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Short-run and long-run comovement of GDP and some expenditure aggregates in Germany, France and Italy

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Abstract

The paper presents empirical work on short-run and long-run comovement between the German, French and Italian aggregates of private consumption, business investment, exports, imports, GDP, and changes in inventories. In country-specific data sets, cointegration analyses are carried out both to identify long-run economic relationships and to remove the trend components from the nonstationary series. Analytically, this is done by reparametrizing the vector error correction model in its common trends representation. The resulting (Beveridge-Nelson) trend and cycle components as well as the series of changes in inventories are analyzed with a focus on synchronicity. To measure cross-country comovement at different frequencies, "cohesion", a summary statistic developed by Croux et al. [2001], is applied. Sampling variability and parameter uncertainty are captured by bootstrapped confidence intervals.

Keywords: cointegration, trend-cycle decomposition, cohesion, bootstrap.

JEL classification: C32, E32.

Non-Technical Summary

Comovement between economic activity in Germany, France and Italy is studied. Apart from the gross domestic product (GDP), important expenditure components such as private consumption, business investment, exports, imports, and changes in inventories are taken into account. In the first step, the paper analyzes the connections between these quantities for each country separately and compares the country results with each other. In the second step, the focus is on synchronicity in economic developments of the three countries. Since the time series of all variables except changes in inventories are trending, the study refers to both trend and cycle components.

In the first part of the paper, co-trending is studied in country-specific vector error correction models. Interestingly, the long-run structure turns out to be quite similar in Germany and France. In both data sets, three cointegating relations are found. The estimates imply that the ratios between consumption and output, investment and output as well as between exports and imports are approximately stable in the long run. These results point to the fact that economic activity is characterized by a dichotomy between internal and external sources of growth. In the long-run, consumption, investment and output are driven by technical progress, whereas exports and imports develop along a trend which is mainly explained by the rising integration of the world economy. However, the results for Italy imply a substantial long-run interaction between internal and external sources of growth.

The second part of the paper focuses on the cross-country dimension of economic developments. According to the results of the vector error correction models, the time series are decomposed in trends and cycles. By means of the concept of cohesion, synchronicity is studied for the cycle components of the integrated time series as well as for the (mean-adjusted) changes in inventories. In the range of frequencies typically attributed to business cycle fluctuations, business investment co-cycles strongest, whereas virtually no synchronicity is found between the GDP cycles derived from this trend-cycle decomposition. However, when expenditure aggregates such as the internal demand components are grouped together, co-cycling is shown to be statistically significant. Finally, cross-country co-trending is studied. The results suggest that synchronicity seems stronger for trend innovations than for cycle components.

Nicht technische Zusammenfassung

Diese Arbeit untersucht den Gleichlauf der wirtschaftlichen Entwicklungen in Deutschland, Frankreich und Italien. Dabei werden das Bruttoinlandsprodukt (BIP) und wichtige Nachfragekomponenten wie der Private Verbrauch, die gewerblichen Investitionen sowie Exporte, Importe und Vorratsveränderungen betrachtet. Das Papier analysiert im ersten Schritt die Zusammenhänge dieser Größen für jedes Land separat und stellt anschließend Bezüge zwischen den Ergebnissen her. Der zweite Teil behandelt die Frage nach der Synchronität der Wirtschaftsentwicklungen in den drei Ländern. Da die Zeitreihen aller betrachteten Größen mit Ausnahme der Vorratsinvestitionen trendbehaftet sind, beziehen sich die Analysen sowohl auf die Zyklus- als auch auf die Trendkomponenten.

Im ersten Abschnitt wird im Rahmen von Vektorfehlerkorrekturmodellen das gemeinsame Trendverhalten der volkswirtschaftlichen Aggregate in jedem Land für sich identifiziert. Dabei zeigen sich interessante Parallelen zwischen Deutschland und Frankreich: In beiden Ländern werden jeweils drei Kointegrationsbeziehungen gefunden, welche im Wesentlichen stabile Quotienten zwischen Konsum bzw. Investitionen und BIP einerseits und Exporten und Importen andererseits implizieren. Das Ergebnis deutet auf eine Dichotomie zwischen binnen- und außenwirtschaftlichen Wachstumskräften hin. Privater Verbrauch, gewerbliche Investitionen und BIP sind langfristig vom technischen Fortschritt determiniert, während sich die Handelsströme (zusätzlich) entlang eines gemeinsamen (Globalisierungs-)Trends entwickeln. Im Gegensatz dazu weisen die Ergebnisse für Italien auf eine langfristig bedeutsame Interaktion zwischen binnen- und außenwirtschaftlichen Wachstumsfaktoren hin.

Im zweiten Teil des Papiers wird der Konjunktur- und Wachstumszusammenhang zwischen den Ländern betrachtet. Die Zeitreihen werden dazu in Trend- und Zykluskomponenten zerlegt, welche aus den geschätzten Vektorfehlerkorrekturmodellen abgeleitet werden. Mittels des Konzepts der Kohärenz werden die zyklischen Komponenten der integrierten Zeitreihen bzw. die (mittelwertbereinigten) Vorratsveränderungen auf Synchronität untersucht. Im Frequenzbereich von Konjunkturschwankungen erscheinen die gewerblichen Investitionen am stärksten korreliert, während zwischen den nach dem vorliegenden Verfahren ermittelten BIP-Zykluskomponenten keine nennenswerte Synchronität gefunden werden kann. Fasst man allerdings verschiedene Nachfragekomponenten – wie etwa die Komponenten der Inlandsnachfrage – zusammen, dann lassen sich signifikante Konjunkturzusammenhänge nachweisen. Schließlich wird das Trendverhalten der Variablen zwischen den Ländern verglichen. Dieser Untersuchung zufolge scheinen die Wirtschaftsentwicklungen der drei Länder in der langen Frist stärker synchron zu verlaufen als im Frequenzbereich von Konjunkturschwankungen.

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1 Introduction

Since the outset of the European monetary union, the topic of business cycle synchronization within the euro area has been attracting much attention. Empirical research has raised the question whether or not a euro area business cycle exists, and if so, how it can be measured. The existing literature may be decomposed into several branches. Descriptive approaches have been applied to derive stylized facts on the European business cycle(s). Lots of pairwise cross correlations as well as synchronicity or concordance measures are documented in this type of examination.[2] Alternatively, econometric systems have been specified and estimated by means of statistical techniques which fit to the scale and the complexity of the respective model structure. When the focus is primarily on measurement, factor models have become very popular. Based on principal components analysis, common cycles can be extracted out of large-scale data sets.[3] In more structural approaches, comovement between European time series has been studied by means of multivariate unobserved components models. This class of models is typically estimated by the Kalman filter technique.[4]

The aim of this paper is to study comovement between economic activity in Germany, France and Italy. This is done not only on the basis of a single measure, say GDP. We will, instead, take a broader position by including some expenditure categories such as private consumption, business investment, exports, imports, and changes in inventories. These aggregates are chosen because they are expected to exert a predominant impact on economic activity in industrialized countries. Within-country and cross-country comove-

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[2]See Artis and Zhang [1995, 1999], Christodoulakis et al. [1995], Dickerson et al. [1998], Altavilla [2004] and Artis et al. [2005] for recent examples. Within the joint research project (JRP), such an approach is adopted by Bulligan [2005].

[3]The most prominent example is perhaps *EuroCoin*, a coincident indicator for the euro area business cycle released monthly by the CEPR; see Altissimo et al. [2001] for details on the construction of this index. The methodological background is the generalized dynamic factor model developed by Forni et al. [2000]. A similar modelling strategy which has been often used as an alternative are the large-scale static factor models proposed by Stock and Watson [1989]. Within the JRP, large-scale factor models are applied by Bruneau et al. [2005] and Cristadoro and Veronese [2005].

[4]Recent examples are Luginbuhl and Koopman [2004], and Carvalho and Harvey [2005].

ment have to be distinguished conceptually. Furthermore, as all series except changes in inventories are nonstationary, comovement splits into a short-run and a long-run aspect (henceforth called "co-cycling" and "co-trending"). This requires an idea about the trend-cycle decomposition to be applied.

The first part of the paper addresses the issue of within-country co-trending in the specific notion of cointegration. In particular, we group the variables country by country and test for cointegration within each set of series. First, the analysis provides insight into the long-run structure of GDP and the expenditure aggregates within each country. Second, the results can be used to decompose the nonstationary series into trend and cycle components. Consequently, synchronicity of economic activity in Germany, France and Italy is studied on the basis of trend-cycle decompositions of the multivariate Beveridge-Nelson [1981] type, i.e. the trend components are modelled as linear combinations of random walks whereas the cycle components describe adjustment processes back to the long-run equilibria. In analytical terms, the estimated vector error correction models (VECMs) are rewritten in their common trends representations.

As argued by Canova [1998], business cycle facts are sensitive to the choice of the detrending method. Thus, the trend-cycle decomposition used should be defendable regarding the empirical properties of the time series and the general purpose of the analysis. It is fair to assume the nonstationary series be integrated of order 1 [henceforth I(1)]. Moreover, there are good reasons to believe that cointegrating relations exist between the series of the same country. Provided that changes in inventories do not exhibit a trend, GDP and the expenditure aggregates have to be interrelated as a consequence of the aggregate income identity and of trade balance mechanisms forcing net exports to be stable in the long run. Within-country cointegration should therefore be fulfilled even if variable-specific growth potentials varied from country to country because of, say, differences in the rate of technical progress or the degree of international trade exposure.

In the second part of the paper, on the basis of the trend and cycle components obtained, the cross-country perspective of comovement is investigated by correlation measures, partly defined in the frequency domain. Precisely, synchronicity is studied by means of the summary statistic "cohesion". In the given context, the measure suggested by Croux et al. [2001] seems appropriate for the following reasons. First, it allows us to examine at which frequency comovement is strongest. Second, in contrast to usual correlation measures, it can be applied to sets of more than two series. Third, in contrast to rank-reduction concepts, it is able to grade synchronicity according to the degree.[5]

The country-specific cointegration analyses provide some interesting results. The long-run comovement of GDP and the expenditure aggregates shows common features in Germany and France while Italy turns out to possess a different structure. Specifically, the same set of restrictions applies to the cointegrating space of the German and the French

[5] Within-country and cross-country comovement are treated asymmetrically. While the latter is regarded as a purely descriptive issue (in the sense that we seek to learn about the degree of synchronicity), the long-run aspect of the former additionally serves a purpose in the modelling exercise needed to perform the trend-cycle decompositions. Hence, cointegration is the appropriate concept in this respect because modelling has to rely on "yes" or "no" decisions.

VECM. This identification scheme implies the existence of two stochastic trends from which the one drives consumption, investment and output, whereas the other can be assigned to the export and import volumes. In Germany and France, economic activity is therefore characterized by a dichotomy between internal and external sources of growth. From a broad perspective, i.e. when all series are grouped together, cross-country cohesion is significantly positive at business cycle frequencies. For the single aggregates, however, the results lack robustness from a statistical point of view, although point estimates achieve comparably high values for private consumption and, especially, business investment. In the case of cross-country co-trending, however, significant values are found for the single aggregates. In this respect, grouping leads to a marked increase of synchronicity. Finally, cross-country comovement seems stronger for trend innovations than for cycle components.

The remainder of the paper is organized as follows. In Section 2, we are going to carry out the cointegration analysis separately for the German, French and Italian data sets. The investigation presents the long-run equilibrium relationships found between the variables under investigation and Beveridge-Nelson decompositions which can be derived from them. In Section 3, the resulting cycle components are used to study cross-country comovement at business cycle frequencies. A look at cross-country co-trending complements the analysis. Section 4 concludes.

2 Cointegration and trend-cycle decomposition

The econometric analysis is carried out in country-specific samples which start in the first quarter of 1970 and terminate in the fourth quarter of 2004. Most macroeconomic time series under consideration are nonstationary. According to the plots of the series,[6] this property is evident for private consumption, business investment, exports, imports, and GDP in all three countries. Standard unit root tests indicate that these series (transformed in natural logarithms) can be regarded as I(1) processes.[7] The well-known concept of cointegration accounts for the observation that I(1) series may be interrelated in a way that linear combinations between them are stationary. The reason is that cointegrated series share common (stochastic) trend factors.

In the present context, cointegration is a useful concept for three reasons. First, the macroeconomic theory gives several suggestions regarding the long-run comovement of the economic quantities. Second, an overwhelming body of econometric literature exists on how cointegrating relations can be identified and estimated in VECMs. Third, trend components can be obtained by rewriting the estimated VECM in its common trends representation. On the one hand, these features allow to base the trend removal on theoretical considerations which can be empirically tested. On the other hand, the analysis of this section generates an output of its own value.

In Section 2.1, the connection between cointegration and the multivariate Beveridge-Nelson decomposition is explained briefly. Sections 2.2 and 2.3 deal with the specification and the estimation of VECMs for the German, French and Italian data sets. The estimated

[6]See Figures 8 through 10 in Appendix A.

[7]The results are reported in Table 3 in Appendix A.

cointegrating vectors and adjustment parameters are discussed in detail. In Section 2.4, diagnostic checks on the VECMs are performed. Finally, the properties of the multivariate Beveridge-Nelson decompositions, especially the resulting cycle components, are analyzed.

2.1 Some methodological notes

Let y_t be a K-dimensional vector of nonstationary time series. In general, the vector process can be decomposed into

$$y_t = y_0 + \tau_t + c_t \tag{1}$$

where τ_t and c_t are the trend and the cycle components, respectively, and y_0 comprises the starting values of the series.

We are interested in investigating comovement on the basis of correlation measures, partly defined in the frequency domain, for which data need to be stationary. If the analysis only stressed the cyclical aspect, the task would be to detrend y_t. Standard approaches proposed in the literature are regression analysis and filtering. Whereas the former assumes that τ_t can be described by a linear combination of known functions in the time index t, differencing, as a prominent example of the latter, uses the property that the q th difference of τ_t will reduce to a constant if τ_t is a q th degree polynomial in t.[8]

However, purely statistical methods may bear interpretational problems with respect to the series which have been made stationary. It could well be that one succeeds in finding a transformation so that the resulting series seem to fulfill the conditions of stationarity, although they stem from an economy whose underlying structure comprises structural breaks.[9] Hence, from an empirical point of view, a theory-based trend-cycle decomposition might be preferable. First, use prior (economic) knowledge to identify the long-run relationships between the series, and second, apply their estimates to annihilate the (stochastic) trends. As a result, the remaining components can be regarded as stationary provided that the imposed structure is correct and does not change over time. Note that the German data set includes an obvious statistical break because the observations prior to 1991 refer to western Germany as the territorial basis.[10] But this shift will be captured within the structure of the model.

