CESifo WORKING PAPERS

10970
2024

February 2024

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
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CESifo *Working Paper No. 10970*

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Abstract

We introduce the technique of band spectral panel regression (BSPR) to analyze global linkages across sectors and frequency bands. It relies on decomposing time series —allowably measured in mixed observation frequency— into "deviation cycle" dynamics by frequency band. We use it to compute measures of real co-movement, trade linkage, financial market integration, and policy coordination band by band. Considering intra-industry as well as inter-industry linkage indicators, it is applied to data of contemporary China and its 20 major trading partners in the pre-trade war and pre-pandemic era. Band-specific fixed effects and band-industry-specific interaction terms are included. For labor intensive industries co-movement through intra-industry trade linkages is found to be band-specific. Moreover, our results clarify the puzzle of financial globalization implying real regionalization or contagious synchronization of cyclical dynamics. We find the latter to hold in the 4–6 years band and the former in the 6–10 years range.

JEL-Codes: C320, C490, E320, F400.

Keywords: spectral regression, frequency domain, cyclical co-movement, sectors.

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We would like to thank Bastian Gawellek and Marco Sunder for their excellent research assistance, Argimiro Arratia, Jörg Breitung, Maximilian Jager, Helmut Lütkepohl, and Gregor von Schweinitz for many valuable comments and suggestions as well as participants of the ITISE Inter-national Work-Conference on Time Series Analysis at the University of Granada, the IWH-CIREQ-GW Macroeconometric Workshop on Mixed Frequency Data in Macroeconomics and Finance, the Workshop on Macroeconomic Research at UEK Cracow University of Economics, and the Leipzig University Economics Lunchtime Seminar for many helpful discussions. The usual disclaimer applies.
Declaration of interest: none.

1 Introduction

At the latest since the collapse of the Bretton Woods exchange rate system in the early 1970s, global linkages, co-movement, and spillover effects across nations of the world economy got in the focus of a broad research agenda both from a theoretical as well as empirical perspective (Cheung and Westermann, 2013). Since the last two decades the theoretical and empirical literature stresses the dependency of these phenomena on the heterogeneity of sectors (Azcona, 2022; Belke and Heine, 2006; Bierbaumer-Polly et al., 2016; Kalemli-Ozcan et al., 2001; Korinek et al., 2010; Shrawan and Dubey, 2022) and on differences in periodicities of analyzed dynamics, that is, on the specific frequency bands considered (Aguiar and Gopinath, 2007; Ahmed et al., 2004; Blonigen et al., 2014; Kose et al., 2012; Nachane and Dubey, 2013, 2018, 2021). The recent United States (US)-China trade war, the COVID-19 pandemic, and the Russia-Ukraine war substantially furthered the discussion (Benguria et al., 2022; Bohn et al., 2021; Li and Su, 2022). Due to the unforessen occurence and mostly exogenous nature of these events, the focus of the present study, however, is on the pre-US-China trade war era.

Sector structures dominated by broadly defined sectors with large common shocks tend to cyclical coupling and ultimately to global interdependence of dynamics at short-term and long-term horizons. The opposite applies to sector structures dominated by broadly defined sectors with idiosyncratic small shocks. In the first case financial constraints are globally contagious across sectors and nations, whereas in the second case they are not or only regionally contagious across emerging market economies (EME). The latter is due to some EME industry potentially benefiting from the decline of the same sector or a related industry in an advanced economy that competes for the same inputs. Asynchronous production dynamics or decoupling results; see, e.g., Korinek et al. (2010).

Ahmed et al. (2004) can be interpreted as suggesting integrated inventory management and other business practices –mostly concerning intra-industry rather than inter-industry interdependency– to imply synchronicity at relatively high frequencies. However, it is unclear whether this applies to both advanced economies and EME. Co-movement due to monetary and fiscal policy coordination is expected primarily at business-cycle frequencies, whereas co-movement due to technological innovations at all frequencies alike. Growth spillovers, on the other hand, can be of "cyclical growth" or "secular growth" nature. This distinction is a well-known difficulty (Aguiar and Gopinath, 2007), in particular, in the

EME context.[1] These type of spillovers are likely to be attributable to trade intensity and specialization, technology transfers, or inflows of foreign direct investment (FDI). Co-movement at distinct, though in any case, rather low-frequency bands might be explained, for instance, by different shades of liquidity and different modes of entry, such as greenfield and mergers and acquisition (Aguiar and Gopinath, 2007; Gawellek et al., 2021).

