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Published in:
European Economic Review

DOI:
[10.1016/j.eurocorev.2007.05.003](https://doi.org/10.1016/j.eurocorev.2007.05.003)

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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2008

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Inklaar, R., Jong-A-Pin, R., & de Haan, J. (2008). Trade and business cycle synchronization in OECD countries: A re-examination. *European Economic Review*, 52(4), 646-666.
<https://doi.org/10.1016/j.eurocorev.2007.05.003>

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Trade and business cycle synchronization in OECD countries—A re-examination

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Received 16 November 2005; accepted 30 May 2007

Available online 8 June 2007

Abstract

This paper re-examines the relationship between trade intensity and business cycle synchronization for 21 OECD countries in the period 1970–2003. Instead of using instrumental variables, we estimate a multivariate model including variables capturing specialization and similarity of economic policies. We confirm that trade intensity affects synchronization, but the effect is much smaller than previously reported. Other factors, like specialization and convergence in monetary and fiscal policies, have a similar impact on business cycle synchronization as trade intensity. The effect of trade on synchronization is not driven by outliers. However, the impact of trade on synchronization is not robust across deciles.

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JEL classification: E32; F42

Keywords: Business cycles; Trade; Synchronization of business cycles

1. Introduction

In their seminal papers, Frankel and Rose (1997, 1998) argue that countries with more intense trade ties have more similar business cycles. This finding has been confirmed in almost all subsequent studies on the determinants of business cycle synchronization. For instance, Baxter and Kouparitsas (2005) find that bilateral trade intensity is robustly

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related to business cycle synchronization using the extreme bounds analysis (EBA) of [Leamer \(1983\)](#) on a dataset that includes over 100 developed and developing countries. However, despite the broad agreement about the role of trade, there is still disagreement about its (relative) importance in affecting business cycle synchronization. Furthermore, previous papers have not examined whether the impact of trade is influenced by outliers and sample heterogeneity.

We re-examine the impact of trade on business cycle synchronization using data for 21 OECD countries for the period 1970–2003. The main question that we pose is how large and robust the impact of trade on business cycle synchronization is if the issues of model specification and sample selection are taken into account. We use EBA to select variables to be included in our structural model, which is similar to the models of [Kalemli-Ozcan et al. \(2001\)](#) and [Imbs \(2004\)](#), and quantile regressions and least trimmed squares (LTS) to examine the importance of sample heterogeneity and outliers.¹

Our paper extends the literature by dealing with four issues that have been discussed in the literature regarding the relation between trade and synchronization. First, we employ a much longer list of potential explanatory variables of business cycle synchronization than examined by [Baxter and Kouparitsas \(2005\)](#). These authors find that many variables that have been suggested to affect business cycle synchronization, including specialization ([Kalemli-Ozcan et al., 2001](#)) and financial integration ([Imbs, 2004](#)), are not robustly related to the co-movement of business cycles. In contrast to [Baxter and Kouparitsas \(2005\)](#), we employ the robustness approach suggested by [Sala-i-Martin \(1997\)](#) since [Leamer's \(1983\)](#) robustness test is extremely restrictive.

Second, we use the variables identified by the EBA in a structural model to take the endogeneity of the trade variable into account. The basic problem here is that countries with intense trade relations are more likely to link their currencies, either explicitly or implicitly. This implies that these countries will have similar monetary policies – and possibly other policies – that may synchronize their business cycles. So it is not only trade that causes the business cycles to be correlated but also the similarity of economic policies. Neglecting these other variables in the regression specification renders the trade coefficient biased and inconsistent. [Frankel and Rose \(1998\)](#) and most subsequent studies therefore employ instrumental variables (IV) estimation, using gravity variables as instruments. However, [Gruben et al. \(2002\)](#) argue that this is not an adequate solution since the gravity variables are likely to affect other variables that influence business cycle synchronization as well, like participation in a currency union and specialization. Our solution to this problem is to specify a multivariate model including policy variables as well as structural characteristics and test for the proper estimation method using the [Hausman \(1978\)](#) test.

Third, we analyze to what extent the relationship between trade intensity and business cycle synchronization is robust across different country pairs. For example, the effect of trade on business cycle synchronization may not be the same for country pairs that are already highly synchronized, like Germany and the Netherlands, and those that are not, like Germany and Japan. The effect of trade on business cycle correlations may also be

¹The papers that comes closest to our work are [Kalemli-Ozcan et al. \(2001\)](#) and [Imbs \(2004\)](#). There are, however, a number of important differences between both studies. Our methodology is quite different as we are primarily interested in the effect of trade intensity on output correlation. Furthermore, we consider a much longer list of potential determinants of business cycle synchronization. [Imbs \(2004\)](#), for instance, does not take the role of monetary and fiscal policy into account, which we find to be important. These studies also do not examine how sensitive their findings are for sample heterogeneity and outliers.

driven by ‘extreme’ country pairs such as the US and Canada. To examine the importance of sample heterogeneity and outliers we use quantile regressions and LTS, respectively. While these problems have not received much attention in this literature so far, they have proven to be important in other areas, such as the determinants of economic growth.²

Finally, we use transformed measures of business cycle synchronization. Frankel and Rose (1998) and almost all subsequent studies measure synchronization of business cycles of two countries as the bilateral correlation of some measure of (detrended) real economic activity. Since the dependent variable lies between -1 and 1 , the error terms in a regression model of the determinants of business cycle synchronization are unlikely to be normally distributed. This problem was stressed by Otto et al. (2001) and we therefore employ transformed correlation coefficients as the dependent variable in our regression models. We also use principal components of related variables to key concepts as trade integration and specialization and use different indicators to measure specialization and financial integration, as a further robustness check.

Our main findings are the following. Trade intensity is found to affect business cycle synchronization, but the effect is much smaller than reported by Frankel and Rose (1998). We also find that apart from the intensity of trade, specialization and similar monetary and fiscal policies have a strong impact on business cycle synchronization. The impact of these factors on business cycle synchronization is about as large as the impact of trade intensity. Finally, our results suggest that the effect of trade on business cycle synchronization is robust for outlying observations. However, the relationship between the correlation of business cycles and bilateral trade is not robust across deciles.

The remainder of the paper is organized as follows. Section 2 explains the methodology and Section 3 presents our data. Section 4 contains the estimation results and discusses the economic relevance of our findings. Section 5 presents the quantile regressions and LTS results. The final section offers some concluding comments.

2. Methodology

Theoretically, trade intensity has an ambiguous effect on the co-movement of output. Standard trade theory predicts that openness to trade will lead to increased specialization in production and inter-industry patterns of international trade. If business cycles are dominated by industry-specific shocks, trade-induced specialization leads to decreasing business cycle correlations.³ However, if trade is dominated by intra-industry trade industry-specific shocks may lead to more symmetric business cycles. Furthermore, in case of intensive trade relations economy-wide shocks in one country will generally have an effect on demand for goods from the other country.

Frankel and Rose (1998) acknowledge the possible contrasting effects of inter- and intra-industry trade on business cycle synchronization, but focus on the net effect of total trade on output co-movement. However, even identifying the net effect of trade is not straightforward since trade intensity is endogenous, which makes an OLS regression of

²See, e.g., Sturm and De Haan (2005) and Barreto and Hughes (2004).

