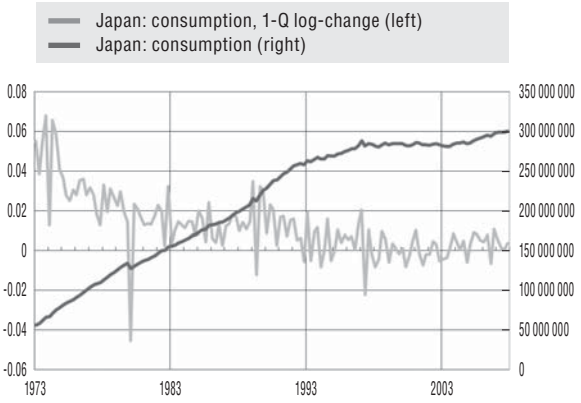

*Source:* Eurostat.




*Source:* Eurostat.

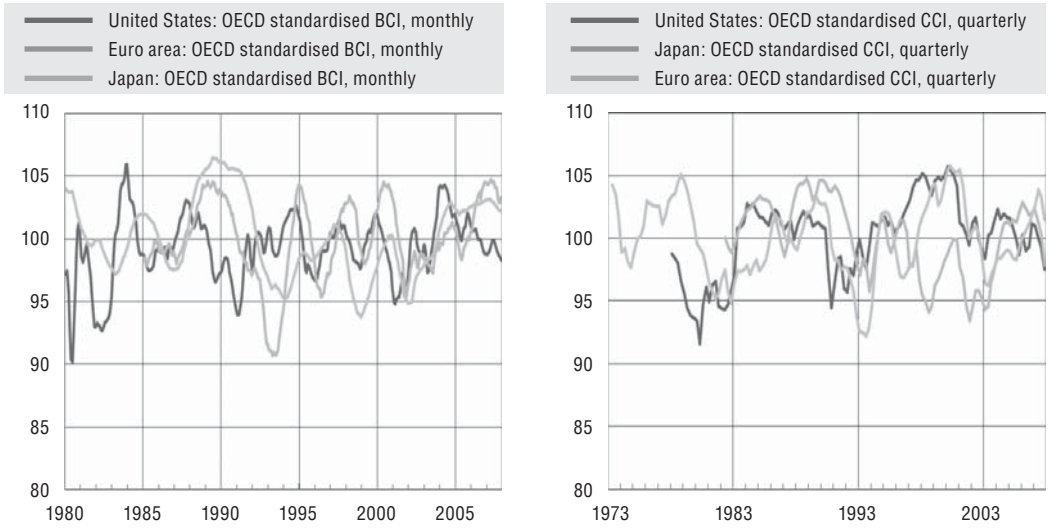



*Source:* Ministry of Economy, Trade and Industry.




*Source:* Economic and Social Research Institute, Cabinet Office, IMF, OECD.

Figure 2. **The OECD Standardised Confidence Indicators**




*Note:* Long term average = 100.

These functions impose clear constraints on the series being analysed: the series should be stationary; and, it is clearly assumed to be generated by linear combinations of harmonic functions. Basic spectral analysis also assumes that different fluctuations in the series stay constant through time, which other than for purely deterministic series, is clearly not the case. To mitigate this particular concern Windowed Fourier analysis was invented to essentially do spectral analysis on "windows" which are passed down the time series. In more conventional statistical language this is called the short time Fourier transform (STFT) with a rectangular window. If this window is simply moved to different parts of the series, we can get abrupt changes (leading to what is known as the Gibbs phenomenon) as well as incorrect estimates of frequencies, particularly if there are local non-stationarities in the series under study. Subsequent developments in spectral analysis focused on development of new windowing techniques and functions, some with overlapping windows, in which case weightings on observations can be specified, giving rise to more complicated windows, such as Hamming, Hann, Bartlett, Triangular, Gauss and Kaiser windows.

Passing a window down the length of a series in which case the analysis is not just confined to the frequency domain, is often called "time-varying spectral" or "time-frequency" analysis. Since its development in the 1970s, more flexible frequency domain analysis techniques have emerged, mostly from other disciplines which rely more heavily on this type of analysis (such as electrical engineering, acoustics and medical imaging).

In the 1980s, a chance meeting between a French mathematician (Daubechies) and signal processor (Mallat) gave birth to wavelet analysis, and in its discrete form what Mallat called "multi-resolution decomposition". The basic idea behind wavelet analysis is to decompose a time series into components corresponding to the fluctuations embedded in the series over pre-defined ranges of frequencies. The concept is to apply different functions other than harmonic functions to time series, such as asymmetric functions (as with the Daubechies wavelet) or other specific features (such as a discrete step "Haar" wavelet function). The mathematical background for wavelets can be found in Daubechies (1992). Much of the background for this approach and some applications in economics and finance can be found in Crowley (2007).

So why is wavelet analysis seen as superior to time-varying spectral analysis using the STFT? The answer lies in the uncertainty principle, formulated by the quantum physicist Heisenberg, which states that locating a particle in a small region of space makes the velocity of the particle uncertain; and conversely, that measuring the velocity of a particle precisely makes the position uncertain. Applying this to frequency domain analysis implies that the exact frequency and time information of a variable at some certain point in the time-frequency plane cannot be known. So, although we can resolve high frequencies very well in time, it is less easy to resolve their exact frequency, but conversely with low frequencies, they can be much better resolved in frequency, but much less well resolved in time. This means the best we can do is to look at the frequency components that exist over any given period, and use different "basis" functions as a means of matching our series with some non-harmonic short function (or wavelet). Wavelets use short functions, and in the discrete version of the multi-resolution decomposition they utilise both a trend wavelet function and a "fluctuation" wavelet (referred to in the literature as "father" and "mother" wavelets respectively). This means wavelets can also analyse non-stationary time-series, which is a further advantage over traditional spectral analysis.

Wavelet analysis, although only around now for 20 years, has had a huge impact on frequency domain analysis. Wavelet analyses come in at least two variations: discrete[4] and continuous.[5] Discrete analysis relies on filter banks to process sampled data observed at discrete points in time, whereas continuous analysis assumes that the observed data reflects a continuous population distribution. Each methodology also has its own drawbacks: first, discrete wavelet analyses rely on arbitrary selections of a wavelet "basis" function, which can inevitably lead to some incomplete results if the matching of the series with the wavelet is suboptimal. Second, wavelet analyses produce a new series for each scale (or frequency range), with continuous wavelet analysis it depends on how fine the frequency ranges are being used, whereas with discrete wavelet analyses the range of each scale is pre-defined in dyadic terms. Therefore, if a particular series had embedded frequencies operating at both a five-year and a seven-year cycle, then as the pre-defined scale ranges from four to eight year cycle fluctuations, these two cycles would be combined and represented by a single series (or "crystal") at one particular scale. Third, there is "leakage" at the edges of each of these pre-defined scales; for example, if using the pre-defined scale as above, and we have a four-year cycle, it might show up in two scale crystals, leading to the impression that there are two separate embedded frequency cycles, where in fact there is only one.

Because of these problems among others, the Hilbert-Huang transform was introduced as an alternative to both spectral and wavelet analysis (as well as other frequency domain methods not discussed here such as waveform dictionaries and the Wigner distribution).

### *3.2. The basics of the Hilbert-Huang transform (HHT)*

#### *3.2.1. Introduction*

The Hilbert-Huang transform (HHT) consists of two steps, of which only the first step is new; namely empirical mode decomposition (EMD). EMD was pioneered by Huang (1998) who, at the time, was an US National Aeronautical and Space Administration (NASA) oceanographer and research scientist. He developed an algorithm which is not mathematically based, as with spectral and wavelet analysis, but instead is an empirical method for extracting the embedded frequencies (or what signal processors call "modes") in any given time series. The method does not rely on any "basis" function as with spectral and

wavelet analysis, and is a method that operates in the time domain rather than in the frequency domain. The second part of the HHT (in its original version) uses the Hilbert transform to obtain instantaneous frequency estimates using the "mode" data around any given point in time. The resulting output is an improved decomposition and better resolution of a series into its constituent frequency components. Probably the best review of the HHT and more recent developments in the methodology can be found in Huang and Wu (2008).

EMD was developed in response to the desire of NASA for a more accurate way of identifying frequency of oscillations. This is an important development in frequency domain research as it acknowledges that many variables have oscillations that are time varying and that many variables are non-stationary. The methodology is still being developed and refined[6] even though it is clear that its flexibility offers major advantages, and in particular its adaptive basis.

Table 2 gives a basic comparison of empirical methods of analysis. In Table 2, the first five entries in the first column (labelled "Feature") refer to whether the characteristic is required for the types of analysis headed up in the other columns. The last two entries in the first column, "Measurement" and "Calculation", refer to how fluctuations are measured and in what domain the calculations are done in.

Table 2. **Comparison of empirical methods**

| Feature | Time Series | Spectral | Wavelet | EMD |
|---|---|---|---|---|
| Stationarity? | Yes | Yes | No | No |
| Linear? | Yes | Yes | No | No |
| Theory? | Yes | Yes | No | No |
| Adaptive? | Limited | No | Limited | Yes |
| Basis? | *A priori* | *A priori* | *A priori* | *A posterior* |
| Measurement | Variance | Energy in frequency domain | Energy in time-frequency space | Energy in time-frequency space |
| Calculations | Time domain | Frequency domain | Frequency or Time domain | Time domain |

*Note:* "Theory?" denotes whether mathematical background is fully developed, "Adaptive?" refers to whether the methodology is able to adapt to structural changes in the series in question, and "Basis?" refers to how each methodology is applied to analyse the series in question.

Very little research has been done in economics using the HHT, but there are two notable exceptions: Huang and Shen (2005) applied HHT to US mortgage rates; and the other by Zhang, Lai and Wang (2007) who applied HHT to oil prices. See Crowley (2009) for more background on the method and some applications to economic and financial time series.

### *3.2.2. EMD process*

EMD employs an iterative process as follows:

1. identify all local local extrema;
2. connect all local maxima using a cubic spline to form an envelope, and do likewise for the minima;
3. calculate the mean of the upper and lower envelopes and denote $m_1$;
4. subtract the mean from the series itself, so in equation form, we are left with the so-called "first protomode":

$$h_1 = x_t - m_1 \tag{4}$$

if $h_1$ does not satisfy stopping criterion, let $x_t = h_1$ and go back to step 1;

5. if $h_1$ satisfies stopping criterion after $k$ iterations, the first intrinsic mode function (IMF) is obtained:

$$c_1 = h_{1k} \tag{5}$$

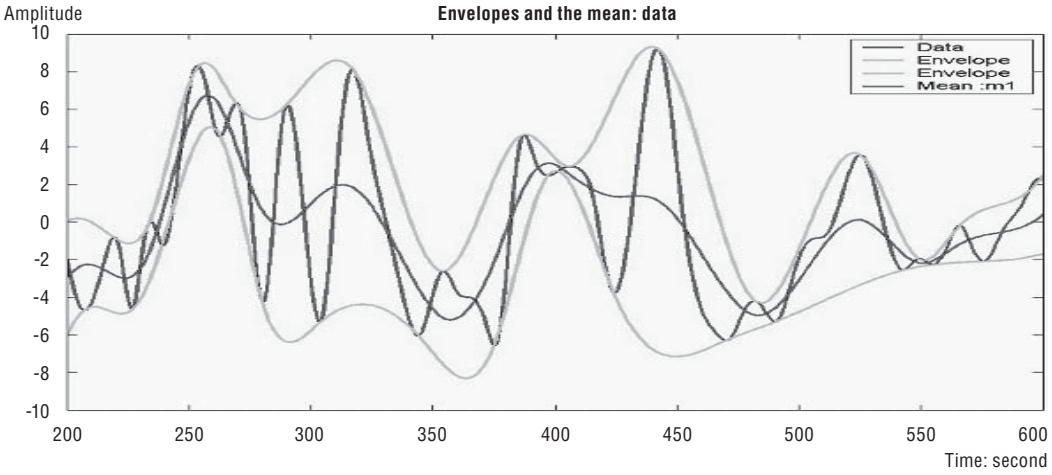
6. subtract this first IMF from the original data to obtain $r_1$, the first "residual":

$$x_t - c_1 = r_1 \tag{6}$$

7. start the whole process from 1 again but using $r_1$ as new data.

Figure 3 illustrates steps 1 to 3 for the EMD process.

Figure 3. **Illustration of EMD process**




The resulting process can be summarised as the decomposition of the original time series into a number of intrinsic mode functions (IMFs) and a residual that describes the trend. This can be mathematically expressed as follows:

$$x_t = \sum_{j=1}^{n} c_j + r_n \tag{7}$$

The output from the whole process is therefore $n$ IMFs and a residual which represents a (non-linear) trend, where the IMFs can be thought of as the equivalent of "crystals" from wavelet analysis, except that they are not confined to lying in the limits imposed by using pre-defined scales.

The stopping criterion endogenously defines the number of iterations $k$, necessary to obtain the $n$ IMFs. The smaller number is the stopping criterion, the higher is $k$ and the greater the number of IMFs obtained.

### *3.2.3. The Hilbert transform and frequency analysis*

The first part of the process described above is uniquely in the time domain, but to obtain frequencies for each mode, the analysis of the output from this process must take place in the frequency domain. The Hilbert spectrum uses a Hilbert transform to obtain an estimate of the instantaneous frequency of any time series.

For a time series $x$ the Hilbert transform, $y_t$ is given by:

$$y_t = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x_t}{t-\tau} d\tau \tag{8}$$

where *P* is the Cauchy principal value of the singular integral. Given the Hilbert transform of any arbitrary function $f(x_t)$ we obtain the analytical output $z_t$, where:

$$z_t = a_t e^{i\theta_t} \tag{9}$$

Note that this output is of necessity complex. The term $a_t$ then represents the amplitude at time t, and the phase of the frequency is given by $\theta_t$, which can then be used to estimate the instantaneous frequency, $\omega$, which is given as:

$$\omega = \frac{d\theta}{dt} \tag{10}$$

The Hilbert transform, therefore, yields a direct estimate of the instantaneous frequency of the cyclical activity embedded in the IMF, and thus this can be used as an estimate of the time-varying frequency of the IMF.

Unfortunately there are two problems regarding the Hilbert transform, notably one of underestimating the true frequency (due to the so-called "Nuttall theorem"), and also incompletely extracting the frequency content of the data but leaving some information in the amplitude variable (due to the so-called "Bedrosian theorem"). Because of these issues, there has been new research (see Huang, Wu, Long *et al*, 2008) which suggests that a direct quadrature method might be an improvement over the Hilbert spectrum for calculating instantaneous frequency. Here we use the direct quadrature method.

### *3.3. Ensemble EMD*

In this article, we use an Ensemble EMD methodology to separate out the embedded frequencies in economic variables. Ensemble EMD (or EEMD) came about because of various problems with EMD associated with "mode mixing". "Mode mixing" occurs when either:

- different frequencies are found to reside in the same IMF, or when
- similar frequencies are found to reside in different IMFs.

Wu and Huang (2004) note that various solutions to this problem (notably the "intermittence test" in Huang, Shen and Long [1999]) were only partially successful in mitigation, so a new approach was needed. Research on EMD done by Flandrin, Rilling and Gonclaves (2004), and Flandrin and Gonclaves (2004a) showed that under certain circumstances the EMD acted like a filter bank (that is, a constant band pass shape), equivalent to analysis by using wavelet analysis. Further research by Flandrin *et al.* (2005) showed that when applied to white noise, the EMD was equivalent to the dyadic filter bank used by the discrete wavelet transform. Later Wu and Huang (2004) realised that by adding white noise to the data and running EMD many times this will properly reduce the problem of "mode mixing", and yield greater resolution of the IMFs. This is mostly due to the cubic spline calculation requiring well-defined extrema and by adding white noise to the data these extrema are more accurately located, giving significant improvements in the EMD results.

In theory, given N ensemble members, and if $\varepsilon$ is the amplitude of the white noise added to the data, then it can be shown that the resultant standard deviation of the error (the difference between the variable and the sum of the corresponding IMFs) amounts to $\varepsilon_n$, where:

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \tag{11}$$

So when adding a certain amount of white noise to the data,[7] the larger the ensemble (N), the lower the error, and so improved results are obtained. The steps of EEMD then are as follows:

1. add white noise to the series;
2. decompose the data with added white noise into IMFs using EMD;
3. repeat 1 and 2 N times, but with different white noise added each time; and
4. obtain the means of the "ensemble" IMFs from each EMD decomposition.

Essentially a chosen amount of white noise is added to each run, which will cancel out when averaged, and consequently the mean IMFs obtained will be less likely to suffer from "mode mixing"[8] and will more likely be better resolved, particularly at higher frequencies.

Wu and Huang (2008) spend considerable time on applications of EMD and show that if executed properly it can extract the embedded frequencies operating in most non-linear and non-stationary empirical data. It has the potential to be of major benefit to any data analysis toolkit.