Astonishingly, these two strands of recent literature, studying the role of sectors for global interdependence on the one hand and of frequency bands on the other, have not been satisfyingly integrated so far. Our study seeks to contribute to the literature in this regard and tries to shed some light on global linkages across sectors and frequency bands. To this end, we consider five broadly defined sectors classified by factor intensity and four different frequency bands in the empirical section of our study.

Our second central contribution is of methodological nature as we introduce the technique of band spectral panel regression (BSPR). The band spectral panel regression (BSPR) model is, in some sense, a panel version of the more general band spectral regression model (Assenmacher-Wesche and Gerlach, 2008a; Corbae et al., 2002; Engle, 1972, 1974). It relies on dissecting time series that can be measured in different frequency –e.g. in monthly, quarterly, and annual frequency– into "deviation cycle" dynamics by frequency band (Artis et al., 2004).[2] The dissected components allow us to compute measures of co-movement, trade linkage, market integration, and policy coordination by frequency band irrespective of the observation-frequency of the underlying time series. The resulting panel structure consists in entities, referring to economies, and frequency bands, referring to periodicities of cyclical dynamics, rather than entities and time as in standard panel models. BSPR models are flexible in allowing for band-specific fixed effects and band-industry-specific interaction terms. Considering intra-industry as well as inter-industry linkage indicators, we apply the proposed method to data of contemporary China and its major trading partner economies from 1997 to 2016, i.e. prior to the US-China trade war. For motives and consequences of the latter against the backdrop of protectionsim and global

[1]The related strand of literature on the Prebisch-Singer hypothesis and secular low frequency super cycles (Erten and Ocampo, 2013; Harvey et al., 2010) in real commodity prices has made some methodological progress in this regard. It consists in substantially increasing the power of augmented Dickey-Fuller (ADF) tests by including a frequency domain component, referred to as flexible Fourier component (FFC), in the ADF testing procedure (Enders and Lee, 2012; Winkelried, 2018).

[2]Note, other decompositions such as empirical mode decompositions in the course of Hilbert-Huang transforms might be considered alternatively (Ju et al., 2014).

linkages see Benguria et al. (2022), Guo et al. (2018), Noland (2018), Sheng et al. (2019).

The remainder of the paper is organized as follows. Section 2 starts with some principles of spectral and band spectral regression analysis underlying the BSPR approach. It continues with an outline of how to implement the BSPR model relying on deviation-cycle filtering. In Section 3 an application of the proposed technique studying global linkages across sectors and frequency bands is given. Section 4 concludes.

2 Band Spectral Panel Regression

2.1 Principles of spectral analysis and band spectral regression

The methodological starting point of spectral analysis as canonical analogue to autocorrelation analysis in the time domain is the representation of a time series X_t as a periodic (sinusoidal) component with known period length, i.e.

$$X_t = R\cos(\omega t + \phi) + z_t, \tag{1}$$

where z_t is assumed to represent a stationary mean-zero random variable, R denotes amplitude, angle $(\omega t + \phi)$ is measured in radians with π radians (i.e. 180 degrees), and ω is denoting the angular frequency (or frequency expressed in radians), i.e. the number of radians per unit of time. Angular frequency ω is related to ordinary frequency f, i.e. the number of completed cycles per unit of time, by $f = \frac{\omega}{2\pi}$. Period or periodicity $\mathbb{P}$ of a cyclic pattern is given by $\mathbb{P} = f^{-1}$. Thus, the highest measurable frequency – referred to as "Nyquist (NQ) frequency"– correponds to $\omega_{NQ} = \pi \Leftrightarrow f_{NQ} = \frac{1}{2} \Leftrightarrow \mathbb{P}_{NQ} = 2$. It describes a two-period cycle, i.e., for a mean-zero stationary series a dynamics alternating from negative support to positive support with peak-to-peak or trough-to-trough distance equaling two periods ($\mathbb{P}_{NQ} = 2$). Given that any series can be expressed as the superposition of several such periodic components with different amplitude, frequency, and phase shift, we may write