³However, as pointed out by Frankel (2005), a positive shock at one point in the chain of value-added in one country will tend to have positive spill-over effects at the other points along the chain in other countries. Thus, trade in inputs and intermediate products gives rise to positive correlations but may be recorded as inter-industry trade.

business cycle synchronization on trade intensity inappropriate. Frankel and Rose (1998) deal with this problem by using gravity variables (distance, border dummy, common language dummy) as instruments to identify the effect of trade on business cycle correlation. However, as pointed out by Gruben et al. (2002), this is not appropriate if the gravity variables (Z) not only affect bilateral trade intensity (T) but are also possibly related to some other variables (F) that affect business cycle synchronization (C), as illustrated in Fig. 1. For instance, neighboring countries are more likely to coordinate their monetary policies, or even to have a common currency, than countries that are further away from each other. In turn, the introduction of a single currency will contribute to reducing trading costs both directly and indirectly, e.g., by removing exchange rate risks (and the cost of hedging) and diminishing information costs (De Grauwe and Mongelli, 2005). Furthermore, trade may also affect other variables (F) that affect business cycle synchronization. As we are interested in the total effect of trade intensity on business cycle synchronization, we also have to take this indirect effect into account.

The regression model that corresponds to the figure above is

$$\begin{aligned} C &= \beta_1 T + \beta_2 F + \varepsilon, \\ T &= c_1 Z + c_2 F + \mu, \\ F &= c_3 Z + c_4 T + \omega. \end{aligned} \quad (1)$$

The model shows that the business cycle correlation depends on bilateral trade as well as other policy related and structural variables. Some of these variables may be influenced by the exogenous gravity variables, while, in turn, they may affect trade intensity. Broadly speaking, these variables can be grouped into the following categories: (1) specialization (see, e.g., Kalemli-Ozcan et al., 2001); (2) monetary integration (see, e.g., Rose and Engel, 2002); (3) financial integration (see, e.g., Imbs, 2004); and (4) similarity of fiscal policies (see, e.g., Clark and van Wincoop, 2001). Apart from these variables many others have been suggested that may be related to business cycle synchronization (see De Haan et al., 2007 for an extensive discussion).

To identify the other variables to be included in our model, we follow Baxter and Kouparitsas (2005) and apply EBA to examine which variables are robustly related to business cycle synchronization in the OECD area. In contrast to Baxter and Kouparitsas (2005), we employ the approach suggested by Sala-i-Martin (1997) since Leamer's (1983) robustness test is extremely restrictive. Using a much longer list of potential explanatory variables than examined by Baxter and Kouparitsas, we identify a number of robust variables, including the similarity of monetary policy (proxied by the correlation of short-term interest rates) and the similarity of fiscal policy (proxied by the correlation of cyclically adjusted budget deficits). Table A1 in the appendix shows the variables that have

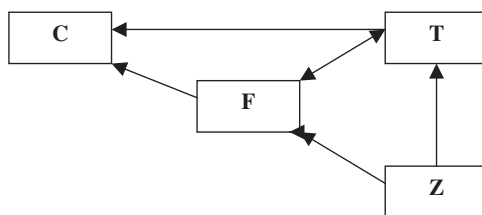


Fig. 1. The relationship between business cycle correlation, trade, gravity variables and other variables.

been used in the analysis and whether they are robust explanatory variables of the business cycle correlation between two OECD countries. When testing for the robustness of these variables, we made sure not to include other proxies for the same “driving force” in the set of control variables. This is especially relevant for financial integration and specialization, since we have two measures of financial integration and three measures of specialization (see Section 3 for further details).

Once a suitable set of explanatory variables has been identified, the appropriate method to estimate the model above depends on the correlation between the error terms of the three equations. Given the exogeneity of gravity variables in the third equation in (1), it is crucial whether μ and ε are correlated. If so, using OLS for the first equation results in inconsistent estimates and instrumental variables estimation should be preferred. If not, OLS estimates are consistent and at least as efficient. We use the Hausman (1978) test to resolve which estimation method should be chosen.

3. Data sources

In our analysis we use two measures of economic activity, namely (quarterly) GDP and the (monthly) index of industrial production (IIP). The latter is attractive as it is available for a long period of time and (for most countries) at a monthly frequency. However, the coverage of the economy is limited to the manufacturing sector. The main reason for using GDP is that it is the most comprehensive measure of economic activity even though it is available at a quarterly frequency, at most, and time series are generally shorter than for industrial production. These trade-offs argue for using both measures.

Most previous papers on the determinants of business cycle synchronization (including Frankel and Rose, 1998) use the Hodrick–Prescott (HP) filter to detrend the original series. The HP filter can be interpreted as a high-pass filter that removes fluctuations with a frequency of more than 32 quarters and puts those fluctuations in the trend. Baxter and King (1999) argue that the combination of a high-pass filter and a low-pass filter (which removes high frequencies) is better since the HP filter still leaves much of the high-frequency noise as part of the cycle. If such a so-called band-pass (BP) filter is applied, the resulting cyclical component does not contain any fluctuations with frequencies beyond the predetermined cut-off points. Since most studies find qualitatively similar results for different filtering methods, we restrict ourselves to the Baxter–King filter.⁴

Following most previous studies, our measure of business cycle synchronization is the correlation coefficient of the detrended measures of economic activity (GDP or IIP). Data are available for the period 1970–2003 for 21 OECD countries. Most countries report industrial production at a monthly frequency back to at least 1970.⁵ Australia, New Zealand and Switzerland only report quarterly industrial production, so their correlation vis-à-vis all countries is based on quarterly data.

Fig. 2 shows the 8-year moving average of the correlation coefficients. This figure suggests that there is no obvious way to split our sample period in particular sub-periods, so we have split our sample into three periods of equal length (i.e., 11 years: 1970–1981,

⁴Artis and Zhang (1997) and Calderón et al. (2007) conclude that the choice of filtering method is not crucial for their conclusions. Likewise, Massmann and Mitchell (2004), who consider the largest number of business cycle measures, report substantive similarities across alternative measures of the business cycle.

⁵Exceptions are Denmark (1974) and Ireland (1975).

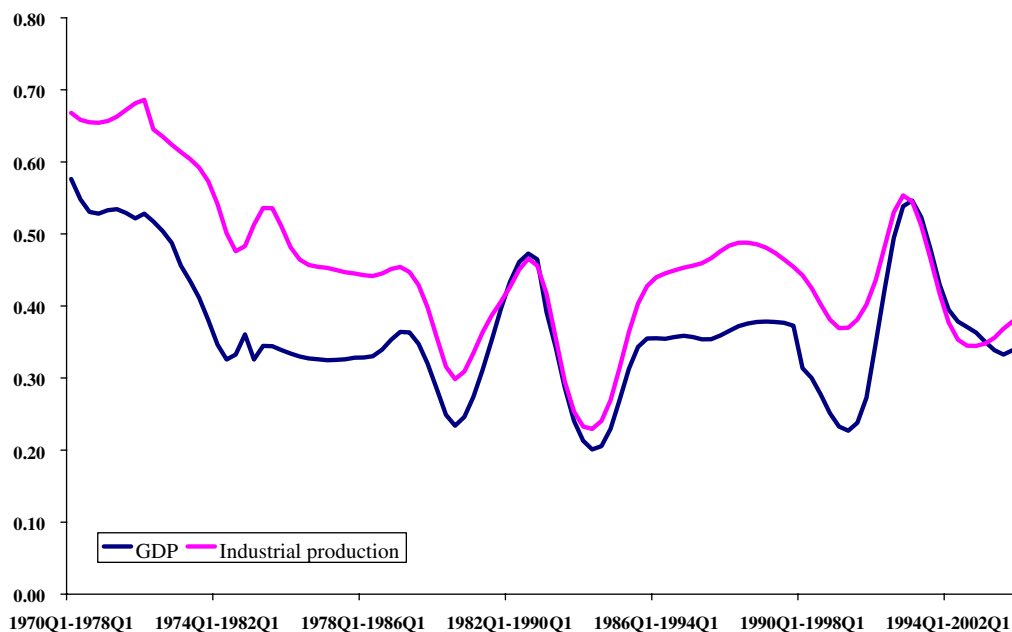


Fig. 2. Average of bilateral business cycle correlations, 8-year moving windows, 1970–2003.