### *3.4. Estimation strategy with economic variables*

Here, as we are mostly concerned with lower frequency IMFs, there should be less concern with using the EMD with economic variables. Nevertheless, the instantaneous frequencies obtained in the analysis occasionally displayed high levels of "mode mixing", particularly in the case of some of the sentiment indicators. As such, most of the indicator variables were run first using basic EMD and then if "mode mixing" occurs, these were re-run using EEMD with white noise variance of 20% of the variance of the actual series added for the ensemble estimation, and a value of N = 400 for the ensemble.[9]

## 4. Results

In all the results that follow, the data used for the economic (counterpart) variable to be analysed is the change in the logged value of the variable, and for the indicators, the actual level of the indicator is used for comparison. This is the most appropriate comparison, as most indicators are constructed so that they "indicate" a rise or fall in the economic variable counterpart.

### *4.1. The US*

#### *4.1.1. Industrial production: US industrial production* vs. *OECD business confidence indicator*

The left hand panel of Figure 4 shows the original series (A) for the economic variable ($\ln[USIP_t]$-$\ln[USIP_{t-1}]$), where $USIP_t$ is the US indus (B to H) and then the last series in the stackchart (I) represents the residual (or adaptive trend). The same is done for the indicator variable, in this case the OECD leading indicator for industrial production, in the right hand panel of Figure 4.

There are several things to note from the plot. First, seven IMFs were extracted from USIP, whereas only six IMFs were extracted from the OECD indicator. Noticeably the more noise in the series to begin with, the higher frequency IMFs will be extracted from the series. On inspection it appears that there is considerable correlation in movements of $IMF_i$(USIP) with $IMF_{i-1}$ (USIPindicator). This correlation appears in the (maximal lag) correlation of the IMFs in Table 3 where the strongest (significant[10]) correlation is between

Figure 4. **US industrial production *vs.* OECD business confidence indicator: IMFs**

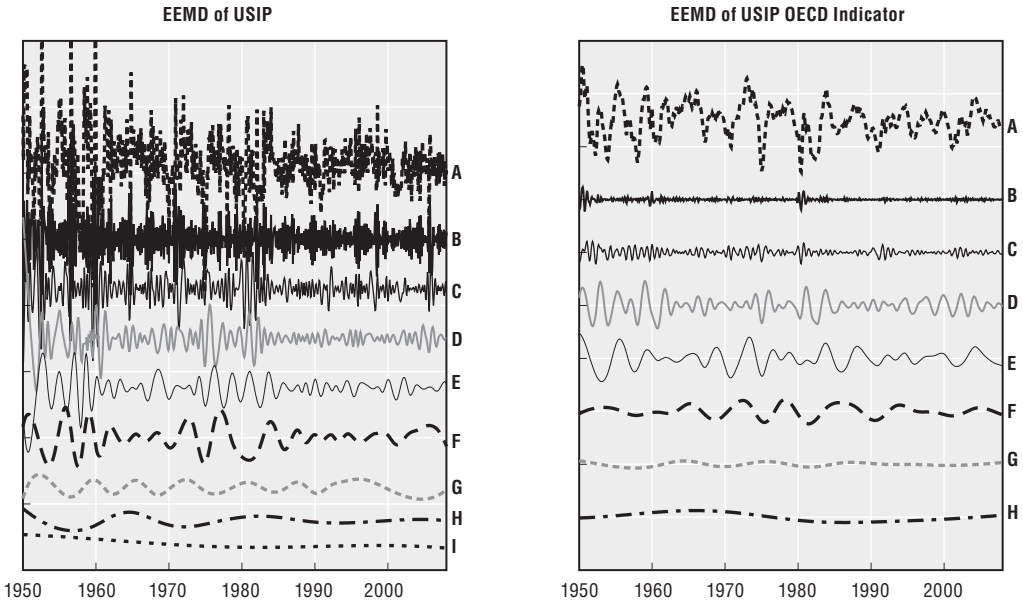



Table 3. **Correlations of IMFs for US industrial production (USIP) and OECD business confidence indicator (overall = 0.5389) with frequencies**

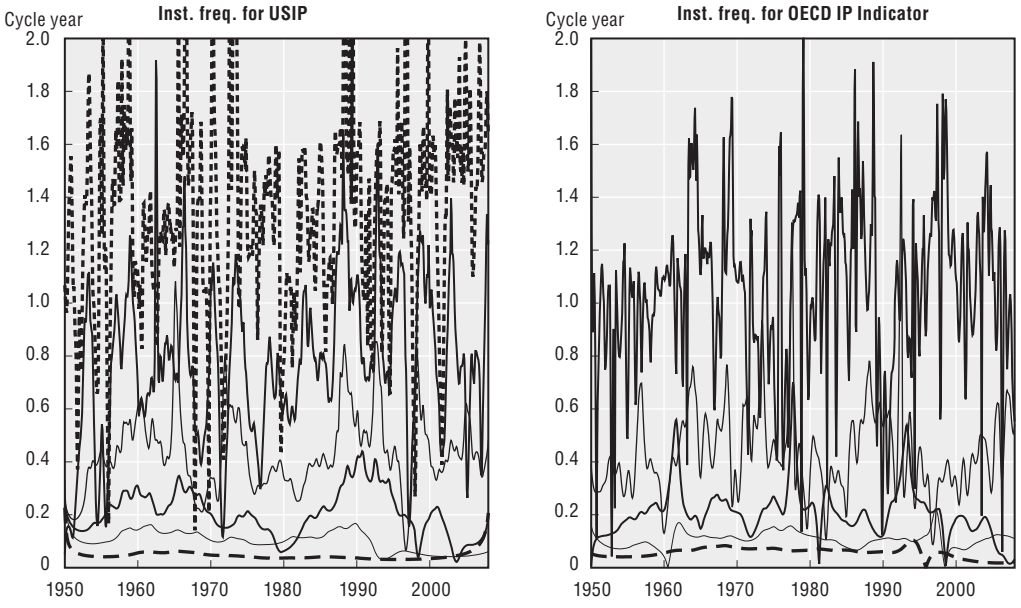
| Correlations of USIP | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | Frequency |
|---|---|---|---|---|---|---|
| IMF2 | 0.4178* | –0.0206 | –0.0207 | 0.0026 | –0.0059 | 1.3477 |
| IMF3 | 0.0998 | 0.366* | 0.2186* | –0.0245 | 0.1038* | 0.7802 |
| IMF4 | 0.0466 | 0.3362* | –0.1329 | –0.028 | –0.1465 | 0.4379 |
| IMF5 | 0.0206 | 0.2922* | 0.6833* | 0.2984* | 0.1725* | 0.2063 |
| IMF6 | 0.0499 | –0.0439 | –0.1519 | 0.2989* | 0.0296 | 0.1007 |
| IMF7 | –0.013 | 0.0213 | 0.0915* | 0.0586 | 0.5609* | 0.0486 |
| Frequency | 1.0464 | 0.4424 | 0.2074 | 0.1062 | 0.0564 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

IMF7 for USIP and IMF6 (0.5609) for the indicator, and IMF5 for USIP against IMF4 for the indicator (0.6833). Second, the business cycle is not separately identified within a particular frequency and its location depends, as might be expected, on the shape of the downturn; so for the short sharp recession of the early 1980s, this downturn is found in IMF5, but for the shallower downturn in the early 2000s, this downturn is located in IMF6. Third, it is apparent that there are other cycles in the data besides the business cycle, and that some of these fluctuations in the data are clearly of major significance in terms of amplitude of fluctuation. These cycles are what Zarnowitz and Ozyildirim (2002) have termed "growth cycles", and we use the same terminology here for the remainder of the article. Fourth, the residual is different for the indicator and for industrial production; the average level of industrial production increases appears to be falling over time, whereas the indicator perhaps appears to have a rather long cycle, although this is difficult to tell without additional data.

The frequency content of the cycles found in the data and the indicator are shown in Figure 5. The separation of the IMFs in terms of frequency is clear for most of the series although in the 1980s, there is "mode mixing" and in the late 1990s it reoccurs with IMF5.

Figure 5. **US industrial production *vs.* OECD business confidence indicator: instantaneous frequency**




The same patterns are evident in the OECD indicator, which implies that the indicator captures some of the changing frequency content associated with the different embedded cycles. Interestingly in terms of longer cycles, there is a 10-year cycle evident in the data as well as a 20-year cycle. Nothing beyond this is detected.

### 4.1.2. *Industrial production: US industrial production* vs. *business sentiment indicator*

In Figure 6 we show the IMFs obtained from the business sentiment index against the industrial production data. Note that this is a shortened time series so we obtain slightly different results for USIP. In Figure 7 the instantaneous frequencies are also plotted.

In this instance we extract the lower frequency for Table 4 despite the fact there is very little evidence of a longer cycle in the short span of data being used. Nevertheless, we know from the full dataset that a longer (around 20-year) cycle is identified in the data. Here the business cycle is identified in USIP in both IMF4 and IMF5, but in the business sentiment index the business cycle is located in IMF5, which appears to be a high-amplitude frequency component. It is noteworthy that IMF4 in USIP is also identified quite well by IMF3 in the business sentiment index, but these growth cycles are less well identified than the business cycle as a whole. In terms of the frequency plots, very little mode-mixing occurs with USIP, but significant mode-mixing appears to occur in the mid-1990s for the sentiment index, but this appears to be a temporary phenomenon.

### 4.1.3. *Consumption: US consumption* vs. *OECD consumer confidence indicator*

Figure 8 shows the IMFs from the EEMD of US consumption growth and the OECD leading indicator.

Here the original series clearly shows the "great moderation" in terms of a narrowing of the amplitude of fluctuations in consumption growth, but this is not readily apparent when looking at the indicator. In terms of the IMFs, the business cycle is contained mostly

Figure 6. **US industrial production *vs.* business sentiment indicator: IMFs**

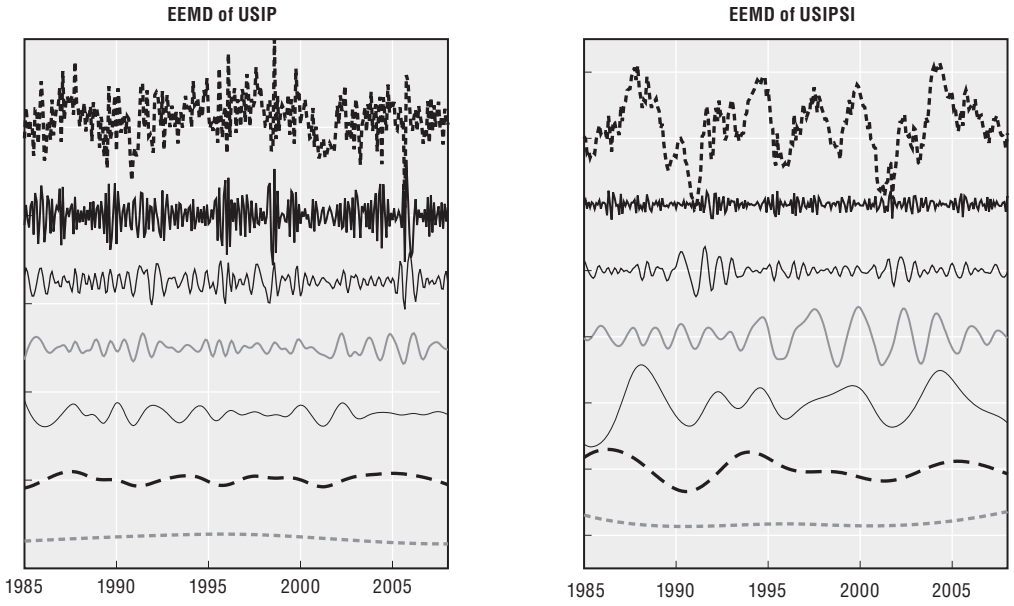
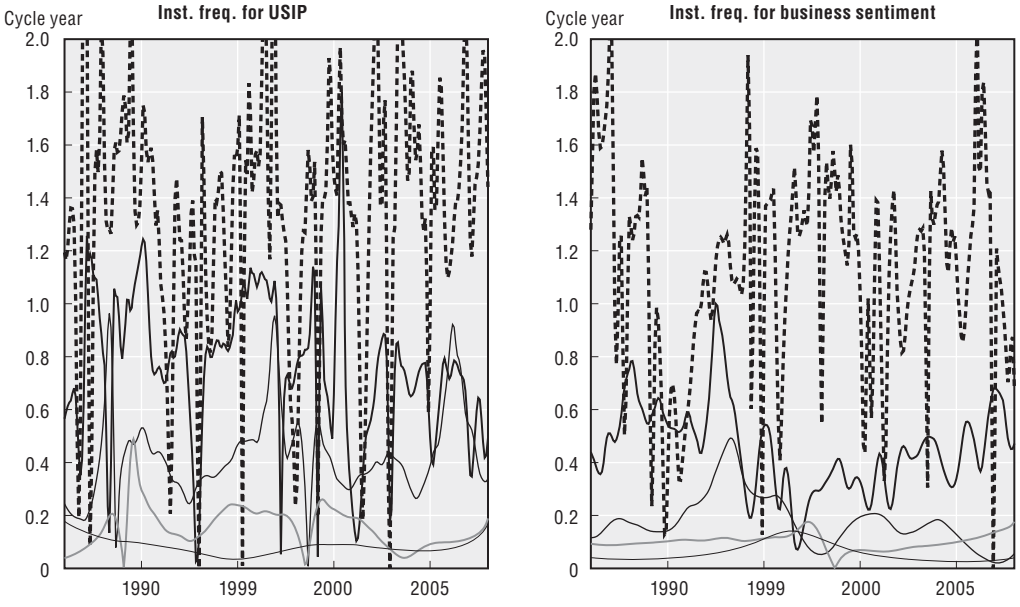



Figure 7. **US industrial production *vs.* business sentiment indicator: instantaneous frequency**




in IMF4 for both the original series and the indicator, with the notable exception being the 1982 recession, which shows up as a shorter frequency fluctuation in IMF2 in both cases. What is particularly interesting here is that the growth cycle in IMF2 and IMF3 are largely reflected in the OECD indicator growth cycles, and that when looking at the business cycle in IMF4, there is a clear dampening in the actual variable but this is not apparent in the indicator variable. This suggests that although economic indicators predict a usual size of amplitude in the business cycle, this does not tend to appear, perhaps due to offsetting measures such as counter cyclical fiscal and monetary policy.

Table 4. **Correlations of IMFs for US industrial production (USIP) and business sentiment indicator (overall = 0.40) with frequencies**

| Correlations of USIP | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | Frequency |
|---|---|---|---|---|---|---|
| IMF2 | 0.2168* | 0.049 | –0.0067 | –0.018 | –0.0137 | 1.3563 |
| IMF3 | 0.3169* | 0.2445* | –0.0009 | 0.0632 | 0.0344 | 0.7433 |
| IMF4 | 0.2332* | 0.5131* | 0.3141* | –0.0987 | 0.016 | 0.4260 |
| IMF5 | 0.0324 | 0.1784* | 0.6824* | 0.4707* | –0.1473 | 0.1499 |
| IMF6 | –0.022 | 0.0647 | 0.1339* | 0.5708* | 0.5425* | 0.0927 |
| Frequency | 1.1053 | 0.4624 | 0.1721 | 0.1013 | 0.0578 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

When looking at the correlation between the cycles (Table 5), it is clear that the correspondence between the IMFs for both consumption growth and the OECD consumption indicator is very good, except for the very high growth cycle frequencies.

Table 5. **Correlations of IMFs for US consumption (USC) and the OECD consumer confidence indicator (overall = 0.40) with frequencies**

| Correlations of USC | IMF2 | IMF3 | IMF4 | IMF5 | Frequency |
|---|---|---|---|---|---|
| IMF2 | 0.0488 | –0.0302 | –0.0111 | –0.0516 | 1.23 |
| IMF3 | –0.0618 | 0.5306* | 0.0679 | –0.1457 | 0.54 |
| IMF4 | 0.1919 | 0.2255* | 0.7229* | 0.1321 | 0.25 |
| IMF5 | –0.0262 | 0.193 | 0.0259 | 0.7892* | 0.08 |
| Frequency | 1.00 | 0.42 | 0.19 | 0.08 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

### *4.1.4. Consumption: USC vs. consumer sentiment indicator*

In this analysis, the Michigan index of consumer sentiment is used and the embedded frequency fluctuations are compared with the growth of consumption expenditures. Figure 8 shows the IMFs obtained from EEMD. The IMF4s appear to correspond well to the business cycle, with the IMF3 identifying the 1974 recession for the sentiment index. One of the surprising aspects of the analysis is that other growth cycles (IMF2 and IMF3 for example) do not appear to be detected as well as might be expected. This is confirmed in Table 6 where consumption growth IMF3 is best identified by two IMFs in the sentiment index (IMF2 and IMF3), but correlations are relatively low (but significant) in each case. This also comes out in the frequency plots in Figure 9, where there appears to be frequency mismatches between the IMFs, but this is actually because some of the features in consumption growth are captured by different IMFs in the consumer sentiment index.