$$E(X_t) = \sum\nolimits_{j=1}^{k} R_j \cos(\omega_j t + \phi). \tag{2}$$

From a central property of trigonometric functions, $\cos(\omega t + \phi) = \cos\omega t \cdot \cos\phi - \sin\omega t \cdot \sin\phi$, it follows that

$$\begin{aligned} E(X_t) &= \sum\nolimits_{j=1}^{k} (a_j \cos\omega_j t + b_j \sin\omega_j t) \quad \text{with} \\ a_j &= R_j \cos\phi_j t;\; b_j = -R_j \sin\phi_j t, \end{aligned} \tag{3}$$

that is, amplitudes are themselves now given by sinusoidal laws of motion.

Periodogram analysis or, in general, the spectrum decomposes the variance of stochastic process X_t into its "p-th harmonics" with $\omega_p = \frac{2\pi \cdot p}{N}$, i.e. p-multiples of $\frac{2\pi}{N}$ with p representing the share of the N-th slice of the unit circle "cake." It can be formalized as

$$\begin{aligned} I\left(\omega_p\right) &= \frac{1}{N\pi}\left[\left(\sum X_t \cos \frac{2\pi p}{N} t\right)^2 + \left(\sum X_t \sin \frac{2\pi p}{N} t\right)^2\right] \\ &= \frac{1}{N\pi}\left\{\left[\sum \left(x_t - \overline{x}\right) \cos \omega_p t\right]^2 + \left[\sum \left(x_t - \overline{x}\right) \sin \omega_p t\right]^2\right\}, \end{aligned} \quad (4)$$

where we dropped the sum operator indices for notational ease. From polynomial multiplication and considering that the cross-products of cosine and sine functions sum to zero, it follows that $I\left(\omega_p\right) = \frac{1}{N\pi} \sum_{s,t-1} \left(x_t - \overline{x}\right)\left(x_s - \overline{x}\right)\left(\cos \omega_p t \cos \omega_p s + \sin \omega_p t \sin \omega_p s\right)$. Considering $\widehat{\gamma}_k = \frac{1}{N} \sum_{t=1}^{N-k} \left(x_t - \overline{x}\right)\left(x_{t+k} - \overline{x}\right)$ as defining the sample autocorrelation function (SACF) and another central property of trigonometric functions, $\cos \omega_p t \cos \omega_p (t+k) + \sin \omega_p t \sin \omega_p (t+k) = 2 \cos \omega_p (t+k-t) = 2 \cos \omega_p k$, as well as Euler's formula allows us to re-write $I\left(\omega_p\right)$ as the discrete Fourier transformation (DFT) of the SACF

$$\begin{aligned} I\left(\omega_p\right) &= \frac{1}{\pi}\left(c_0 + 2 \sum_{k=1}^{N-1} \widehat{\gamma}_k \cos \omega_p k\right) \\ &= \sum_{-(N-1)}^{N-1} \widehat{\gamma}_k e^{-\frac{1}{\pi} \cdot i \omega_p k}. \end{aligned} \quad (5)$$

Hence, the un-smoothed periodogram-estimate of the spectrum is given by

$$\widehat{f}_{xx}(\omega) = \left(\gamma_0 + 2 \sum_{k=1}^{\infty} \widehat{\gamma}_k \cdot \cos \omega k\right). \quad (6)$$

As shown by Engle (1972, 1974), if $y_t = x_t'\beta + \varepsilon_t$ for $t = 1, ..., N$ is a valid regression model in the time domain, it can be transformed into the frequency domain by applying a DFT to both its dependent variable and its independent variables. Denoting accordingly transformed variables as $\widetilde{y}$, $\widetilde{x}$, the regression in the frequency domain is $\widetilde{y} = \widetilde{x}'\beta + \widetilde{\varepsilon}$. The DFT notably does not affect the standard regression structure. The estimator $\widehat{\beta}$ can be written as

$$\widehat{\beta} = \left[\sum_{k=0}^{N-1} \widehat{f}_{xx}\left(\omega_k\right)\right]^{-1} \sum_{k=0}^{N-1} \widehat{f}_{xy}\left(\omega_k\right), \quad (7)$$

where $\widehat{f}_{xy}(\omega)$ is a vector of cross-periodograms. Note, since $\widehat{\beta}$ averages over periodograms, there is no need to smooth these as is necessary when estimating the spectrum.[3] In contrast