1981–1992 and 1992–2003), leaving us with a maximum of 630 observations ($0.5 \times (3 \times 21 \times 20)$).⁶ For the quantile regression results shown in Section 4, we split the sample in eight periods of equal length in order to increase the number of observations.⁷

In our regressions we use Fisher's z -transformations of the correlation coefficients as dependent variable. The transformed correlation coefficients are calculated as $C_t = 1/2 \ln((1 + C)/(1 - C))$, where C is the pairwise correlation coefficient for each country pair. Since a (Pearson's) correlation coefficient is bounded at -1 and 1 , the error terms in a regression model of the determinants of business cycle synchronization are unlikely to be normally distributed if the untransformed correlation coefficients are used. This complicates reliable inference. The transformed correlations do not suffer from this problem, since the transformation ensures that they are normally distributed (see David, 1949). This issue has not been addressed in most previous papers using these types of model, presumably under the assumption that the deviation from normality is sufficiently small. However, Fig. 3a – showing kernel density estimates of the untransformed correlation coefficients – suggests that this conjecture is false and hence it is necessary to transform the dependent variable. Fig. 3b shows that the transformed correlation coefficients are much closer to being normally distributed.⁸

In previous studies on the determinants of business cycle synchronization various indicators for trade intensity have been used.⁹ For instance, Frankel and Rose (1998) employ total trade (i.e. exports X and imports M) between two countries (i, j) scaled by

⁶Frankel and Rose (1998) followed a similar approach, using four periods of about 9 years.

⁷The results are generally robust to distinguishing from two up to eight different periods.

⁸See also Otto et al. (2001).

⁹The source for all our data on trade between countries is the new database by Feenstra et al. (2005).

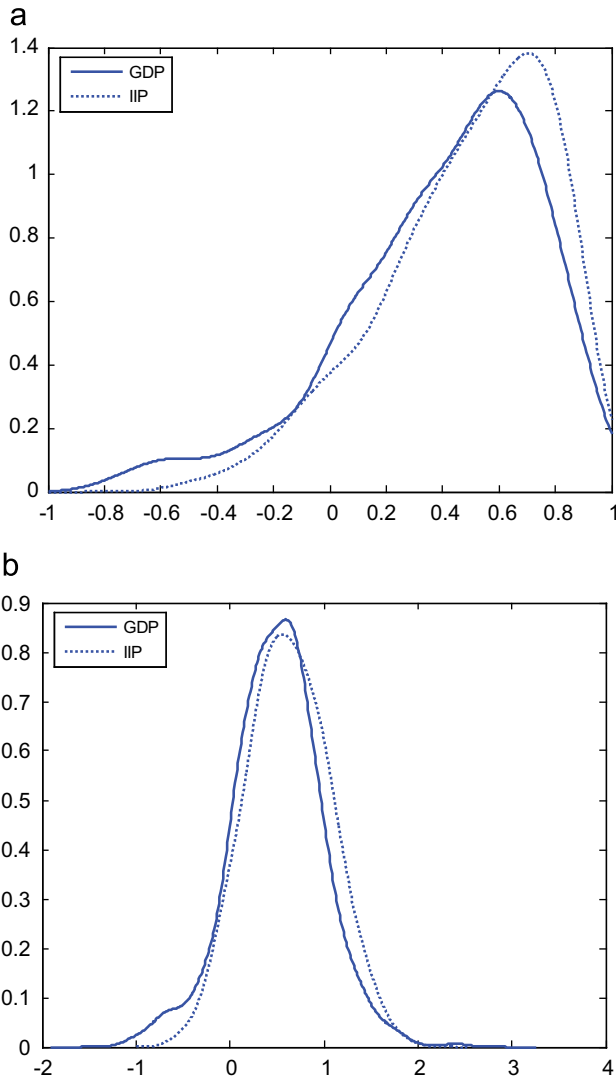


Fig. 3. (a) Estimated density plot of untransformed business cycle correlations. (b) Estimated density plot of transformed business cycle correlations.

total GDP (Y) or total trade.¹⁰ These are our first two indicators of trade intensity. Instead of using the sum of trade or GDP of the two countries as scaling factor, some authors prefer scaling by the product of GDP or trade of the two countries concerned (see, for instance, Clark and van Wincoop, 2001) as this indicator is not size-dependent. This yields

¹⁰As pointed out by Otto et al. (2001), the first measure suffers from obscuring one-way interdependence, the second suffers from not measuring the relative importance of trade in the total economy. Note that when using GDP as a scaling factor, we convert GDP at current national prices to US dollars using purchasing power parities from the OECD (2002) to take price differences between countries into account. All trade data are already converted using current exchange rates.

Table 1
Correlation coefficients between trade intensity measures

Correlation	TINT2	TINT3	TINT4	TINT5	TINT6
TINT1	0.52*	0.84*	0.73*	0.27*	0.58*
TINT2		0.58*	0.52*	0.60*	0.48*
TINT3			0.57*	0.29*	0.78*
TINT4				0.64*	0.57*
TINT5					0.51*

Notes: (*) denotes correlation significantly different from zero at 5% level. TINT1: bilateral trade, normalised by total trade of the two countries. TINT2: normalised by minimum of total trade of the two countries, TINT3: normalised by the product of total trade of the two countries. TINT4–6: same, but with GDP.

our third and fourth indicator of trade intensity. Finally, [Otto et al. \(2001\)](#) take the maximum of

$$\sum_t \frac{X_{ijt} + M_{ijt}}{Y_{it}}, \quad \sum_t \frac{X_{ijt} + M_{ijt}}{Y_{jt}}, \quad (2)$$

arguing that what matters is whether or not at least one country is exposed to the other. This is our fifth indicator of trade intensity. In this measure also trade can be used for normalization, yielding our final indicator of trade intensity. [Table 1](#) shows the correlation matrix of the six trade intensity measures. As these indicators are all (imperfect) proxies for trade intensity and it is not obvious which one has to be preferred, we combine them into a single measure using principal component analysis. Our trade intensity measure is therefore based on the common variation in the six individual trade intensity measures.¹¹ This combined measure is based on the largest eigenvalue and accounts for 64% of the total variance.¹²

We use three indicators of *specialization*, namely measures based on: Industrial specialization, export similarity and the share of intra-industry trade.

[Imbs \(2004\)](#) suggests the following measure for industrial specialization:

$$\frac{1}{T} \sum_t \sum_{n=1}^N |S_{in} - S_{jn}|, \quad (3)$$

where $s_{n,i}$ denotes the GDP share of industry n in country i .¹³ We have constructed three measures based on industrial (industrial?) specialization. Apart from the index suggested by [Imbs](#), we also use the squared differences — instead of the absolute difference of output shares as in [Eq. \(3\)](#)¹⁴ — as well as the correlation between the shares. Following [Baxter and Kouparitsas \(2005\)](#), we recast these specialization measures as similarity measures by subtracting the specialization measure from one. We have constructed these indicators using the 60-industry database of the Groningen Growth and Development Centre

¹¹However, we have also performed all analyses using the different trade intensity measures. Our results are robust for the selection of a particular trade measure (results available on request).