As shown by Stock and Watson [1988], a VECM has a common trends representation whose general structure is equivalent to (1). More precisely, a K-dimensional vector autoregressive model with r cointegrating relations possesses $K-r$ common trends which may be described by random walks with or without drifts. Note that the common trends representation is the multivariate extension of the Beveridge-Nelson [1981] decomposition, i.e. the cycle components are stationary sequences representing adjustment processes towards the trend paths modelled as random walks.

[8]See, for instance, Priestley [1981], Section 7.7, for details on trend removal prior to spectral analysis.

[9]See also Granger [1967] on this issue.

[10]More precisely, the structural break is due to the German unification. Until the fourth quarter of 1990, national accounts rely on western Germany. From the first quarter of 1991, the territorial basis switched to Germany as a whole. Further details on the break may be found in Appendix A.

To illustrate the formal link between the VECM and the common trends representation, let the data generating process of y_t be described by

$$y_t = [\mu_0 + \mu_0^b \,\mathsf{S}(t \geq T_B)] + [\mu_1 + \mu_1^b \,\mathsf{S}(t \geq T_B)]\, t + x_t \tag{2}$$

where μ_0, μ_0^b, μ_1, μ_1^b are K-dimensional parameter vectors and $\mathsf{S}(t \geq T_B)$ is a step dummy variable which is unity for $t \geq T_B$ and zero otherwise. The model allows for a structural break at time T_B, $0 < T_B < T$, which may take a flexible form. In particular, the series might obey a mean shift and a broken trend. The stochastic component x_t is assumed to follow a p th order vector autoregression which can be written in error correction form as

$$\Delta x_t = \Pi x_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + \varepsilon_t \tag{3}$$

where Π and $\Gamma_1, ..., \Gamma_{p-1}$ are $(K \times K)$ parameter matrices, and ε_t is a K-dimensional Gaussian residual process with zero mean and a nonsingular covariance matrix Ω.[11]

Suppose the cointegration rank be r, $0 < r < K$, which implies that $\Pi = \alpha\beta'$ where α and β are $(K \times r)$ matrices of full column rank. Let the $(K \times (K - r))$ matrices $\alpha_\perp$ and $\beta_\perp$ denote the orthogonal complements of α and β, respectively, and let $\Psi \equiv I_K - \sum_{i=1}^{p-1} \Gamma_i$ where I_K is a K-dimensional identity matrix. According to the Granger representation theorem,[12] x_t can be expressed by

$$x_t = C(1) \sum_{i=1}^{t} \varepsilon_i + C^*(L)\, \varepsilon_t \tag{4}$$

where $C(1) = \beta_\perp(\alpha_\perp' \Psi \beta_\perp)^{-1}\alpha_\perp'$ and $C^*(L) \equiv (1-L)^{-1}[C(L) - C(1)]$, $C_j^* \equiv -\sum_{i=j+1}^{\infty} C_i$.

As regards the deterministic part of the model, assume $\beta'\mu_1 = \beta'\mu_1^b = 0$. The former condition means that the cointegrating vectors annihilate both the stochastic and the deterministic trends (which is sometimes called “deterministic cointegration”), while the latter additionally imposes “drift co-breaking”.[13] Note that μ_1 and μ_1^b have the same left null space as $C(1)$. Consequently, one can write $\mu_1 = C(1)\bar{\mu}_1$ and $\mu_1^b = C(1)\bar{\mu}_1^b$.

By substituting (4) in (2), the observable vector y_t can be represented by[14]

$$y_t = [\mu_0 + \mu_0^b \,\mathsf{S}(t \geq T_B)] + C(1) \left\{ [\bar{\mu}_1 + \bar{\mu}_1^b \,\mathsf{S}(t \geq T_B)]\, t + \sum_{i=1}^{t} \varepsilon_i \right\} + C^*(L)\, \varepsilon_t. \tag{5}$$

Following Stock and Watson [1988], let us define $H \equiv [\,\alpha : \alpha_\perp]$ so that $C(1)H = [\,0 : \Phi\,]$ where $\Phi \equiv C(1)\alpha_\perp$ is a $(K \times (K - r))$ matrix of loading parameters. Then, (5) yields the common trends representation

$$y_t = [\mu_0 + \mu_0^b \,\mathsf{S}(t \geq T_B)] + \Phi\zeta_t + C^*(L)\, \varepsilon_t \quad \text{with} \quad \Delta\zeta_t = \kappa + \kappa^b \mathsf{S}(t \geq T_B) + \nu_t \tag{6}$$

[11]Note that $\Delta \equiv 1 - L$ denotes the difference operator where L is the lag operator, i.e. $L^k x_t = x_{t-k}$.

[12]See, for instance, Engle and Granger [1987] and Johansen [1991] for the proof.

[13]For a detailed discussion of different forms of co-breaking, see Clements and Hendry [1999], Chapter 9.

[14]For a proof of the Granger representation theorem in the presence of structural breaks in the deterministic trends, see Johansen et al. [2000], Theorem 2.1.

where $\kappa \equiv (\alpha'_\perp \alpha_\perp)^{-1}\alpha'_\perp \bar{\mu}_1$ and $\kappa^b \equiv (\alpha'_\perp \alpha_\perp)^{-1}\alpha'_\perp \bar{\mu}_1^b$ are $(K-r)$-dimensional parameter vectors and $\nu_t \equiv (\alpha'_\perp \alpha_\perp)^{-1}\alpha'_\perp \varepsilon_t$ is a $(K-r)$-dimensional vector white-noise process. Hence, the process ζ_t describes a multivariate random walk.

The (potential) structural break in y_t can be decomposed into mean shifts and broken trends at the same time. Owing to (6), the latter are modelled by a change in the drift parameter vector of the random walk. Furthermore, with $\tau_t = \Phi\zeta_t$ and $c_t = C^*(L)\,\varepsilon_t$, the common trends representation (6) suggests a trend-cycle decomposition of the form (1). For the subsequent empirical application, this implies that the cycle components can be obtained by the following two-step procedure. First, specify and estimate an appropriate VECM specification for y_t, and second, compute the cycle components according to (6) by $\hat{c}_t = y_t - \hat{\tau}_t - y_0$ where $\hat{\tau}_t$ is the estimate of the trend components. In the absence of structural breaks, the initial value y_0 is simply given by μ_0. Otherwise, the model depends on two initial conditions which are related to the parameters μ_0 and μ_0^b.

An estimable VECM specification for y_t is obtained by amalgamating (2) and (3), i.e.

$$\Delta y_t = \delta D_{t-1} + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \sum_{i=0}^{p-1} \xi_i I_{t-i} + \varepsilon_t \tag{7}$$

where δ is a parameter matrix attached to the intercept term and potentially the step dummy variable, i.e. $D_t \equiv [\mathsf{c} \,:\, \mathsf{S}(t \geq T_B)]$. In the case of a structural break, the model also includes a set of impulse dummy variables I_{t-j} which are unity for $t = T_B + j$ and zero otherwise. Consequently, $\xi_0, \xi_1, ..., \xi_{p-1}$ are K-dimensional parameter vectors which are attached to these additional dummy variables.[15]

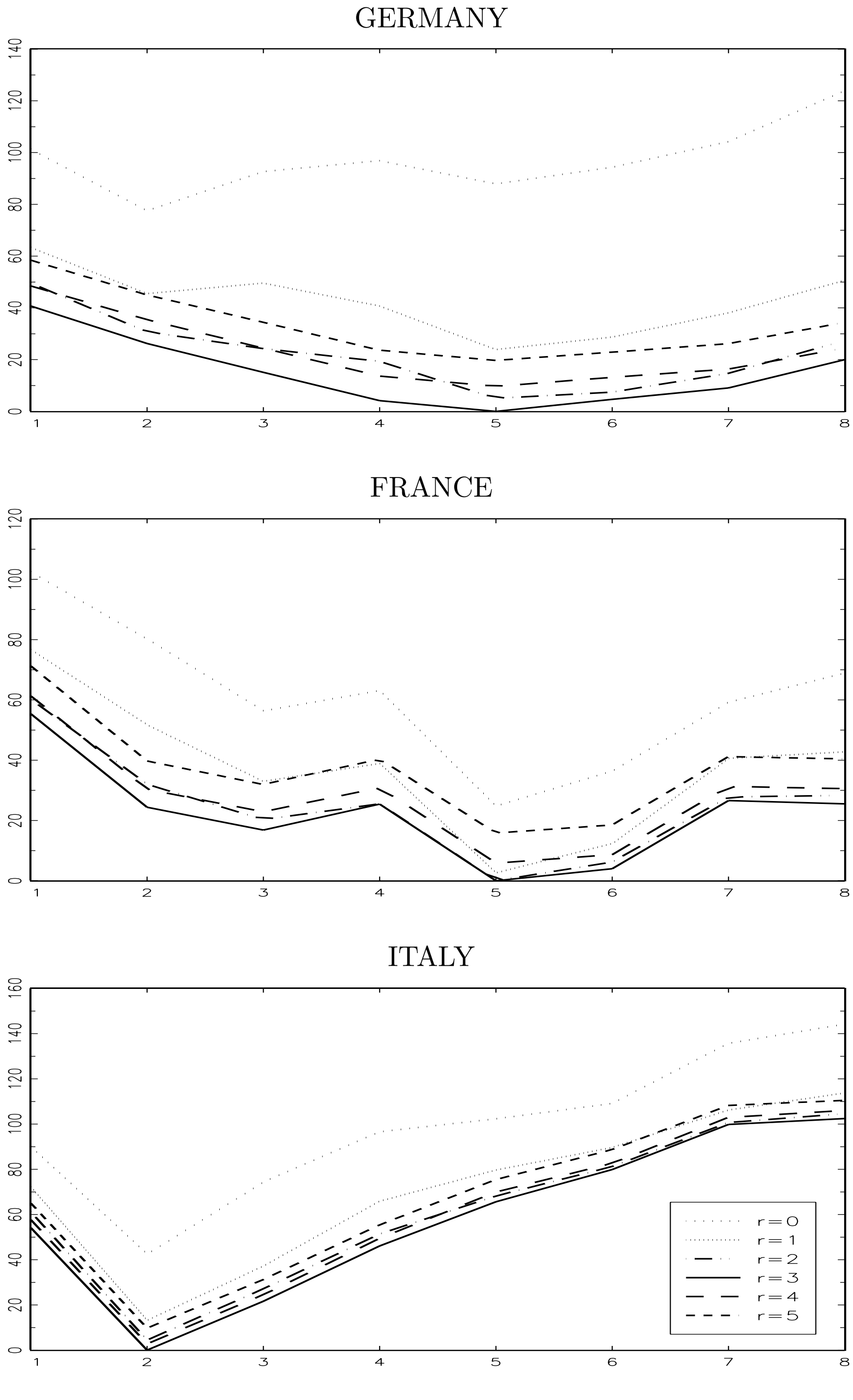
2.2 Determining the lag order and the cointegration rank

For the first step of the cointegration analysis, we define a (country-specific) vector containing all series but changes in inventories. Requiring this vector be described by a cointegrated vector autoregression, we have to specify the lag order p and the cointegration rank r. Contrary to the conventional practice where these parameter are selected one by another,[16] we base our choice on a simultaneous search over the two-dimensional space spanned by $p = 1, ..., 8$ and $r = 0, 1, ..., 5$. In fact, we will select the combination (p^*, r^*) minimizing Akaike's information criterion (AIC). This procedure is justified by the fact that a structural break has to be modelled in the case of Germany. Under these

[15]Note that the coefficients collected in δ and ξ_i, $i = 0, ..., p-1$, are algebraic expressions of the parameters of the data generating process documented in (2) and (3). For the nature of these relations in a similar case, see Saikkonen and Lütkepohl [2000], for instance. If the specification (7) was estimated, a set of restrictions would actually have to be taken into account. As this is not straightforward to do, we decide to estimate the VECM unrestrictedly. In the model specification step, however, the impulse dummies are not regarded as "full" regressors. Compared with the other, they only count one half in the penalty term of the information criterion.

[16]Specifically, one chooses first the lag order p by applying an appropriate information criterion (see Lütkepohl [1993], Chapter 4, for an overview on information criteria) and then, conditional on p, one tests for the cointegration rank using the multivariate technique proposed by Johansen [1991], for instance.

Figure 1: Specification search



The graphs depict the AIC values resulting from VECM estimations with lag orders $p = 1, ..., 8$ and cointegration ranks $r = 0, ..., 5$. For the sake of better depictability, AIC values are adjusted according to the equation $\overline{\mathrm{AIC}}(p,r) = \mathrm{AIC}(p,r) - \mathrm{AIC}^m$, where AIC^m is the (country-specific) minimum.

circumstances, a cointegration analysis on the basis of Johansen's [1991] LR trace statistic is rather complicated.[17] Alternatively, one could use information criteria to determine the cointegration rank, too. As a matter of consistency, the search for r could then be performed simultaneously with the determination of the lag order p.[18]

Figure 1 shows the results of the specification search. The first observation is that the lines indicating the various cointegration ranks mostly move in parallel, while the optimal choices for p differ amongst the countries. For the German system, $p = 5$ is optimal. In the case of France, the AIC suggests $p = 5$ as well, and for Italy, the minimum is given by the relatively short lag order 2. The second observation is that, except for the hypothesis of no cointegration at all, the lines are more or less clustered together. However, $r = 3$ minimizes the AIC for all countries at almost all lag orders. Especially in the case of France and Italy, the optimal optimal choice $r = 3$ is closely followed by the hypothesis $r = 2$.

For the VECM specification exercise, we should therefore take into account $r = 2$ and $r = 3$ as possible cointegration ranks. The final choices, however, will be determined in a comprehensive specification process where, in addition to statistical inference, economic intuition plays a role. First, the estimated cointegrating vectors should be reasonable in terms of economic theory, and second, the resulting cycle components should fit to basic characteristics which are typically assigned to them in applied business cycle research. But also the chosen lag orders may be questioned during the modelling exercise. One reason is that the series of changes in inventories is not considered here, while it belongs to the vector of endogenous variables later on. Thus, p might be adequate for the nonstationary series but too short for changes in inventories.

