# Business Cycle Co-movement and Trade Intensity in the Euro Area: Is there a Dynamic Link?

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## Abstract

This paper extends the recent literature that exclusively looks at the static link between bilateral trade intensity and business cycle synchronisation. A cross section augmented VAR framework with an unobserverd common factor structure is used in order to apply the concept of Granger causality to test for dynamic links between variables. We conclude that although countries with intensive trade linkages also tend to have more similar business cycle in the long-run, the trade channel does not help to explain much of the short-run variation of business cycle co-movement in the euro area. These results are robust with respect to different measures of business cycle co-movement and bilateral trade intensity.

**JEL Classification**: E32, F14, C32, C33

**Key Words**: Business cycles, synchronisation, international trade, dynamic factor model

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# 1 Introduction

In the theory of optimum currency area, the synchronicity of business cycles is considered as an important criterion for countries to form a successful currency union. Twelve European economies share a single currency for almost a decade by now and for the Member States of the euro area a high degree of average business cycle correlation can indeed be observed. However, still substantial variations of cyclical similarity between individual country-pairs exist. The question what causes cyclical similarity has received considerable attention and trade is considered to be the major channel for the transmission and correlation of business cycle fluctuations by most open macroeconomic models. In particular in open regions or currency unions with minimum or very few barriers to trade this channel could be of main importance. However, the theoretical prediction of the magnitude and sign of the relationship between trade and synchronisation is ambiguous and generally depends on the source of disturbances and relative importance of inter-industry and intra-industry trade between countries. If increased trade openness promotes specialisation in the production of goods and services due to comparative advantage and economies of scale, then inter-industry trade (trade in goods from different industries) may be dominant and sector-specific shocks are limited to the country that specialised to the affected sector. But if trade between countries is dominated by intra-industry trade (trade between goods of the same industry), the reduction of trade barriers leads to a diffusion of demand shocks across countries. In addition, if trade induces technological and knowledge spill-overs, higher output correlations should be the result.

The majority of empirical studies relies on static cross-section approaches and estimates a significant and positive relationship between trade intensity and cycle synchronisation that is considered as long-run relationship with a causal direction running from trade to synchronicity (Frankel and Rose, 1998, Imbs, 2004). Due to the endogeneity of trade, instrumental variables (IV) techniques are commonly employed which allow to identify the effect of trade on business cycle co-movement. Some studies even find that trade is the the only or among the few robust determinants of cyclical synchronicity (Baxter and Kouparitsas, 2005, Böwer and Guillemineau, 2006). Others qualify the strong trade

influence on cyclical co-movement but still find it to be existent and positive (Gruben *et al.*, 2002, Inklaar *et al.*, 2005). Furthermore, the positive link between trade and synchronisation is often seen as indication that intra-industry trade dominates the inter-industry spill-over channel for shocks. In particular for the euro area, intra-industry is found to be most relevant.

Besides investigating the static relation between trade and cyclical co-movement, the dynamic direction of influence is also an interesting empirical question since the answer does not seem obvious. Co-movement of business cycles in any set of countries is due to international interdependencies such as trade and capital account transactions in assets on the one hand and the presence of common, global shocks that affect countries simultaneously on the other hand. If two countries are simultaneously affected by a global shock so that cycles move in the same direction, changes in trade activity between the affected countries are likely to *lag* cyclical synchronicity through feedback of the shock on demand for foreign exports. On the contrary, if country-specific demand or supply shocks are an important source of business cycle fluctuations, interdependence through trade will lead to spill-overs and in this case changes in bilateral trade intensity may *lead* cyclical co-movement.

Against this background, this paper extends the literature that exclusively looks at the static link between bilateral trade intensity and business cycle synchronisation. The dynamic feedback between these variables in the euro area is investigated by using a cross-section *and* time series based approach. Specifically, estimation is based on a panel VAR model with an unobserved common factor structure to accommodate cross-section dependence and the concept of Granger causality is employed to test for the direction of influence. Since we consider all possible country-pairs in the study of business cycle similarity and bilateral trade intensity among the euro area countries, the possibility of pooling test statistics emerges. A pooling and aggregating strategy to summarise results allowing for cross-sectional dependent test statistics will be employed.

The order of presentation in the paper is as follows: Section 2 explains our measures of business cycles, co-movement and trade intensity and relates these concepts, which

are partly new, to the existing literature. In section 3, the empirical model and estimation strategy will be presented and section 4 contains corresponding estimations and test results for dynamic interdependencies between trade intensity and business cycle co-movement among the euro area countries. The last section discusses the overall outcomes with references to findings of other studies and concludes.

# 2 Measures of business cycles, co-movement and trade intensity

## 2.1 Business cycles

The central variable in our investigation is the cyclical component of real economic activity. While there is certainly a professional consensus that real GDP offers the broadest view on real economic activity, the question of how to measure the cyclical part of it is controversial. A detailed examination of methods and their properties commonly employed for detrending macroeconomic time series is given by Canova (1998) and Massmann and Mitchell (2004). In keeping with the existing literature on the topic of interest, we proxy the cycle with several detrending methods to investigate the sensitivity of outcomes with regard to alternative concepts of business cycle measurement. More precisely, we estimate the cycle of seasonally adjusted real quarterly GDP for ten individual euro area countries by the following statistical procedures:

- The Hodrick-Prescott (HP) filter, which obtains the trend components of a time series after selecting the degree of smoothness for the trend component. The central variable in this method is the smoothing parameter $\lambda$ which is used to input indirect assumptions about the typical duration of the reference cycle in the computing procedure. If $\lambda$ is close to zero, the smoothed component is equal to the original time series. This corresponds to the assumption of the standard real business cycle theory according to which all output movements are equal to fluctuations in the trend value. In contrast, very large values of $\lambda$ produce a smoothed component that

corresponds with a linear time trend in the limit and all actual output developments around this time trend are assigned to the cyclical component. In our computations we use these standard parameter value of 1600 for quarterly data.

- The asymmetric Christiano-Fitzgerald (CF) filter. From the class of non-parametric methods, the commonly used are the "band-pass filters" of CF and Baxter-King[1], which both eliminate the trend and irregular components of a time series while preserving business cycle components. This filter requires a specification of a typical cycle length, which we set at 1.5 to 8 years. The symmetry of the standard CF and Baxter-King filter implies that observations will be lost from both the beginning and the end of the original sample, which can be regarded as serious constraint. Thus, we use the CF filter as the asymmetric version that does not lead to a truncation and can be computed for the entire sample.[2] The CF is an ideal filter and isolates the frequency which can be set exactly prior to filtering.

- An unobserved components model (UC). The model assumes that output can be decomposed in a trend, a cycle and an irregular component. We use the same specification as Massmann and Mitchell (2004) who employ a smooth local linear trend model which goes back to Harvey (1993). In this model, the trend component is a second order random walk, while the cycle is specified as trigonometric function. The cycle measure is the difference between the estimated trend and the actual output series. The model parameters are estimated via the Kalman filter recursion and numerical optimisation of the likelihood function. The unobservable trend component is obtained with the aid of the fixed interval Kalman smoother.