What does this imply in economic terms? It implies that consumers know when shocks occur, but have less information about the medium to longer term impact on consumer spending of these shocks (whether permanent or transitory, for example), and this shows up in our results. This is in direct contrast to the results obtained for industrial production, where producers appear to have a better idea about the medium to long-term impact of shocks on output (perhaps through greater networking and greater monitoring of economic indicators than for consumers).

Figure 8. **US consumption *vs.* consumer sentiment indicator: IMFs**

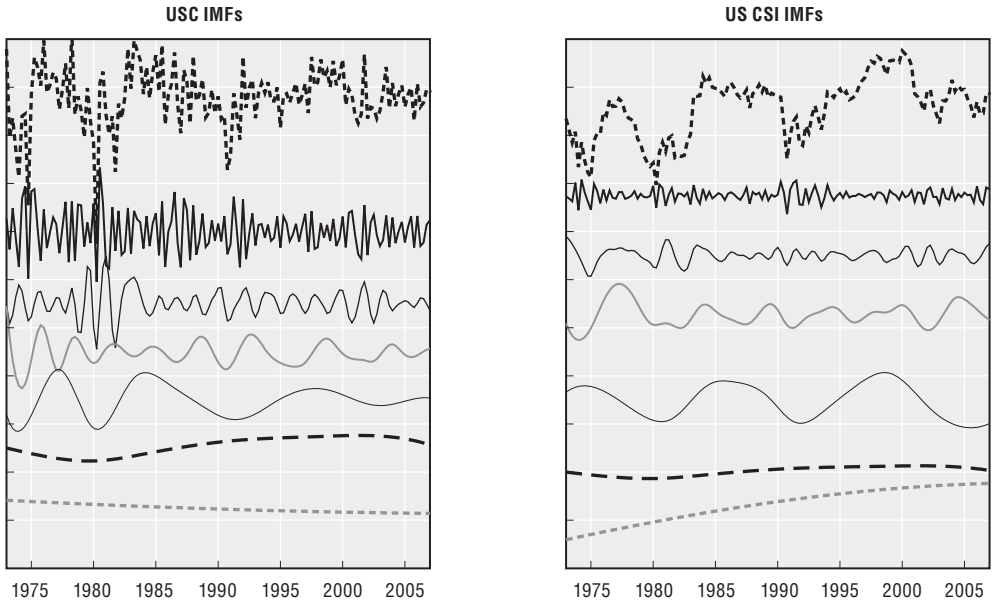
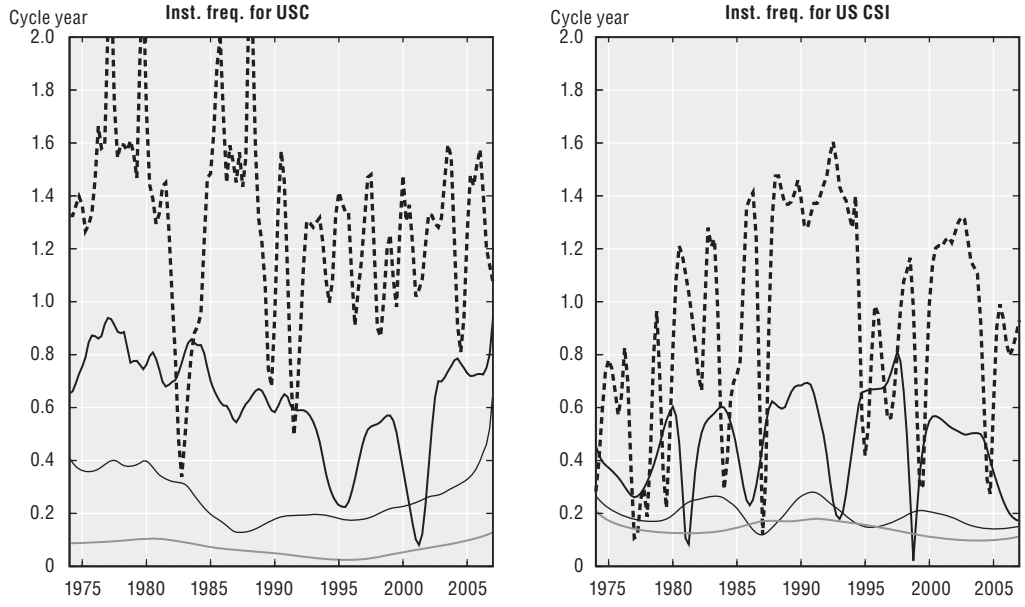



Table 6. **Correlations of IMFs for US consumption (USC) and consumer sentiment indicator (overall = 0.458) with frequencies**

| Correlations of USC | IMF2 | IMF3 | IMF4 | IMF5 | Frequency |
|---|---|---|---|---|---|
| IMF2 | 0.0934 | 0.0063 | –0.0056 | –0.01 | 1.293 |
| IMF3 | 0.2127* | 0.2913* | –0.0572 | 0.0141 | 0.662 |
| IMF4 | 0.1465 | 0.5864* | 0.4419* | 0.1332 | 0.296 |
| IMF5 | 0.0008 | –0.0484 | 0.0799 | 0.4457* | 0.0711 |
| Frequency | 0.916 | 0.458 | 0.197 | 0.143 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

Figure 9. **US consumption *vs.* consumer sentiment indicator: instantaneous frequencies**



### *4.2. Euro area*

#### *4.2.1. Industrial production: Euro area industrial production vs. OECD business confidence indicator*

Euro area industrial production and the OECD leading indicator are used in this analysis. Data prior to 1999 is synthetic, so care has been taken with interpretation during the pre-EMU period. Figure 10 shows that with both the euro area as with the US, there is a strong similarity between the IMFs of industrial production growth and the OECD leading indicator but at the (i-1)th IMF level, where i is the IMF number for industrial production growth. Another immediately apparent feature of euro area industrial production growth is that it has a strong high frequency cycle with a length of around two years, as well as a 10-year cycle, which presumably reflects the business cycle. Table 7 shows this, with the strongest correlation being between IMF5 for industrial production and IMF4 for the OECD indicator. The business cycle is left in the residual for industrial production growth, but is clearly highly correlated (value 0.8487) with IMF5 in the indicator variable. It is a weak cycle, however when compared with the other growth cycles found in industrial production, it is more obvious in the composition of the leading indicator.

Figure 10. **Euro area industrial production *vs.* OECD business confidence indicator: IMFs**

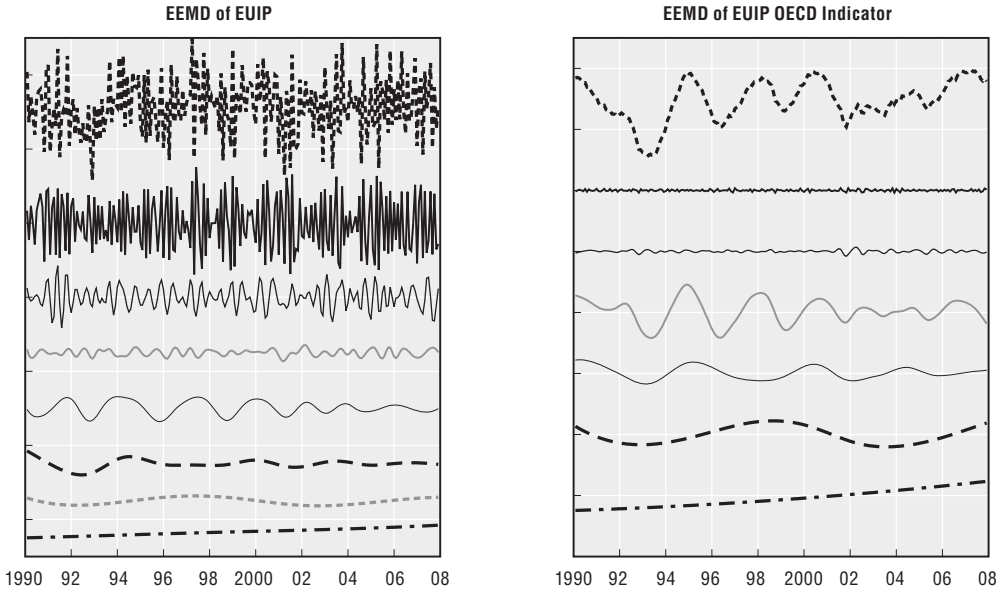


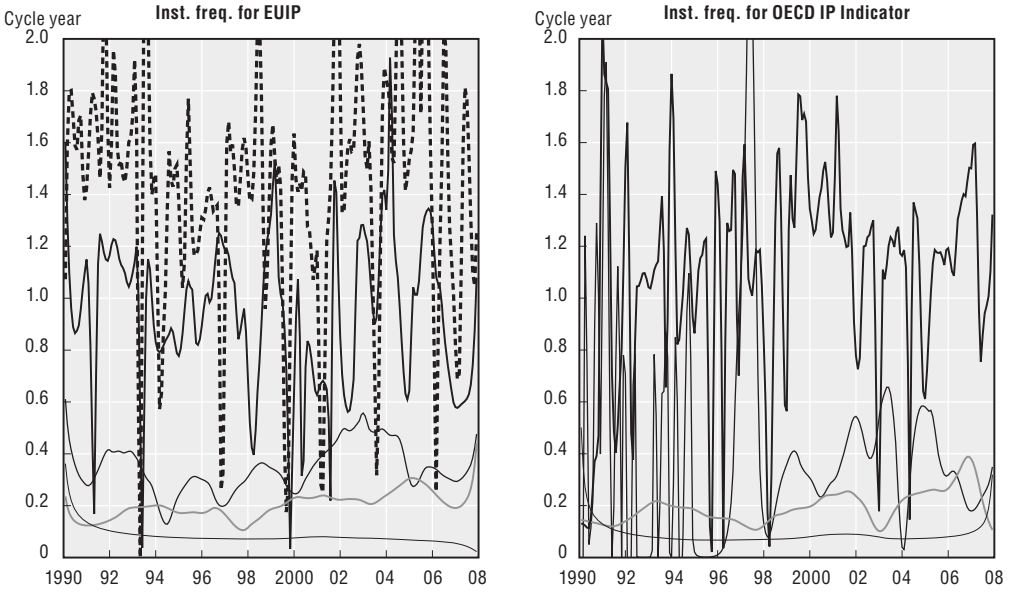

Table 7. **Correlations of IMFs for euro area industrial production (EUIP) and OECD business confidence indicator (overall = 0.182) with frequencies**

| Correlations of EUIP | IMF2 | IMF3 | IMF4 | IMF5 | Frequency |
|---|---|---|---|---|---|
| IMF2 | 0.1629* | –0.0045 | –0.0061 | –0.0175 | 1.44 |
| IMF3 | 0.2013* | –0.0393 | –0.0201 | 0.0253 | 0.94 |
| IMF4 | –0.0004 | 0.1613* | –0.0621 | –0.047 | 0.345 |
| IMF5 | –0.002 | 0.3377* | 0.5901* | 0.2216* | 0.201 |
| IMF6 | –0.027 | 0.08 | 0.095 | 0.8487* | 0.083 |
| Frequency | 1.086 | 0.400 | 0.193 | 0.091 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

When looking at the frequencies of the IMFs in Figure 11 it is clear that IMF2 for the OECD leading indicator has been constructed prior to 1999 as the frequency response is very different from other IMFs. Both a 5-year and a 10-year cycle can be detected in the data, and this comes through in both industrial production growth and the OECD leading indicator.

Figure 11. **Euro area industrial production (EUIP) *vs.* OECD business confidence indicator: instantaneous frequency**




### 4.2.2. *Consumption: Euro area consumption* vs. *OECD consumer confidence indicator*

In this analysis, euro area consumption growth is decomposed alongside the OECD leading indicator for the euro area. Figure 12 shows the IMFs and that once again, the longer cycles present in consumption growth are evident in the leading indicator. Shorter cycles though are much less evident in the leading indicator, and this is also apparent from the size of the correlations reported in Table 8, where shorter cycles have lower correlations than the longer cycles. Here the instantaneous frequencies shown in Figure 13 move together at lower frequencies, but less so at higher frequencies, although there is some mode mixing particularly when these movements in higher frequencies do not match.

## 4.3. *Japan*

The case of Japan is an interesting one, as it is a country that underwent a sustained period of stagnation and depression in the 1990s, so hopefully the EEMD approach will still be able to reveal any growth cycles that occurred during this prolonged contractionary period.

### 4.3.1. *Industrial production: Japanese industrial production* vs. *OECD business confidence indicator*

Figure 14 shows the IMFs for Japanese industrial production and the OECD leading indicator. Unlike in the US or euro area case, in this analysis the OECD indicator is clearly non-stationary, but this poses little problem when applying the EEMD approach as the

Figure 12. **Euro area consumption *vs.* OECD consumer confidence indicator: IMFs**

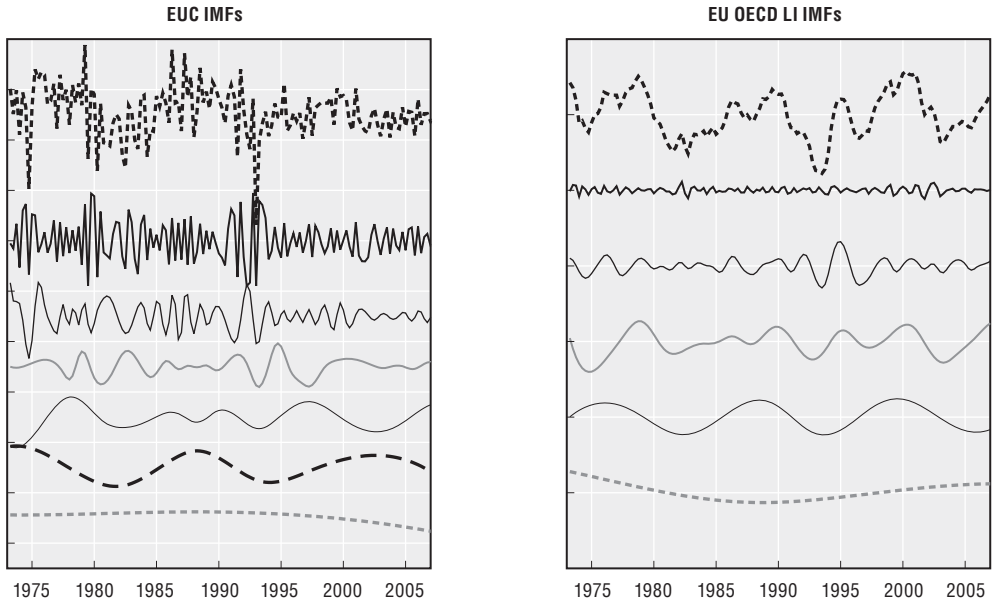



Table 8. **Correlations of IMFs for euro area consumption (EUC) and OECD consumer confidence indicator (overall = 0.182) with frequencies**

| Correlations of EUC | IMF2 | IMF3 | IMF4 | Frequency |
|---|---|---|---|---|
| IMF2 | 0.2198* | 0.0012 | –0.0156 | 0.9 |
| IMF3 | 0.6155* | 0.1612* | 0.0321 | 0.5 |
| IMF4 | 0.0577 | 0.6624* | 0.1297 | 0.21 |
| IMF5 | –0.0061 | –0.1884 | 0.7232* | 0.11 |
| Frequency | 0.578 | 0.271 | 0.133 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

Figure 13. **Euro area consumption *vs.* OECD consumer confidence indicator: instantaneous frequency**