2.3 Estimating the parameters of the cointegrating space

In contrast to the previous analysis, the vector to be modelled comprises all six series under consideration. Formally, let us write $y_t \equiv [\,\mathsf{cons}_t,\, \mathsf{inv}_t,\, \mathsf{exp}_t,\, \mathsf{imp}_t,\, \mathsf{gdp}_t,\, \Delta\mathsf{st}_t\,]'$.[19] Given the values pre-selected for the lag order and the cointegration rank, we are going to specify and estimate country-specific VECMs. Although the short-term dynamics represented by the parameter matrices Γ_i, $i = 1, ..., p-1$, also affect the trend-cycle decompositions, our focus

[17] See Johansen et al. [2000] for the asymptotics of LR trace tests for the cointegration rank in the context of structural breaks. Recall that we generally allow for mean shifts in the cointegrating relations together with broken trends in the series. Especially in this setup, the limiting distributions of the LR trace test statistics are shown to be strongly affected by nuisance parameters.

[18] A simultaneous search for p and r has been discussed in Chao and Phillips [1999]. They advocate the Posterior Information Criterion (PIC) which differs from the Schwarz criterion through a twice-as-high penalty term on the parameters of the cointegrating matrix. Despite weaker performance detected in their simulation exercise, we nonetheless use the less parsimonious AIC because, in our investigation, it is important to ensure the whiteness of residuals. A further argument for the use of the AIC is that the lag order selection need not prioritize the limitation of the number of short-run parameters because they will be reduced in a second step. This is done by an automatic procedure which successively imposes zero restrictions on the parameters possessing t-statistics below a threshold in absolute values.

[19] The acronym cons denotes private consumption, inv business investment, exp exports, imp imports, and $\Delta\mathsf{st}$ changes in inventories. More information on the series is given in Appendix A.

here is on the parameters of the cointegrating space, i.e. the cointegrating matrix β and the matrix of adjustment parameters α. The reason is that implications from economic theory are mostly related to the long-run parameters.

The identification and estimation process is structured as follows. First, we try to find an identification scheme for the cointegrating matrix β. Second, zero restrictions are imposed on the adjustment parameter matrix α whenever possible. During this process, the trend-cycle decompositions which are implied by the diverse specifications under review are thoroughly checked in terms of whether the cycle components follow stationary processes and whether these cycles show features which correspond to the conventional wisdom on the cyclical behavior of GDP and the expenditure aggregates in these countries. The specification exercise exhibits the need to reduce the lag order in the case of France. The reason is that the French VECM tends to fail stability for lag orders equal to or greater than 5. Hence, we decide to reduce the lag length to 3 which is found to be a local minimum in Figure 1(b). In the case of Italy, diagnostics point to a lag augmentation because, with $p = 2$, serial correlation is present in the residual series of changes in inventories.

The most striking result of the identification exercise is that, under $r = 3$, the same set of restrictions on β can be applied to the German and the French VECM. As regards internal demand, we are able to identify a cointegrating relation between private consumption and GDP as well as between business investment and GDP. Consequently, the cointegrating relations can be labelled as consumption-output and investment-output relation respectively. In both countries, all series but one, namely private consumption for the former and business investment for the latter cointegrating relation, are weakly exogenous. Furthermore, there is a third linear combination in the system which is found to be stationary. Since this involves exports and imports, we call it "external trade relation". The variables bearing the adjustment process back to the third long-run equilibrium relationship are exports in the case of Germany and imports in the case of France.

For the **German data set**, the long-run part of the VECM(5) with $D_t = [\,\mathsf{c},\, \mathsf{S(91{:}1)}\,]'$ is given by[20]

$$\hat\beta' y_t = \begin{bmatrix} \mathsf{cons}_t & -\underset{(0.04)}{0.98}\mathsf{gdp}_t \\ \mathsf{inv}_t & -\underset{(0.13)}{1.23}\mathsf{gdp}_t \\ \mathsf{exp}_t & -\underset{(0.08)}{1.19}\mathsf{imp}_t \end{bmatrix} \quad \text{and} \quad \hat\alpha = \begin{bmatrix} \underset{(0.09)}{-0.17} & 0 & 0 \\ 0 & \underset{(0.06)}{-0.16} & 0 \\ 0 & 0 & \underset{(0.08)}{-0.12} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{array}{l} \mathsf{cons}_t \\ \mathsf{inv}_t \\ \mathsf{exp}_t \\ \mathsf{imp}_t \\ \mathsf{gdp}_t \\ \Delta\mathsf{st}_t \end{array}. \tag{8}$$

[20]Standard errors are given in parentheses. To the right of the estimated adjustment parameter matrix, we indicate to which left-hand side variable the corresponding row of $\hat\alpha$ belongs.

For the **French data set**, a VECM(3) with an unrestricted constant is specified. The estimates of the cointegrating space are

$$\hat{\beta}' y_t = \begin{bmatrix} \mathsf{cons}_t & -\underset{(0.03)}{0.92}\mathsf{gdp}_t \\ \mathsf{inv}_t & -\underset{(0.07)}{1.43}\mathsf{gdp}_t \\ \mathsf{exp}_t & -\underset{(0.05)}{0.93}\mathsf{imp}_t \end{bmatrix} \quad \text{and} \quad \hat{\alpha} = \begin{bmatrix} -\underset{(0.04)}{0.07} & 0 & 0 \\ 0 & -\underset{(0.04)}{0.09} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \underset{(0.04)}{0.06} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \cdot \begin{array}{c} \mathsf{cons}_t \\ \mathsf{inv}_t \\ \mathsf{exp}_t \\ \mathsf{imp}_t \\ \mathsf{gdp}_t \\ \Delta\mathsf{st}_t \end{array} \tag{9}$$

Against the hypothesis of just-identification of the cointegrating vectors and no restrictions on the matrix of adjustment parameters, on the 5% level, LR tests do not reject the set of restrictions which are imposed to obtain these estimates.[21]

The estimates of the bulk of cointegrating vectors are theoretically appealing because they are close to $(1, -1)'$, implying that the simple ratio between the respective variables can be given an interpretation in terms of a long-run equilibrium relationship. The sole clear exception is the French investment-output relation. Furthermore, it is an interesting observation that the adjustment parameters are always smaller (in absolute values) in the case of France than in the case of Germany. Consequently, the adjustment processes back to the three long-run equilibrium relationships last longer in France than in Germany, which in turn implies that cycle components are expected to be more persistent.

From an interpretational point of view, the identification scheme of the cointegrating matrices is interesting because it allows us to separate the trend components of GDP and the internal demand aggregates from those driving export and import volumes. Each group is characterized by its specific stochastic trend. In the long run, there is a dichotomy between the internal and the external sides of the economy. The internal trend might be due to technical progress leading to productivity shocks with permanent character.[22] Owing to standard trade balance mechanisms, export and import volumes ought to share a trend which might be explained by the rising integration of the world economy.

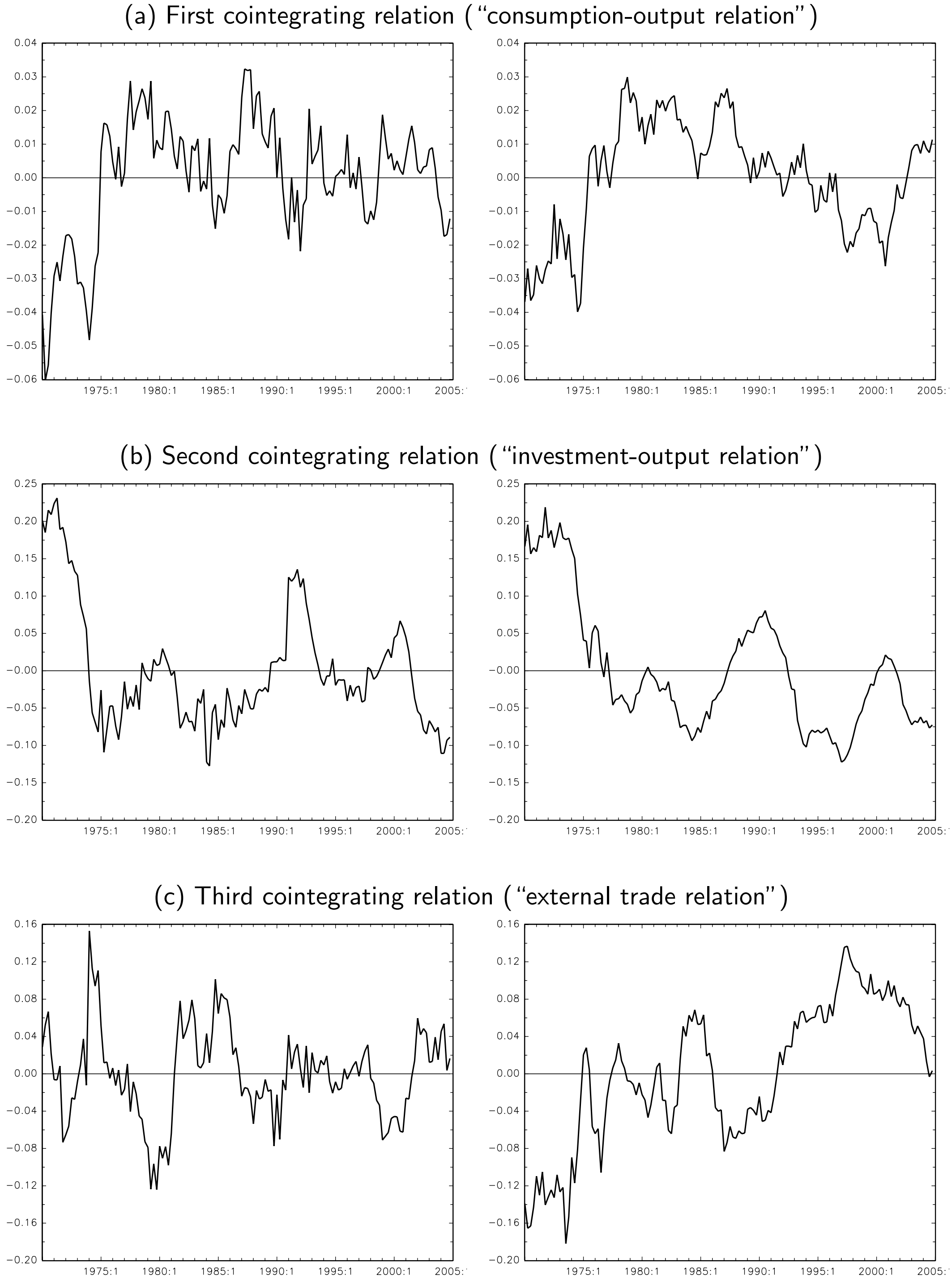
Since the German and the French data possess the same long-run structure, the error correction terms of the respective cointegrating relations can be compared directly. These long-run residual series are plotted in Figure 2.[23] Although the estimates of the free

[21] The test statistics are 26.55 and 25.49 for the German and the French data set, respectively. As these LR tests are asymptotically χ^2 distributed with 21 degrees of freedom, the marginal significance levels are 0.186 and 0.227; see Johansen [1995], Chapters 7 and 8, for hypothesis testing on the parameters of the cointegrating space.

[22] According to King et al. [1991], standard neoclassical growth models suggest that the consumption-to-output and the investment-to-output ratios (the so-called "great ratios") should be stationary when (exogenous) technical progress is specified by shocks to productivity with permanent character.

[23] The long-run residual series are defined as the residuals obtained from regressing the error correction terms on the set of deterministic regressors relevant to the cointegrating space. In the case of Germany, it consists of a constant and a step dummy. In the case of France, the error correction terms need to be mean-adjusted.

Figure 2: Cointegrating relations – GERMANY and FRANCE



The plots depict the long-run residual series (as a percentage) obtained by regressing the cointegrating relation on an intercept and, in the case of Germany, additionally on a step dummy modelling the unification break.

parameter in the investment-output relation differ somewhat, the long-run residuals implied by the second cointegrating relation show the most similar pattern. The long-run residual series are not only comparable in duration and volatility but also in the timing of cyclical phases. The long-run residuals derived from the consumption-output relation show a looser connection in cyclical terms. In the 1970s and 1980s, private consumption behaved rather similarly in both countries. But whereas the consumption-to-GDP ratio remained more or less stable in Germany since the unification, it was on a downward trend in France during the 1990s before it recovered strongly in the first years of the new millenium. The long-run equilibrium relation between the export and import volumes does not show any commonality between Germany and France. This comes as no surprise taking into account the fact that the two countries are main trading partners for each other. Offsetting forces are likely to be at play. First, the export-to-import ratios should comove when both countries are symmetrically hit by global developments. Second, if external shocks are asymmetric and the domestic parts of the economies are in different shapes, the close trade relations are likely to mitigate the economic consequences in the two countries.