- Finally, year-on-year differences (D4). Although this transformation does not rely on a sophisticated statistical framework to decompose trend and cycle, it offers quite intuitive interpretations. For instance, these are the transformations commonly referred to when new economic data are officially released and communicated by census bureaus or statistical offices. The basic assumption of this detrending method

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[1]Cf. Baxter and King (1999)
[2]Cf. Christiano and Fitzgerald (2003) for computational details.

is that the secular component of the series is a random walk without drift, that the cyclical component is stationary and that the two components are uncorrelated.

## 2.2 Business cycle co-movement

Empirical studies on the determinants of business cycle synchronisation typically build on Pearson correlation coefficients computed over the entire sample range available for estimation. In studies that employ a panel structure it is common to compute correlation coefficients over several non-overlapping sub-periods of equal size. If we want to analyse dynamics between cyclical similarity and trade intensity in a more timely manner, correlation coefficients are not an option. For the similarity between business cycles of two countries we therefore use the Euclidean distance between the output gap estimates, which are expressed as a percent of trend GDP. The similarity between the output gap of country $i$ and the gap of country $j$ in period $t$ is defined as

$$\rho_{ijt} = |g_{it} - g_{jt}|. \tag{1}$$

For $n$ countries in the group under consideration, $N = \frac{n(n-1)}{2}$ bilateral distance measures per time-unit can be obtained. A low value of $\rho_{ijt}$ signifies a high degree of business cycle co-movement whereas a high value points to dissimilarity.

The use of the absolute values for the gap differences makes a regression approach based on such a dependent variable special. A consequence of computing the similarity measure in such a way is that the variable is bounded by zero from below. Therefore, a regression of a set of explanatory variables on (1) can, technically speaking, not imply a regression error which can take on arbitrarily positive or negative values. For this reason we use the natural logarithm of $\rho_{ijt}$ in the estimations in order to map the variable to an unbounded interval.

## 2.3 Trade intensity

A particular advantage for testing the dynamic relationship between trade intensity and business cycle correlation is data availability. Bilateral trade data are published monthly by the International Monetary Fund (IMF) in its *Direction of Trade Statistics*. The standard set of indicators to measure the degree of bilateral trade intensity is used in our study. As in Frankel and Rose (1998), the trade intensity between two countries $i$ and $j$ at a point in time is measured by two indices. The first is

$$WT_{ijt} = \frac{x_{ijt} + m_{ijt}}{x_{it} + x_{jt} + m_{it} + m_{jt}} \tag{2}$$

in which $x_{ijt}$ denotes total nominal exports from country $i$ to country $j$ and $m_{ijt}$ total nominal imports from country $i$ to country $j$. The variables $x_{it}$ and $m_{it}$ denote the total global exports and imports of country $i$. The second measure uses the same numerator but scales it by nominal GDP instead of total trade. It is computed as

$$WY_{ijt} = \frac{x_{ijt} + m_{ijt}}{y_{it} + y_{jt}}. \tag{3}$$

In equation (3), $y_{it}$ is the level of nominal GDP in country $i$ at period $t$. Higher values of both $WT_{ijt}$ and $WY_{ijt}$ indicate greater trade intensity between two countries. A drawback is that the size dependency of these measures may lead to an underestimation of the importance of the trade channel for business cycle transmission. This is in particular relevant if the scaled trade shares of two trading partners are highly asymmetric. For example, bilateral trade intensity may be a highly important business cycle transmission channel for a country that mainly exports or imports from one big country whereas for the big country the smaller trading partner may be less relevant. To some extant, such an asymmetric trade relationship can be observed for Germany and the Netherlands. What matters is whether for one of the countries bilateral trade has a high share or not. Otto *et*

*al.* (2001) propose an indicator that captures these aspects which will also be considered here. It is computed as

$$WTM_{ijt} = \max \left\{ \frac{x_{ijt} + m_{ijt}}{x_{it} + m_{it}}, \frac{x_{ijt} + m_{ijt}}{x_{jt} + m_{jt}} \right\} \qquad (4)$$

Again, nominal GDP can be used in the denominator to scale the trade flows. The resulting measure will be denoted $WYM$. As Frankel and Rose (1998) note, it is difficult to judge from the outset whether normalising by total trade or by GDP is more appropriate. We therefore conduct our analyses with both type of measures. However, as will be illustrated in section 4.1, the dynamic behaviour of these measures differ somewhat, but offer a complementary view on the development of trade intensity among the euro area countries over the past decades. Other trade measures have been also considered (cf. Inklaar *et al.*, 2005, for alternatives) but the two considered here are of the type that have been studied most often.

Our quarterly seasonally adjusted bilateral trade flows, measured in current dollars, are from the IMF's *Direction of Trade Statistics*. Bilateral trade data for Belgium and Luxembourg is only available since 1997 for what reason we do exclude these countries from the estimations. Therefore, our sample consists of 10 euro area countries ($n = 10$) for which $N = \frac{n(n-1)}{2}$ bilateral gap and trade measures are computed, i.e. the cross-section comprises 45 units.

# 3   Model and methodology

The aim of the study is to investigate the dynamic feedback between trade intensity and business cycle co-movement with the concept of Granger causality and a cross-sectional time series sample. For this purposes, we specify and estimate a stationary VAR model similar to Chudik and Pesaran (2007) and Dées *et al.* (2007) which builds on an unobservered common factor model. The common factor component serves two purposes: (i) it takes into account unobservable influences that explain the variables of the VAR and (ii) it accommodates cross-sectional dependence among the units. The economies of the

euro area are closely linked for what reason it is essential to account for cross-sectional dependence in the empirical framework. Given that the focus is on analysing *stationary* business cycle co-movement variables we do not consider cointegration issues from the outset. Evidence on the degree of integration of the trade variables by panel unit root tests which allow for cross-sectional dependence is provided in section 4.1.

## 3.1 A cross section augmented (CA) VAR model

The model considered is as follows. It is assumed that the $2 \times 1$ vector $\mathbf{x}_{\imath t} = (\ln \rho_{\imath t}, \ln WT_{\imath t})'$, which comprises the logarithms of the gap distances and the bilateral trade intensities, is generated by[3]

$$\mathbf{x}_{\imath t} = c_{\imath} + \mathbf{\Gamma}_{\imath}\mathbf{f}_t + \mathbf{u}_{\imath t}. \tag{5}$$

The $2 \times m$ matrix $\mathbf{\Gamma}_{\imath}$ holds unit-specific factor loadings for the $m \times 1$ vector of unit-invariant unobserved factors $\mathbf{f}_t$. The number of unobserved factors is assumed to be fixed and small but need not be known a priori. The scalar $c_{\imath}$ is a time-invariant fixed effect. In line with the reference framework adopted, it is further assumed that the $2 \times 1$ vector $\mathbf{u}_{\imath t}$ and the factors follow linear stationary processes with absolute summable autocovariances, i.e. $\mathbf{f}_t = \mathbf{\Lambda}(L)\eta_t$ and $\mathbf{u}_{\imath t} = \mathbf{\Psi}_{\imath}(L)\nu_{\imath t}$ with $\nu_{\imath t} \sim IID(\mathbf{0}, \mathbf{I_2})$ and $\eta_t \sim IID(\mathbf{0}, \mathbf{I_m})$. The lag polynomials in the $m \times m$ and $2 \times 2$ coefficient matrices are given by $\mathbf{\Lambda}(L) = \sum_{l=0}^{\infty} \mathbf{\Lambda}_l L^l$ and $\mathbf{\Psi}_{\imath}(L) = \sum_{l=0}^{\infty} \mathbf{\Psi}_{\imath l} L^l$.