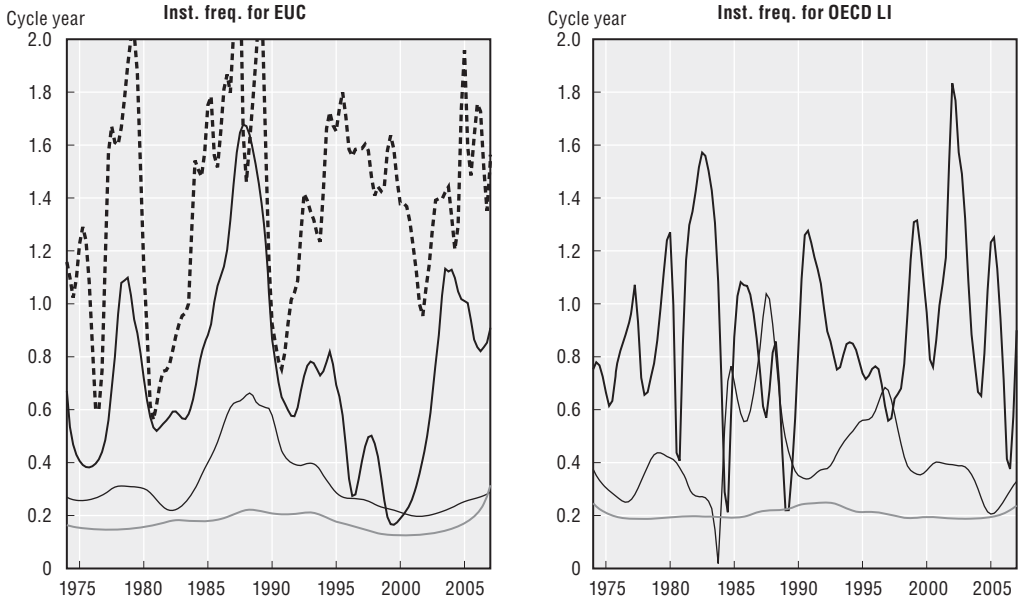
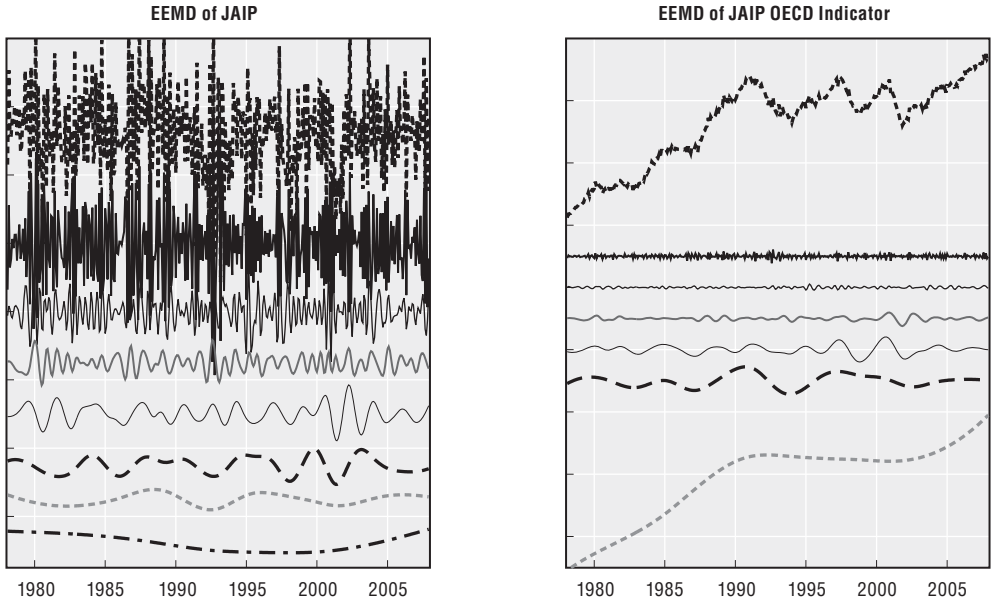


Figure 14. **Japanese industrial production *vs.* OECD business confidence indicator: IMFs**




trend component is found in the residual. The actual long cycle containing the depression of the 1990s is contained in the JIP residual, but this has no direct corresponding IMF in the indicator. This suggests that the indicator did not anticipate the longevity of the depression and that policy efforts to revive the economy, although appearing in the indicators, largely failed to appear in actual industrial production growth. The level of correlation between industrial production and the indicator is not high, and the highest significant correlation is reported to be between high frequency IMFs. Visual inspection of Figure 14 suggests that the most prominent IMF from the leading indicator (IMF5) appears to lag that of the similar IMF (IMF4) in the industrial production data.

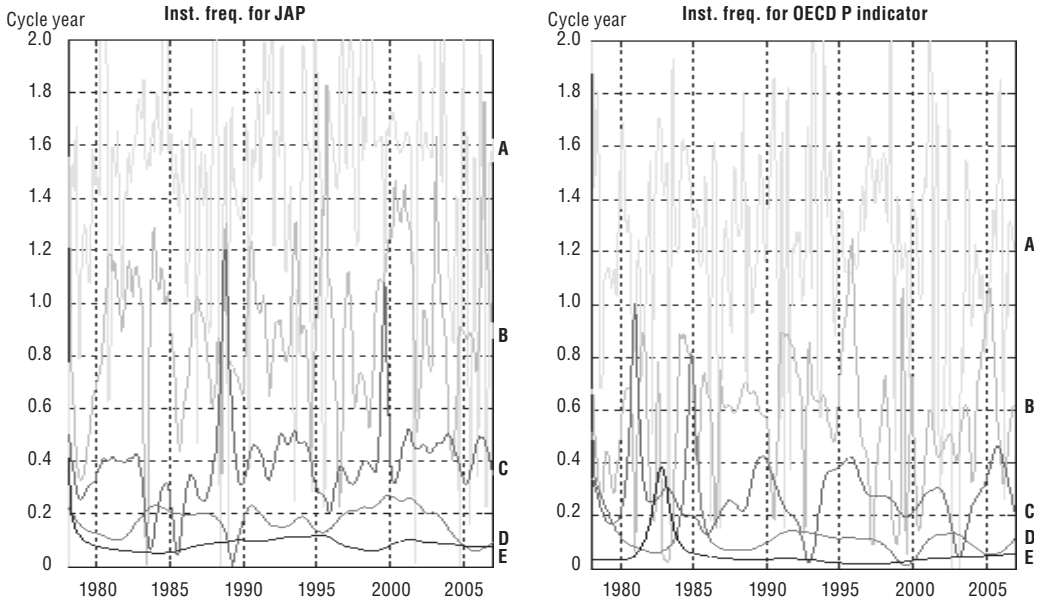
Table 9 shows a clear frequency mismatch across all cycles, and for longer frequencies the indicator suggests roughly a 20-year cycle in output growth, where as the longest cycle found in the actual data is an 11.5-year cycle. This is shown graphically in Figure 15.

Table 9. **Correlations of IMFs for Japanese industrial production (JAIP) and OECD business confidence indicator (overall = –0.0293) with frequencies**

| Correlations of JAIP | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | Frequency |
|---|---|---|---|---|---|---|
| IMF2 | 0.212* | –0.0047 | –0.0149 | –0.0103 | 0.0088 | 1.475 |
| IMF3 | 0.2356* | 0.122* | 0.0534 | 0.0202 | 0.0028 | 0.889 |
| IMF4 | 0.0132 | 0.1168 | 0.057 | –0.0063 | –0.0173 | 0.393 |
| IMF5 | –0.0046 | 0.0439 | –0.0176 | 0.0073 | 0.0037 | 0.170 |
| IMF6 | 0.0045 | –0.0049 | –0.0167 | 0.1787* | 0.1105 | 0.086 |
| Frequency | 1.198 | 0.548 | 0.270 | 0.126 | 0.053 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

Figure 15. **Japanese industrial production *vs.* OECD business confidence indicator: instantaneous frequency**




### 4.3.2. *Industrial production: Japanese industrial production* vs. *business sentiment indicator*

In this analysis, we use the sentiment indicator for Japanese output and decompose it alongside industrial production growth. Figure 16 shows the IMFs from the decomposition and once again there appears to be little in common between the IMFs although the there does appear to be a similar pattern in fluctuations between IMF6 for industrial production and IMF2 and/or IMF3 for the sentiment indicator. Table 10 shows the correlations and Figure 17 plots the instantaneous frequencies. Surprisingly, there is only one significant correlation.

Once again, there is a clear mismatch between industrial production growth and the business sentiment index in terms of frequencies of embedded cycles. Why this is the case, is an interesting question as expectations of economic fluctuations are clearly not aligned with those in the actual data.

### 4.3.3. *Consumption: Japanese consumption expenditure* vs. *OECD consumer confidence indicator*

Compared to industrial production, consumption growth yields much greater concordance between the indicator and the actual economic variable, as shown in Figure 18. For this analysis, similar components for longer frequencies are extracted (with also a very similar pattern found in the residual), but there appears to be much less similarities at higher frequencies. Table 11 shows correlations and frequencies, with very high correlations at lower frequencies but as expected much lower correlations at lower frequency fluctuations. This also appears with the instantaneous frequency plot shown in Figure 19, where a 20-year cycle is clearly identified in both the indicator and in consumption growth, but higher frequency growth cycles appear to be mismatched between the IMFs.

Figure 16. **Japanese industrial production *vs.* business sentiment indicator: IMFs**

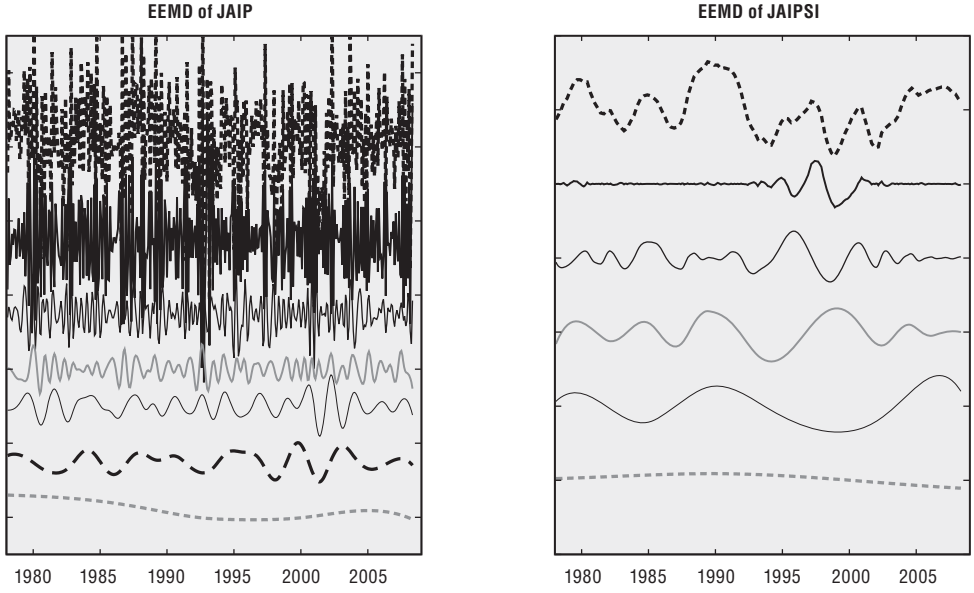



Table 10. **Correlations of IMFs for Japanese industrial production (JAIP) and business sentiment indicator (overall = 0.077) with frequencies**

| Correlations of JAIP | IMF2 | IMF3 | IMF4 | Frequency |
|---|---|---|---|---|
| IMF2 | –0.0341 | 0.009 | 0.0135 | 1.475 |
| IMF3 | 0.0198 | 0.0072 | –0.0113 | 0.889 |
| IMF4 | –0.0524 | 0.0501 | –0.0432 | 0.393 |
| IMF5 | 0.2911* | 0.0715 | –0.0016 | 0.170 |
| Frequency | 0.3385 | 0.1501 | 0.0643 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

Figure 17. **Japanese industrial production *vs.* business sentiment indicator: instantaneous frequency**

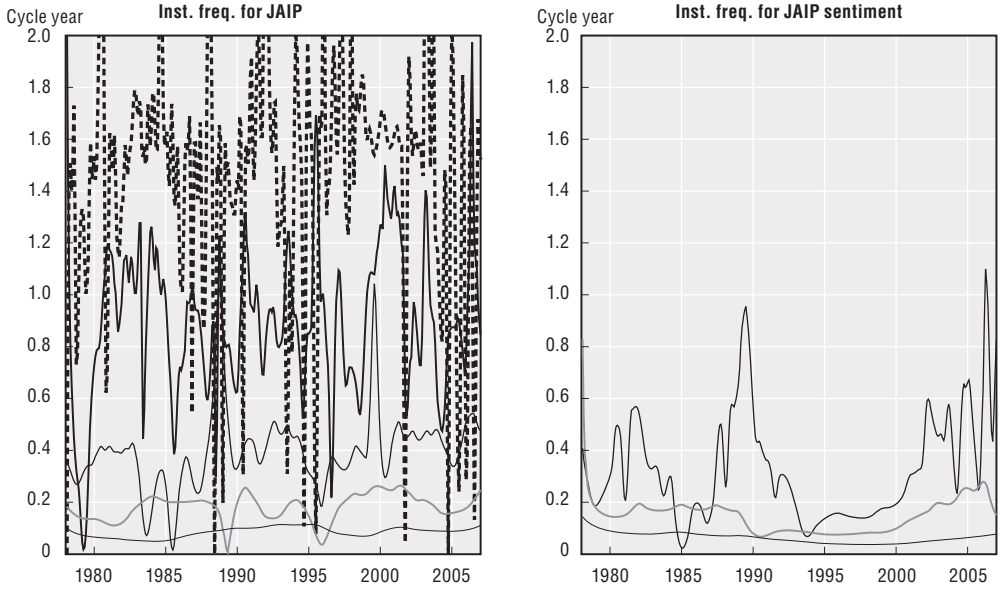


Figure 18. **Japanese consumption *vs.* OECD consumer confidence indicator: IMFs**

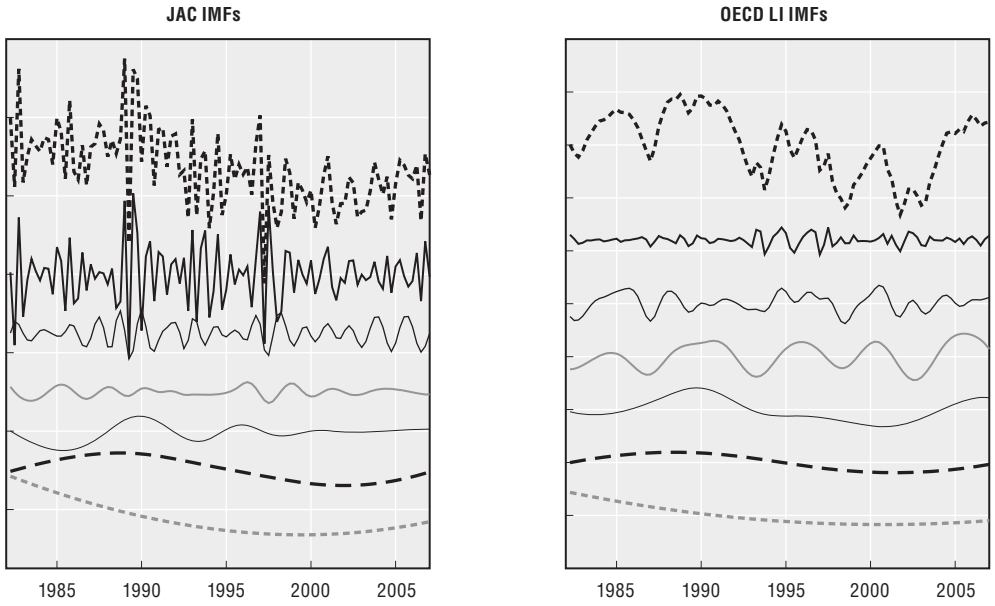
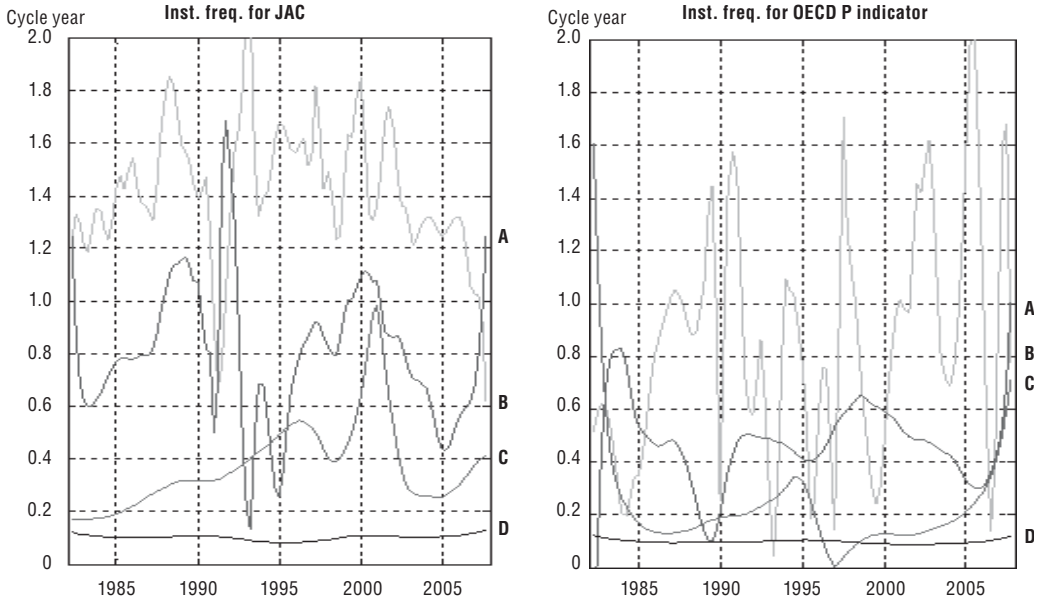



Table 11. **Correlations of IMFs for Japanese consumption (JAC) and OECD consumer confidence indicator (overall = 0.483) with frequencies**

| Correlations of JAC | IMF2 | IMF3 | IMF4 | IMF5 | Frequency |
|---|---|---|---|---|---|
| IMF2 | 0.0008 | –0.0461 | –0.013 | –0.0143 | 1.420 |
| IMF3 | 0.1769 | 0.2457* | 0.0302 | –0.0617 | 0.803 |
| IMF4 | –0.0366 | 0.4997* | 0.4299* | –0.1253 | 0.374 |
| IMF5 | 0.066 | –0.0128 | 0.7975* | 0.9964* | 0.101 |
| Frequency | 0.853 | 0.466 | 0.231 | 0.097 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

Figure 19. **Japanese consumption *vs.* OECD consumer confidence indicator: instantaneous frequencies**



### 4.3.4. *Consumption: Japanese consumption* vs. *consumer sentiment indicator*

In Figure 20, we decompose over the same time period as for the OECD indicator. It appears to possess a similar correspondence between consumption growth and the consumer sentiment index in lower frequency cycles as the OECD indicator does, with less correspondence at the higher frequencies.[11] It is also notable that for Japanese data the amount of high frequency volatility appears to have been reduced in consumption growth, but that volatility in sentiment appears to have increased in both the IMF1 and IMF3 components. Table 12 shows that apart from the long cycle found in the data there is a significantly correlated shorter cycle of about four years in the data. Figure 21 shows that the frequency profile of this IMF (IMF4 in both cases) appears to be similar. However, in terms of amplitude, Figure 18 suggests that this cycle has been losing energy despite that the sentiment index IMF4 appears to still possess a fairly significant amount of energy.