[3]For this point and the argumentation in the remaining part of the present paragraph see Assenmacher-Wesche and Gerlach (2008b, p. 423-424).

to the FFC-enriched ADF testing literature (Enders and Lee, 2012; Winkelried, 2018), DFT components are not included as additional regressors. Our strategy rather consists in a frequency domain transformation of the regression model in its entirety. The benefit of translating the entire regression model into the frequency domain is the opportunity to check whether a specific model applies to some but not to all frequencies. To do so, the regression model is multiplied by an $N \times N$ matrix A with unity on the main diagonal for each included frequency and zero entries elsewhere

$$A\widetilde{y} = A\widetilde{x}'\beta + A\widetilde{\varepsilon}, \quad \text{where } E\left(A\widetilde{\varepsilon}\right)\left(A\widetilde{\varepsilon}\right)^{*} = \sigma^2 A \tag{8}$$

with asterisk '*' denoting complex conjugate transpose. Thus, to compute vector $\widehat{\beta}$ we sum over a particular frequency band rather than over the full range of frequencies as in (7). If (7) is estimated only for a subset of frequencies, but holds true for all frequencies, the estimator is consistent but inefficient as it does not use all available information.

The logics of Engle's argument can be analogously applied to a valid period-specific (or time-fixed-effects) panel model $y_{it} = \alpha_t + x_{it}'\beta + \nu_i + \varepsilon_{it}$, where $i = 1, ..., I$ denotes cross-sectional entities and ν_i fixed effects with b observations per group i, or just as well to a frequency-band-specific (or band-fixed-effects) panel model in the frequency domain

$$y_{jb} = \alpha_b + x_{jb}'\beta + \nu_j + \varepsilon_{jb} \quad \text{with} \quad E\left(\varepsilon_{jb} | \alpha_b, \nu_j, x_{jb^H}, ..., x_{jb^L}\right) = 0, \tag{9}$$

and b^H corresponding to the frequency band comprising the highest frequencies including the Nyquist (or near-Nyquist) frequency $\mathbb{P}_{NQ}$,[4] and b^L containing the lower bound value of considered frequency or upper bound value of periodicity, i.e. to $\mathbb{P}^H$, where $\mathbb{P}^H$ might be chosen such that a corresponding cyclicality replicates itself, at least, once over the considered period of length N. Here, $j = 1, ..., J$ and ν_j denote cross-sections and corresponding fixed effects, respectively.

2.2 Implementing band spectral panel regressions

In the following, we develop a procedure to implement BSPR model (9). It makes use of the notion of band-pass deviation cycles. Artis et al. (2004) define deviation cycle dynamics

[4] Nyquist frequency $\mathbb{P}_{NQ}$ corresponds to the lowest periodicity, $\mathbb{P}^L$, at stake. If the raw series y_t and x_t of the same or different entities at stake are of different frequency of observation ("mixed frequency"), $\mathbb{P}^L$ might be chosen so as to capture a periodicity that represents $\mathbb{P}_{NQ}$ of the series with the lowest resolution of observation-frequency; e.g., a two years periodicity in the case of annual series representing the lowest resolution series in terms of frequency of observation.

in terms of a cyclical dynamics deviating from trend or potential. Their definition, thus, implies that the deviation cycle represents an unobserved component within an additive or multiplicative unobserved components model, that is, a signal-noise decomposition or, more specifically, a trend-cycle decomposition.