In the model for the Italian economy, it is not possible to identify three cointegrating vectors which are satisfying from the standpoint of economic theory and which lead to reasonable cycle components. The reduction of the cointegration rank to 2, however, yields a better result. Hence, the **Italian data set** is appropriately represented by a VECM(3) including an unrestricted constant where the estimates of the cointegrating space are

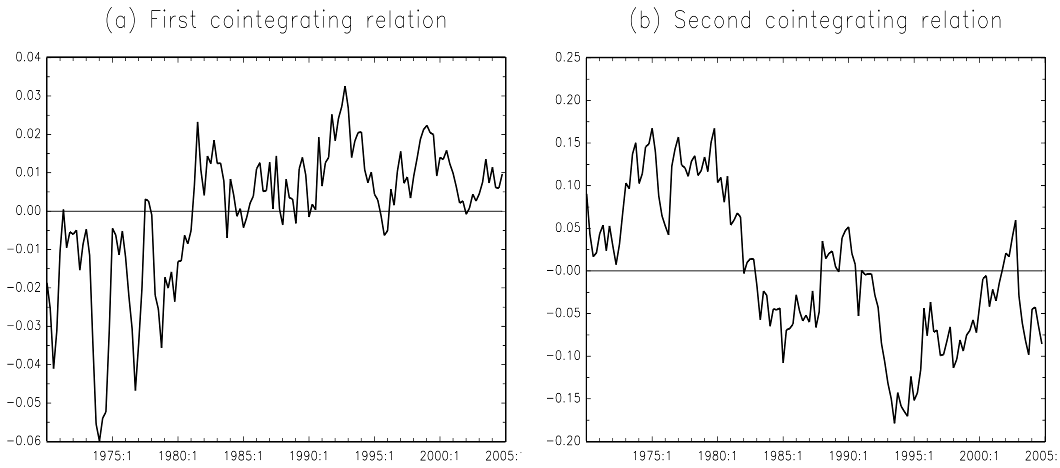
$$\hat{\beta}' y_t = \begin{bmatrix} \mathsf{cons}_t & +\underset{(0.03)}{0.11}(\mathsf{exp}_t - \mathsf{imp}_t) & -\underset{(0.01)}{1.08}\mathsf{gdp}_t \\ \mathsf{inv}_t & -\underset{(0.04)}{0.64}\mathsf{imp}_t & \end{bmatrix} \text{ and } \hat{\alpha} = \begin{array}{c} \begin{bmatrix} \underset{(0.03)}{-0.13} & 0 \\ 0 & \underset{(0.03)}{-0.10} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \end{array} \begin{array}{c} \mathsf{cons}_t \\ \mathsf{inv}_t \\ \mathsf{exp}_t \\ \mathsf{imp}_t \\ \mathsf{gdp}_t \\ \Delta\mathsf{st}_t \end{array} . \tag{10}$$

The set of restrictions which are imposed to obtain these estimates is accepted by an LR test where the alternative hypothesis is just-identification of the cointegrating vectors and an unrestricted matrix of adjustment parameters.[24]

In contrast to Germany and France, the long-run equilibrium relationships do not imply a dichotomy between the internal and external sides of the economy. It is therefore not straightforward to assign an economic meaning to the three common trends in the Italian data set. First, neither private consumption nor business investment is directly cointegrated with GDP. Second, there is no stable long-run relationship between exports and imports. Nonetheless, the second cointegrating relation may be regarded as an investment equation in which, in contrast to the other two countries, the import volume is given a direct impact. This could be explained by the specialization of the Italian industrial sector in

[24]The test statistic is 11.84 implying a marginal significance level of 0.691 on the basis of a χ^2 distribution with 15 degrees of freedom.

Figure 3: Cointegrating relations – ITALY



The plots depict the long-run residual series (as a percentage) obtained by regressing the cointegrating relation on an intercept.

consumer goods, which in turn implies that capital goods have to be imported to a large extent. The first cointegrating relation establishes the result that the consumption-to-output ratio and the ratio between exports and imports are inter-connected in the long run, although each ratio is nonstationary itself. In economic terms, a surplus in the trade balance coincides with a "consumption sacrifice" of Italian households in the sense that a comparably low consumption-to-output ratio occurs. The long-run residuals resulting from the two cointegrating relations are plotted in Figure 3.

2.4 Residual checks

To model the German, French and Italian data sets, VECMs are estimated. In this section, some diagnostic checks on the VECM residuals are performed. This is done in order to substantiate that the models are well specified and to ensure that the parametric bootstrap is founded on a sound basis.

Through the parameter matrix Ψ, the trend-cycle decomposition is *inter alia* dependent on the short-term parameters of the model collected in the matrices $\Gamma_1, ..., \Gamma_{p-1}$. In a six-dimensional system, even lag orders of medium size result in an enormous number of coefficients to be estimated. Bootstrap procedures, however, may suffer from distortions if zero restrictions are not imposed, although coefficients are actually zero. Hence, the dimension of the parameter space is reduced by successively eliminating regressors whose t-statistic is lower than a threshold in absolute value. Brüggemann and Lütkepohl [2001] showed that, in single-equation models, this testing procedure is equivalent to a sequential elimination of regressors on the basis of information criteria. In general, the threshold

Table 1: Diagnostic checks on the residual series

I. GERMANY

Residual test statistic	Series					
	cons_t	inv_t	exp_t	imp_t	gdp_t	$\Delta\mathsf{st}_t$
AC-LM(1)	0.50 [0.481]	1.59 [0.207]	0.00 [0.976]	0.89 [0.346]	0.98 [0.323]	0.05 [0.815]
AC-LM(4)	4.44 [0.350]	3.25 [0.517]	2.45 [0.654]	3.16 [0.531]	2.39 [0.664]	4.89 [0.299]
ARCH-LM(2)	3.08 [0.215]	$10.97^{\star\star}$ [0.004]	$8.40^{\star}$ [0.015]	1.78 [0.411]	1.32 [0.517]	0.79 [0.674]
JB normality	2.34 [0.311]	$9.74^{\star\star}$ [0.008]	$12.90^{\star\star}$ [0.002]	2.47 [0.291]	$17.90^{\star\star}$ [0.000]	$6.73^{\star}$ [0.035]

II. FRANCE

Residual test statistic	Series					
	cons_t	inv_t	exp_t	imp_t	gdp_t	$\Delta\mathsf{st}_t$
AC-LM(1)	0.22 [0.641]	2.52 [0.112]	0.31 [0.579]	2.30 [0.129]	$3.09^{(\star)}$ [0.079]	0.31 [0.579]
AC-LM(4)	1.97 [0.741]	2.53 [0.639]	$10.82^{\star}$ [0.029]	7.18 [0.127]	5.48 [0.242]	4.46 [0.347]
ARCH-LM(2)	1.42 [0.491]	1.68 [0.431]	1.28 [0.526]	1.09 [0.581]	1.39 [0.499]	$8.45^{\star}$ [0.015]
JB normality	1.49 [0.475]	0.348 [0.840]	1.93 [0.381]	0.03 [0.984]	0.78 [0.677]	$6.79^{\star}$ [0.033]

III. ITALY

Residual test	Series					
	cons_t	inv_t	exp_t	imp_t	gdp_t	$\Delta\mathsf{st}_t$
AC-LM(1)	0.17 [0.680]	0.17 [0.682]	1.20 [0.273]	0.73 [0.393]	0.68 [0.408]	0.23 [0.634]
AC-LM(4)	3.76 [0.440]	4.89 [0.299]	3.86 [0.425]	5.11 [0.276]	1.23 [0.874]	5.35 [0.253]
ARCH-LM(2)	$14.57^{\star\star}$ [0.001]	$6.95^{\star}$ [0.031]	2.54 [0.280]	$7.95^{\star}$ [0.019]	3.32 [0.190]	$5.79^{(\star)}$ [0.055]
JB normality	3.29 [0.193]	3.44 [0.179]	1.87 [0.393]	$9.10^{\star}$ [0.011]	0.30 [0.860]	1.58 [0.454]

The statistics of the residual tests are asymptotically χ^2 distributed. Marginal significance levels are given in brackets. **,* ,$^{(\star)}$ mean rejection of the null hypothesis at the 1%, 5% and 10% level respectively.

depends on the chosen criterion, the length of the time series, and the number of regressors in each step of the procedure. In system approaches, an exact correspondence cannot be established. In order to mimic the sequential elimination of regressors on the basis of the AIC, we decide to use the constant threshold $\sqrt{2}$ as an approximation.[25] The resulting subset VECMs have substantially smaller numbers of parameters to be estimated.[26]

In Table 1, standard diagnostic checks on the VECM residual series are reported. These include LM tests for remaining autocorrelation (AC-LM) of order 1 and 4, an LM test for autoregressive conditional heteroscedasticity (ARCH-LM) of order 2 and the Jarque-Bera (JB) test for normality. Serial correlation is absent in the residual series of the German system. However, the error terms of the investment and the export equation possess significant conditional heteroscedasticity. Solely the residuals of the consumption and import equation can be regarded as being drawn from a normal distribution. In the case of France, problems with remaining serial correlation of order 4 exist in the residual series of the export equation. The absence of ARCH effects and distributional normality is rejected only for the residuals of changes in inventories. In the case of Italy, autocorrelation does not seem present in any error sequence. ARCH effects are found in the majority of residual series, however. All error terms but those of imports can be taken as drawn from a Gaussian distribution.

In general, residual series which significantly deviate from an identical and independently distributed random draw must be regarded as detrimental. However, taking into account the fact that the chosen lag orders are already large, the benefit from possibly erasing some deficiencies might not outweigh the cost of additional parameters to be estimated if the lag length were augmented in these high-dimensional systems. In the diagnostic checks, the focus is mainly on the avoidance of serial correlated residual terms. The rejection of distributional normality is less severe in this context because the applied estimation techniques, albeit based on the maximum likelihood principle, are robust to potential non-normality and the bootstrap directly draws from the realized residuals so that their specific distribution is preserved.

2.5 The trend-cycle decompositions

As discussed in Section 2.1, the VECMs can be rewritten in their common trends representations providing trend-cycle decompositions of the multivariate Beveridge-Nelson type. Evans and Reichlin [1994] argued that the multivariate version typically assigns more volatility to the cycle components than the univariate one.[27] In applied business

[25]The threshold value is derived from the formula presented in Brüggemann and Lütkepohl [2001], Proposition 1, by setting $c_T = 2$ (AIC) and assuming $T \gg K + j$ where j is the step of the testing procedure.

[26]Precisely, 100 out of initially 186 coefficients which belong to either the deterministic part or the short-term dynamics of the German VECM need to be estimated in the final subset model. In the case of France and Italy, the numbers are 49 and 39 out of 78.

[27]Intuitively, this result is explained by the fact that the forecast error variance is typically smaller in multivariate models than in univariate models because the information set upon which the forecasts are conditioned is larger. Better predictability, however, leads to an increase in the variance of the cycle component in a Beveridge-Nelson decomposition.

Table 2: Statistics of the trend-cycle decomposition

Country	cons_t	inv_t	exp_t	imp_t	gdp_t	$\Delta\mathsf{st}_t$
	A. standardized trend variance					
GERMANY	0.78	0.13	1.24	0.88	0.80	
FRANCE	0.96	0.32	1.08	1.02	1.89	
ITALY	2.76	0.48	0.56	0.71	1.38	
	B. cycle-trend variance ratio					
GERMANY	0.34	5.01	0.59	0.54	0.19	
FRANCE	0.87	2.38	0.17	1.34	0.37	
ITALY	0.77	1.86	0.39	0.55	0.59	
	C. cycle variability					
GERMANY	0.017	0.080	0.047	0.028	0.012	3.22
FRANCE	0.021	0.078	0.017	0.078	0.009	1.71
ITALY	0.029	0.082	0.017	0.031	0.013	1.73
	D. cycle persistence					
GERMANY	0.840	0.893	0.813	0.830	0.892	0.667
FRANCE	0.929	0.955	0.864	0.930	0.817	0.754
ITALY	0.932	0.939	0.324	0.646	0.810	0.482

The standardized trend variance and the cycle-trend variance ratio are defined in the text. The variability of the cycle components is measured by the standard deviation. Cycle persistence is approximated by the first-order autocorrelation coefficient.

cycle research, the latter has often been criticized because of the noisy cycles it generates. Along this line of criticism, it may be interesting to know how large the variance of the extracted trends is in comparison with the series itself, i.e. $\text{var}(\Delta\tau_t^k)/\text{var}(\Delta y_t^k)$, $k = 1, ..., K$. Note that this standardized trend variance is lower than unity when the trend component is smoother than the series. With reference to Evans and Reichlin's paper, we also compute the cycle-trend variance ratio, i.e. $\text{var}(\Delta c_t^k)/\text{var}(\Delta\tau_t^k)$, $k = 1, ..., K$. This measure is greater than unity when the volatility of changes in the cycle components exceeds that of trend innovations and vice versa. Moreover, we will analyze the cycle components of the five trending series as well as changes in inventories in mean-adjusted form. Apart from a rough visual assessment, we are going to report some simple descriptive measures in order to describe key characteristics of the cycle components.

Table 2, Panel A, reports the standardized trend variance for the nonstationary series. As expected, it is common to all countries that business investment is clearly more volatile than its trend. Otherwise, the results seems quite different across countries. In the case of Germany, all variables but exports possess trend components which are smoother than the actual series. In the case of France, the standardized trend variance is close to unity for private consumption and the external trade aggregates, while trend output is almost twice as volatile as GDP itself. Given that French GDP is particularly smooth, it is not surprising that a well-behaved estimate of the output gap is achieved by a relatively volatile trend component. In the case of Italy, it is private consumption whose estimated trend component is much more volatile than the actual series. While business investment and the trade volumes possess a smooth trend component, the variance of the Italian trend output exceeds that of GDP by about 40 per cent.