Since $[\mathbf{\Psi}_{\imath}(L)]^{-1} \approx \sum_{l=0}^{p_{\imath}} \mathbf{\Phi}_{\imath l} L^l = \mathbf{\Phi}_{\imath}(L)$, equation (5) has an approximate $VAR(p_{\imath})$ representation

$$\mathbf{\Phi}_{\imath}(L)(\mathbf{x}_{\imath t} - c_{\imath} - \mathbf{\Gamma}_{\imath}\mathbf{f}_t) \approx \nu_{\imath t}. \tag{6}$$

Now, different strategies to estimate unobserved factors models have been proposed which comprise principal components analysis (Forni *et al.*, 2000, Stock and Watson, 2002, or Eickmeier, 2007), Kalman filter methods (Gregory *et al.*, 1997), or structural VAR

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[3]For ease of notation the double indexing of country-pairs is abandoned and the index $\imath = 1, \ldots, N$ is used throughout, i.e. $\imath = 1$ is equivalent to the country-pair $i = 1$ and $j = 2$, $\imath = 2$ is equivalent to the country-pair $i = 1$ and $j = 3$ and so on.

approachs as in Stock and Watson (2005). A simpler and more intuitive approach is considered here which follows Pesaran (2006) and Dées *et al.* (2007). The basic result of Pesaran (2006) is that the common factors in (5) can be consistently estimated by cross-sectional averages of country-specific variables and their lagged values. A simplified illustration to see the intuition behind this is as follows.[4] To begin with, write equation (5) in terms of cross-sectional averages

$$\overline{\mathbf{x}}_t = \overline{c} + \overline{\mathbf{\Gamma}}\mathbf{f}_t + \overline{\mathbf{u}}_t \tag{7}$$

where $\overline{\mathbf{x}}_t = \frac{1}{N}\sum_{\imath=1}^{N}\mathbf{x}_{\imath t}$, $\overline{c} = \frac{1}{N}\sum_{\imath=1}^{N}c_\imath$, $\overline{\mathbf{\Gamma}} = \frac{1}{N}\sum_{\imath=1}^{N}\mathbf{\Gamma}_\imath$ and $\overline{\mathbf{u}}_t = \frac{1}{N}\sum_{\imath=1}^{N}\mathbf{\Psi}_\imath(L)\nu_{\imath t}$. If the matrix of the average factor loadings $\overline{\mathbf{\Gamma}}$ has full column rank, then from (7) it follows that

$$\mathbf{f}_t = (\overline{\mathbf{\Gamma}}\,\overline{\mathbf{\Gamma}}')^{-1}\overline{\mathbf{\Gamma}}(\overline{\mathbf{x}}_t - \overline{c} - \overline{\mathbf{u}}_t). \tag{8}$$

Suppose that the unit-specific shocks $\nu_{\imath t}$ are independently distributed across $\imath$ and have bounded and positive definite variances (as assumed above), then Lemma 1 in Pesaran (2006) establishes that $\overline{\mathbf{u}}_t \xrightarrow{q.m.} \mathbf{0}$ for each $t$ as $N \to \infty$, where $\xrightarrow{q.m.}$ denotes convergence in quadratic mean. From this it immediately follows that $\mathbf{f}_t \xrightarrow{q.m.} (\overline{\mathbf{\Gamma}}\,\overline{\mathbf{\Gamma}}')^{-1}\overline{\mathbf{\Gamma}}(\overline{\mathbf{x}}_t - \overline{c})$ which justifies the use of the cross-sectional averages as factor proxies.

The above outlined model framework motivates us to estimate the following unrestricted, cross section augmented (CA) VAR with which hypotheses about the dynamic link between trade and business cycle co-movement can be tested:

$$\mathbf{x}_{\imath t} = \tilde{c}_\imath + \tilde{\mathbf{\Phi}}_\imath(L)\mathbf{x}_{\imath t-1} + \mathbf{B}_\imath(L)\overline{\mathbf{x}}_t + \epsilon_{\imath t} \tag{9}$$

To test for Granger non-causality in this model is straightforward. The relevant hypotheses are

$$H_0^a(\ln WT_{\imath t} \nrightarrow \ln \rho_{\imath t}) : \tilde{\phi}_{\imath 12}^{(l)} = 0 \quad \forall l = 1, \ldots, p_i \tag{10}$$

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[4]Cf. Pesaran (2006) or Chudik and Pesaran (2007) for rigorous proofs.

and

$$H_0^b(\ln \rho_{it} \nrightarrow \ln WT_{it}) : \tilde{\phi}_{i21}^{(l)} = 0 \quad \forall l = 1, \ldots, p_i \tag{11}$$

where $\tilde{\phi}_{inm}^{(l)}$ are the $(l, n, m)$ elements of the coefficient matrices $\tilde{\mathbf{\Phi}}_{il}$, $l = 1, \ldots, p_i$, for unit $i$. Under $H_0^a$, bilateral trade intensity does not Granger cause business cycle co-movement whereas $H_0^b$ states that cyclical co-movement does not Granger cause trade. In the same way hypotheses about Granger non-causality of the cross section averages can be tested.

## 3.2   A pooled test for Granger non-causality

The Granger tests are run for all units separately and signify for which country-pairs the null hypothesis is not rejected. From these results, we can identify the countries for which bilateral trade may be an important channel for business cycle spill-overs. Besides that, it is also interesting to uncover a possible overall dynamic effect in the euro area countries which can be accomplished by the combination of test statistics—or more precisely—by the combination of the individual $p$-values of the Granger non-causality tests. The combination of significance levels has a tradition in clinical studies and has recently also been applied to econometrics in the context of panel unit root testing. Maddala and Wu (1999) and Choi (2001) are early proponents of such a proceeding. Whereas the results of these papers rely on asymptotic theory that assumes independent test statistics, Hartung (1999) and Demetrescu *et al.* (2006) have extended the framework to the situation where the individual test statistics are stochastically dependent. Dependence of test statistics across units is an issue in the model (9) since the distribution of common effect augmented panel estimators depend on the cross-sectional averages and their lagged values (cf. Chudik and Pesaran, 2007). It is intuitively clear that the individual regressions cannot be independent since they share the cross-sectional averages as common regressors. A way to deal with dependence of test statistics in combining $p$-values offers the modified inverse normal method suggested by Hartung (1999).

The inverse normal method can be summarised as follows. Let $W_i$ be the $F$ statistics to test the hypothesis given by (10) or (11) and let $p_i = \mathrm{Pr}\{W_i > w_{i0}\}$ be the one-tailed $p$-value for the $i^{th}$ unit, where $w_{i0}$ is the sample realisation of $W_i$. Under $H_0^a$ (or $H_0^b$), $W_i$

is distributed $\chi^2_p$ and consequently $p_i$ is distributed uniformly on the unit interval $[0, 1]$. Furthermore, denote $t_1 = \Phi^{-1}(p_1)$ as the probit which corresponds to $p_1$, where $\Phi^{-1}$ is the inverse of the standard normal cumulative distribution function. By definition, each probit follows a standard normal distribution. Hartung (1999) shows that the dependence in the original statistics $W_1$ leads to dependency in the probits which is equivalent to some correlation of the $t_1$'s.