¹²The selection of one principal component is based on both the latent root criterion and the scree plot criterion. Furthermore, a measure based on the largest two eigenvalues has a correlation of 0.99 with the measure we use.

¹³This measure was first suggested by [Krugman \(1991\)](#).

¹⁴This measure was first suggested by [Kalemli-Ozcan et al. \(2001\)](#).

(GGDC, 2004), which has data on 56 industries covering the entire economy at the 2-digit and sometimes 3-digit level of industry detail (according to the ISIC revision 3 classification).¹⁵ As might be expected, the three measures of output similarity are highly correlated (between 0.87 and 0.96), so following similar reasoning and criteria as for the trade intensity measures, we use the first principal component of the three industrial specialization measures as our first indicator of specialization.¹⁶

Following Baxter and Kouparitsas (2005), we consider the similarity of exports as our second main indicator of specialization. As these authors point out, countries with similar baskets of traded goods will be affected similarly in the event of sector-specific shocks hitting their export and/or import sectors. Using the trade data by commodity (at the 4-digit SITC revision level of detail) of Feenstra et al. (2005), export shares are calculated for each country. The same three similarity measures as for industrial output shares are calculated for export shares. The correlation between these export similarity measures varies between 0.54 and 0.84, and the first principal component accounts for 78% of the variance and is justified by the selection criteria. Therefore, the first principal component of our three export similarity measures will be used as our second specialization indicator.

As a final indicator for specialization we use the intra-industry share, *IIT*. The variable *IIT* measures the share of bilateral trade that can be attributed to intra-industry trade. This index is defined as follows:

$$IIT_{ij} = 1 - \frac{\left| \sum_k (E_{ij}^k - E_{ji}^k) \right|}{\sum_k (E_{ij}^k + E_{ji}^k)}. \quad (4)$$

The share of intra-industry trade is calculated as one minus the absolute difference between exports of industry k from country i to country j and exports from country j to country i , divided by total bilateral trade (see Grubel and Lloyd, 1971). We calculate these indices using the database of Feenstra et al. (2005). The trade data by commodity are allocated to industries using a detailed concordance.¹⁷

Financial linkages could result in a higher degree of business cycle synchronization by generating large demand side effects. For instance, contagion effects that are transmitted through financial linkages could result in heightened cross-country spill-over effects of macroeconomic fluctuations. However, international financial linkages could also stimulate specialization of production through the reallocation of capital in a manner

¹⁵See www.ggdc.net for a thorough documentation of this database, as well as the most recent version. This database has a more extensive coverage than a possible alternative, i.e. the long-run UNIDO dataset. For manufacturing, both databases contain roughly the same number of industries (28 for UNIDO, 27 for GGDC), but the Groningen data are based on a more recent industrial classification (ISIC revision 3, vs revision 2 for UNIDO), containing more detailed information about industries that have become more important in recent decades, such as computers and other electronic equipment. This coverage is full and consistent over the entire period of the database (1970–2003). There is also a UNIDO database with more extensive industry detail, but this only contains data going back to 1990. More importantly though, the 60-industry database also covers a large number of non-manufacturing industries (29). As one of our synchronization measures uses GDP as the output measure, including non-manufacturing industries in the calculation of the specialization measure should be more appropriate since industry-specific productivity shocks may be an important factor.

¹⁶The first principal component accounts for 94% of the variance.

¹⁷Industries are defined at the 4-digit level of the international standard classification (ISIC rev. 2). See <http://www.maclester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html>.

consistent with countries' comparative advantages. Following Imbs (2004), we consider two indicators for *financial integration*: An indicator for capital account restrictions, and the (absolute) difference between the net foreign asset (NFA) positions of a country pair. The capital account restriction variable is based on information provided by Lane and Milesi-Ferretti (2001) and updated using the IMF publication *Exchange arrangements and exchange restrictions*, which gives an overview of capital and current account restrictions for each country. Our first measure of financial integration is the number of years in which at least one of the countries had a capital account restriction relative to the total number of years in the period as our proxy for capital account restrictions. For the NFA data, we again rely on Lane and Milesi-Ferretti (2001). They present two estimates, one based on cumulated current account data and one based on cumulated capital accounts. As the capital account-based measure is available for fewer years in most countries, we rely on the cumulated current accounts. Our second financial integration measure is calculated as the absolute difference between accumulated current account to GDP ratios.

4. Estimation results

The first two rows of Panel A of Table 2 present our replication of the main results of Frankel and Rose (1998), i.e. the OLS and instrumental variables estimates of the effect of trade on business cycle correlation. In addition to the instruments used by Frankel and Rose (1998), i.e. distance, an adjacency dummy and a dummy for common language, we also use a variable measuring geographical remoteness and a dummy for common legal origin.¹⁸

The OLS and instrumental variables estimates of the trade coefficient are positive and highly significant and comparable for the two measures of economic activity. Like Frankel and Rose, we find that the coefficients are lower and less significant when bilateral trade intensity is normalized by output. The instrumental variables estimates are similar in magnitude as those reported by Frankel and Rose (1998) and considerably higher than the OLS estimates.

Row 3 of Panel A of Table 2 shows the results using our preferred indicator of trade intensity (the first principal component of six different measures of trade), while row 4 presents the findings if we transform the dependent variable. The coefficients of our preferred trade indicator are highly significant, suggesting that the qualitative conclusion that trade intensity is positively related to business cycle correlation is not sensitive to the measurement of trade intensity. Transforming the dependent variable yields higher coefficients, but due to the transformation it is not straightforward to compare the coefficients with the estimates of rows 1–3. In order to make a meaningful comparison, Panel B of Table 2 presents the standardized trade coefficients. We not only show the point estimates, but also the 95% confidence interval. These results suggest that the use of the

¹⁸All these instruments are highly significant in explaining trade intensity and the F-statistic of the first-stage regression is 157. Legal origin has also been used to directly explain output co-movement (e.g. Otto et al., 2001) but we argue that the main effect of a common legal origin is via trade: The correlation between legal origin and trade intensity is 0.40, while the correlation with the GDP and IP correlations are 0.23 and 0.11, respectively. As the 95% lower bound of the legal origin-trade intensity correlation is 0.27, the link with trade is significantly stronger than the link with output correlations.