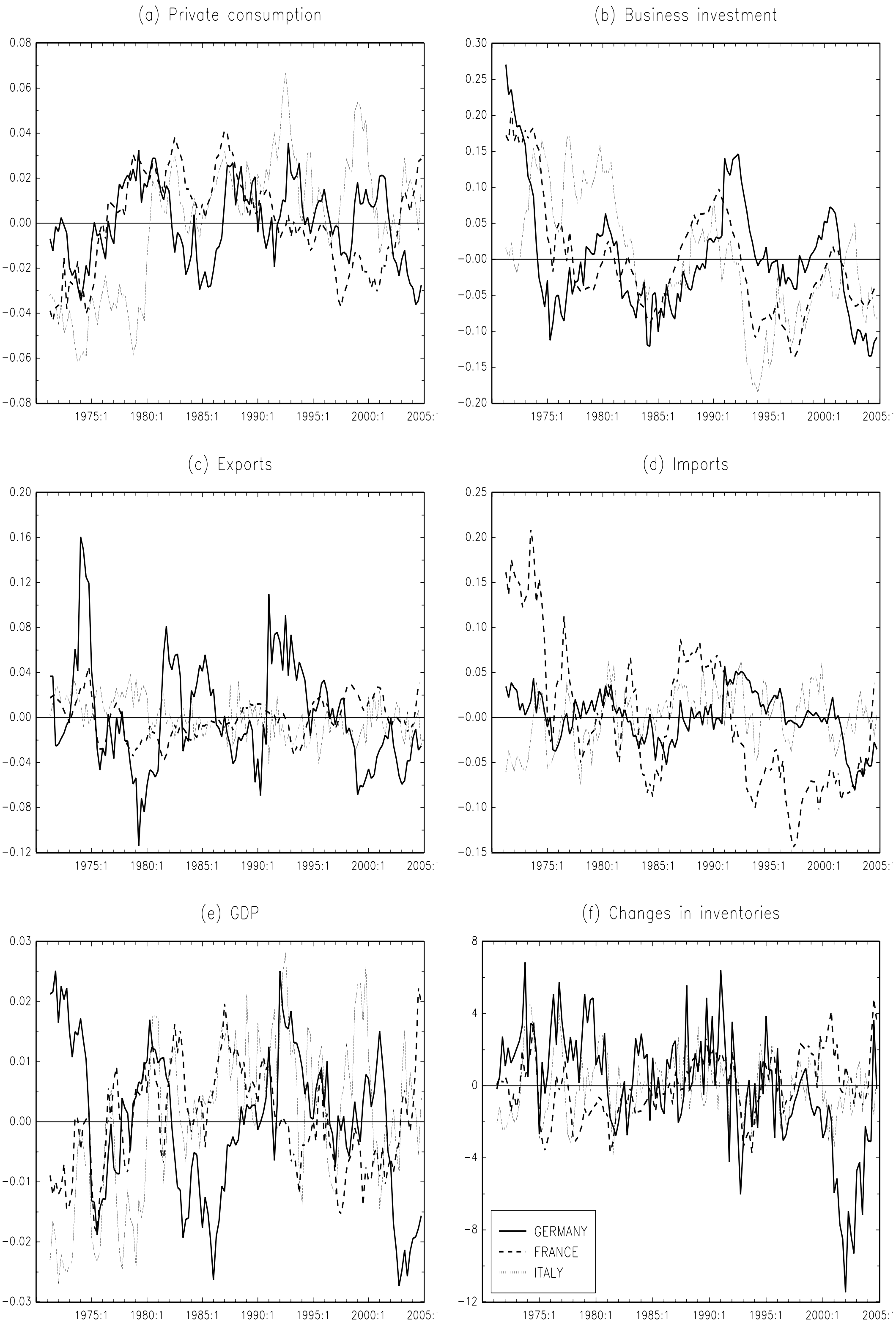
With respect to the cycle-trend variance ratios which are reported in Table 2, Panel B, the results obey a more uniform pattern. In all countries, it is found that the cycle changes of business investment are more volatile than the trend innovations, while the opposite holds true for private consumption, exports and GDP. In the case of imports, the French aggregate differs from those of Germany and Italy in the sense that the cycle-trend variance ratio exceeds unity. Extreme values (in either direction) are mostly found for the German aggregates. In the case of business investment, for instance, the variance of cycle changes is five times larger than the variance of trend innovations. In France and Italy, the factor is only about two. Conversely, the trend-cycle variance ratios reported for GDP and private consumption are markedly lower in Germany than in the other two countries.

Next, it is worth looking at the plots of the cycle components in Figure 4.[28] Except for Italian exports, the multivariate Beveridge-Nelson cycles of all series under consideration turn out to pass the visual test of possessing a "reasonable" cyclical shape. By conventional standards, the estimates do not exhibit fluctuations that are too noisy. Apart from this general common feature, there are important differences along both the variable-dimension and the country-dimension. Only the cycle components of business investment turn out to show a marked degree of comovement in the cross-country perspective. As regards private consumption and especially GDP, the cyclical relationships between the three countries seem surprisingly loose, although the cycle components look similar in terms of persistence and amplitude. The cyclical factors of the external trade volumes, however, do not even have these characteristics in common. Whereas the cycle component of German exports fluctuates with a considerably greater amplitude than its counterparts, it is the French import series whose cycle component has a comparably high variability. This difference is explained by the fact that the large and persistent long-run residuals of the external trade cointegrating relation are "corrected" by exports in the case of Germany and by imports in the case of France. Changes in inventories are too noisy to assess the degree of comovement by a visual check. From the plots in Figure 4(f), it is obvious that the very negative values observed for German inventory investment since 2000 are exceptional—both in historical terms and in a country comparison.

Further insight into the statistical properties of the cycle components can be gained from some simple descriptive measures which point to the duration and the amplitude of the oscillations. Whereas the variability of the cycle components is measured by the standard deviation, persistence is approximated by the first-order autocorrelation coefficient. The results are found in Table 2, Panels C and D, respectively. Note that, insofar as the

[28] Figure 4(f) does not depict a Beveridge-Nelson cycle component. Changes in inventories are only mean-adjusted.

Figure 4: Plots of the cycle components



standard deviation is concerned, changes in inventories should be taken aside in within-country comparisons because its dimension is billion euro (rather than a percentage as in the case of the other aggregates). Cross-country comparisons, however, are valid, of course.

As regards variability, the cycle components can be ordered quite similarly in all countries. It comes as no surprise that business investment is the most volatile aggregate. Furthermore, the output cycles are less volatile than the consumption cycles. In quantitative terms, the cross-country perspective shows no great differences in volatility for private consumption, business investment and GDP. With respect to exports and changes in inventories, the German volumes are markedly more volatile than those of France and Italy, whereas the standard deviation of the French import cycle is more than twice as high as its German and Italian counterparts.

Finally, it is worth mentioning that the cycle components of all nonstationary series but Italian exports are quite persistent. As expected, changes in inventories are less persistent, although the estimated serial correlations are still substantial. In all countries, the highest first-order autocorrelation is observed for business investment. In Germany and Italy, private consumption and GDP are ordered between investment on the one side and the external trade volumes on the other. Surprisingly, in the case of France, the GDP cycle shows the lowest first-order autocorrelation amongst the nonstationary variables under study. But this estimate is still slightly higher than its Italian counterpart. In the cross-country perspective, it is noticeable that the cycle components of the French expenditure aggregates are most persistent. This is particularly valid for private consumption, business investment and imports. This high persistence is a consequence of comparably long-lasting error correction processes implied by the low adjustment parameters documented in (9).

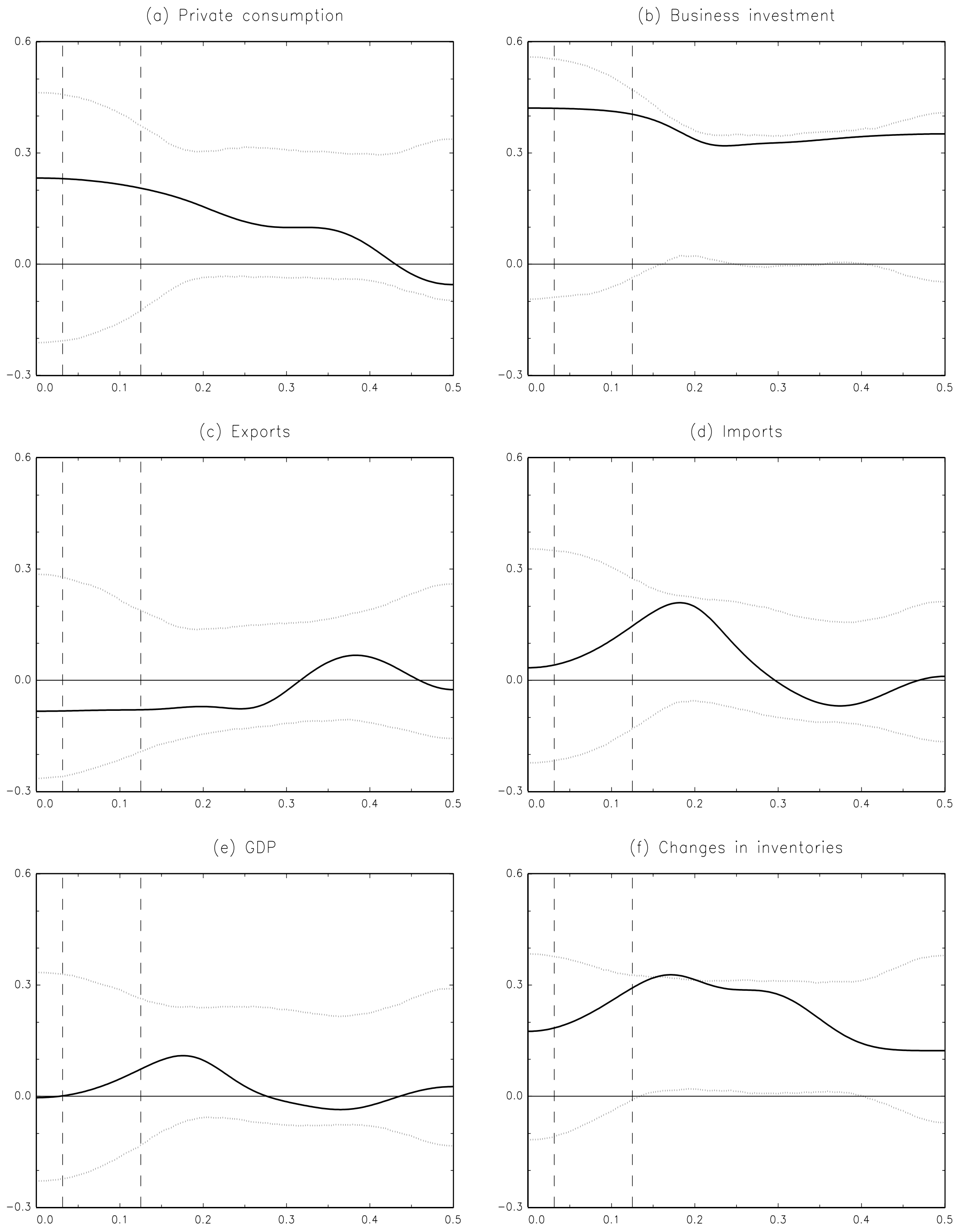
3 Cross-country comovement

Comovement between nonstationary series has a short-run and a long-run aspect. Long-run comovement between the series of the same country has been studied by the cointegration analysis. However, there are good reasons to believe that co-trending is present in the cross-country dimension, too. This issue will be addressed in Section 3.2. First, we are going to study cross-country co-cycling. This analysis uses the Beveridge-Nelson cycle components of the nonstationary series as well as the series of changes in inventories.

3.1 Cross-country co-cycling

In studying the synchronicity of business cycles in Germany, France and Italy, it is of main interest to analyze cross-country correlations of GDP and the expenditure aggregates. If comovement ought to be studied at distinct cycle periodicities, the concept of "dynamic correlation" could be applied in general. This measure translates the simple interpretation of the standard (static) cross correlation into the frequency domain. But as its time-domain counterpart, dynamic correlation is a bivariate concept. Hence, it is not fully appropriate for the present application. A multivariate extension was proposed by Croux et al. [2001],

Figure 5: Cross-country co-cycling – single aggregates



The graphs depict the point estimates of cohesion (solid line) together with the 95% confidence bands resulting from thebootstrap procedure (dotted lines). The abscissa scale is frequency divided by 2π. The dashed vertical lines limit the frequency band attributed to periodicities of two and eight years ("business cycle frequencies").

however. This measure called "cohesion" summarizes the dynamic correlations which can be constructed by combining pairwise all series in the set of variables under study.[29] In the context of this summary statistic, a weighting scheme has to be chosen. We decide to give an equal weight to Germany, France and Italy because the countries are comparable in size. An equal-weight cohesion of three series may take values ranging from -0.5 to 1.[30] Negative cohesions would be difficult to interpret in the present context, however.

In Figure 5, the cross-country cohesions of the cycle components of GDP and the expenditure aggregates are plotted. Let us first look at the point estimates only. At around 0.4, cohesion is found to be highest for business investment. In the range of business cycle frequencies, the cohesion of private consumption amounts to about 0.25. Compared with this level, the cohesion graphs of imports and changes in inventories exhibit higher peaks. But as these are located around the frequency $2\pi/5$, synchronicity is concentrated at cycles with a very short duration, namely below two years. The Beveridge-Nelson cycles of exports and GDP are not synchronized at all. While this does not seem very surprising in the former case, the evidence for GDP runs counter to economic intuition. In fact, one would actually expect that the output gaps of the three countries should be strongly correlated owing to their close economic connections. However, by looking at the plots in Figure 4(e), we are able to convince ourselves visually as well that comovement between the output gap estimates is largely absent. In order to interpret the evidence that the cycle components of private consumption and business investment are synchronized across Germany, France and Italy, while the production cycles are not, one has to bear in mind that the three countries are well integrated in international trade, enabling that the economies to specialize in the production of specific goods despite similar consumer preferences and production technologies.

The point estimates of cohesion are informed by bootstrapped 95% confidence intervals. These are rather wide and include the horizontal axis, at least in the range of business cycle frequencies. In a strict statistical sense, cross-country co-cycling cannot be proven to be significant for any single expenditure aggregate under study. This statement is also valid for business investment despite high point estimates and the visual impression in Figure 4(b). In general, the width of the confidence intervals dashes the hope that cycle components would bear statistically robust common features if they were generated by the multivariate Beveridge-Nelson decomposition, which is based on a number of econometrically demanding test and estimation procedures. In this respect, neither the careful search for an identification scheme of the cointegrating space nor the data-dependent reduction of the set of short-run parameters has obviously succeeded in sufficiently diminishing the uncertainty surrounding the VECM estimates.

It is worth looking at cohesions of groups of aggregates because, from a statistical perspective, grouping might average out sampling variability to some extent. But also

[29] Further details on this measure may be found in Appendix B.

[30] Whenever correlation between series is perfectly positive, cohesion is unity. Whereas the upper limit is fixed, the lower bound depends on the number of series and the weighting scheme. In the current context, the lower bound will be reached if dynamic correlation is perfectly positive between two of them while it is perfectly negative between these two and the third.