Figure 20. **Japanese consumption *vs.* consumer sentiment indicator: IMFs**

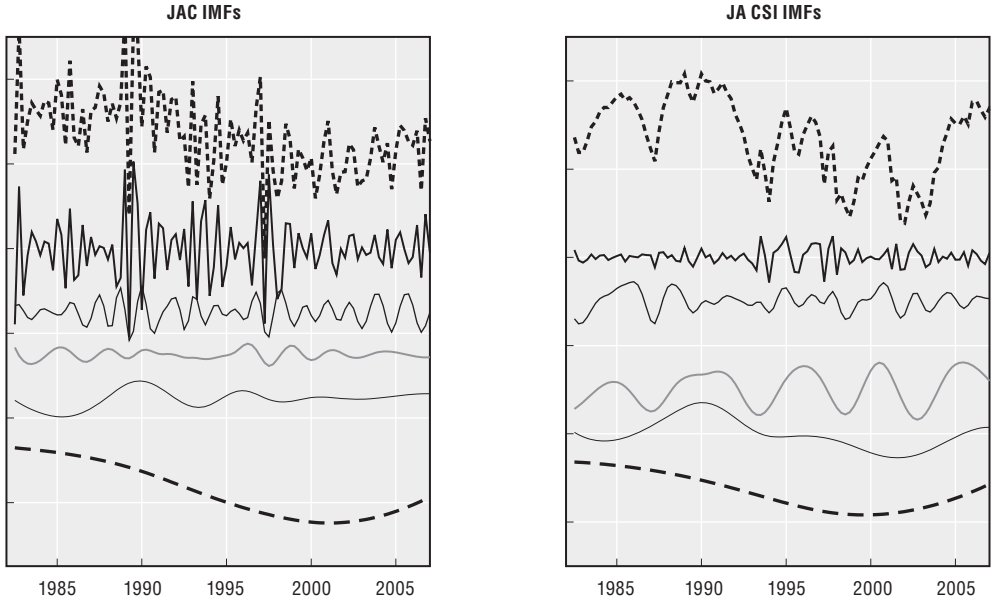
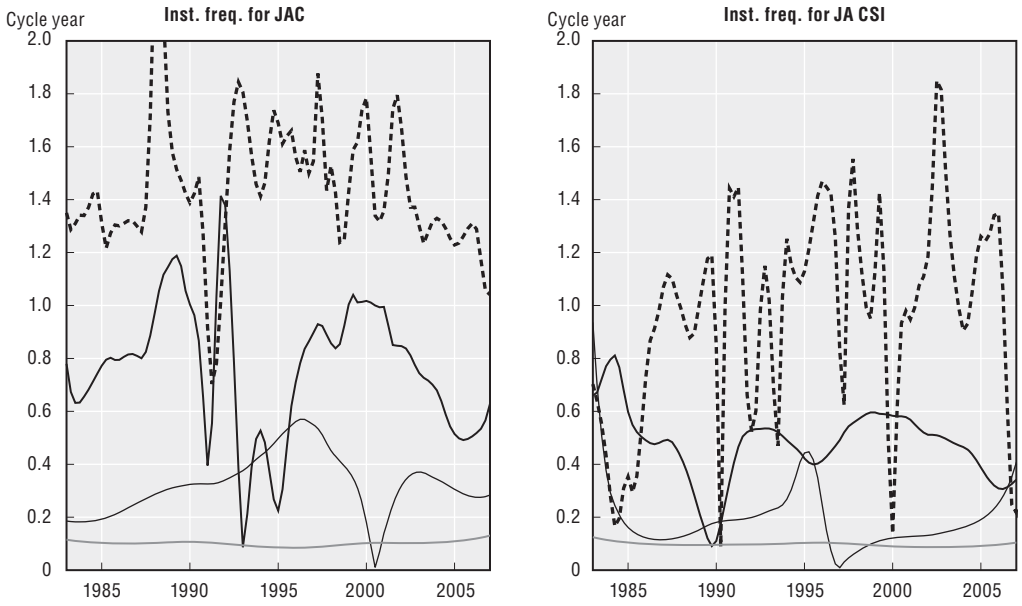



Table 12. **Correlations of IMFs for Japanese consumption and Consumer sentiment indicator (overall = 0.5101) with frequencies**

| Correlations of JAC | IMF2 | IMF3 | IMF4 | Frequency |
|---|---|---|---|---|
| IMF2 | –0.0243 | –0.0238 | –0.0074 | 1.443 |
| IMF3 | 0.1264 | 0.2357 | 0.0202 | 0.764 |
| IMF4 | –0.1218 | 0.4444* | 0.5218* | 0.376 |
| Frequency | 0.959 | 0.465 | 0.247 | |

*Note:* Correlations that are significant at the 5% level are denoted with an asterisk.

Figure 21. **Japanese consumption *vs.* consumer sentiment indicator: IMFs**




## 5. Conclusions

In this article, industrial production and consumption growth, two major drivers of economic growth, were decomposed in the frequency domain using Ensemble Empirical Mode Decomposition (EEMD) alongside two different types of indicators for these variables: a comparable confidence indicator obtained from the OECD, and; the other a nationally published sentiment indicator.

EEMD is an empirical methodology that permits the decomposition of economic variables into intrinsic mode functions (IMFs) that represent the cycles embedded in the variable in a meaningful way. In this study we show how the technique can be used to separate out the business cycle from other cycles that exist in macroeconomic variables, and estimate the frequency of the components. The method has potential advantages over other frequency domain methods as it does not require stationarity (as with spectral analysis) and yields estimates of instantaneous frequency of each individual frequency component embedded in the series (something which discrete wavelet analysis does not).

A first result that pertains in particular to the US because of the long data series available, concerns the length of long cycles in the data. Although Granger (1966) found that long cycles had the greatest amplitude, this is not found in our results, as highlighted in Crowley (2010). For US industrial production growth nothing beyond a 20-year cycle appears in the data, and for US consumption growth there is nothing beyond a 12.5-year cycle. This result is perhaps due to the fact that EEMD does not require stationarity where as spectral analysis does. Consequently any attempt to frequency decompose economic variables using spectral analysis requires some kind of transformation to ensure stationarity, which was not done by Granger or most of the economists employing spectral analysis thereafter.

In relation to OECD confidence indicators and national sentiment indicators, the results we obtain show that there are generally many more cycles embedded in actual economic variables than in their corresponding indicators or sentiment measures. This is

to be expected, as there is a certain amount of noise operating in the measurement and reporting of actual economic variables. In addition, the reporting in sentiment indicators is much more likely to put more emphasis on medium and longer-term trends in output growth. For the US and the euro area, OECD indicators have quite similar frequency content to industrial production and consumption growth, but for Japan there appears to be a frequency mismatch, with little similarity between the frequency of cycles, in particular for industrial production.

One of the most interesting results that we obtained is that the sentiment measures of output from producers of goods and services appears to contain cycles that roughly correspond to the growth cycles found in actual economic variables. Sentiment measures of consumption expenditure by consumers however, do not appear to contain as much information, but rather focus much more on the business cycle.

A further insight that is gained by analysing data in the frequency domain is that indicators capture longer-term trends much better than shorter-term trends. This is because the correlation between embedded cycles at shorter frequencies is generally lower than for those at lower frequencies.

### *Notes*

1. We would like to acknowledge the help of Oskari Vähämaa (Bank of Finland) in collecting some of the economic data used here, as well as Zhaohua Wu (Center for Ocean-Land-Atmosphere Studies, Calverton, MD, USA) for providing the MATLAB programs for the basic EEMD analysis (available online at *http://rcada.ncu.edu.tw*). We would also like to thank the Bank of Finland for their kind hospitality during the summers of 2008 and 2009, during which most of this research was undertaken. Tony Schildt (Danske Capital) was employed at the Bank of Finland when this paper was originally written and a previous version of this paper appeared as *Bank of Finland Discussion Paper 33/2009*. We would like to acknowledge the help of Oskari Vähämaa (Bank of Finland) in collecting some of the economic data used here, as well as Zhaohua Wu (Center for Ocean-Land-Atmosphere Studies, Calverton, MD, USA) for providing the MATLAB programs for the basic EEMD analysis (available online at *http://rcada.ncu.edu.tw*).

2. See, for example, Hughes Hallett and Richter (2004 and 2006), Ritschl and Uebele (2009), and Korotayev and Tsirel (2010).

3. Perhaps the two exceptions here would be James Ramsay (NYU) and Ramadan Gencay (Simon Fraser University).

4. Applications of discrete wavelet analysis in economics include Crowley and Lee (2005), Yogo (2008), and Crowley and Hughes Hallett (2011).

5. Applications of continuous wavelet analysis in economics include Aguiar-Conraria, Soares and Azevedo (2008), Crowley and Mayes (2009), and Rua (2010).

6. See *http://rcada.ncu.edu.tw/research1.htm* for a website devoted to research on the HHT.

7. The amount of white noise to be added to series is not specified and is variable in EEMD. The objective is to minimise mode mixing and resolution.

8. "Mode-mixing" refers to where the frequency of one IMF intersects with the frequency of another IMF.

9. MATLAB code for EEMD can be found at *http://rcada.ncu.edu.tw/research1_clip_program.htm*.

10. The p-value is computed by transforming the correlation to create a t statistic having n-2 degrees of freedom, where n is the number of rows being correlated and the variable is assumed to have a multivariate normal distribution. The confidence bounds are based on an asymptotic normal distribution of 0.5*log[(1+R)/(1-R)] with variance equal to 1/(n-3).

11. Once again if the lowest frequency IMF is extracted (here IMF5), the correlation between the two would be 0.99 with both possessing a frequency of roughly 0.05.

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# On the change in the Austrian business cycle

*by*
Sandra Bilek-Steindl*

*This paper analyses the change in the Austrian business cycle over time using data back to 1954. The change in the cyclical pattern is captured using a non-linear univariate structural time series model where the time of the break point is estimated. Results for GDP series suggest a break in the frequency of the cycle and in the parameter covering the variance of the disturbances of the cycle taking place in the mid 1970s and early 1980s, respectively. Using data for GDP components a break in these variables is found too, but the timing of the break differs among the series. In a further step the paper assesses the relevance of these findings for forecasting purposes. It is shown that during certain periods the out-of-sample forecasting performance of GDP does improve when a break in one of the two parameters is explicitly modelled.*

*JEL classification: C51, C53, E32*

*Keywords: Structural time series models, business cycles, forecasting performance*

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## 1. Introduction

Since the mid-1980s cyclical fluctuations in the United States tend to be less pronounced compared to the decades earlier. This observation is referred to as the *Great Moderation* and has been heavily investigated by the empirical literature. The first studies reporting the decline in macroeconomic volatility of US time series comprise (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001; Stock and Watson, 2002), where the change was either reported to be a trend decline (Blanchard and Simon, 2001; Stock and Watson, 2002) or a discrete step reduction (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000). Blanchard and Simon (2001) show that this steady decline was interrupted in the 1970s and early 1980s and returned back to the trend line in the late 1980s and 1990s. The most common way to measure macroeconomic volatility in the literature is using the standard deviation of an output gap, the cyclical component of the GDP series or of the changes in GDP itself. Creal *et al.* (2008) introduce stochastically time-varying variances of the cyclical and the irregular component in a multivariate structural time series model to capture the *Great Moderation* in US time series. Besides dynamics in the volatility of the common cycle, they report changes in the volatility of the irregular components.

In Europe and other non European OECD countries, cyclical fluctuations also became more dampened (Dalsgaard *et al.*, 2002; Barrell and Gottschalk, 2004; European Commission, 2007; Malgarini, 2007; Barrell *et al.*, 2009; Bodman, 2009). For Germany, Buch *et al.* (2004) and Aßman *et al.* (2009) give evidence of a downward trend in output volatility. Also for Austria some empirical literature on the decline in macroeconomic volatility exits, but so far no explicit timing of the regime shift was observed. Hahn and Walterskirchen (1992) use a quarterly data set spanning 1960-1992. Comparing the standard deviation of the cyclical GDP component over three time periods, they reported a higher variation in the period 1974-1982 compared to the periods 1960-1973 and 1983-1992. Leitner (2007) divides the total time series of 1970-2004 into two parts. Using the standard deviation of real GDP growth and its expenditure components, she found for most series a higher volatility in the subperiod 1970-1983 compared to the subperiod 1983-2004. Similarly, the European Commission (2007) reports a sharp decrease in the standard deviation of year-on-year GDP growth rates since the end of the 1970s.

While there is general evidence that the volatility (or the amplitude) of the business cycle has decreased over time, there is not much evidence regarding the duration (or the frequency) of the cycle. From observed changes in the persistence of output gaps (measured using the first order auto-correlation) Dalsgaard *et al.* (2002) suggest an increase in the duration of the business cycle in certain countries (Australia, Austria, Canada, France, New Zealand, Norway, Sweden and United Kingdom), while the persistence of the cycle has been found more or less unchanged in the euro area (aggregate), Italy, Japan, Spain and the United States. Using a multivariate time series model and dividing the US

data set in two subperiods, Creal *et al.* (2008) noted a decrease in the frequency parameter (increase in the average period between business cycles) in the sample after the year 1984.

Economic moderation has been stopped abruptly by the end of 2008, but there is still the question if it continues after the phase-out of the global recession. Even if much more pronounced, this would be a break similar to that reported by Blanchard and Simon (2001) in the 1970s and early 1980s. The answer to that question depends on the reason of the decline in volatility beforehand, which is still not clear. The literature refers to many reasons for the change in the volatility of macroeconomic time series. They cover *good policy, good luck* and *good practices*. The first point usually refers to improvements in monetary policy (Clarida *et al.*, 2000), the second stresses good luck in terms of smaller and fewer shocks (Stock and Watson, 2002), while the third regards changes in the economic structure like sectoral shifts (Buch *et al.*, 2004), globalisation and openness to trade (Buch, 2002; Cavallo and Frankel, 2008), technological developments (Arias *et al.*, 2007), inventory management (Kahn *et al.*, 2002; Irvine and Schuh, 2005) demographic changes (Jaimovich and Siu, 2009) or financial openness and innovations (Buch *et al.*, 2005; Dynan *et al.*, 2006) as the main factors for the reduced cyclical volatility. Especially the latter were recently discussed in the course of the financial crisis and the global recession starting at the end of 2008. On the one hand, financial innovations have lessened macroeconomic volatility, but on the other hand, they make financial crises much larger and more severe (Hahn, 2008).

The aim of this paper is to analyse the change in the Austrian business cycle over time and to determine the timing of the regime switch. The potential change in the cyclical pattern is captured using a non-linear univariate structural time series model. In the first place, the linear model following (Harvey, 1989; Harvey and Trimbur, 2003) is extended to allow for a break in the frequency of the cycle and in the parameter covering the variance of the disturbances of the cycle. Results for GDP suggest a longer average duration of the cycle after the mid 1970s and a decrease in the amplidute in the early 1980s. Using series of GDP components (private consumption, investment in machinery and equipment, construction investment, total exports and total imports) these results were found too, but the timing of the break differs both, among the components, and compared to GDP. Secondly, I assess the relevance of these findings for forecasting GDP. It can be shown that the non-linear models outperform the linear models during certain periods, but not globally.

The outline of the paper is as follows: Section 2 describes the data set used, Section 3 shows the model specifications of the standard model following Harvey (1989) and Harvey and Trimbur (2003) as well as two non-linear extensions to decompose the time series into its structural components and to determine the break point of a regime switch. Sections 4 and 5 give the results for Austrian GDP and its components, respectively. Section 6 evaluates the forecast performance of the non-linear models using GDP series, and Section 7 concludes.