Table 2
Replication of the Frankel–Rose model using our data (effect of trade intensity on output correlation)

	OLS		IV	
	IIP	GDP	IIP	GDP
<i>Panel A</i>				
(1) Bilateral trade, normalised by total trade	0.031** (6.5)	0.025** (4.3)	0.060** (7.1)	0.061** (5.4)
(2) Bilateral trade, normalised by total GDP	0.009** (6.7)	0.010** (6.3)	0.016** (7.7)	0.016** (6.2)
(3) Bilateral trade, factor score	0.074** (7.1)	0.086** (6.2)	0.125** (8.3)	0.140** (6.7)
(4) Bilateral trade, factor score, transformed correlation	0.127** (7.0)	0.125** (6.0)	0.204** (8.4)	0.203** (6.7)
<i>Hausman test (H0: OLS is consistent; critical 5% value: 6.0)</i>				
Bilateral trade, normalised by total trade			21.0	18.3
Bilateral trade, normalised by total GDP			24.6	11.4
Bilateral trade, factor score			22.2	13.3
Bilateral trade, factor score, transformed correlation			24.5	14.5
<i>Panel B</i>				
<i>Standardized coefficients</i>				
Bilateral trade, normalised by total trade	0.08	0.07	0.07	0.08
Bilateral trade, normalised by total GDP	0.08	0.09	0.08	0.08
Bilateral trade, factor score	0.07	0.08	0.10	0.11
Bilateral trade, factor score, transformed correlation	0.13	0.12	0.16	0.15
<i>Lower bound–upper bound of standardized coefficient</i>				
Bilateral trade, normalised by total trade	[0.06–0.11]	[0.04–0.10]	[0.05–0.09]	[0.05–0.11]
Bilateral trade, normalised by total GDP	[0.06–0.10]	[0.06–0.12]	[0.06–0.10]	[0.06–0.11]
Bilateral trade, factor score	[0.05–0.09]	[0.06–0.11]	[0.08–0.12]	[0.08–0.14]
Bilateral trade, factor score, transformed correlation	[0.09–0.16]	[0.08–0.16]	[0.12–0.20]	[0.11–0.19]

Notes: t-statistics, consistent for heteroscedasticity, are in parentheses.

**Significantly different from zero at 1% level.

transformed dependent variable leads to a somewhat stronger impact of trade on business cycle synchronization.

Next, we estimate a structural model representing Fig. 1. The model consists of three equations (see below for further details). For the variables to be included in F , we rely on the results of the EBA as described in the appendix. It turns out that both financial integration measures are not robustly related to business cycle synchronization. This finding is in line with the results of Baxter and Kouparitsas (2005). In contrast, all three specialization measures appear robustly related to business cycle synchronization.¹⁹ It follows from Table A1 that apart from the specialization measures also some other variables are considered robust. The correlation of short-term interest rates and the correlation of cyclically adjusted budget deficits are robustly related to business cycle

¹⁹The measure of industrial similarity does not pass the test with GDP as the dependent variable, but we include it to facilitate the comparability of results across specifications.

synchronization no matter whether we focus on GDP correlation or IP correlation. For the GDP-based measure of synchronization, exchange rate variability is also robust.²⁰

Our model is formulated as follows.²¹ In Eq. (5a), the transformed correlation coefficient (C) is the dependent variable and the explanatory variables are those suggested by the EBA analysis reported in the Appendix, i.e., our indicators of trade (T), specialization (S), fiscal policy (D), monetary policy (M) and (for the GDP model) exchange rate variability (E). In Eq. (5b), T is the dependent variable while the explanatory variables are the gravity variables (G), specialization (S), fiscal policy (D), monetary policy (M) and exchange rate variability (E). In Eq. (5c), specialization (S) is explained by the gravity variables (G), trade (T) and financial integration (I). We suppress country suffixes:

$$C = \alpha_0 + \alpha_1 T + \alpha_2 S + \alpha_3 D + \alpha_4 M + \alpha_5 E + \varepsilon, \quad (5a)$$

$$T = \beta_0 + \beta_1 G + \beta_2 S + \beta_3 D + \beta_4 M + \beta_5 E + \mu, \quad (5b)$$

$$S = \delta_0 + \delta_1 G + \delta_2 T + \delta_3 I + \omega. \quad (5c)$$

Table 3 shows the estimation results for the model. Apart from the three stage least squares (3SLS) model, we also have estimated Eq. (5a) via OLS. On the basis of the Hausman (1978) test we decide whether the 3SLS or the OLS model should be preferred. As we are mainly interested in the effect of trade on business cycle synchronization, we only report the results for Eq. (5a) in Table 3.²²

It follows from Table 3 that almost all explanatory variables are significant with the expected sign. So more correlated monetary policy, more similar fiscal policy,²³ more similar industrial and export structures, more intra-industry trade and less exchange rate variability are related to more similar business cycles.

One concern with our results is that our policy variables (the correlation of short-term interest rates and the correlation of cyclically adjusted budget deficits) might be endogenous to trade. We have dealt with this issue in the following way. First, we have done an EBA for both policy variables, using all the variables in our data set as potential explanatory variables. Lacking solid theoretical or empirical guidance, we selected the variables in the M -vector on the basis of a general-to-specific approach and included the remaining variables in the Z -vector. It turned out that our trade variable was not robustly related to our policy variables (the cumulative distribution function (CDF) (0) tests were 0.51 for the correlation of short-term interest rates and 0.54 for the correlation of budget deficits). Second, we have expanded our structural model and included equations to explain our variables for the similarity of monetary and fiscal policy. To identify the (approximately) exogenous variation in these variables, we added an Economic and Monetary Union (EMU) dummy in the equation for the correlation of short-term interest rates and the instruments used in a similar context by Darvas et al. (2007) in the equation

²⁰For the IP correlations, measures reflecting differences in capital stocks and arable land are also robust for some combinations of financial integration and specialization measures. Since they frequently fail this test and are also not robustly related to the GDP-based measure of synchronization, we have not included them here.

²¹Our model is similar to the model of Imbs (2004), except that we do not have an equation for financial integration as this variable did not pass the EBA robustness test.

²²All other results are available on request.

²³Independent of our research, Darvas et al. (2007) find for a panel of 21 OECD countries and 40 years of annual data also that fiscal convergence (in the form of persistently similar ratios of government surplus/deficit to GDP) is systematically associated with more synchronized business cycles.

Table 3
Effect of trade intensity on output correlation using a structural model

Specialization measure	Industrial similarity		Export similarity		Share of intra-industry trade	
	OLS	3SLS	OLS	3SLS	OLS	3SLS
<i>GDP</i>						
Trade	0.055** (2.64)	0.051 (1.61)	0.060** (2.81)	0.132** (3.23)	0.052* (2.22)	0.099* (2.03)
Specialization measure	0.044 (1.93)	0.121 (1.61)	0.070** (3.59)	0.030 (0.46)	0.358* (2.39)	0.332 (1.12)
Correlation of short-term interest rates	0.271** (5.00)	0.271** (4.83)	0.159** (2.95)	0.160* (2.21)	0.168** (3.10)	0.153* (2.46)
Correlation of cyclically adjusted budget deficits	0.196** (5.34)	0.193** (4.71)	0.159** (4.23)	0.153** (3.72)	0.152** (4.08)	0.147** (3.58)
Exchange rate variability	-1.798** (3.70)	-1.809** (3.59)	-1.540** (3.33)	-1.113* (2.17)	-1.549** (3.38)	-1.201* (2.37)
<i>IIP</i>						
Trade	0.094** (4.60)	0.110** (4.76)	0.072** (3.95)	0.133** (4.93)	0.049* (2.49)	0.104** (3.32)
Specialization measure	0.077** (4.55)	0.046 (0.81)	0.124** (7.90)	0.089* (2.15)	0.759** (7.45)	0.556** (2.75)
Correlation of short-term interest rates	0.389** (9.39)	0.390 (8.75)**	0.175** (4.34)	0.183** (3.93)	0.182** (4.67)	0.191** (4.54)
Correlation of cyclically adjusted budget deficits	0.149** (4.50)	0.150** (4.34)	0.176** (6.05)	0.174** (5.39)	0.167** (5.70)	0.169** (5.33)
<i>Hausman test (H0: OLS is consistent), prob > χ^2</i>						
GDP		0.68		0.08		0.56
IIP		0.92		0.01		0.53

Notes: constant included; robust t-statistics, consistent for heteroscedasticity are in parentheses. Significantly different from zero at 5% level (*) or at 1% level (**).

for the correlation of cyclically adjusted budget deficits. In a second variant, we also included the gravity variables in the equations for the similarity of monetary and fiscal policy. The results of these five-equations models were very similar to those reported in Table 3, suggesting that endogeneity concerns play no major role in our main result.²⁴

The main finding in Table 3 is that the trade coefficients are much smaller than those previously found. For instance, whereas the standardized coefficient in the Frankel–Rose specification for the GDP-based model is 0.12, in our structural model it is only 0.05. The standardized trade coefficients for the IP-based model are 0.13 and 0.05, respectively.²⁵ The Hausman tests confirm that the model specification has improved compared to Table 2: Most tests no longer reject the null hypothesis that the OLS estimates are

²⁴All results are available on request.