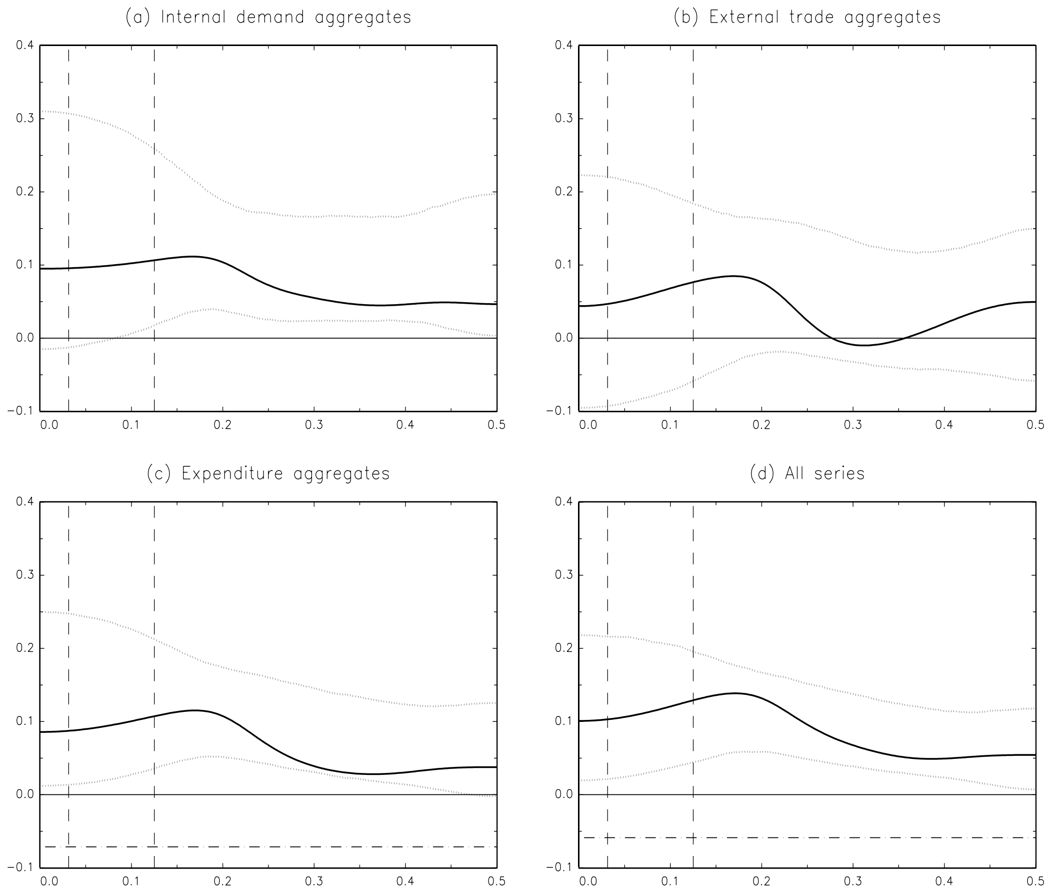
from an interpretational point of view, it may also be interesting to study synchronicity on a broader basis. For instance, it is reasonable to summarize private consumption, business investment and changes in inventories as internal demand factors, while export and import volumes logically group together because they both belong to external trade. However, when demand categories with or without GDP are combined, it is a difficult task to find an appropriate weighting scheme. For instance, using the GDP shares of the accounting identity is not a good idea for obvious reasons. Imports would have to be given a negative weight and changes in inventories a very small weight. Apart from these arithmetical problems, the example of inventory investment makes clear that an expenditure aggregate with a marginal proportion of GDP may have an enormous impact on output fluctuations nonetheless. Instead, the impact on output fluctuations would principally be the preferable standard. However, since this is exactly the object of the empirical investigation, we should take a neutral position at the beginning. Otherwise, the results risk being determined by the chosen weights. As a consequence, all series are given the same weight in the variable-dimension as well as in the country-dimension.

Apart from sorting the internal demand and the external trade aggregates, two further groups are formed. They comprise all expenditure categories—the one excluding GDP and the other including GDP. In Figure 6, the cohesions of these four groups are plotted. A look at the bootstrapped confidence intervals shows that grouping does, in fact, help to reduce the uncertainty surrounding the point estimates. Confidence bands are still large in the case of the internal demand and the external trade aggregates, where cohesion is only based on nine and six series, respectively. However, if 15 or all 18 series of the data set are considered, confidence intervals reduce substantially. Hence, statements on the extent of co-cycling are the more reliable, the larger the set of variables for which cohesion is computed. Moreover, with more series included, the point estimates tend to become more stable, too.

Except for the group of external trade aggregates, the point estimates of cohesion are about 0.1 at business cycle frequencies. All graphs peak slightly outside this range, implying that strongest synchronicity is found for very short-term cycles. Interestingly, in Figures 6(c) and (d), confidence bands are found to be above the horizontal axis. In a strict statistical sense, this is the only piece of evidence which allows us to conclude that the Beveridge-Nelson cycle components of GDP and the expenditure aggregates in Germany, France and Italy do, in fact, comove in the range of business cycle frequencies. Taking into account the loose synchronicity of the single aggregates in the cross-country dimension, this result actually means that cycle components turn out to be more correlated within countries than across countries.

In sum, there is synchronicity of the cycle components between GDP and the expenditure aggregates in Germany, France and Italy. In terms of statistical significance, however, this conclusion can only be drawn when aggregates are grouped together. Overall, co-cycling at short-term periodicities seems slightly stronger than at long cycle durations. The cycle components of the single aggregates do not show statistically significant cohesion across the three countries, although, at least within the range of business cycle frequencies, the point estimates for private consumption and, especially, business investment exhibit comparably high values. Perhaps the most striking observation is that, regarding output gap synchronicity, even the point estimates are close to zero in the business cycle range.

Figure 6: Cross-country co-cycling – groups of aggregates

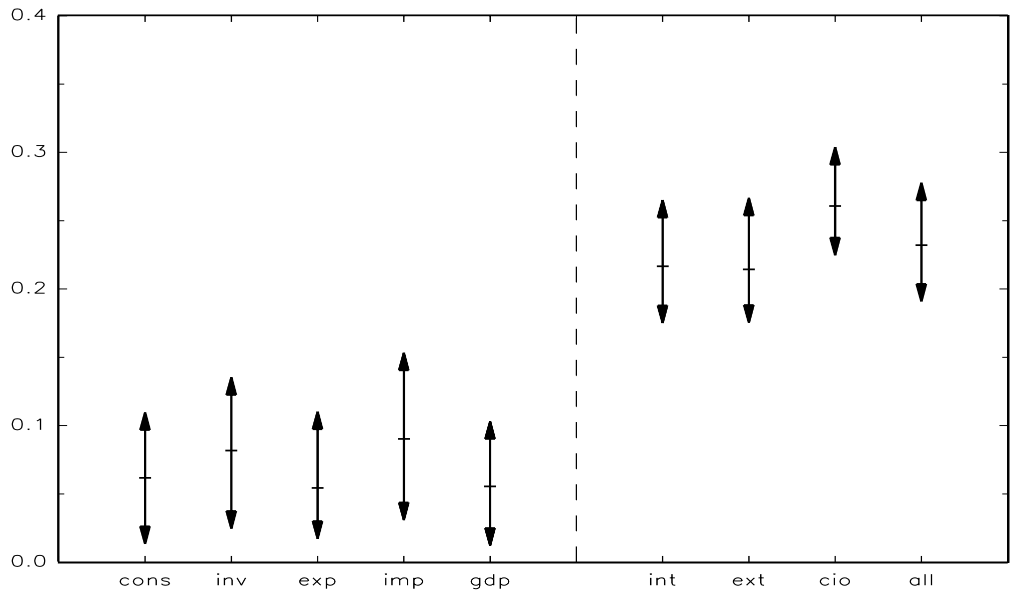


The graphs depict the point estimates of cohesion (solid line) together with the 95% confidence bands resulting from the bootstrap procedure (dotted lines). The abscissa scale is frequency divided by 2π. The dashed-dotted horizontal line shows the lower limit of admissible values. The dashed vertical lines limit the frequency band attributed to periodicities of two and eight years ("business cycle frequencies").

3.2 Cross-country co-trending

In this section, let us address the cross-country dimension of co-trending. Precisely, we are going to study comovement between the trend components of the nonstationary series. Although generally possible, this issue is not tackled by a cointegration analysis. Instead, we take up the procedure of the previous section by evaluating cross-country cohesions. Two peculiarities of the current approach are worth noting, however. First, owing to the

Figure 7: Cross-country co-trending



Cross-country co-trending is measured by (static) cohesion of the trend components transformed in first differences. The short horizontal lines indicate the point estimates while the vertical arrows span the 95% confidence intervals resulting from the bootstrap procedure. On the left-hand side, the trend cohesion of the single aggregates are plotted. The right-hand part of the figure comprises four arrows depicting the trend cohesion of groups of aggregates. The acronyms mean the following: int = trending internal demand aggregates, ext = external trade aggregates, cio = the group comprising consumption, investment and GDP, all = all (nonstationary) variables.

I(1) property, the analysis is based on the first differences of the trend components.[31] Second, since these follow white-noise processes by construction, the cohesion measure can be built on static rather than dynamic correlations. For each set of variables, we therefore obtain only one value which indicates the extent of what we call trend cohesion for brevity. In Figure 7, the point estimates of trend cohesion are depicted by small horizontal strokes within the vertical arrows indicating the bootstrapped 95% confidence intervals. On the left-hand side, the trend cohesions of the five nonstationary aggregates are depicted. As in the analysis of cross-country co-cycling, grouping may be advantageous. Hence, we also report the estimates of trend cohesion for some groups of aggregates which are found in the right-hand part of the figure.

With some adjustments, the groups formed in the previous section can be adopted in the analysis of co-trending, too. As the series of changes in inventories do not exhibit

[31]In these calculations, the structural break in the German data set is considered as follows. The mean shifts are removed from the trend components. The potential change in the drift parameter vector of the random walk component is regarded as part of the trending behavior of the German time series, however.

a trend, the group of internal demand aggregates only consists of private consumption and business investment. The external trade group is taken over unchanged. Of course, with “all”, only the trending series are meant in this context. Furthermore, a fourth group (called “cio”) is formed which summarizes consumption, investment and output. If exports and imports were equally affected by the external trend factor, GDP would solely be driven by the internal trend factor as a consequence of the accounting identity. Understood as technical progress, for instance, the internal trend should be the driving force behind the upward drift in consumption, investment and output. Cross-country co-trending of this group of variables would therefore imply that the three countries face the same shocks to productivity with permanent character.[32]

The first observation is that all arrows lie entirely in the positive range. Hence, the hypothesis that the trend innovations of all expenditure aggregates are positively correlated across countries cannot be statistically rejected on the 5% level. The second observation is that trend cohesion is substantially lower for the single aggregates than for the groups. Of course, this comes as no surprise in the light of the fact that the trend-cycle decomposition explicitly uses the property that variables of the same country share common trends.

In terms of magnitude, we do not find marked differences when comparing co-trending of the single aggregates. The point estimates are all below 0.1. The highest values are documented for imports and business investment. With respect to the groups, however, the point estimates of trend cohesion are between 0.2 and 0.3. It is conspicuous that co-trending within the “cio”-group is strongest. In particular, its confidence set does not contain the point estimate of trend cohesion of the external trade group. This might be regarded as evidence supporting the view that technical change disseminates rather quickly, whereas the three countries differ with respect to the degree they participate in the dynamic development of international trade integration.

Finally, let us briefly examine whether co-trending is stronger than co-cycling or vice versa. Owing to the large confidence sets documented in Figure 5, any satisfying answer to this question cannot be derived on the basis of the single aggregates. By regarding all series as a group, we find that the confidence set of trend cohesion is mainly located above 0.2. This level, however, is not exceeded by the upper bound of the confidence band in Figure 6(d), at least when averaging over all frequencies of the business cycle range. Hence, the broad view would suggest that cross-country synchronicity is higher in the very long run than at business cycle frequencies.

4 Conclusion

We have studied short-run and long-run comovement of GDP and some expenditure aggregates in Germany, France and Italy. Economic activity is multidimensional by nature. Thus, it does not seem sufficient to look at a single measure such as GDP. Rather, the specific information which can be drawn from private consumption, business investment,

[32]This is the interpretation of the common trend suggested by the neo-classical growth models of the style documented in King et al. [1991], for instance. See also Footnote 22.

exports and imports as well as changes in inventories must not be neglected. As all variables but the latter are nonstationary, a trend-cycle decomposition has been chosen in order to receive series to which correlation measures can be applied. Concretely, we have applied multivariate Beveridge-Nelson decompositions which result from rewriting the estimated country-specific VECMs into their common trends representations.

The cointegration analysis, necessary to specify the VECMs, is also interesting from an interpretational point of view. We have been able to study the long-run comovement of economic variables within the countries. For instance, the same set of restrictions can be applied to identify the three cointegrating vectors which have been found in the German and the French data sets. More precisely, stable long-run relationships exist between consumption and output, investment and output as well as between exports and imports. With one exception, the estimated cointegrating vectors are close to $(1, -1)'$. The five nonstationary series are thus driven by two common stochastic trends. There is a internal trend forcing consumption, investment and output and an external trend factor driving exports and imports. Hence, we have been able to conclude that, in a long-run perspective, the German and the French expenditure aggregates are dichotomized into an internal and an external part. The results which have been derived from the Italian data set differ from this interpretationally appealing structure in several respects. First, only two cointegrating relations are established. Second, the estimated long-run relationships imply that the export and imports interfere with the internal demand aggregates. Third, there is no straightforward assignment of the three common trends to economic sources.

Except for changes in inventories which have been solely mean-adjusted, the estimated VECMs have been used to extract cycle components from the nonstationary series. The resulting multivariate Beveridge-Nelson cycle components meet many characteristics which are common knowledge in applied business cycle research. In particular, the cycle components do not seem to be unrealistically noisy. As regards cross-country comovement, we have distinguished between co-cycling and co-trending. Both aspects have been measured by the concept of cohesion. While the former is based on the estimated cycle components, the latter evaluates the first differences of the trend components. A parametric bootstrap procedure has been applied to construct confidence intervals around the point estimates capturing both sampling variability and parameter uncertainty. In the cross-country dimension, the cycle components exhibit statistically significant synchronicity only if the variables are grouped together. Although high point estimates of cohesion have been found for private consumption and, especially, business investment, in the range of business cycle frequencies, confidence bands are so wide that they all contain the zero axis. Reasons for this are the uncertainty of the VECM estimates and the intrinsically low degree of stability of frequency-domain statistics. Co-trending, however, is statistically significant for the single aggregates, although the point estimates are rather low. For groups of variables, the extent of co-trending rises to higher values. This is affected by the common-trends assumptions which have been imposed on the country-specific data sets. Finally, it has been found that co-trending is stronger than co-cycling.

A Data and unit root tests

In the econometric investigations, we analyze the time series properties of private consumption, business investment, exports, imports, and GDP as well as changes in inventories for Germany, France and Italy. The series are seasonally and working-day adjusted and in real terms (i.e. in billions of 1995 euro). Furthermore, the first five series are taken in natural logarithm. In the remainder, we denote the series by cons_t, inv_t, exp_t, imp_t, gdp_t, and $\Delta\mathsf{st}_t$, $t = 1, ..., T$, respectively. The sample starts in the first quarter of 1970 and ends in the fourth quarter of 2004. The sample size is $T = 140$.