## 2. Data description

I use quarterly seasonally adjusted data for Austria for the period 1954Q1-2009Q3[1]. Following Scheiblecker (2008) different data sets – all taken from the WIFO (Austrian Institute of Economic Research) database – were used to construct one consistent quarterly time series starting 1954Q1. The most recent quarterly national accounts data going back

to 1988Q1 were used (publication date November 2009). Their respective corresponding annual figures go back until 1976, with both annual and quarterly figures measured in chained values with 2005 as the reference year. For the time period before 1988, quarterly data are chained back using national accounts data of earlier releases: annual national accounts GNP series (1954-1978), annual national accounts data according to SNA 68 definition in 1976 prices (1964-1988), quarterly GNP series (1954Q1-1978Q4), quarterly national accounts data according to SNA 68 definition in 1976 prices (1964Q1-1989Q1) and quarterly national accounts data according to ESVG 79 definition measured in 1983 prices (1976Q1-1999Q3). First, the actual annual figures covering 1976-2008 were chained back to receive one annual time series ranging from 1954-2008. Second, to obtain the quarterly pattern from 1954Q1-1987Q4 the Chow and Lin (1971) method of temporal disaggregation was used, with the chained national accounts data of the former releases being the indicator series. Thus, quarterly series summing up to the chained back annual figures are produced. Besides GDP, the constructed data set contains the following expenditure side GDP components: private consumption, investment in machinery and equipment, construction investment, total exports and total imports. All data are available from the author on request.

The quarter-on-quarter GDP growth rates (Figure 1) reveal a high cyclical volatility in the first part of the series (especially well pronounced at times of the oil price shocks in the 1970s), which is followed by a smoother cyclical pattern in the second part of the time series. Splitting the time series into two parts with the high fluctuations of the oil price shocks in the 1970s in the first sample, the standard deviation of the growth rates is reduced from 0.013 (1954Q2-1979Q4) to 0.009 (1980Q1-2009Q3). The mean of the growth rates declined too, indicating more pronounced upswings in the first part of the series compared to the second part. A similar pattern exists in the components of GDP. Table 1 shows the evolution of the standard deviation and the mean of the quarter-on-quarter growth rates of GDP and its components over time.

Figure 1. **Quarter-on-quarter GDP growth rates, seasonally adjusted, 1954Q2-2009Q3**

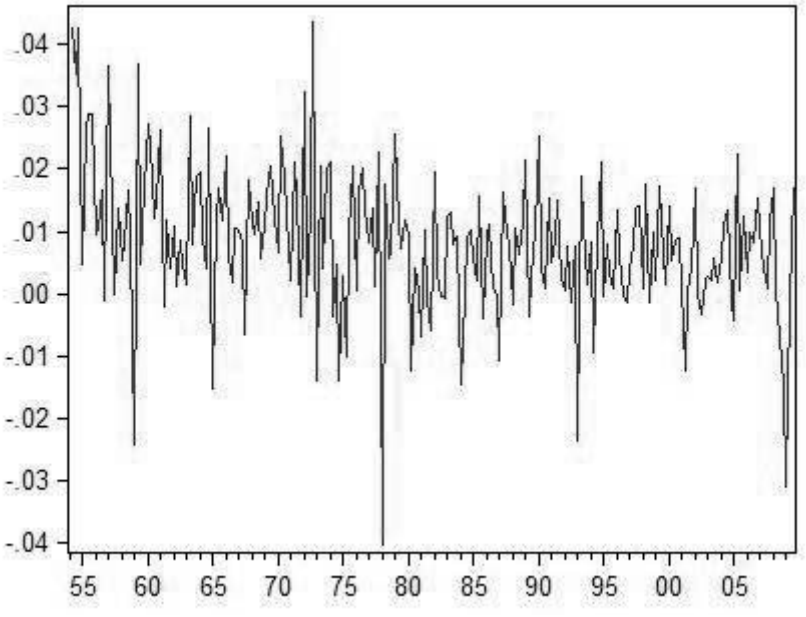


Table 1. **Standard deviation and mean of quarter-on-quarter growth rates, GDP and components**

| Component | Sample | Stdev. | Mean |
|---|---|---|---|
| GDP | 1954Q2-1979Q4 | 0.0133 | 0.0120 |
| | 1980Q1-2009Q3 | 0.0091 | 0.0051 |
| Private consumption | 1954Q2-1979Q4 | 0.0203 | 0.0111 |
| | 1980Q1-2009Q3 | 0.0123 | 0.0046 |
| Investment in machinery and equipment | 1954Q2-1979Q4 | 0.0730 | 0.0163 |
| | 1980Q1-2009Q3 | 0.0469 | 0.0046 |
| Construction investment | 1954Q2-1979Q4 | 0.0461 | 0.0173 |
| | 1980Q1-2009Q3 | 0.0328 | 0.0027 |
| Total exports | 1954Q2-1979Q4 | 0.0335 | 0.0211 |
| | 1980Q1-2009Q3 | 0.0282 | 0.0113 |
| Total imports | 1954Q2-1979Q4 | 0.0458 | 0.0243 |
| | 1980Q1-2009Q3 | 0.0279 | 0.0094 |

## 3. Model specifications

### *3.1. Standard model*

I use a structural time series model which is formulated in terms of components that have a direct interpretation. The estimation results of the hyperparameters reveal information about the two characteristics of the cycle, which are in the interest of the paper: its frequency and its amplitude.

Following the commonly used model by Harvey (1989) the seasonally adjusted log GDP series ($Z_t$) is decomposed into a trend component, a cyclical component and an irregular component in an additive form:[2]

$$z_t = \mu_t + \psi_t + \varepsilon_t,\ \varepsilon_t \sim \mathrm{NID}(0, \sigma_\varepsilon^2). \tag{1}$$

The components are allowed to evolve stochastically over time. The trend component ($\mu_t$), is specified as

$$\mu_t = \mu_{t-1} + \kappa_{t-1} + \eta_t,\ \eta_t \sim \mathrm{NID}(0, \sigma_\eta^2), \tag{2}$$

$$\kappa_t = \kappa_{t-1} + \delta_t,\ \delta_t \sim \mathrm{NID}(0, \sigma_\delta^2), \tag{3}$$

with the slope of the trend ($K_t$) and $\varepsilon_t$, $\eta_t$ and $\delta_t$ mutually uncorrelated, and where the cyclical component $\psi_t$ is specified as

$$\begin{bmatrix}\psi_t \\ \psi_t^*\end{bmatrix} = \left\{\rho \begin{bmatrix}\cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda\end{bmatrix}\right\}\begin{bmatrix}\psi_{t-1} \\ \psi_{t-1}^*\end{bmatrix} + \begin{bmatrix}\theta_{t-1} \\ \theta_{t-1}^*\end{bmatrix}, \tag{4}$$

$$\begin{bmatrix}\theta_{t-1} \\ \theta_{t-1}^*\end{bmatrix} \sim \mathrm{NID}\left[0, \begin{matrix}\sigma_\theta^2 & 0 \\ 0 & \sigma_\theta^2\end{matrix}\right],$$

where $\rho \in [0, 1]$ (the damping factor) and $\lambda \in [0, \pi]$ (the cyclical frequency in radians with $2\pi/\lambda$ as the period of the cycle) are constants and $E(\theta_t \theta_t^*) = 0$.

Without imposing any restrictions on the variances in equation (2) and (3), the trend component is a random walk with variable drift, which is equivalent to an ARIMA(0,2,1) process. If $\sigma_\delta^2 = 0$ the trend component reduces to a random walk with drift. Furthermore, if $\sigma_\eta^2 = 0$ as well, the trend process of the variable reduces to a linear deterministic time trend. If only $\sigma_\eta^2 = 0$, the resulting model exhibits a smoothing changing I(2) trend. The

cycle $\psi_t$ is modeled as mixture of sine and cosine waves. It can also be represented as ARMA(2,1) process. The auxiliary process $\psi_t^*$ appears by construction.

Harvey and Trimbur (2003) further extend the general model given above towards a model with stochastic cycles of higher order. This specification has been found useful in modeling cyclical behaviour of US investment series. The extracted cycle was smoother and more clearly defined, which allows to date turning points more easily. A cycle of order 2 can be written as a stochastic cycle of order 1 – as described in equation (4), with the variance of the disturbance term for the auxiliary process $\psi_{2,t}^*$ set to zero instead of $\theta_{t-1}^*$ – where the error process itself follows a stochastic cycle:

$$\begin{bmatrix}\psi_{2,t}\\ \psi_{2,t}^*\end{bmatrix} = \left\{\rho\begin{bmatrix}\cos\lambda & \sin\lambda\\ -\sin\lambda & \cos\lambda\end{bmatrix}\right\}\begin{bmatrix}\psi_{2,t-1}\\ \psi_{2,t-1}^*\end{bmatrix} + \begin{bmatrix}\psi_{1,t}\\ 0\end{bmatrix}, \tag{5}$$

$$\begin{bmatrix}\psi_{1,t}\\ \psi_{1,t}^*\end{bmatrix} = \left\{\rho\begin{bmatrix}\cos\lambda & \sin\lambda\\ -\sin\lambda & \cos\lambda\end{bmatrix}\right\}\begin{bmatrix}\psi_{1,t-1}\\ \psi_{1,t-1}^*\end{bmatrix} + \begin{bmatrix}\theta_{t-1}\\ 0\end{bmatrix}.$$

The model represented by equations 1-4 and 1-5, respectively, is transformated into state-space form and the hyperparameters $\sigma_\varepsilon^2$, $\sigma_\eta^2$, $\sigma_\delta^2$, $\sigma_\theta^2$, $\lambda$ and $\rho$ are estimated using maximum likelihood.

### 3.2. *Non-linear extensions*

The model stated above can be extended to allow for breaks in structure and switching regimes. In order to account for a break in the cyclical pattern, first I substitute $\lambda$ in equation (4) and (5) by

$$\lambda(\tau) = \lambda_1 I(t \leq \tau) + \lambda_2 I(t > \tau), \tag{6}$$

where *I(t)* is an indicator function taking the value one before the break point $\tau$, and zero after the break point $\tau$. $\tau$ is estimated using a grid search over the time variable. Differences between $\lambda_1$ and $\lambda_2$ imply differences in the cycle length before and after $\tau$.

Second, following the idea by Creal *et al.* (2008), a break in the variance of the cycle is assessed. According to Harvey (1989), the variance of the cycle is determined by the variance of its error process and the damping factor: $Var(\psi_t) = \sigma_\theta^2/(1-\rho^2)$. Thus, I allow for a break in the variance of the error process of the cyclical component $\sigma_\theta^2$ and replace the parameter in equation (4) and (5) by

$$\sigma_\theta^2(\tau) = \sigma_{\theta_1}^2 I(t \leq \tau) + \sigma_{\theta_2}^2 I(t > \tau). \tag{7}$$

I provide a simple and flexible framework for modeling regime switches in business cycles. By introducing a break in the damping factor $\rho$ this setting could also be used to model the change in the mean of the growth rates as shown in Table 1.

## 4. Estimation results for GDP

### 4.1. *Standard model (type A)*

I first estimate the standard model characterised by equations (1) to (4) for the whole time period 1954Q1-2009Q3 (model 1A) in the time domain. The model with the smooth trend ($\sigma_\eta^2 = 0$) provides the most accurate fit. The obtained cycle and the dating of its turning points coincide with those of former studies summarised in Scheiblecker (2008)[3]. However, with an estimated length of 28.5 quarters, the duration is longer compared to the mentioned studies where the average cycle length ranges from 13 to 26 quarters. I further

estimate the same model over the shorter time period 1964Q1-2008Q4 (model 2A) because of two reasons: first, the national accounts definition changes between 1954 and 1963 and the time beyond (see Section 2), and second, data for 2009 are obtained from an early vintage and are subject to further revisions. The observed peaks and troughs of the obtained cycle again confirm those detected in the studies summarised in Scheiblecker (2008. It deviates from the trend by a maximum of 2.5%. The duration of the business cycle is estimated to amount 20.9 quarters. Then model 2A² is estimated over the same time sample as model 2A (1964Q1-2008Q4), imposing stochastic cycles of second order according to equation (5). As expected the cycle is smoother compared to the one obtained by the models 1A and 2A and the estimated variance $Var(\psi_t)$ is smaller. Again, peaks and troughs coincide with previous studies. The left column of Figure 2 shows the cyclical components extracted by the three linear models. Vertical lines denote peaks (continuous lines) and troughs (dashed lines) based on a structural time series model (for the time span 1966-1990) and a Baxter-King filter (for the time span 1991-2005) previously determined and summarised in Scheiblecker (2008).

In order to assess a possible change in the parameters over time, the time series is split into two subsamples, with the first covering the period 1964Q1-1979Q4 (model 3A) and the second 1980Q1-2008Q4 (model 4A). The lower coefficient estimate for the frequency parameter $\lambda$ in the second subsample (0.22 in model 4A compared to 0.35 in model 3A) supports the idea of a different data generating process in the two samples. The average duration of the cycle is found to be 17.9 quarters in the first sample (model 3A) and increases to 28.5 quarters in the second time period (model 4A). Further, the persistence parameter $\rho$ is lower in the second subsample, suggesting a smaller mean growth rate and a dampened cyclical volatility. The latter can also be seen in the estimated variance of the cycle, $Var(\psi_t)$, which is smaller in model 4A, covering the second subsample. The maximum likelihood estimates of the hyperparmeters of all linear models are summarised in the first lines in Table 2.

Goodness of fit of all models is assessed by the estimated prediction error variance of the signal $\sigma^2$, the coefficient of determination $R_D^2$ and the AIC. Further, diagnostic tests concerning autocorrelation, homoscedasticity and normality of the standardised residuals are carried out. According to $R_D^2$ all models show an improvement in goodness of fit over a random walk plus drift. The assumption of independence is violated for all models apart from model 2A² imposing stochastic cycles of second order and model 3A covering only the time span 1964Q1-1979Q4. Homoscedasticity is checked against the *F*-distribution, again not all models fulfill this criterion. Considering normality, a more satisfactory situation is found. All results are summarised in the Appendix, Table A.1.

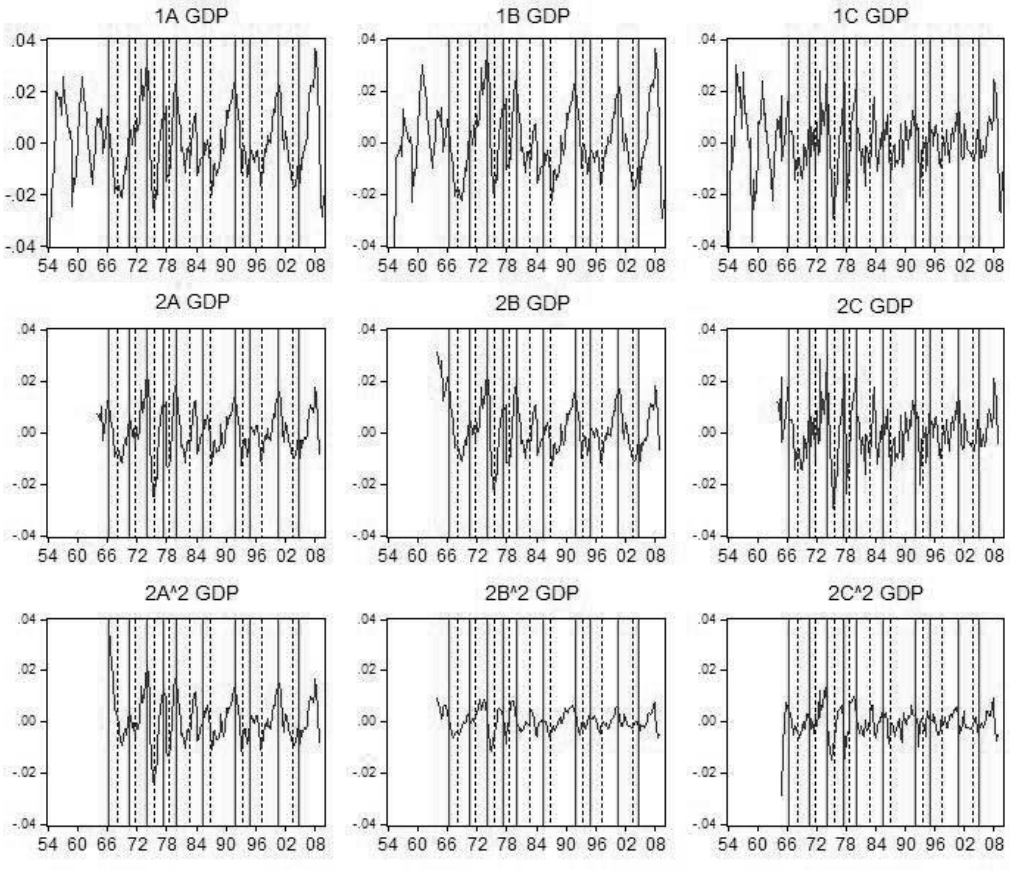
### *4.2. Non-linear extensions (type B and C)*

I estimate the model with the non-linear generalisation covered in equation (6) to determine the break point $\tau$ and the two representations of the cycle. First I cover the whole sample period 1954Q1-2009Q3 (model 1B). Second, I consider the shorter time span 1964Q1-2008Q4 (model 2B). The results are similar. I find a break occurring at 1972Q3 (model 1B) and 1974Q3 (model 2B), respectively. Before this point of time, the estimate of the frequency parameter $\lambda_1$ is close to zero, which means the cycle follows an AR(1) process. For the later time period the estimate of $\lambda_2$ is 0.24 (model 1B) and 0.21 (model 2B) corresponding to a cycle length of 26.5 (model 1B) and 29.9 quarters (model 2B). The cycle length of both models seems to be reasonable. As check of robustness, I further estimate

the model imposing stochastic cycles of second order (model 2B²). The breakpoint was found in 1974Q2. Before this point in time, the cycle also follows an AR(1) process. Later, $\lambda_2$ is 0.38, corresponding to an average cycle length of 16.5 quarters. Looking at the variance of the cycle, $Var(\psi_t)$ is again smaller in the model imposing stochastic cycles of second order. In all three models, at a point during the early 1970s, the break occurred earlier than expected, but the models provide a reasonable fit to the data, concerning the dating of the cycle. Figure 2 (second column) gives a picture of the obtained cycles of 2A, 2B and 2B². The observed peaks and troughs confirm those detected in the linear model (type A). The results of the estimated parameters are summarised in the middle of Table 2.