Given these relations, the (unweighted) test statistic of the inverse normal method is

$$t(\widehat{\rho}^*, \kappa) = \frac{\sum_{1=1}^{N} t_1}{\sqrt{N + N(N-1)\left[\widehat{\rho}^* + \kappa\sqrt{\frac{2}{N+1}}(1 - \widehat{\rho}^*)\right]}} \tag{12}$$

where $\widehat{\rho}^* = \max\left(-\frac{1}{N-1}, \widehat{\rho}\right)$, $\widehat{\rho} = 1 - \frac{1}{N-1}\sum_{1=1}^{N}(t_1 - \bar{t})^2$ and $\bar{t} = \frac{1}{N}\sum_{1=1}^{N} t_1$ is the arithmetic mean of the probits. The parameter $\kappa$ is intended to regulate the actual significance level in small samples. Hartung (1999) proposes to use $\kappa = \kappa_1 = 0.2$ or $\kappa = \kappa_2 = 0.1(1 + \frac{1}{N-1} - \widehat{\rho}^*)$. Under the null hypothesis $t(\widehat{\rho}^*, \kappa) \sim N(0, 1)$ and the test rejects for large negative values.

# 4 Results

The empirical section begins with an illustrative presentation of the key features that appear in the data, presents outcomes from the panel unit root tests of Bai and Ng (2004) and shows the results of simple cross section regressions which estimate the long-run effect of trade on cyclical co-movement. These estimates serve as a rough benchmark for the static cross-sectional estimation framework that dominates other empirical analyses. Finally, findings of the panel VAR models and Granger non-causality tests, which are the actual concern of the study, are presented and discussed.

## 4.1 Data overview and preliminary diagnostics

The figures 1 and 2 show the cross-sectional averages of the logarithms of the business cycle co-movement and trade measures for the four detrending methods and four indices

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of bilateral trade intensity. These are also the variables that serve as proxies for the unobserved common factors in the CA VAR models, the estimation results of which will be presented in section 4.2. Note that large *negative* values of the business cycle measures point to co-movement whereas large *positive* values of the trade measures signify intensive trade activity. A downward trend in the average co-movement measures and thus increasing business cycle similarity can be observed for all cycle measures except for the one that is based on the year-on-year differences. A part of this downward trend in the averages of the bilateral gap distances is certainly attributable to the generally decreased volatility of output gaps in many Western countries during the last decades. In the US, the term "Great Moderation" has been coined to denote the recent era which is characterised by a continuing drop in output volatility and an increase in economic stability over the past years. Factors such as good policies, structural change or simply good luck have been brought up to explain this phenomenon.

Figure 2 displays the measures $WT$, $WY$, $WTM$ and $WTY$ which show a continuing increase in average trade intensity. Central achievements such as the completion of the Single Market Program, the Maastricht Treaty and the introduction of the single currency promoted European integration and stimulated trade among the Member Countries of the European Union and the euro area during the last decades. The dynamics of the trade measures are somewhat different from each other. In particular the measure $WTM$ which computes the maximum value of the trade flows—scaled by total trade—between two country-pairs at each point in time shows a jump in the mid of the eighties which is—however not to this extent— also visible in the $WT$ measure but not in the GDP scaled trade indices. On the one hand, this marked increase in average trade intensity coincides with the prolonged recovery phase after the second oil price shocks. On the other hand, it is also interesting to relate the conspicuous behaviour of $WTM$ and $WT$ to the exchange-rate regime as in Massmann and Mitchell (2004) and Gayer (2007). The period from 1970 to the mid eighties, for instance, was characterised by the aftermath of the Bretton Woods fixed exchange-rate regime with a number of exchange rate re-alignments taking place. In contrast, from the late eighties on the European Monetary System has been rather stable with a particular strengthening since the mid nighties in the course of

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the entry requirements for the European Monetary Union. The positive trade effects of going from an unstable to a reliable and stable exchange-rate regime are nicely reflected in the measures $WTM$ and $WT$.
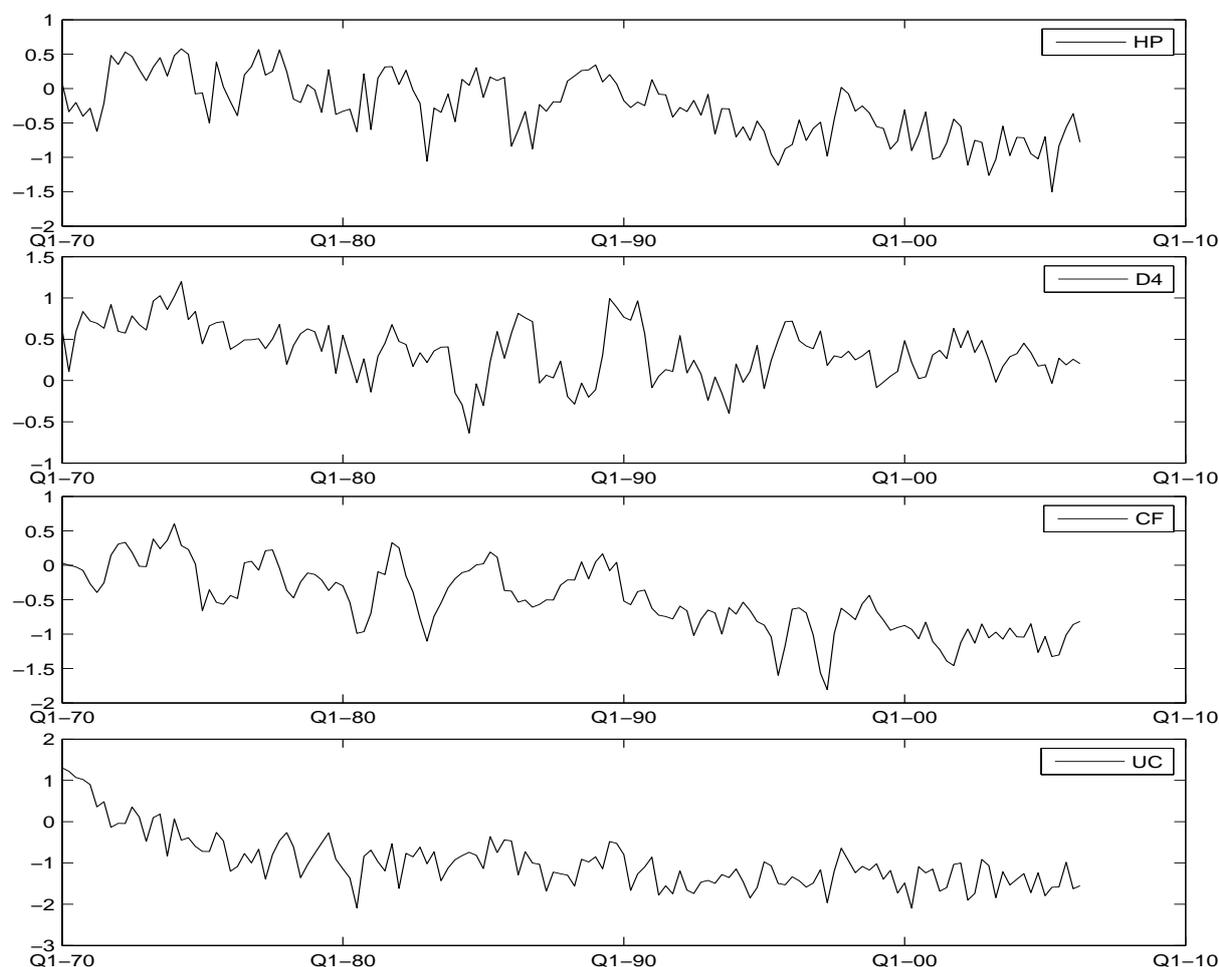