²⁵These figures are based on the OLS results for Eq. (5a). Since the trade variable is not significant in Eq. (5c), the standardized coefficients of the 3SLS estimates are very similar.

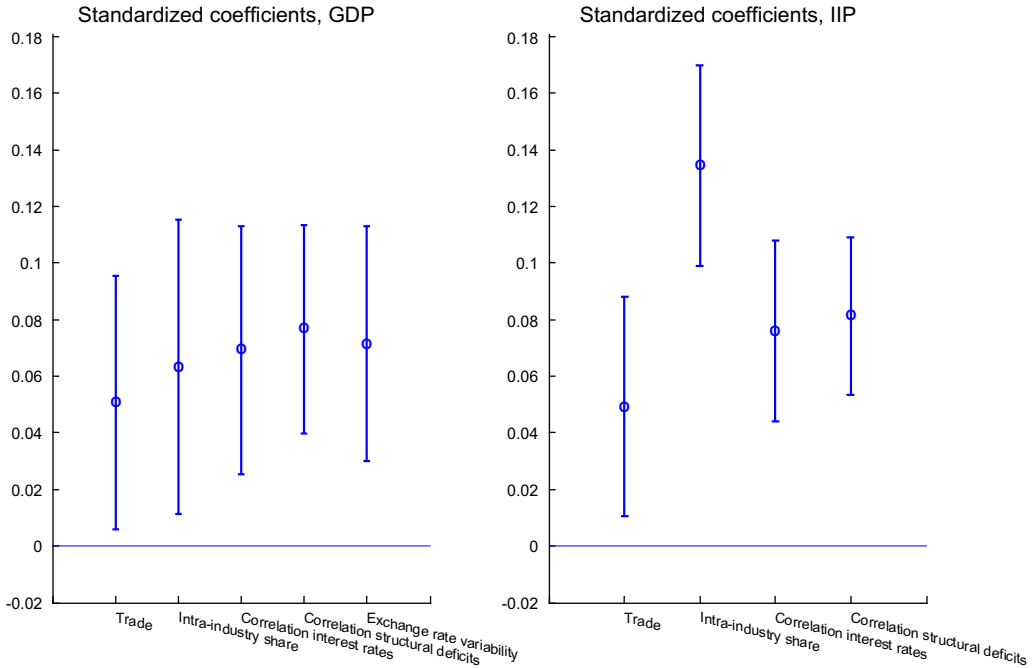


Fig. 4. Standardized coefficients of explanatory variables (intra-industry specification, absolute values).

consistent. Because Frankel and Rose (1998) did not specify a full model, they overestimated the impact of trade on output correlation.

Fig. 4 shows the standardized coefficients of the model with the share of intra-industry trade as specialization measure. The point estimate as well as the 95% confidence interval is shown. It follows that the point estimate of the impact of almost all variables — like the correlation of short-term interest rates or the correlation of cyclically corrected budget deficits — is similar to the impact of trade intensity. So our evidence suggests that variables that reflect common economic policies and specialization are at least as important as strong trade ties for synchronization of business cycles.

Finally, Fig. 5 compares the standardized coefficients of the three specialization measures that we use. Again, the point estimate as well as the 95% confidence interval is shown. It follows that the point estimate of the impact of industrial similarity is the lowest. In view of the upper and lower bounds one has to be careful in drawing too strong conclusions, but the evidence suggests that trade-based specialization measures have a larger impact on business cycle synchronization than industry-structure-based specialization measures. This is most visible for the standardized coefficients of the models based on industrial production.

5. Sample heterogeneity and outliers

So far, we have focused on the conditional mean of business cycle correlations as a linear function of bilateral trade and other structural and policy related variables. However, it is

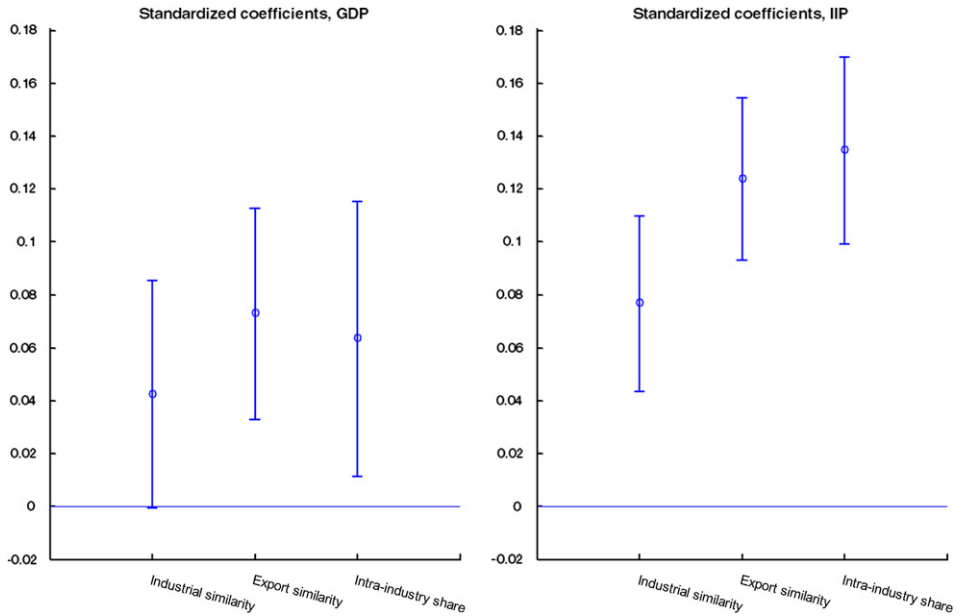


Fig. 5. Standardized coefficients of specialization measures.