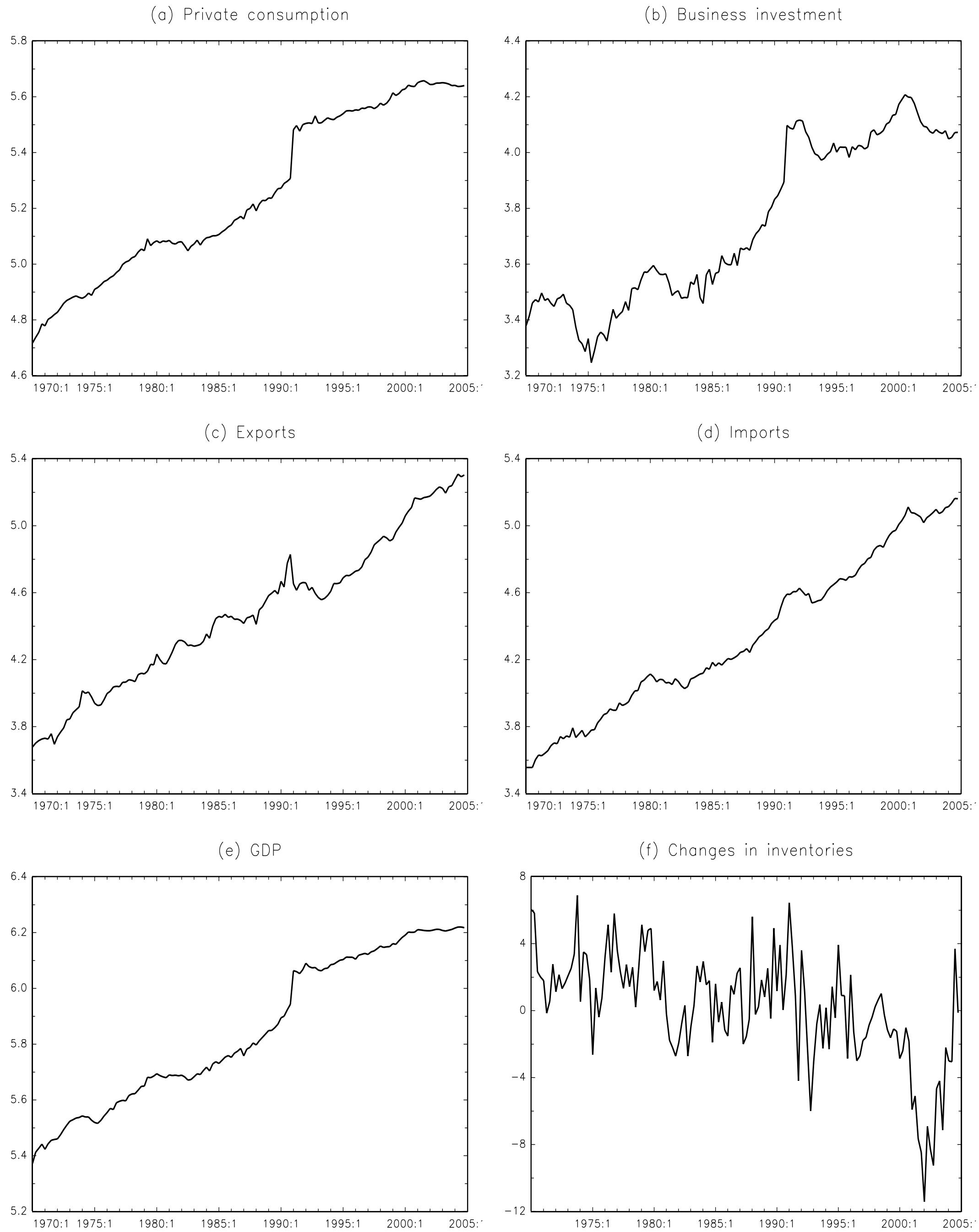
In Figures 8 through 10, all series under consideration are plotted. At first glance, private consumption, business investment, exports, imports, and GDP appear to be nonstationary, whereas the series of changes in inventories seems to exhibit properties of a stationary process. In all countries, the investment aggregate is most volatile while private consumption turns out to be at least slightly smoother than GDP. Moreover, the export and import volumes seem to be closely connected in terms of both trending and cycling behavior. Finally, in the German case, a statistical break in the first quarter 1991, when the territorial basis changed from western Germany to Germany as a whole, has to be taken into account, although it appears to be visible only in the series of GDP, private consumption, and less obviously, business investment.[33]

In order to obtain more information on the trending behavior of the time series, unit root tests are performed. In Table 3, the results of standard procedures are reported. Namely, we apply the augmented Dickey-Fuller (ADF), the Phillips-Perron (PP),[34] and the test proposed by Kwiatkowski et al. [1992] (KPSS). Whereas the ADF and the PP procedures test for a unit root in the series, the KPSS test assumes (trend-)stationarity under the null hypothesis. The testing setup for all trending series includes a constant c and a deterministic trend t; for the series of changes in inventories, only an intercept term is included. In the case of Germany, the alternative hypothesis is trend-stationarity including a break in mean and in trend at the (known) date of unification for all series but changes in inventories. Following Perron [1988], the ADF and the PP test can be applied to the residual series resulting from the auxiliary regression on c, t, the step dummy variable $\mathsf{S(91{:}1)}$ and the broken trend dummy $\mathsf{t\,S(91{:}1)}$ where $\mathsf{S(91{:}1)}$ is unity from the first quarter of 1991 onwards and zero otherwise. Unit root tests have nonstandard limiting distributions. Critical values are taken from MacKinnon [1991] for the ADF and the PP test and from Kwiatkowski et al. [1992] for the KPSS test, respectively. In the case of structural breaks, the Dickey-Fuller distribution is subject to nuisance parameters dependent on the date of the break T_B. Here, we apply the critical values tabulated in Perron [1988], Table VI.B, for $T_B/T = 0.6$. Critical values of the KPSS test for trend-stationarity around a break in mean and in trend are taken from Kurozumi [2002], Table 1d.

[33] The behavior of exports is special around the unification break because, in the run-up of unification, intra-German trade was measured in the west German trade volumes, whereas it logically disappeared in the data for Germany as a whole. Consequently, the enormous flow of goods from western to eastern Germany inflated the export figures in 1990, while the transition to the national accounts statistics for Germany as a whole caused a negative break in this aggregate.

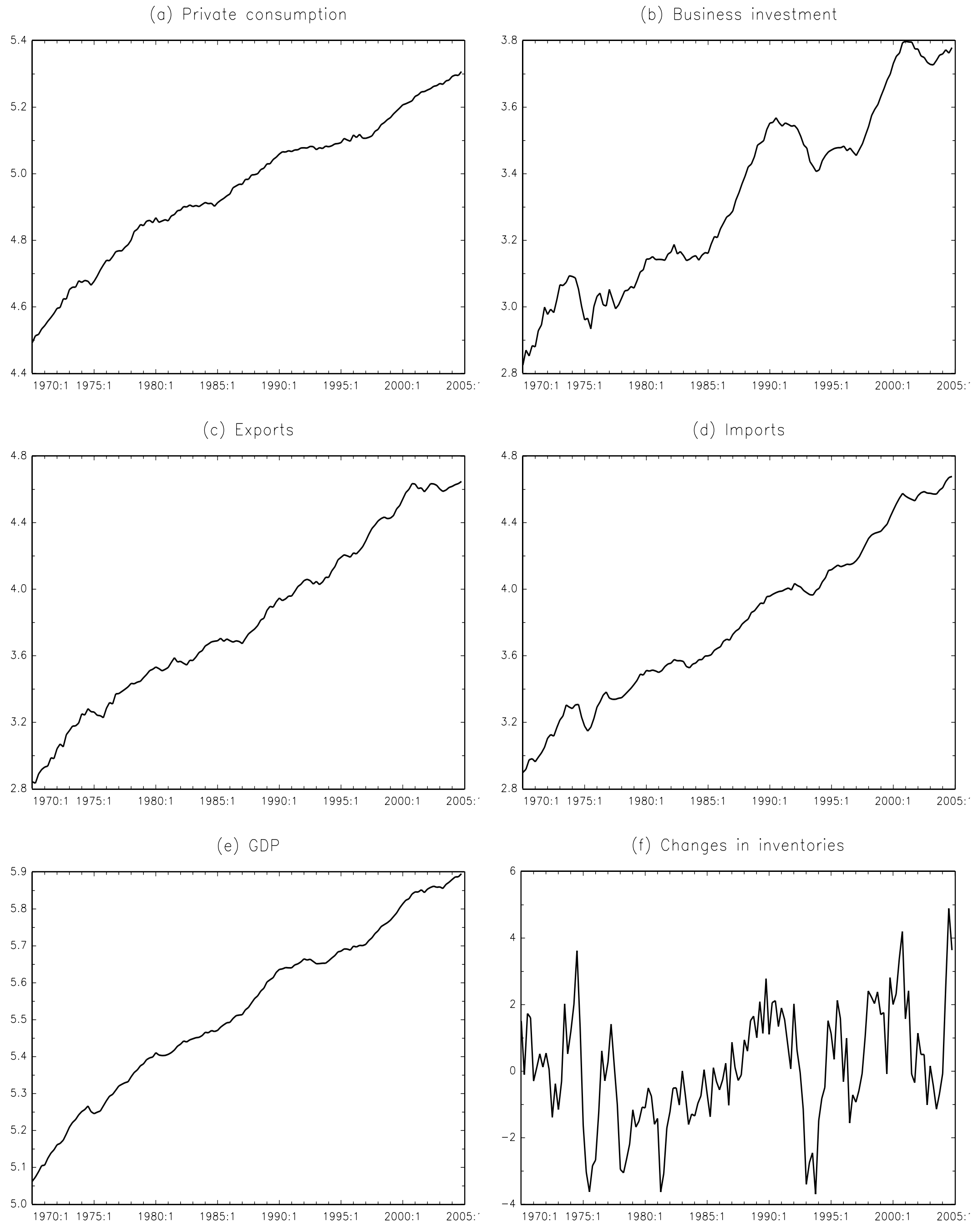
[34] Details on the ADF and the PP test are given in Hamilton [1994], Chapter 17, for instance.

Figure 8: Series plots – GERMANY



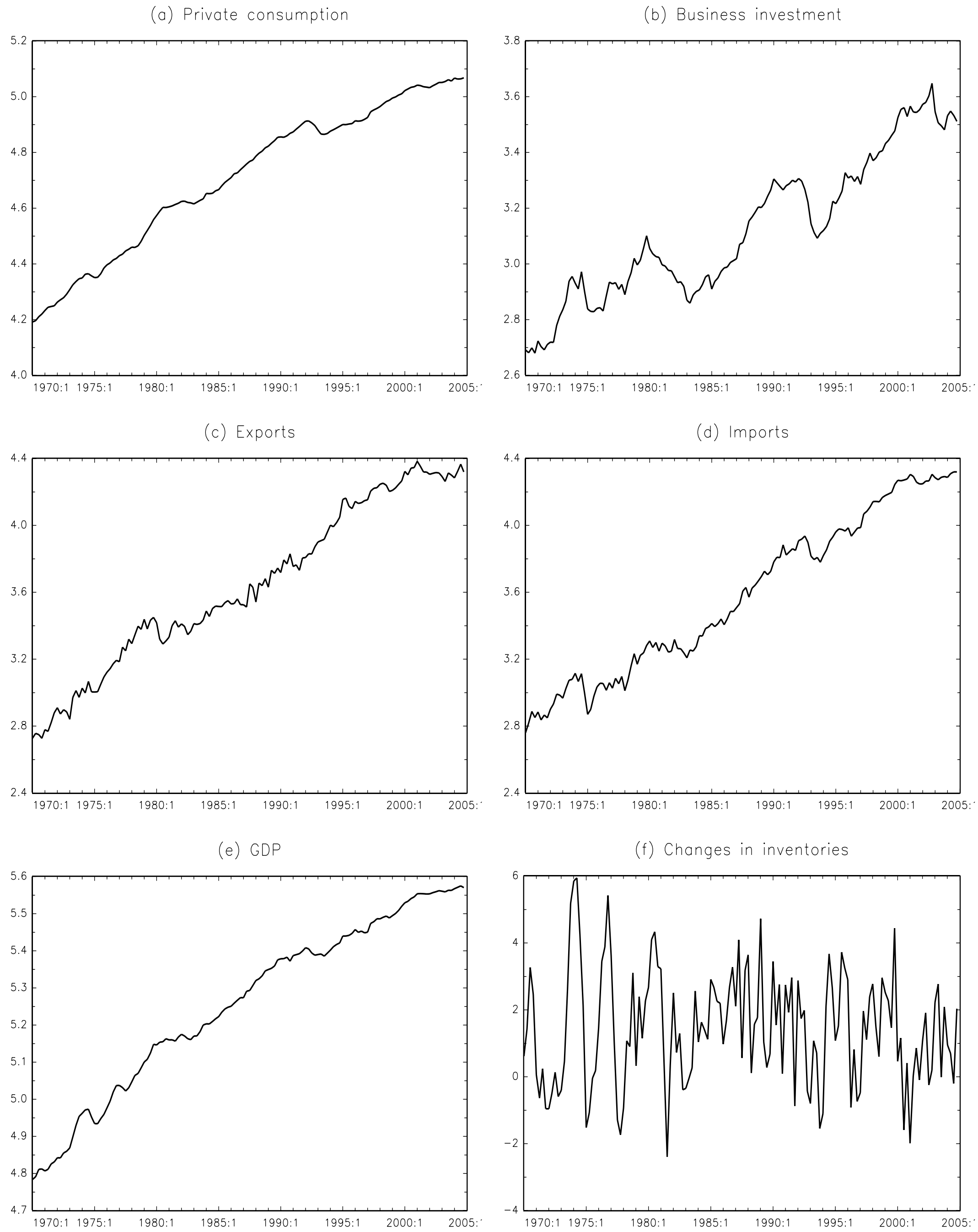
The plots in Charts (a) through (e) depict the series in natural logarithm, while Chart (f) shows the original series. All variables are measured in 1995 euro.

Figure 9: Series plots – FRANCE



The plots in Charts (a) through (e) depict the series in natural logarithm, while Chart (f) shows the original series. All variables are measured in 1995 euro.

Figure 10: Series plots – ITALY



The plots in Charts (a) through (e) depict the series in natural logarithm, while Chart (f) shows the original series. All variables are measured in 1995 euro.