**Figure 1:** Cross-sectional averages of business cycle co-movement measures (logarithms)

To summarise, the visual inspection of the data suggests that co-movement of business cycles in the euro area was accompanied by an increase in trade intensity among the Member Countries in the past. The considerations above also make clear that various factors influenced the business cycle co-movement and trade intensity measures of which many are unobservable to the econometricians but which may be proxied by such cross-sectional averages.

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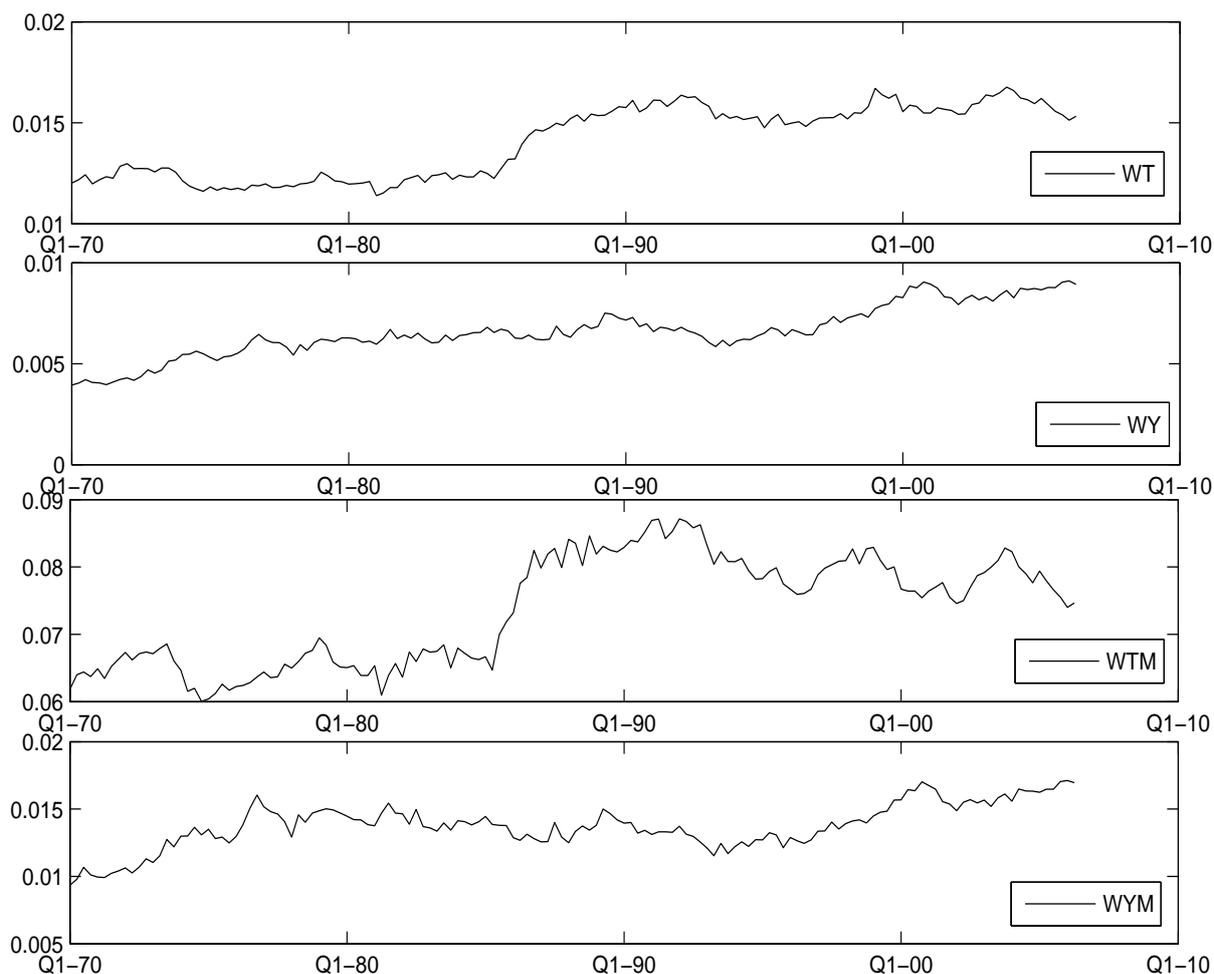
**Figure 2:** Cross-sectional averages of bilateral trade intensity measures (logarithms)

### 4.1.1 Panel unit root tests

The section above illustrated the presence of trends in the trade intensity measures. In this section, it will be tested whether these trends are deterministic or stochastic. For these purposes, panel unit root tests that take cross-section dependence among units into account ("second generation tests") are applied to test for non-stationarity and the order of integration of the trade data. Although the gap differences are stationary by construction, for the sake of completeness we also test for the presence of unit roots in these variables. The assessment of the order of integration is an important preliminary diagnosis for the decision whether to include the trade variables in levels of first differences.

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The literature offers a fair variety of procedures to test for unit roots with panel data under cross-sectional dependence. Surveys are provided by Gengenbach *et al.* (2004), Breitung and Pesaran (2005), Hurlin (2007), or Kappler (2008). Most approaches consider a factor structure to specify cross-section dependence just as in the panel VAR model of section 3. Here, we chose to base the decision about whether to difference the trade date or not on the outcomes of the panel unit root test of Bai and Ng (2004, BN henceforth). This approach offers a broader view on the data properties than its various "competitors" in that it (i) builds on a multi-factor structure to capture cross-section dependence (in contrast to the one-factor approaches of Pesaran, 2007, or Phillips and Sul, 2003), (ii) is explicitly designed to test for the presence of unit roots in the common factors and the individual-specific components separately, (iii) does not impose the same order of integration of the common factor(s) and individual-specific elements under the null hypothesis (as the tests of Moon and Perron, 2004, or Pesaran, 2007, for instance do) and (iv) consistently estimates the unobserved common factors whether they are stationary or not.