In the next stage I allow for a break in the variance of the error process of the cyclical component $\sigma_\theta^2$ [equation (7)]. In the same manner as above, first I cover the whole sample period 1954Q1-2009Q3 (model 1C), second, the shorter time span 1964Q1-2008Q4 (model 2C) and third, I estimate the model imposing stochastic cycles of second order (model 2C²). In all three cases, estimation results suggest a break in the variance in the early 1980s: 1984Q2 (model C1), 1982Q2 (model 2C) and 1985Q3 (model 2C²). In all three cases the results for $\sigma_{\theta_1}^2$ and $\sigma_{\theta_2}^2$ confirm the assumption that the variance of the cyclical part decreased after the break point $\tau$: from 86.3 to 49.4 (model 1C), from 70.1 to 21.7 (model 2C) and from 63.2 to 21.5

Figure 2. **Cyclical component of GDP, extracted from linear (type A) and non-linear models (type B and C)**




*Note:* Vertical lines denote peaks (continuous lines) and troughs (dashed lines) previously determined and summarised in Scheiblecker (2008).

Table 2. **Estimation results of the structural time series models, GDP**

| | | $\sigma_\varepsilon^2$ | $\sigma_\delta^2$ | ρ | λ | 2π/λ | $\lambda_1$ | $\lambda_2$ | $2\pi/\lambda_2$ | $\sigma_\theta^2$ | $\sigma_{\theta_1}^2$ | $\sigma_{\theta_2}^2$ | τ | $Var(\psi_t) = \sigma_\theta^2/(1-\rho^2)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1A | 54Q1-09Q3 | 18.9* | 0.3 | 0.87** | 0.22** | 28.5 | – | – | – | 60.2** | – | – | – | 0.015 |
| 2A | 64Q1-08Q4 | 23.0* | 0.9* | 0.81** | 0.30** | 20.9 | – | – | – | 40.1** | – | – | – | 0.005 |
| 2A² | 64Q1-08Q4 | 26.9** | 0.9* | 0.71** | 0.26* | 24.4 | – | – | – | 24.0** | – | – | – | 0.001 |
| 3A | 64Q1-79Q4 | 45.4** | 2.2 | 0.84** | 0.35** | 17.9 | – | – | – | 33.2 | – | – | – | 0.004 |
| 4A | 80Q1-08Q4 | 0.0 | 2.8** | 0.80** | 0.22** | 28.5 | – | – | – | 30.0** | – | – | – | 0.002 |
| 1B | 54Q1-09Q3 | 20.9** | 0.3 | 0.88** | – | – | 0.0 | 0.24** | 26.5 | 57.1** | – | – | 72Q3 | 0.014 |
| 2B | 64Q1-08Q4 | 24.6** | 0.7* | 0.81** | – | – | 0.0 | 0.21** | 29.9 | 38.4** | – | – | 74Q3 | 0.004 |
| 2B² | 64Q1-08Q4 | 25.6** | 1.0* | 0.73** | – | – | 0.0 | 0.38** | 16.5 | 2.2** | – | – | 74Q2 | 0.001 |
| 1C | 54Q1-09Q3 | 12.0 | 0.42* | 0.83** | 0.25 | 25.1 | – | – | – | – | 86.3** | 49.4** | 84Q2 | – |
| 2C | 64Q1-08Q4 | 0.0 | 1.9** | 0.85** | 0.25** | 24.7 | – | – | – | – | 70.1** | 21.7** | 82Q2 | – |
| 2C² | 64Q1-08Q4 | 0.0 | 1.1** | 0.62** | 0.25** | 24.8 | – | – | – | – | 63.2** | 21.5** | 85Q3 | – |

*Note:* All variances are multiplied with $10^5$.
** denotes significance at 5% level, * denotes significance at 10% level, underlined parmaters are fixed.
Considering the naming of the models, note that:
The alphabetic character denotes the model characteristics while the number stands for the sample period (1 covers 54Q1-09Q3, 2 covers 64Q1-08Q4, 3 covers 64Q1-79Q4 and 4 covers 80Q1-08Q4.
The model type A is the linear model, B indicates the non-linear model with a break in λ, C indicates the model with a break in $\sigma_\theta^2$.
The extension ² denotes a model with second order stochastic cycles.

(model 2C²). All parameter results are summarised in the bottom of Table 2. Figure 2 (left column) shows a picture of the obtained cycles of the three models 2C, 2C and 2C². Again, peaks and troughs coincide with those of the other models.

Diagnostic tests of the models of type B and C are summarised in the Appendix, Table A.1. Like in the linear case (models type A) there are some problems concerning the assumption of independence.

## 5. Estimation results for GDP components

This section examines the cyclical behaviour of the following GDP components: private consumption, investment in machinery and equipment, construction investment, total exports and total imports. As documented already in Table 1, a decline in the standard deviation of the growth rates over time is found, with a break-point *a priori* fixed in 1980.

To determine the time of the change in the cyclical behaviour, like in the case of GDP, non-linear extensions of the standard structural components model with a break in λ (model 2B) and a break in the variance of the error process of the cyclical component $\sigma_\theta^2$, respectively (model 2C) are estimated. First, the standard model (model 2A) is estimated. By observing the duration of the cycles of the GDP components the following pattern was observed: while the average duration of the business cycle in private consumption and imports are similar to the one of GDP, the average investment and export cycles are found to be longer. Using quarterly data for GDP components for 1964-1992, similar results for Austria were observed by Hahn and Walterskirchen (1992). All parameter results can be found in Table 3.

Estimating model 2B (with a break in the frequency parameter λ) for all observed time series apart from private consumption, the break was found in 1974Q2 or 1974Q3. In the successive quarters for most components the estimate of $\lambda_2$ is similar to the estimate of λ in the standard model (model 2A). A more pronounced difference between the two parameters was found only in the series of investment in machinery and equipment, where λ = 0.19 and $\lambda_2$ = 0.13. This means a longer duration of the cycle of investment in machinery and equipment after 1974. Before 1974, for the series construction investment,

Table 3. **Estimation results of the structural time series models, GDP components, 64Q1-08Q4**

| | $\sigma_\varepsilon^2$ | $\sigma_\delta^2$ | ρ | λ | 2π/λ | $\lambda_1$ | $2\pi/\lambda_1$ | $\lambda_2$ | $2\pi/\lambda_2$ | $\sigma_\theta^2$ | $\sigma_{\theta_1}^2$ | $\sigma_{\theta_2}^2$ | τ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2A private consumption | 0.0 | 2.9** | 0.82** | 0.32** | 19.5 | – | – | – | – | 3.8** | – | – | – |
| 2B private consumption | 0.0 | 0.1** | 0.79** | – | – | 0.45** | 14.0 | –0.08 | – | 7.4** | – | – | 88Q4 |
| 2C private consumption | 0.0 | 1.6** | 0.77 | 0.32 | 19.5 | – | – | – | – | – | 5.0** | 3.0** | 95Q4 |
| 2A construction investment | 22.9** | 0.6** | 0.82 | 0.17 | 37.0 | – | – | – | – | 28.4** | – | – | – |
| 2B construction investment | 26.1** | 0.6** | 0.82** | – | – | 0.00 | – | 0.18 | 34.9 | 23.2* | – | – | 74Q3 |
| 2C construction investment | 21.3** | 0.5* | 0.82** | 0.17 | 37.0 | – | – | – | – | – | 38.8** | 15.0 | 93Q3 |
| 2A investment in M&E | 86.1** | 0.1 | 0.95** | 0.19** | 32.7 | – | – | – | – | 39.4* | – | – | – |
| 2B investment in M&E | 61.7** | 0.1 | 0.84** | – | – | 0.00 | – | 0.13* | 48.3 | 86.1** | – | – | 74Q2 |
| 2C investment in M&E | 90.4** | 0.0 | 0.94** | 0.19 | 33.1 | – | – | – | – | – | 59.9** | 24.9** | 82Q2 |
| 2A total exports | 17.7** | 0.1 | 0.90** | 0.17 | 37.7 | – | – | – | – | 40.1** | – | – | – |
| 2B total exports | 18.0** | 0.0 | 0.91** | – | – | 0.00 | – | 0.18** | 34.9 | 39.6** | – | – | 74Q3 |
| 2C total exports | 8.1 | 0.2 | 0.89** | 0.17 | 37.7 | – | – | – | – | – | 80.3** | 32.5** | 86Q1 |
| 2A total imports | 29.0** | 0.2 | 0.89** | 0.24** | 25.8 | – | – | – | – | 38.2** | – | – | – |
| 2B total imports | 29.1** | 0.3 | 0.83** | – | – | 0.00 | – | 0.27** | 22.7 | – | – | – | 74Q3 |
| 2C total imports | 15.0** | 0.2* | 0.87** | 0.24 | 26.2 | – | – | – | – | – | 127.2** | 30.3** | 78Q1 |

*Note:* All variances are multiplied with $10^5$.
** denotes significance at 5% level, * denotes significance at 10% level, underlined paramaters are fixed.
The model type A is the linear model, B indicates the non-linear model with a break in λ, C indicates the model with a break in $\sigma_\theta^2$.
M&E = machinery and equipment.

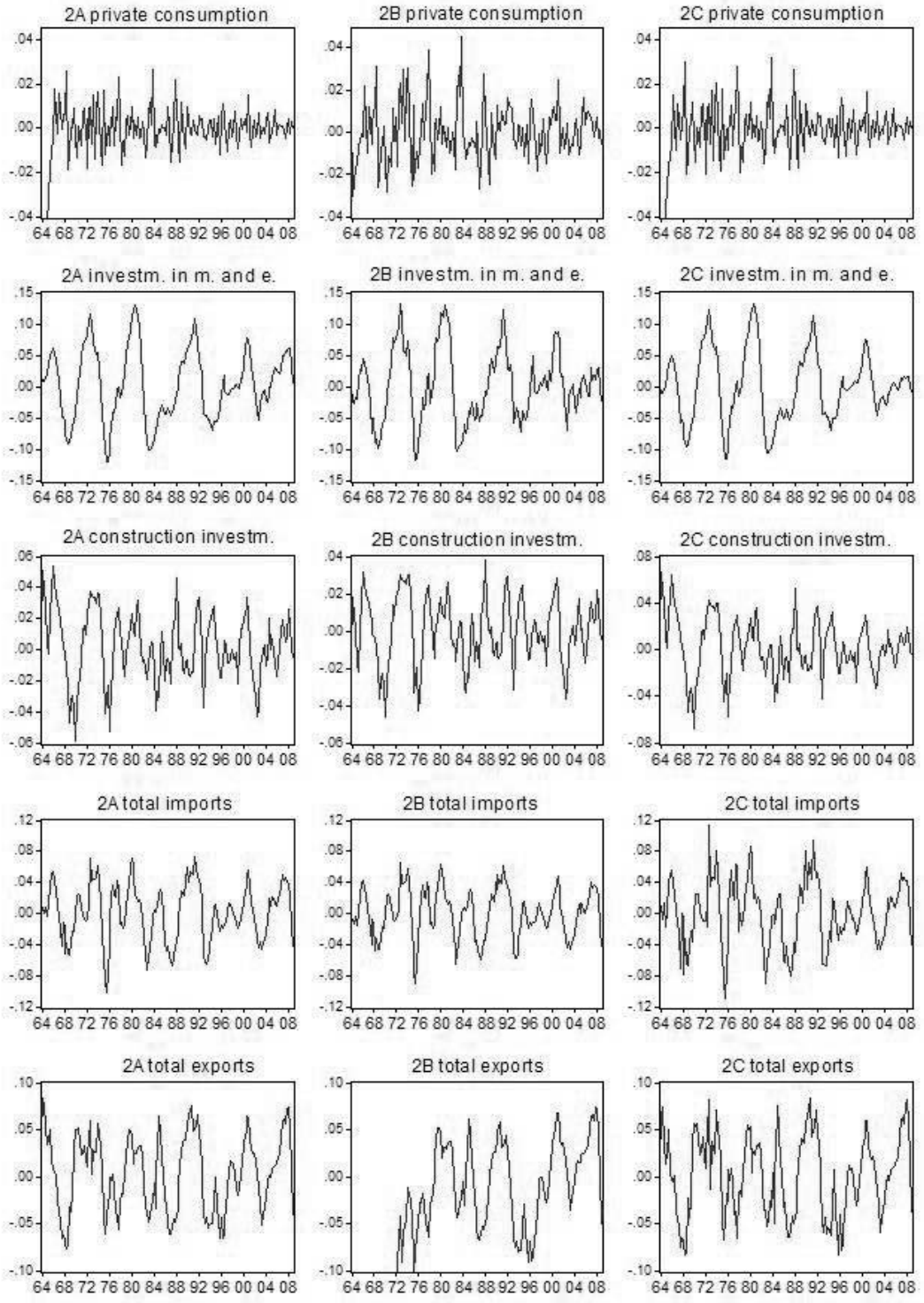
investment in machinery and equipment, total exports and total imports, the estimate of the frequency parameter $\lambda_1$ is close to zero and the cycle follows an AR(1) process. For the series of private consumption the break in λ was found to be only in 1988. While the results of all other GDP components show a good correspondence to those of GDP itself (break in λ in the 1974), this is not the case for private consumption, even if it is a large part of GDP.

Considering model 2C (with a break in $\sigma_\theta^2$), for all time series a reduction in the estimated variance of the error process of the cyclical component $\sigma_\theta^2$ has been found. To put it in other words, the variance of the cyclical part decreased after the break point. The timing of the break point varies over the components between 1978Q1 and 1995Q4 and for all time series it was found to occur after the break in λ. For total imports the break occurred in 1978Q1, for investment in machinery and equipment in 1982Q2, for total exports in 1986Q1, for construction investment in 1993Q3 and private consumption in 1995Q4, respectively. All parameter results are summarised in Table 3, diagnostic tests are shown in the Appendix, Table A.2. The obtained cycles of the models can be found in Figure 3. The left column shows the cycles obtained from standard model (2A), the middle column those obtained from the model with a break in the frequency parameter λ (2B) and the right column those obtained from the model with a break in $\sigma_\theta^2$ (2C).

## 6. Does the forecast performance improve using non-linear models?

In this section I evaluate whether the non-linear models (1B, 1C, 2B, 2C, $2B^2$ and $2C^2$) help to improve GDP predictions compared to the standard models (1A, 2A and $2A^2$). Therefore, I first estimate the models as specified above for the sample up to 1997Q1 (pre-forecast period). Based on these models, a *k*-step ahead forecast is carried out. As the interest lies in short-term forecasting, *k* = 1 ...8 (e.g. if *k* = 8: 1997Q2-1999Q1). Following, the pre-forecast period is extended for one period (up to 1997Q2). I estimate the model and carry out a *k*-step ahead forecast (e.g. if *k* = 8: 1997Q3-1999Q2) again. This procedure is

Figure 3. **Cyclical component of GDP components, extracted from linear (type A) and non-linear models (type B and C)**




*Note:* m. and e. = machinery and equipment.

repeated for 40 times, at the end yielding the out-of-sample period 2007Q1-2008Q4 (if $k = 8$). The whole out-of-sample period 1997Q2-2008Q4 is chosen to include two full cycles. For all 40 forecasts, each of the $k$-step ahead forecasts is evaluated by calculating the root mean squared forecasting error *RMSFE*:

$$\mathrm{RMSFE}(y_{t+k}) = \sqrt{\sum_{i=1}^{N-1} \frac{(y_{t+k}^{f} - y_{t+k})^2}{N}}, \tag{8}$$

where $k = 1 \ldots 8$ are the forecast steps, $N = 40$ and $y_{t+k}^{f}$ denotes the k-step ahead forecast of $y_t$. I further calculate the *RMSFE* of the linear models (1A, 2A and 2A²) and compare them with the results from the non-linear models (1B, 1C, 2B, 2C, 2B² and 2C²). Considering the time series starting in 1954Q1 and comparing the models 1B and 1C with 1A, for all 8- forecast steps, the forecast based on the linear model (1A) gives a lower *RMSFE*. The same result can be found when the sample starts in 1964Q1. The *RMSFE* of the forecast using model 2A is smaller compared to forecast based on the models 2B and 2C. Considering the models with stochastic cycles of higher order only for the 1-step ahead forecast the *RMSFE* of 2C² is smaller than the *RMSFE* of 2A². All these results can be seen in the first eight lines in Table 4.