Table 3: Unit root tests

I. GERMANY

Series	Deterministic terms	ADF		PP		KPSS			
cons_t	$\mathsf{c, t, S(91{:}1), t\ S(91{:}1)}$	(5)	−2.77	(14)	−3.75	(4)	0.201**	(14)	0.074$^{(\star)}$
inv_t	$\mathsf{c, t, S(91{:}1), t\ S(91{:}1)}$	(5)	−3.93	(13)	−3.01	(4)	0.162**	(14)	0.061$^{(\star)}$
exp_t	$\mathsf{c, t, S(91{:}1), t\ S(91{:}1)}$	(2)	−4.17$^{(\star)}$	(5)	−3.83	(4)	0.077**	(14)	0.039
imp_t	$\mathsf{c, t, S(91{:}1), t\ S(91{:}1)}$	(3)	−3.31	(11)	−3.21	(4)	0.112**	(14)	0.045
gdp_t	$\mathsf{c, t, S(91{:}1), t\ S(91{:}1)}$	(0)	−3.93	(10)	−4.26*	(4)	0.120**	(14)	0.051
$\Delta\mathsf{st}_t$	c	(4)	−2.69$^{(\star)}$	(15)	−5.96**	(4)	1.806**	(14)	0.811**

II. FRANCE

Series	Deterministic terms	ADF		PP		KPSS			
cons_t	$\mathsf{c, t}$	(5)	−2.96	(6)	−3.42$^{(\star)}$	(4)	0.586**	(14)	0.228**
inv_t	$\mathsf{c, t}$	(3)	−2.77	(12)	−2.63	(4)	0.141$^{(\star)}$	(14)	0.059
exp_t	$\mathsf{c, t}$	(4)	−2.54	(6)	−2.65	(4)	0.319**	(14)	0.135$^{(\star)}$
imp_t	$\mathsf{c, t}$	(9)	−2.82	(8)	−2.89	(4)	0.306**	(14)	0.141$^{(\star)}$
gdp_t	$\mathsf{c, t}$	(4)	−3.65*	(9)	−3.37$^{(\star)}$	(4)	0.412**	(14)	0.174*
$\Delta\mathsf{st}_t$	c	(3)	−4.40**	(8)	−4.18**	(4)	0.773**	(12)	0.478*

III. ITALY

Series	Deterministic terms	ADF		PP		KPSS			
cons_t	$\mathsf{c, t}$	(1)	−1.48	(8)	−1.17	(4)	0.796**	(14)	0.300**
inv_t	$\mathsf{c, t}$	(4)	−3.33$^{(\star)}$	(11)	−2.71	(4)	0.218**	(14)	0.096
exp_t	$\mathsf{c, t}$	(1)	−2.28	(13)	−3.00	(4)	0.187*	(14)	0.081
imp_t	$\mathsf{c, t}$	(0)	−3.26$^{(\star)}$	(5)	−3.34$^{(\star)}$	(4)	0.226**	(13)	0.112
gdp_t	$\mathsf{c, t}$	(6)	−1.32	(10)	−1.45	(4)	0.767**	(14)	0.300**
$\Delta\mathsf{st}_t$	c	(4)	−6.08**	(6)	−6.93**	(4)	0.081	(4)	0.081

The numbers in parentheses indicate the lag length in the ADF procedure and the bandwidth parameter in the PP and KPSS procedures. In the version including a deterministic trend, MacKinnon's [1991] critical values for the ADF and the PP tests are −4.03, −3.44 and −3.15 for significance at the 1%, 5% and 10% level respectively; in the version with an intercept term only, they are given by −3.48, −2.88 and −2.58. For the KPSS testing the null of trend-stationarity, the asymptotic values are 0.216, 0.146 and 0.119, and 0.739, 0.463 and 0.347 in the test for stationarity. For the ADF and the PP including a structural break, critical values are tabulated in Perron [1988], Table VI.B, which are −4.88, −4.24 and −3.95 in the given setup. For the KPSS including a structural break, they are found in Kurozumi [2002], Table 1d.: 0.091, 0.066 and 0.056. **,* ,$^{(\star)}$ mean rejection of the null hypothesis at the 1%, 5% and 10% level respectively.

For any trending series, the existence of a unit root cannot be rejected by both the ADF and the PP test if we accept the 5% level. For all series but French business investment, nonstationarity is confirmed by the KPSS test results as far as the short lag truncation is regarded as relevant.[35] Although somewhat optimal, with the bandwidth parameter chosen by the automatic procedure suggested by Newey and West [1994], the KPSS test turns out to suffer from considerable power erosion in the samples at hand. In sum, we are able to conclude that private consumption, business investment, export, imports and GDP (all in logs) are described by unit root processes.

With respect to changes in inventories, results are not clear-cut. Only in the case of Italy, we obtain what is expected *a priori*, namely that the ADF and PP tests reject the presence of a unit root while the two KPSS versions accept the stationarity hypothesis. According to the ADF and PP tests, the French series does not possess a unit root while the KPSS tests tend to reject stationarity at the same time. The signs for nonstationarity are even more accentuated in the case of the German aggregate where both KPSS versions reject stationarity at the 1% level and only the PP test is able to reject the presence of a unit root at the 5% level. In drawing conclusions from these results, however, we should be aware of the fact that, for real time series, it is not always possible to unambiguously answer the question on the degree of integration. There are cases in between, and those are obviously relevant to the German and the French series of changes in inventories. Once again looking at the time series plots, we may find reasons for this. In the German case, a potential source of nonstationarity might be seen in the phase of extraordinary destocking during the period 2001 through 2003. In the French case, changes in inventories show a marked degree of persistence. Despite these observations, we think that it is fair to conclude that the series of changes in inventories do not contain a unit root. As a working hypothesis for the analysis, they will be consequently taken as I(0) series.

B Cohesion

This appendix introduces cohesion which is a frequency-domain summary statistic developed by Croux et al. [2001]. After a brief description of the concept, we are going to show how cohesion can be estimated. This includes an outline of a parametric bootstrap procedure which is used to set up confidence bands around the point estimates.[36]

B.1 Concept

Let c_t^k, $k = 1, ..., K$, denote the cycle component of the nonstationary series k stacked in the K-dimensional vector y_t. The cycle components are assumed to be zero-mean covariance-

[35] The short bandwidth parameter value results from applying the rule of thumb integer$[4(T/100)^{1/4}]$ which was *inter alia* suggested by Schwert [1989] in his influential Monte Carlo investigation of unit root tests and which was also used by Kwiatkowski et al. [1992].

[36] The presentation is aimed to equip the reader with sufficient knowledge to be able to follow the empirical investigation. However, the explanation of these elements is necessarily rather brief. Many details are omitted. The reader who is interested in further information is referred to the cited literature.

stationary, and any bivariate pair of them fulfill the condition of stationary correlation: for all $t = 1, ..., T$ and $k, l = 1, ..., K$,

- the mean: $E(c_t^k) = 0$,
- the variance: $\gamma_k(0) \equiv E(c_t^k\, c_t^k) < \infty$,
- the auto-covariances: $\gamma_k(s) \equiv E(c_t^k\, c_{t-s}^k) < \infty\ \forall\ s > 0$, and
- the cross-covariances: $\rho_{kl}(s) \equiv E(c_t^k\, c_{t-s}^l) < \infty\ \forall\ s > 0,\ l \neq k$.

Let $S_k(\omega)$, $-\pi \leq \omega < \pi$, represent the spectral density function of c_t^k. Comovement between two cycle components, say k and l, can be analyzed by using their cross-spectral density function $S_{kl}(\omega) = C_{kl}(\omega) + iQ_{kl}(\omega)$ where the cospectrum and the quadrature spectrum are denoted by $C_{kl}(\omega)$ and $Q_{kl}(\omega)$, respectively, and $i \equiv \sqrt{-1}$.

In the frequency domain, a standard measure of co-cycling between two series is squared coherency. This statistic is real and symmetric. It measures the degree of linear association, i.e. the proportion of the variance of one series at frequency ω that is accounted for by variation in the other series. However, the squared coherency disregards phase differences between the series, i.e. it takes the same value for c_t^k and c_t^l as for c_t^k and c_{t-j}^l. Croux et al. [2001] therefore doubt its adequacy for measuring correlation at different frequencies. Alternatively, they suggest using the statistic

$$R_{kl}(\omega) \equiv \frac{C_{kl}(\omega)}{\sqrt{S_k(\omega)\, S_l(\omega)}} \tag{11}$$

which is called "dynamic correlation" between the variables k and l. Notice that the dynamic correlation is nothing else than the correlation coefficient between real waves of frequency ω in the interval $0 \leq \omega < \pi$. In general, it is real and symmetric, and just like a static correlation, it varies between -1 and 1.

To measure the degree of comovement for more than two variables, Croux et al. developed the concept of cohesion, which is a weighted average over the dynamic correlations of all bivariate combinations within the set of variables. In our example, it is interesting to calculate the cohesion of the variable k between $N \geq 2$ countries defined by

$$G_k(\omega) \equiv \frac{\sum_{m \neq n}^{N} w_{m.k} w_{n.k} R_{mn.k}(\omega)}{\sum_{m \neq n}^{N} w_{m.k} w_{n.k}}, \quad m, n = 1, ..., N, \tag{12}$$

where $w_{n.k} \geq 0$ is the weight of country n's variable k. In general, $|G_k(\omega)| \leq 1$ and, if all bivariate pairs of series are perfectly correlated, $G_k(\omega) = 1$. The lower bound, however, depends on the number of variables and the weighting scheme. For $N = 2$ and perfectly negative correlation, $G_k(\omega) = -1$; for $N > 2$, the lower bound lies somewhere between -1 and 0 because pairwise negative correlation between more than two variables cannot exist, of course. In the important case of equal weights, $G_k(\omega)$ cannot fall below $-1/(N-1)$.

B.2 Point estimation

To compute cohesion, we need estimates of $S_k(\omega)$ and $C_{kl}(\omega)$ in the interval $0 \leq \omega \leq \pi$ for all k and $l \neq k$.[37] In general form, consistent estimates are given by

$$\hat{S}_k(\omega) = (2\pi)^{-1} \sum_{s=-M}^{M} \kappa_M(s)\hat{\gamma}_k(s) \cos \omega s \tag{13}$$

$$\hat{C}_{kl}(\omega) = (2\pi)^{-1} \left[\hat{\rho}_{kl}(0) + \sum_{s=1}^{M} \kappa_M(s) \Big(\hat{\rho}_{kl}(s) + \hat{\rho}_{lk}(s) \Big) \cos \omega s \right] \tag{14}$$

where $\hat{\gamma}_k(\cdot)$ and $\hat{\rho}_{kl}(\cdot)$ are consistent estimates of the variances, autocovariances and cross-covariances, respectively, and $\kappa_M(\cdot)$ is a symmetric lag window with $M < T - 1$.

In the subsequent analysis, we apply the lag window suggested by Parzen [1961], i.e.

$$\kappa_M(s) = \begin{cases} 1 - 6(s/M)^2 + 6(|s|/M)^3, & |s| \leq M/2, \\ 2(1 - |s|/M)^3, & M/2 \leq |s| \leq M, \\ 0, & |s| > M \end{cases} \tag{15}$$

where M is the number of auto-covariances used.

It is well known that a trade-off exists between the bias and the variance of a spectral estimate. Whereas the estimate becomes more stable as M increases, the bias goes up at the same time because fine characteristics of the spectrum are "smoothed away".[38] In the empirical application, we set $M = 8$, implying a relatively high degree of smoothness. The low value has to be chosen in order to ensure the stability of the point estimates in comparison with the bootstrapped confidence bands.

B.3 Bootstrapped confidence bands

Asymptotic confidence bands may be misleading for two reasons. First, the asymptotic distribution can only approximate the sampling properties of the statistic of interest in finite samples. Second, and perhaps more importantly, the series which are to be analyzed by correlation measures cannot be observed directly. Hence, their estimation is subject to parameter uncertainty which generally affects the width of the confidence bands, too.

Bootstrap methods can be applied to correct for those effects.[39] In fact, the proposed trend removal gives a natural basis for the application of a residual based resampling because the VECM residual series $\hat{\varepsilon}_t$ can be regarded as realizations of vector white-noise processes. From the empirical residuals, bootstrap innovations are generated by resampling with replacement. Pseudo-data for the endogenous vector process y_t is obtained on the

[37] See, for instance, Priestley [1981] or Brockwell and Davis [1987] for a closer look at the estimation of (cross-)spectral density functions.

[38] The exact expressions for the asymptotic bias and variance of a spectral density estimate are derived in Priestley [1981], Section 6.2.4, for instance.

[39] For an overview on bootstrap techniques for time series models, see Li and Maddala [1996] and Berkowitz and Kilian [2000], for instance.

basis of the estimated VECM and p initial observations. The pseudo-data is then used to re-estimate the VECM in order to receive the trend-cycle decomposition from the constructed series. Once this procedure is repeated many times,[40] we are finally able to set up confidence bands around the point estimate of the statistic of interest.

In order to provide some details on the bootstrap procedure, denote the statistic of interest by $\hat{\theta}$ and its bootstrap equivalent by $\hat{\theta}^*$. To form bootstrap confidence bands for $\hat{\theta}$, the standard method would simply use the $(a/2)$- and $(1-a/2)$-quantiles of the bootstrap distribution of $\hat{\theta}^*$, where a is the significance level. In the context of vector autoregressions, the standard bootstrap algorithm is usually not optimal because the ordinary least squares estimator of the slope coefficients is systematically biased so that resulting coverage rates are often unsatisfactory.[41] We follow two suggestions proposed in the literature which help to reduce this deficiency.[42] First, the empirical residuals will be corrected for the bias prior to bootrapping. Second, in contrast to the standard method, we are going to use the so-called "percentile method" where the $(a/2)$- and $(1-a/2)$-quantiles are taken from the distribution of $(\hat{\theta}^* - \hat{\theta})$.

[40]In the application, we run 5,000 replications. In order to preserve the correlation structure within and across countries, the seat of the residuals is randomly chosen in each bootstrap replication.

[41]See, for instance, Berkowitz and Kilian [2000] for further details and the literature.

[42]Once again, the reader who is interested in more details is referred to the survey articles Li and Maddala [1996] as well as Berkowitz and Kilian [2000], for instance.

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