BN assume that the data is generated by

$$x_{\imath t} = d_{\imath t} + \lambda_{\imath}' \mathbf{F}_t + e_{\imath t} \tag{13}$$

where the vector of common factors $\mathbf{F}_t$ and the idiosyncratic errors $e_{\imath t}$ follow $AR(1)$ models with a polynomial lag structure of iid shocks. Concerning the deterministic elements $d_{\imath t}$, an intercept or an intercept and a linear trend are allowed. The strategy of consistently estimating the individual components of (13), even if some or all elements of $\mathbf{F}_t$ and $e_{\imath t}$ are integrated of order one, is as follows. In the first step, the $x_{\imath t}$'s are differenced in the case that $d_{\imath t}$ includes an intercept only. If the model comprises an intercept and a time trend, the data is differenced and demeaned, i.e. $\tilde{x}_{\imath t} = \Delta x_{\imath t} - \overline{\Delta x_{\imath}}$ is computed in the first step, with $\overline{\Delta x_{\imath}} = \sum_{t=1}^{T} x_{\imath t}$. Then the principal component method is employed with the differenced (or differenced and demeaned) data and the common factors, factor loadings and residuals are estimated. In the next step, the estimates of the differenced factors and idiosyncratic error components (residuals) are re-integrated à la $\widehat{x}_t = \sum_{s=2}^{t} \Delta \widehat{x}_s$ and tested separately for unit roots.

For unit root testing, BN propose to employ the usual $t$ statistics of ADF regressions in the common factor and idiosyncratic components, respectively. For the model with an intercept only, the $t$ statistics to test the common factor for a unit root is denoted $ADF_{\widehat{F}}^c$ and $ADF_{\widehat{F}}^{c,\tau}$ in the case of the intercept and linear trend model. If there is more than one common factor, the BN procedure determines $r_1$, the number of independent stochastic trends underlying the $r$ common factors. For these purposes, BN proposes a successive testing procedure similar to Johansen's trace and eigenvalues tests and construct two test statistics. Here, we focus on only one of these, $MQ_c^j, j = c, \tau$, to test for $r_1$ since it allows the factor estimates to have fairly general dynamics in contrast to the $MQ_f^j$ statistic that is only valid when the trends follow exact finite order $AR(p)$ processes. The superscripts $c$ and $\tau$ distinguish the intercept only and intercept and linear trend model. The limiting distributions of both statistics are non-standard and simulated critical values are tabulated by BN in their paper. In contrast, the asymptotic distributions of the ADF $t$ statistics for the idiosyncratic components coincide with the usual DF distribution in the intercept only and intercept and linear trend case, respectively.

For independent $e_{1t}$, a pooled test for unit roots in $\widehat{e}_{1t}$ due to Choi (2001) that builds on combining $p$-values $p_{\widehat{e}}^j(1), j = c, \tau$ of the underlying ADF tests can be constructed. The pooled tests are given by

$$P_{\widehat{e}}^j = \frac{-2 \sum_{1=1}^N \log p_{\widehat{e}}^j(1) - 2N}{\sqrt{4N}}, \quad j = c, \tau, \quad 1 = 1, \ldots N. \tag{14}$$

Both statistics follow standard normal distributions under the joint null hypothesis of non-stationarity of the individual idiosyncratic components and reject for large positive values. Note that the pooled test of BN is in the same spirit as the pooled test for Granger non-causality presented above. The difference here is that the pooled test of BN assumes independent units which is a plausible assumption since the source of cross-section dependence (the common factors) has been removed from the idiosyncratic components.

**Table 1:** BN panel unit root tests: Intercept only case

|  | $P_{\hat{e}}^c$ | $\hat{r}$ | $\hat{r}_1$ |
|---|---|---|---|
| $\ln \rho(HP)$ | 21.359 (0.00) | 1 | -5.788 (0.01) |
| $\ln \rho(D4)$ | 21.877 (0.00) | 1 | -9.863 (0.01) |
| $\ln \rho(CF)$ | 21.897 (0.00) | 0 | - |
| $\ln \rho(UC)$ | 8.610 (0.00) | 1 | -5.987 (0.01) |
| $\ln WT$ | 0.980 (0.16) | 4 | 4 |
| $\ln WY$ | -1.226 (0.90) | 4 | 4 |
| $\ln WTM$ | 3.150 (0.00) | 3 | 3 |
| $\ln WYM$ | -1.642 (0.95) | 4 | 4 |
| $\Delta \ln WT$ | 9.757 (0.00) | 5 | 0 |
| $\Delta \ln WY$ | 10.174 (0.00) | 4 | 0 |
| $\Delta \ln WTM$ | 6.261 (0.00) | 4 | 0 |
| $\Delta \ln WYM$ | 11.087 (0.00) | 4 | 0 |

**Notes:** $p$-values are in parentheses. $\hat{r}$ is the number of unobserved common factors which is estimated with the aid of the $BIC_3$ criterion by Bai and Ng (2002). The maximum number of factors is equal to 8. The number of independent stochastic trends $\hat{r}_1$ among the $\hat{r}$ factors is estimated by $MQ_c^c$ at the 5%-level of significance. In the case that $\hat{r} = 1$, the entry in the last column refers to the $ADF_{\hat{F}}^c$ statistic along with the corresponding $p$-value.

The results are summarised in table 1 and 2. In each case, the number of common factors $r$ is estimated according to the $BIC_3$ criterion by Bai and Ng (2002).[5] From the outset it is not clear whether to consider a linear time trend or not for the alternative hypothesis. Therefore, results for both cases, the intercept only case (table 1) and the intercept and trend case (table 2) are reported.

The results of the gap differences merely confirm the fact that the gap estimates are stationary by construction: The $P_{\hat{e}}^c$ statistics are large and significant, the estimated number of common factors is at most one and the corresponding $ADF_{\hat{F}}^c$ statistics are significant as well. For the trade measures in levels, the $P_{\hat{e}}^c$ statistics are insignificant for $\ln WT$, $\ln WY$ and $\ln WYM$ which implies integrated idiosyncratic components. In addition, it turns out that four independent non-stationary factors are affecting these

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[5]From the 12 criteria that Bai and Ng (2002) consider, they found the $BIC_3$ criterion to perform best in small samples. In our application, we found the other information criteria to be very sensitive with regard to the choice of the maximum number of factors in that they always chose the maximum value.

variables. For $\ln WTM$, the $P_{\hat{e}}^c$ statistics diagnoses stationary idiosyncratic components but at the same time the presence of three non stationary common factors is found. The lower part of table 1 contains test outcomes for the first differences of the trade intensity measures. These are characterised by stationary idiosyncratic elements and the absence of non-stationary common factors.

Table 2 tests against the trend stationarity hypothesis and confirms the previous outcomes: Non stationarity is not rejected for $\ln WT$, $\ln WY$ and $\ln WYM$ which in this case is due to the presence of four independent non-stationary factors. However, for $\ln WTM$, the test rejects the null for both the idiosyncratic and factor components and the evidence here is in favour of the trend stationarity hypothesis.

**Table 2:** BN panel unit root tests: Intercept and trend case

|            | $P_{\hat{e}}^c$ | $\hat{r}$ | $\hat{r_1}$ |
|------------|-----------------|-----------|-------------|
| $\ln WT$   | 13.556 (0.00)   | 4         | 4           |
| $\ln WY$   | 9.625 (0.00)    | 4         | 4           |
| $\ln WTM$  | 12.552 (0.00)   | 3         | 0           |
| $\ln WYM$  | 9.765 (0.00)    | 4         | 4           |

**Notes:** $p$-values are in parentheses. $\hat{r}$ is the number of unobserved common factors which is estimated with the aid of the $BIC_3$ criterion by Bai and Ng (2002). The maximum number of factors is equal to 8. The number of independent stochastic trends $\hat{r_1}$ among the $\hat{r}$ factors is estimated by $MQ_c^\tau$ at the 5%-level of significance.