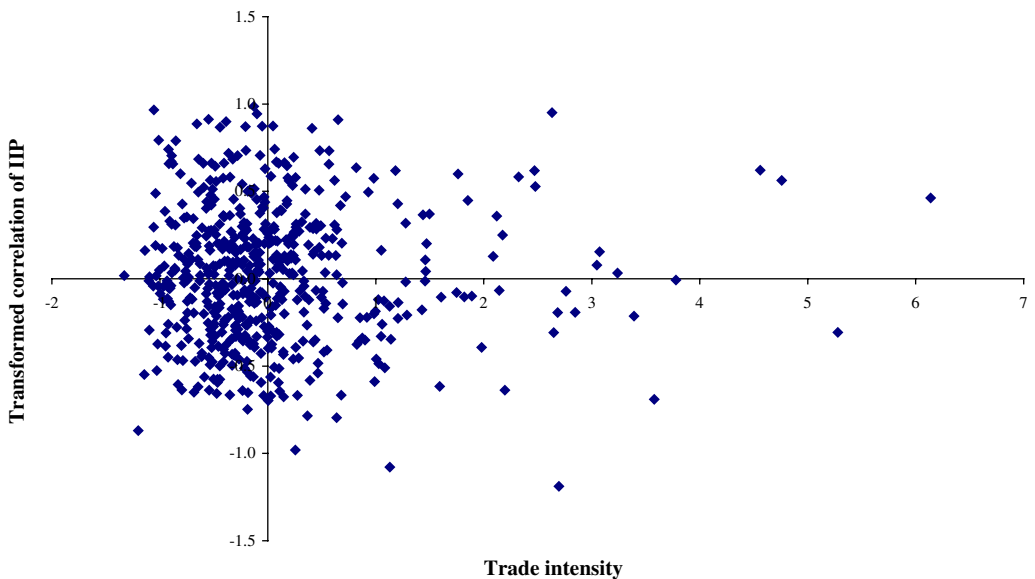


Fig. 6. Scatter diagram of industrial production correlations and trade (after conditioning on control variables).

well known that outliers in the regressand as well as the regressors may seriously influence OLS estimates. Fig. 6, which shows a scatter diagram of industrial production correlations and trade (after conditioning on control variables), suggests that there are various

Table 4
OLS vs LTS/RWLS

Specialisation measure	Industrial similarity		Export similarity		Share of intra industry	
	OLS	LTS/RWLS	OLS	LTS/RWLS	OLS	LTS/RWLS
<i>GDP</i>						
Trade	0.055** (2.64)	0.05** (2.38)	0.060** (2.81)	0.04* (2.14)	0.052* (2.22)	0.03 (1.55)
Specialisation measure	0.044 (1.93)	0.06** (3.11)	0.070** (3.59)	0.07** (3.78)	0.358* (2.39)	0.51** (4.40)
Correlation of short-term interest rates	0.271** (5.00)	0.30** (6.27)	0.159** (2.95)	0.20** (4.58)	0.168** (3.10)	0.20** (4.55)
Correlation of structural deficits	0.196** (5.34)	0.18** (4.99)	0.159** (4.23)	0.18** (5.41)	0.152** (4.08)	0.18** (5.55)
Exchange rate variability	-1.798** (3.70)	-1.77** (-4.21)	-1.540** (3.33)	-1.86** (-4.81)	-1.549** (3.38)	-1.53** (-3.95)
<i>IIP</i>						
Trade	0.094** (4.60)	0.14** (7.77)	0.072** (3.95)	0.08** (5.29)	0.049* (2.49)	0.05** (3.12)
Specialisation measure	0.077** (4.55)	0.07** (4.24)	0.124** (7.90)	0.12** (7.47)	0.759** (7.45)	0.75** (7.74)
Correlation of short-term interest rates	0.389** (9.39)	0.41** (9.84)	0.175** (4.34)	0.24** (6.18)	0.182** (4.67)	0.22** (5.75)
Correlation of structural deficits	0.149** (4.50)	0.17** (5.22)	0.176** (6.05)	0.18** (6.07)	0.167** (5.70)	0.18** (5.80)

Notes: constant included; robust t-statistics, consistent for heteroscedasticity are in parentheses. Significantly different from zero at 5% level (*) or at 1% level (**).

observations that are quite far away from the bulk of the observations and these may drive our results.²⁶ In this section, we therefore report the estimation results using the LTS estimator of Rousseeuw (1984, 1985) to identify outlying observations. Furthermore, we employ quantile regressions to examine sample heterogeneity (see Koenker and Bassett, 1978 or Koenker and Hallock, 2001 for a non-technical overview).

The basic principle of LTS is to fit the majority of the data, after which outliers may be identified as those points that lie far away from the robust fit. LTS typically minimizes the sum of squares over half the observations, the chosen half being the combination that gives the smallest residual sum of squares. Although this method is particular suited to identify leverage points, it is not suited for inference. As proposed by Rousseeuw (1984), this can be resolved by using re-weighted least squares (RWLS). A simple, but effective, way is to give a weight of zero to all observations identified as outliers and a weight of one to all other observations (Sturm and De Haan, 2005).

Table 4 shows the results of the LTS/RWLS estimates. For comparison purposes, we first repeat the OLS results of Table 3. Overall, there are no large differences between the OLS estimates and the robust estimates. However, there are exceptions. In the models for the GDP-based correlations, the bilateral trade coefficient loses significance in one specification. This is quite remarkable, as almost all other variables remain significant at

²⁶Fig. 6 shows the residuals of the regression of business cycle correlation for industrial production on the control variables against the residuals of the regression of bilateral trade on these same control variables.