To test whether the differences in the forecasting ability are significant, further the Diebold-Mariano test (Diebold and Mariano, 1995) is conducted. For a given k-step ahead forecast the Diebold-Mariano test statistic $S_1$ is written as

$$S_1 = \left[\hat{V}(\bar{d})\right]^{-\frac{1}{2}} \bar{d} \tag{9}$$

and has an asymptotic standard normal distribution. $\bar{d}$ is the average difference between the squared forecasting errors of the models being compared. $\hat{V}(\bar{d})$ is the estimated asymptotic variance of $\bar{d}$:

$$\hat{V}(\bar{d}) = \frac{1}{n}\left[\hat{\gamma}_0 + 2\sum_{i=1}^{k-1} \hat{\gamma}_i\right], \tag{10}$$

where $n$ is the number of forecasts which are investigated and $\hat{\gamma}_i$ is the estimated autocovariance of the difference between the squared forecast errors of order $i$. The results of the Diebold-Mariano test are reported in Table 4 in the form of significance levels.

According to the results of the Diebold-Mariano test for most of the k-step ahead forecasts the null hypothesis for equal forecast accuracy of the linear model (type A) and the non-linear models (type B and C) can not be rejected at the conventional significance levels. But at certain forecasting horizons the linear model outperforms the non-linear models significantly.

In the next step I consider certain subperiods in the above mentioned out-of-sample period. Therefore the out-of-sample period 1997Q2-2008Q4 is split into three subsamples characterised by an upswing phase (1997Q3-2000Q3), a downswing phase (2000Q4-2003Q3) and an upswing phase (2005Q3-2008Q3) again. During the two upswing phases certain step ahead forecasts using the non-linear models give a smaller *RMSFE* compared to the linear models. In the out-of-sample period 1997Q3-2000Q3, this is the case for model 1C, 2B, 2C, 2B² and 2C². Moreover, in the out-of-sample period 2005Q3-2008Q3 most of the forecast steps give smaller *RMSFE*s using the non-linear models compared to use of their linear counterparts. In those cases where the *RMSFE*s are smaller from forecast of the non-linear models (1B, 1C, 2C, 2B² and 2C²) than of the corresponding linear models (type A) the numbers are marked bold in Table 4. During the upswing 2005Q3-2008Q3, the Mariano-

Diebold test gives evidence that the models 1C, 2C, 2B² and 2C² outperform their linear counterparts (type A) significantly in most of the 1 to 8 step ahead forecasts significantly. Considering the out-of-sample period 2000Q4-2003Q3 (downswing phase), a less convincing evidence in favour of the non-linear models is found. The bold numbers and the outcome of the Diebold-Mariano test in Table 4 indicate that only model 1B improves

Table 4. ***RMSFE* of the forecasts, GDP**

| Out-of-sample period 1997Q2-2008Q4 | 1A | 1B | 1C | 2A | 2B | 2C | 2A² | 2B² | 2C² |
|---|---|---|---|---|---|---|---|---|---|
| 1-step ahead forecast | 0.00763 | 0.00766 | 0.00770 | 0.00758 | 0.00795 | 0.00794 | 0.00770 | 0.00803 | **0.00769** |
| 2-step ahead forecast | 0.01073 | 0.01103 | 0.01125 | 0.01060 | 0.01133 | 0.01155 | 0.01101 | 0.01176 | 0.01101 |
| 3-step ahead forecast | 0.01336 | 0.01389 | 0.01483* | 0.01328 | 0.01428 | 0.01521* | 0.01384 | 0.01478 | 0.01414 |
| 4-step ahead forecast | 0.01536 | 0.01607 | 0.01673 | 0.01520 | 0.01669 | 0.01706* | 0.01599 | 0.01740 | 0.01622 |
| 5-step ahead forecast | 0.01809 | 0.01903 | 0.01932 | 0.01794 | 0.01992* | 0.01970 | 0.01880 | 0.02045 | 0.01922 |
| 6-step ahead forecast | 0.02076 | 0.02188 | 0.02243 | 0.02067 | 0.02314* | 0.02270 | 0.02176 | 0.02370 | 0.02230 |
| 7-step ahead forecast | 0.02358 | 0.02489 | 0.02645 | 0.02336 | 0.02677** | 0.02663 | 0.02499 | 0.02734 | 0.02609 |
| 8-step ahead forecast | 0.02635 | 0.02752 | 0.03096* | 0.02639 | 0.03034** | 0.03115** | 0.02790 | 0.03109 | 0.03028 |
| 1997Q3-2000Q3 Upswing | 1A | 1B | 1C | 2A | 2B | 2C | 2A² | 2B² | 2C² |
| 1-step ahead forecast | 0.00786 | 0.00813 | 0.00879 | 0.00809 | 0.00814 | 0.00893 | 0.00809 | **0.00728**** | 0.00842 |
| 2-step ahead forecast | 0.00903 | 0.00940 | **0.00899** | 0.00910 | 0.00962 | **0.00890** | 0.00906 | **0.00761*** | **0.00816** |
| 3-step ahead forecast | 0.01147 | 0.01239* | 0.01261 | 0.01188 | 0.01188 | 0.01276 | 0.01171 | **0.00985** | **0.01070** |
| 4-step ahead forecast | 0.01486 | 0.01629* | **0.01422** | 0.01503 | **0.01493** | **0.01455** | 0.01504 | **0.01258** | **0.01240**** |
| 5-step ahead forecast | 0.01538 | 0.01722** | **0.01329**** | 0.01555 | **0.01500** | **0.01402** | 0.01568 | **0.01240**** | **0.01236**** |
| 6-step ahead forecast | 0.01933 | 0.02169** | **0.01714** | 0.01937 | **0.01857** | **0.01737** | 0.01967 | **0.01596**** | **0.01584**** |
| 7-step ahead forecast | 0.02168 | 0.02448** | **0.01577**** | 0.02162 | **0.02059** | **0.01495*** | 0.02175 | **0.01763**** | **0.01576**** |
| 8-step ahead forecast | 0.02671 | 0.02971** | **0.02195**** | 0.02669 | **0.02566** | **0.02129** | 0.02688 | **0.02199**** | **0.02138**** |
| 2000Q4-2003Q3 Downswing | | | | | | | | | |
| 1-step ahead forecast | 0.01085 | **0.01040*** | **0.00889** | 0.01067 | 0.01269 | **0.00893** | 0.01090 | 0.01236* | **0.00936** |
| 2-step ahead forecast | 0.01808 | **0.01786** | 0.01840 | 0.01786 | 0.02047 | 0.01895 | 0.01854 | 0.02045** | **0.01852** |
| 3-step ahead forecast | 0.02264 | **0.02212*** | 0.02566* | 0.02202 | 0.02559 | 0.02616** | 0.02357 | 0.02633* | 0.02442 |
| 4-step ahead forecast | 0.02377 | **0.02294**** | 0.02637 | 0.02276 | 0.02727 | 0.02668* | 0.02513 | 0.02886* | 0.02616 |
| 5-step ahead forecast | 0.02543 | **0.02465**** | 0.02550 | 0.02438 | 0.02928* | 0.02575 | 0.02697 | 0.03176** | 0.02778 |
| 6-step ahead forecast | 0.02905 | **0.02871** | **0.02770** | 0.02729 | 0.03323* | 0.02795 | 0.03079 | 0.03625** | 0.03143 |
| 7-step ahead forecast | 0.03552 | 0.03564 | **0.03432** | 0.03335 | 0.04028* | 0.03452 | 0.03762 | 0.04354** | 0.03856 |
| 8-step ahead forecast | 0.04090 | 0.04145 | **0.04001** | 0.03860 | 0.04621 | 0.04031 | 0.04332 | 0.04957** | 0.04460 |
| 2005Q3-2008Q3 Upswing | | | | | | | | | |
| 1-step ahead forecast | 0.00597 | **0.00578** | **0.00571** | 0.00599 | 0.00613 | 0.00609 | 0.00580 | **0.00527** | 0.00601 |
| 2-step ahead forecast | 0.01012 | **0.00981** | **0.00694*** | 0.01013 | 0.01053** | **0.00734** | 0.00999 | **0.00876** | **0.00810*** |
| 3-step ahead forecast | 0.01375 | **0.01350** | **0.01012*** | 0.01372 | 0.01419 | **0.01098** | 0.01369 | **0.01109** | **0.01172*** |
| 4-step ahead forecast | 0.01648 | **0.01621** | **0.01141**** | 0.01649 | 0.01726* | **0.01234*** | 0.01668 | **0.01311*** | **0.01358**** |
| 5-step ahead forecast | 0.01961 | **0.01954** | **0.01355**** | 0.01963 | 0.02058 | **0.01462**** | 0.01999 | **0.01514**** | **0.01580**** |
| 6-step ahead forecast | 0.02405 | 0.02440 | **0.01590**** | 0.02390 | 0.02500 | **0.01654**** | 0.02439 | **0.01816**** | **0.01849**** |
| 7-step ahead forecast | 0.02632 | 0.02723 | **0.01719**** | 0.02598 | 0.02721 | **0.01764**** | 0.02642 | **0.01880**** | **0.01974**** |
| 8-step ahead forecast | 0.02640 | 0.02776 | **0.01745**** | 0.02607 | 0.02738 | **0.01810**** | 0.02666 | **0.01799**** | **0.01961**** |

*Note:* The model type A is the linear model, B indicates the non-linear model with a break in λ, C indicates the model with a break in $\sigma_\theta^2$. The extension ² denotes a model with second order stochastic cycles.
The bold numbers indicate that the *RMSFE* from the non-linear model is smaller compared to the *RMSFE* of the corresponding linear model.
** denotes significance at 5% level, * denotes significance at 10% level using the Diebold-Mariano test.

the forecast efficiency significantly compared to its linear rival 1A at certain forecasting horizons.

Although we can not find a general evidence that using non-linear models help to improve forecasting GDP, in certain stances of the business cycle (an upswing or downswing phase) they may yield a better forecast performance in certain cases. In order to benefit from this feature of the non-linear models it is necessary to have some information about the stance of the business cycle in the forecast period. Especially around turning points this is not always the case and limits therefore the usability of the model for forecasting. Further it can not be observed from this analysis that one of the non-linear models (type B versus type C) always yields a better forecast performance than the other one.

## 7. Conclusions

The paper analyses the change in the cyclical behaviour of the Austrian business cycle. Using quarterly data for GDP and its components starting in 1954 (or in 1964 in the case of the GDP components), for all series a break was observed in the average duration of the cycle as well as in the variance of the cycle. Using a non-linear extension of the standard model Harvey (1989) and Harvey and Trimbur (2003), results for GDP series suggest that a break in the frequency parameter $\lambda$ occurred in the mid 1970s, while a break in the parameter covering the variance of the disturbances of the cycle was found in the early 1980s. To put it in other words, after the mid 1970s the duration of the business cycle increased, while after the early 1980s the amplitude of the cycle decreased. Using series of GDP components (private consumption, investment in machinery and equipment, construction investment, total exports and total imports) similar results were found, but the timing of the break differs both among the components, and compared to GDP.

Modeling non-linearities does not help to improve the forecast performance over the business cycle. But results for GDP suggest, that there are certain stances of the business cycle (during an upswing or a downswing phase) where non-linear models may yield a better forecast performance than the linear models. However, benefiting from this feature implies to have some knowledge about the stance of the business cycle in the forecast period.

### *Notes*

1. It is discussed in the literature that seasonal adjustment affects the cyclical pattern and shifts turning points in business cycle analysis. However, data in this case are adjusted beforehand in order to keep the model tractable. All time series were seasonally adjusted using Census X12.
2. There is still an ongoing debate of the possibility of the neat separation between business cycles and long-run economic growth. See for example Chapter 8 in Aghion and Howitt (1998).
3. Scheiblecker (2008) give an overview over different dating calendars for Austria based on a Hodrick-Prescott filter, a Baxter-King filter, dynamic factor models and a structural time series model. Most of these models show cycles with quite similar dates compared to the results of model 1A. In the course of this paper, I compare the obtained cycles of my models with those obtained by the structural time series model and the Baxter-King filter shown in Scheiblecker (2008).

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# *Appendix A*

Table A.1. **Diagnostic tests of the structural time series models, GDP**

| | | $\sigma^2$ | $R_D^2$ | AIC | Q(10) | Q(15) | *H(h)* | *N* |
|---|---|---|---|---|---|---|---|---|
| 1A | 54Q1-09Q3 | 0.00012 | 0.143 | –5.783 | – | 16.100 | 1.473 | 9.143 |
| 2A | 64Q1-08Q4 | 0.00011 | 0.006 | –5.765 | – | 16.627 | 2.343 | 7.402 |
| 2A² | 64Q1-08Q4 | 0.00011 | 0.003 | –5.575 | – | 14.314 | 2.268 | 9.902 |
| 3A | 64Q1-79Q4 | 0.00015 | 0.046 | –4.417 | 8.527 | – | 2.592 | 13.688 |
| 4A | 80Q1-08Q4 | 0.00005 | 0.306 | –5.606 | 21.702 | – | 1.340 | 1.147 |
| 1B | 54Q1-09Q3 | 0.00011 | 0.135 | –5.884 | – | 18.651 | 1.559 | 13.744 |
| 2B | 64Q1-08Q4 | 0.00010 | 0.072 | –5.933 | – | 19.419 | 2.545 | 11.400 |
| 2B² | 64Q1-08Q4 | 0.00011 | 0.026 | –5.761 | – | 17.729 | 2.312 | 5.757 |
| 1C | 54Q1-09Q3 | 0.00009 | 0.327 | –5.796 | – | 16.739 | 1.032 | 29.332 |
| 2C | 64Q1-08Q4 | 0.00004 | 0.662 | –5.394 | – | 37.578 | 1.047 | 0.285 |
| 2C² | 64Q1-08Q4 | 0.00005 | 0.579 | –5.494 | – | 22.929 | 1.013 | 1.454 |

*Note:* The Box-Ljung statistic *Q(P)*, based on the first *P* autocorrelations, is calculated for P = 10 and P = 15. The statistics is compared to the $\chi^2$ statistic with (P + 1 = number of estimated hyperparameters) degrees of freedom. In case of the linear models (type A) Q(10) is tested against $\chi^2_{6;0.05}$ = 12.592 and Q(15) against $\chi^2_{9;0.05}$ = 16.919. In the case of the non-linear models (type B and C) Q(15) is tested against $\chi^2_{8;0.05}$ = 15.507. Homoscedasticity is checked against the *F*-distribution, which is close to 2. Normality is tested against the $\chi^2$ statistic: $\chi^2_{5;0.05}$ = 11.070 (type A), $\chi^2_{6;0.05}$ = 12.592 (type B and C).

Table A.2. **Diagnostic tests of the structural time series models, GDP components, 1964Q1-2008Q4**

| | $\sigma^2$ | $R_D^2$ | AIC | Q(15) | *H(h)* | *N* |
|---|---|---|---|---|---|---|
| 2A private consumption | 0.00011 | 0.493 | –3.653 | 68.063 | 4.059 | 9.074 |
| 2B private consumption | 0.00009 | 0.574 | –4.781 | 49.367 | 3.793 | 7.305 |
| 2C private consumption | 0.00008 | 0.644 | –4.087 | 58.370 | 3.101 | 8.391 |
| 2A construction investment | 0.00082 | 0.039 | –3.800 | 15.610 | 1.447 | 0.901 |
| 2B construction investment | 0.00081 | 0.044 | –3.891 | 15.722 | 1.539 | 0.540 |
| 2C construction investment | 0.00061 | 0.287 | –3.811 | 15.659 | 1.101 | 0.735 |
| 2A investment in M&E | 0.00198 | 0.120 | –2.902 | 35.746 | 1.021 | 2.083 |
| 2B investment in M&E | 0.00200 | 0.111 | –2.969 | 45.700 | 1.193 | 2.258 |
| 2C investment in M&E | 0.00175 | 0.225 | –2.921 | 34.844 | 1.171 | 1.900 |
| 2A total exports | 0.00085 | 0.019 | –3.749 | 10.423 | 1.764 | 24.903 |
| 2B total exports | 0.00084 | 0.031 | –3.812 | 11.147 | 1.719 | 17.563 |
| 2C total exports | 0.00058 | 0.329 | –3.792 | 11.795 | 1.286 | 31.330 |
| 2A total imports | 0.00107 | 0.062 | –3.513 | 22.540 | 3.448 | 14.882 |
| 2B total imports | 0.00106 | 0.067 | –3.625 | 34.575 | 3.270 | 43.009 |
| 2C total imports | 0.00071 | 0.371 | –3.605 | 27.435 | 1.720 | 13.194 |

*Note:* M&E = machinery and equipment.

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The *Journal of Business Cycle Measurement and Analysis* is jointly published by the OECD and CIRET to promote the exchange of knowledge and information on theoretical and operational aspects of economic cycle research, involving both measurement and analysis.

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