Taken together, we conclude that $WT$, $WY$ and $WYM$ may be regarded as difference stationary time series. The panel unit root diagnostics suggest the presence of stochastic trends in these trade intensity indices. Therefore, the trade intensity variable $WT$, $WY$ and $WYM$ enters the VAR equations in first differences. $WTM$ turns out to be trend stationary. Therefore, the linear trend is removed from $WTM$ by regressing each individual country pair on a linear time trend and an intercept.

### 4.1.2 Cross section estimates

For a further preliminary data inspection, we estimate pure cross-sectional relationships. Most papers on business cycle similarity and trade intensity run a static regression for which the right hand side (rhs) variables are computed as cross-section averages over long time spans. If the researcher is interested in the average long-run effect of the independent on the dependent variable, such an approach may be justified since it has be shown that the cross-section estimator is consistent and robust with respect to both slope heterogeneity and dynamic misspecification (Pesaran and Smith, 1995). For $T$ and $N$ large, the average of the long-run trade coefficient can be estimated by the following cross-section regression

$$\widetilde{\ln \rho_\iota} = \alpha + \beta \widetilde{\text{Trade}_\iota} + \varepsilon_\iota \tag{15}$$

where $\widetilde{\ln \rho_\iota} = \frac{1}{T} \sum_{t=1}^{T} \ln \rho_{\iota t}$ and $\widetilde{\text{Trade}_\iota} = \frac{1}{T} \sum_{t=1}^{T} \text{Trade}_{\iota t}$, whereas the latter time average refers to one of the above discussed measures of trade intensity. Clearly, such a regression ignores the problem of the possible endogeneity of the trade variable and omitted variable bias. Nevertheless, it is good for checking whether our newly used left hand side (lhs) variables roughly point to the same effects that other studies found.

Cross-section estimates for the various measures of trade intensity and cyclical co-movement are tabulated in table 3. The upper part of the table shows results for the case that levels of the trade intensities are used as regressors for each business cycle co-movement measure whereas the lower part presents cross-section estimates for the first differences of the trade variables. For the level variables, we generally obtain negative and significant coefficient estimates which point to a positive long-run effect of greater trade intensity on business cycle similarity among the euro area countries. This finding is in line with the consensus view and the evidence provided by Frankel and Rose (1998), Gruben *et al.* (2002), Imbs (2004), Baxter and Kouparitsas (2005), and Böwer and Guillemineau (2006). Furthermore, the long-run estimates are not very sensitive with respect to the de-trending method, which is also a typical result in the literature. However, the magnitude of the coefficient estimates is somewhat dependent on the trade intensity measure: Whereas scaling by total trade or GDP is not relevant, using $\ln \widetilde{WTM}$ and $\ln \widetilde{WYM}$,

which are both based on the maximum value of the trade flows between two countries, lowers coefficient estimates.

**Table 3:** Cross section estimates for different measures of trade intensity and business cycle co-movement

|  | $\widetilde{\ln \rho}(\text{HP})$ | $\widetilde{\ln \rho}(\text{CF})$ | $\widetilde{\ln \rho}(\text{UC})$ | $\widetilde{\ln \rho}(\text{D4})$ |
|---|---|---|---|---|
| $\widetilde{\ln WT}$ | -0.237 | -0.179 | -0.246 | -0.275 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **( 0.00)** |
| $\widetilde{\ln WY}$ | -0.251 | -0.180 | -0.246 | -0.284 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\widetilde{\ln WTM}$ | -0.124 | -0.109 | -0.147 | -0.159 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\widetilde{\ln WYM}$ | -0.102 | -0.095 | -0.137 | -0.133 |
|  | **(0.03)** | **(0.01)** | **(0.06)** | **(0.02)** |
| $\Delta \widetilde{\ln WT}$ | 13.107 | 3.983 | 14.916 | 32.946 |
|  | (0.20) | (0.65) | (0.35) | **(0.00)** |
| $\Delta \widetilde{\ln WY}$ | -5.423 | -9.041 | -7.490 | 10.484 |
|  | (0.55) | (0.24) | (0.60) | (0.30) |
| $\widetilde{\ln WTM_{-Trend}}$ | -0.115 | -0.094 | -0.136 | -0.152 |
|  | **(0.00)** | **(0.00)** | **(0.02)** | **(0.00)** |
| $\Delta \widetilde{\ln WY}M$ | -15.082 | -13.099 | -32.086 | 1.006 |
|  | **(0.09)** | **(0.09)** | **(0.02)** | (0.92) |

**Notes:** OLS estimates of $\beta$ from equation (15). $p$-values in parentheses. Intercepts not reported. Time averages of the variables are computed over the period from 1971Q2 to 2007Q2. $N=45$.

A more differentiated picture emerges if stationary counterparts of the trade intensity measures are employed in the cross-section regressions. When business cycle co-movement is regressed on the time averages of the *change* in $\widetilde{\ln WT}$ ($\Delta \widetilde{\ln WT}$), the coefficient estimates are insignificant and positive. In the regressions of co-movement on $\Delta \widetilde{\ln WY}$ also insignificant coefficient estimates result which in this case are negative for all de-trending methods except for the year-on-year differences ($\widetilde{\ln \rho}(\text{UC})$). Significant estimates are obtained for $\widetilde{\ln WTM_{-Trend}}$ and $\Delta \widetilde{\ln WY}M$ and the negative signs once more point to a long-run positive connection between trade and cyclical similarity (an exception is the regression of $\Delta \widetilde{\ln WY}M$ on $\widetilde{\ln \rho}(\text{D4})$ which yields an insignificant coefficient estimate).

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Taken together, the static cross-sectional estimates basically confirm the results of the recent literature which finds vast evidence of an economically and statistically significant link between international trade and business cycle synchronisation. However, the results presented here also demonstrate that it makes a difference whether business cycle co-movement is related to the level or the change of the trade intensity measures. The latter are the appropriate variables in a dynamic regression framework that seeks to explain business cycle co-movement which—by definition and construction—is proxied by stationary variables.

## 4.2   CA VAR models and Granger non-causality

The causality tests imply that neither lagged trade variables help to predict business cycle co-movement nor do lagged co-movement variables help to improve forecasts of trade intensity. However, the $F$ tests for block exogeneity of the factor proxies do reject in almost all cases and imply that these have for both variables significant predictive power. This main message clearly emerges from the Granger non-causality test that are detailed in the tables below. Table 4 reports the test statistics for non-causality of business cycle co-movement; table 5 depicts the same for bilateral trade intensity. The tables are in matrix form and each cell displays the pooled test statistic $t(\rho^*, \kappa_2)$ along with the corresponding $p$-values in parentheses for a certain variable combination. The entry in the upper left corner of table 4, for instance, tests whether trade intensity, given by the variable $\Delta \ln WT$, does not Granger cause business cycle co-movement, which in this case is measured by $\ln \rho(\text{HP})$. Note that $t(\rho^*, \kappa_2)$ rejects the null hypothesis for large negative values and $p$-values which point to significance at conventional levels are marked in bold. The number of lagged co-movement and trade variables has been chosen by the minimum of the Akaike information criterion and the factor proxies, i.e. the cross-sectional averages, enter each VAR contemporaneously and with two lags.[6]

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[6]Alternative specification strategies with respect to model dynamics have been conducted but left the overall results unaffected. Diagnostics statistics of the presented models are satisfactory with respect to explanatory power and residual serial correlation.