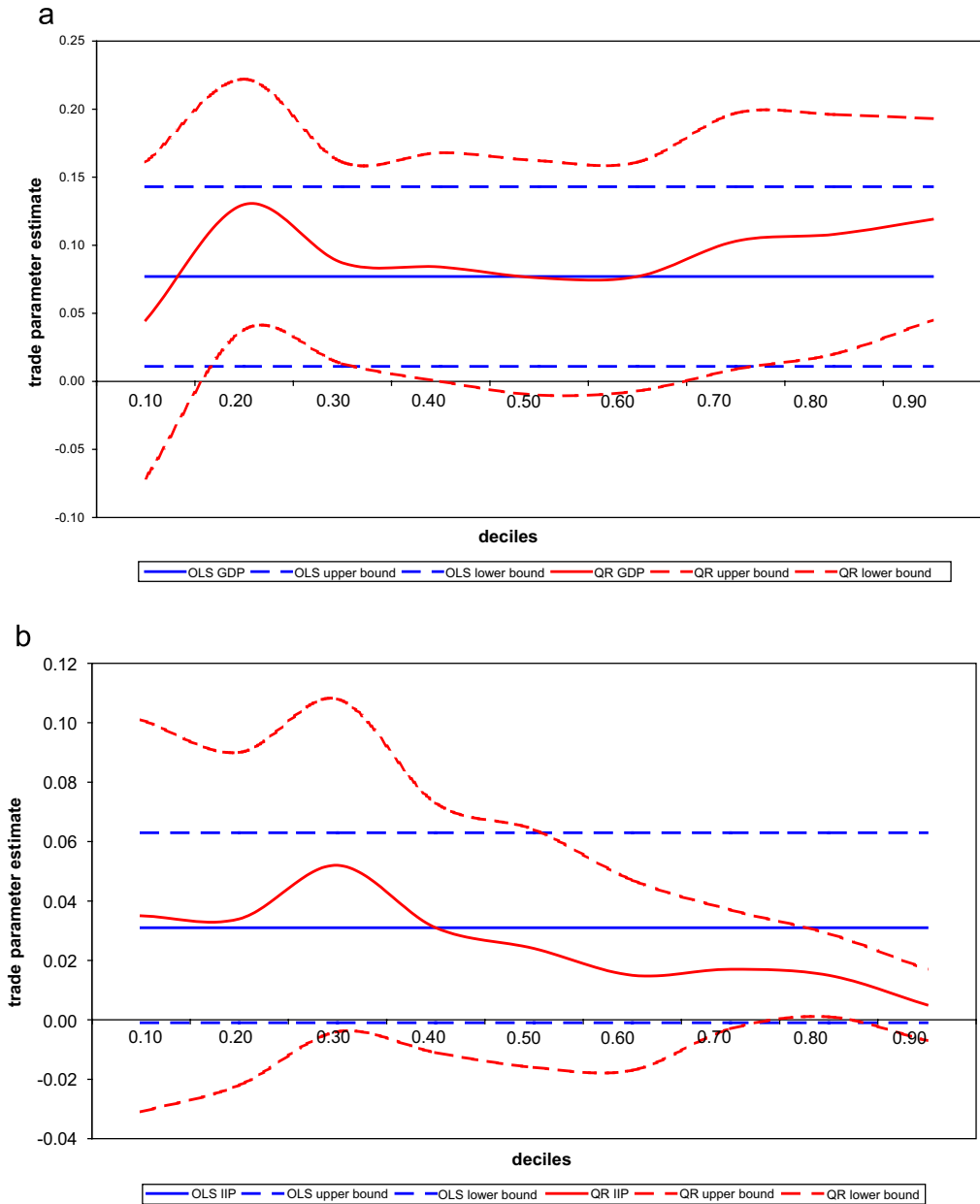


Fig. 7. (a) Quantile regression plot, GDP model. (b) Quantile regression plot, IIP model.

the 5% level. Still, in the models for industrial-production-based correlations the significance of the trade variable increases. So we therefore conclude that, in general, the effect of trade on business cycle synchronisation is not driven by outliers.

Quantile regression is an appropriate tool to address sample heterogeneity across different quantiles as shown by [Koenker and Bassett \(1978\)](#). OLS focuses on the mean of

the dependent variable given the explanatory variables. Quantile regressions are used to analyze other parts of the conditional distribution, such as the (conditional) median or specific deciles. In order to increase the degrees of freedom, we divide the sample period 1970–2003 into eight different periods and ran the same regressions as in Table 3.

Fig. 7 shows the estimated coefficients of the trade intensity variable for each decile, using the model in which the share of intra-industry trade is used as specialization measure.²⁷ It follows that the relationship between the correlation of business cycles and bilateral trade is not robust across deciles. Although the estimates for the trade coefficient are very similar to the OLS estimates and always lie within the 95% confidence interval of the OLS estimates, the coefficient is only significant for some conditional deciles. Moreover, the estimates of the IIP model suggest that the trade effect is decreasing for country pairs in the higher deciles. That is, for countries with already highly synchronized business cycles trade has a somewhat smaller effect on the correlation of business cycles.

6. Concluding comments

We have re-examined the relationship between trade intensity and business cycle synchronization for a sample of 21 OECD countries over the period 1970–2003, using the Fisher transformed bilateral correlation of detrended real economic activity (GDP and industrial production) as dependent variable. Including variables capturing similarity of monetary and fiscal policies, financial integration and specialization in a multivariate model, we confirm the finding that trade intensity affects business cycle synchronization, but the effect is much smaller than previously reported. Furthermore, the other factors included in the model have at least as strong an effect on business cycle synchronization as trade intensity. Finally, our results suggest that the effect of trade on business cycle synchronization is robust for outlying observations, but the relationship between the correlation of business cycles and bilateral trade is not robust across deciles.

Our results suggest that the well-known critique of the EMU that a common monetary policy may not be equally good for all countries in the union (“one size does not fit all”), may have lost force due to the economic and monetary integration process. Since monetary and fiscal policies have become more similar in Europe and intra-industry trade has increased substantially, our findings suggest that the “fit” of the common monetary policy has increased as the member countries’ business cycles have become more aligned.

Acknowledgments

We thank Kees Bouwman, Paul Bekker, Jan Jacobs and the other participants in the IEE seminar as well as Jan-Egbert Sturm for their comments and suggestions. We are also very grateful to two anonymous referees for their very helpful comments on a previous version of this paper.

²⁷For brevity, only the estimates across deciles for bilateral trade are shown. Full results are available upon request.

Appendix A

The extreme bounds analysis (EBA) used to select the variables used in the structural model are given in Table A1.

Table A1

Variable	Source	Suggested by	Robust in model for	
			GDP correlation	IP correlation
Short-term interest rate correlation	IMF, International Financial Statistics (IFS)	Otto et al. (2001)	Yes	Yes
Cyclically adjusted budget deficits correlation	OECD Economic Outlook (vol. 76)	Camacho et al. (2007)	Yes	Yes
Capital account restrictions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Difference (absolute) in Net foreign asset positions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Share of intra-industry trade (IIT)	Feenstra et al. (2005)		Yes	Yes
Industrial similarity	GGDC 60-industry database	Imbs (2004)	No	Yes
Export similarity	Feenstra et al. (2005)	Baxter and Kouparitsas (2005)	Yes	Yes
Exchange rate variability	IFS	Otto et al. (2001)	Yes	No
Average openness	IFS and GGDC Total Economy Database	Baxter and Kouparitsas (2005)	No	No
Import similarity	Feenstra et al. (2005)	Baxter and Kouparitsas (2005)	No	No
Human capital difference	OECD Labour Force Statistics	Baxter and Kouparitsas (2005)	No	No
Physical capital difference	GGDC Total Economy Growth Accounting Database	Baxter and Kouparitsas (2005)	No	No
EMS-dummy		Frankel and Rose (1998)	No	No
Average oil import share	World Bank, World Development Indicators (WDI)	Artis (2004)	No	No
Correlation of inflation rates	IFS	Camacho et al. (2007)	No	No
Variability in inflation rate difference	IFS	Camacho et al. (2007)	No	No
Current account restrictions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Human capital (tertiary education)	OECD Labour Force Statistics	Baxter and Kouparitsas (2005)	No	No
Arable land difference	WDI	Baxter and Kouparitsas (2005)	No	No
Relative labour productivity level	GGDC Total Economy Database	Baxter and Kouparitsas (2005)	No	No
Relative financial structure (credit/stock)	Beck et al. (1999)	Artis (2004)	No	No
Difference in national savings ratio	OECD National Accounts	Camacho et al. (2007)	No	No

Notes: A more detailed description of the variables and sources, as well as the data is available at www.rug.nl/economics/inklaarrc.

The EBA as suggested by Leamer (1983) and Levine and Renelt (1992) is used to determine the list of variables to be included in the structural model outlined in the main text. The EBA has been widely used in the economic growth literature (see Sturm and De Haan (2005) for a further discussion). Baxter and Kouparitsas (2005) also use this methodology (using a different set of countries and a more limited number of possible explanatory variables than in the present paper) to examine which variables are robustly related to business cycle synchronization. The EBA can be exemplified as follows. Equations of the following general form are estimated:

$$Y = \alpha M + \beta F + \gamma Z + u, \quad (\text{A.1})$$

where Y is the dependent variable (output correlation); M is a vector of ‘standard’ explanatory variables; F is the variable of interest; Z is a vector of up to three (here we follow Levine and Renelt, 1992) possible additional explanatory variables, which according to the literature may be related to the dependent variable and u is an error term. In our analysis only trade intensity is included in the M vector. As explained in the main text, the various proxies for financial integration and specialization are not considered simultaneously. Following Sala-i-Martin (1997), we use the unweighted cumulative distribution function (CDF (0)), i.e. the fraction of the cumulative distribution function lying on one side of zero, and the percentage of the regressions in which the coefficient of the variable of interest differs significantly from zero. Following Sturm and De Haan (2005), a variable is considered to be robust if the CDF (0) test statistic > 0.95 and if the variable has a significant coefficient (at the 5% significance level) in 90% of all regressions ran.

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