**Table 4:** Granger non-causality results for business cycle co-movement

|  | $\ln \rho(\text{HP})$ | $\ln \rho(\text{CF})$ | $\ln \rho(\text{UC})$ | $\ln \rho(\text{D4})$ |
|---|---|---|---|---|
| Trade intensity $\nrightarrow$ business cycle co-movement | | | | |
| $\Delta \ln WT$ | -0.478 | -0.427 | -0.631 | -0.831 |
|  | (0.32) | (0.33) | (0.26) | (0.20) |
| $\Delta \ln WY$ | -0.453 | -0.736 | -0.699 | -0.425 |
|  | (0.33) | (0.23) | (0.24) | (0.34) |
| $\ln WTM_{-Trend}$ | -0.289 | -0.269 | -0.922 | -0.953 |
|  | (0.39) | (0.39) | (0.18) | (0.17) |
| $\Delta \ln WYM$ | -0.376 | -0.856 | -0.789 | -0.299 |
|  | (0.35) | (0.20) | (0.22) | (0.38) |
| | | | | |
| Factor proxies $\nrightarrow$ business cycle co-movement | | | | |
| $\Delta \ln WT$ | -6.302 | -5.178 | -6.785 | -4.780 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\Delta \ln WY$ | -6.148 | -5.042 | -6.843 | -4.634 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\ln WTM_{-Trend}$ | -6.661 | -4.792 | -6.729 | -4.555 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\Delta \ln WYM$ | -6.330 | -4.903 | -6.748 | -4.568 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |

**Notes:** The table shows pooled results for different measures of trade intensity and business cycle co-movement. Entries are $t(\rho^*, \kappa_2)$. $p$-values in parentheses. The number of lags, $p_1$, of the individual VAR models was selected with the aid of the Akaike information criterion and the maximum lag length was set to 12. The cross-sectional averages (factor proxies) enter the VARs contemporaneously and with two lags in each model. The observation period is from 1971Q2 to 2007Q2. $N=45$.

As seen from the upper parts of the tables 4 and 5, the hypothesis of no bi-directional causality between co-movement of the euro area cycles and the bilateral trade links can not be rejected at the usual levels of significance. This results holds for either directions of causality and is robust with respect to both the methodology of estimating the business cycle and measures of trade intensity. In contrast, present and lagged values of the cross-sectional averages carry information about the similarity of Member Countries' cycles at

**Table 5:** Granger non-causality results for trade intensity

|  | $\ln \rho(\text{HP})$ | $\ln \rho(\text{CF})$ | $\ln \rho(\text{UC})$ | $\ln \rho(\text{D4})$ |
|---|---|---|---|---|
|  | Business cycle co-movement $\nrightarrow$ trade intensity | | | |
| $\Delta \ln WT$ | -0.500 | -0.466 | -0.147 | -0.390 |
|  | (0.31) | (0.32) | (0.44) | (0.35) |
| $\Delta \ln WY$ | 0.138 | -0.465 | -0.342 | -0.488 |
|  | (0.55) | (0.32) | (0.37) | (0.31) |
| $\ln WTM_{-Trend}$ | -0.478 | -0.327 | -0.797 | -0.136 |
|  | (0.32) | (0.37) | (0.21) | (0.45) |
| $\Delta \ln WYM$ | -0.070 | -0.301 | -0.268 | -0.444 |
|  | (0.47) | (0.38) | (0.39) | (0.33) |
|  |  |  |  |  |
|  | Factor proxies $\nrightarrow$ trade intensity | | | |
| $\Delta \ln WT$ | -4.736 | -4.741 | -4.250 | -4.757 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\Delta \ln WY$ | -8.834 | -8.343 | -8.514 | -8.983 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\ln WTM_{-Trend}$ | -5.560 | -5.127 | -5.230 | -5.020 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |
| $\Delta \ln WYM$ | -8.779 | -8.008 | -8.273 | -8.580 |
|  | **(0.00)** | **(0.00)** | **(0.00)** | **(0.00)** |

**Notes:** The table shows pooled results for different measures of trade intensity and business cycle co-movement. Entries are $t(\rho^*, \kappa_2)$. $p$-values in parentheses. The number of lags, $p_1$, of the individual VAR models was selected with the aid of the Akaike information criterion and the maximum lag length was set to 12. The cross-sectional averages (factor proxies) enter the VARs contemporaneously and with two lags in each model. The observation period is from 1971Q2 to 2007Q2. $N=45$.

a given point in time. Again, Granger causality of the factor proxies does not depend on the specific bilateral trade measure.

# 5   Discussion and conclusion

Motivated by the evidence of many recent studies that suggests a significant and robust static relationship between trade intensity and similarity of business cycles between coun-

try pairs, the present paper asks the obvious but simple question, namely, whether there also exists a *dynamic* bi-directional link. We investigate this question for the euro area countries with cross-sectional time series data and the concept of Granger causality and conclude that the answer is no. Lagged effects from bilateral trade intensity do not produce dynamic business cycle co-movement so that two countries that trade more today will not have more similar cycles tomorrow. There is also no evidence for a reverse dynamic relationship. However, the static cross section estimates confirm that there may be a long-run connection between trade linkages and the similarity of business cycle fluctuations. Importantly, all findings appear to be robust against different measures of bilateral trade intensity and the business cycle.

The absence of a dynamic feedback between trade and business cycle linkages implies that trade may not be such an important transmission channel for cyclical shocks. Business cycle synchronisation arises from a number of interdependencies such as linkages through foreign direct investments, the integration of equity markets, similar economic structure or shared economic confidence and sentiment. However, the outcome of the Granger tests for the factor proxies show that common components help to explain common movements in international business cycles. These results are consistent with the findings of other studies that take a different route to identify common or "world" factors as a source of cyclical co-movement. The paper of Kose *et al.* (2003), for instance, reports about a significant common component in business cycle fluctuations which particularly explains much of the output fluctuations in developed countries. Also Stock and Watson (2005) conclude by the application of factor structural VAR models that most of the variance of GDP growth in the G7 countries is attributed to common (global) and idiosyncratic shocks. International spill-overs, expected to be present if dynamic trade effects lead to international co-movement, do not account for GDP growth forecast error variance at one-quarter horizons and only a minor variance fraction at longer horizons. Dées and Vansteenkiste (2007) look at spill-overs of the impact of US domestic demand shocks of countries and regions such as the euro area, Latin America and Emerging Asia and compare trade-effects to overall effects in a Global VAR model covering finance and price channels as well as policy reactions. They find that output in other countries and regions

than the US, in particular in the euro area, reacts much higher to a shock originating in the US than the the purely trade-related effect would suggest. Again, this study demonstrates that other factors than pure trade linkages play an important role for the transmission of impulses between economies.

Taken together, this paper provides an interesting and important piece of information for the understanding of the trade-synchronisation nexus that is still dominated by the static view. Although countries with intensive trade linkages also tend to have more similar business cycle in the long-run, the trade channel does not help to explain much of the short-run variation of business cycle co-movement in the euro area.

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