The smoothed minimum mean square estimator of the signal, i.e. the trend component μ_t, of the local linear trend model for series y_t given by

$$\begin{aligned} y_t = & \quad \mu_t + \epsilon_t, & \epsilon_t \overset{i.i.d.}{\sim} N\left(0, \sigma_\epsilon^2\right) \\ \mu_t = & \quad \mu_{t-1} + \beta_{t-1} + \eta_t, & \eta_t \overset{i.i.d.}{\sim} N\left(0, \sigma_\eta^2\right) \\ \beta_t = & \quad \beta_{t-1} + \zeta_t, & \zeta_t \overset{i.i.d.}{\sim} N\left(0, \sigma_\zeta^2\right) \end{aligned} \tag{10}$$

for $t = 1, 2, ..., N$ with restrictions $\sigma_\eta^2 = 0$ and $\sigma_\epsilon^2 / \sigma_\zeta^2 = \lambda$, minimizes the penalized least square (PLS) criterion

$$PLS = \sum\nolimits_{t=1}^{N} \left(y_t - \mu_t\right)^2 + \lambda \sum\nolimits_{t=3}^{N} \left(\Delta^2 \mu_t\right)^2, \tag{11}$$

where Lagrange multiplier λ captures the variability of the noise, i.e. the cyclical, component relative to that of μ_t. For σ_η^2 approaching zero, λ goes to infinity, and the limiting represenation of $\widehat{\mu}_t$ is a straight line (Hodrick and Prescott, 1997). The noise, i.e. irregular or cyclical, component is $y_t - \widehat{\mu}_t$.

Assuming the availability of a double-sided infinite sample, y_{t+j}, $j = -\infty, ..., +\infty$, the Wiener-Kolmogorov filter (Harvey and Proietti, 2005) provides the minimum mean square linear estimator of μ_t, that is

$$\widetilde{\mu}_{t|\infty} = w\left(L\right) y_t \quad \text{with} \quad w\left(L\right) = \frac{\sigma_\zeta^2}{\sigma_\zeta^2 + \left|1 - L\right|^2 \sigma_\epsilon^2} = \frac{1}{1 + \lambda \left|1 - L\right|^4} \tag{12}$$

and $\left|1 - L\right|^2 = \left(1 - L\right)\left(1 - L^{-1}\right)$. Let $L = 1$, it can be seen that the weights of the filter sum up to one. The frequency response function of this filter is

$$w\left(e^{-i\omega}\right) = \frac{1}{1 + 4\lambda \left(1 - \cos\omega\right)^2}. \tag{13}$$

It equals one at zero frequency and decreases monotonically for ω approaching π (i.e. the Nyquist frequency). Hence, (12) is to be interpreted as a low-pass filter with corresponding high-pass filter $1 - w\left(L\right)$. The implicit cut-off frequency ω_c corresponds to a gain $\left|w\left(e^{-i\omega}\right)\right| = \frac{1}{2}$. It satisfies

$$\lambda = \left[4\left(1 - \cos\omega_c\right)^2\right]^{-1} = \frac{0.25}{\left(1 - \cos\omega_c\right)^2}. \tag{14}$$

From (14), it is straightforward to construct an approximate band-pass filter without suffering from unavailability of end-of-sample estimates, as is the case for two-sided (centered) or one-sided MA-filters such as the filters proposed by Baxter and King (1999); Bry and C. Boschan (1971); Christiano and Fitzgerald (2003), which seem inappropriate given the notoriously short period of observation of economic time series. The latter applies, in particular, in the case of EME. The approximate band-pass filter is achieved by what is widely known in the engineering sciences as a parallel circuit application of a low-pass filter. It is given in the present context by

$$\widetilde{y}_t\left(\lambda^L,\lambda^H\right)=\widetilde{\mu}_t\left(\lambda^L\right)-\widetilde{\mu}_t\left(\lambda^H\right)\quad\text{with}\quad\left\{\begin{array}{l}\lambda^L=\left\{4\left[1-\cos\left(2\pi/\mathbb{P}^L\right)\right]^2\right\}^{-1}\\ \lambda^H=\left\{4\left[1-\cos\left(2\pi/\mathbb{P}^H\right)\right]^2\right\}^{-1}\end{array}\right.. \tag{15}$$

Each of these transformed series varies cross-sectionally with $j=1,...,J$ and across frequency bands indexed by $b=1,...,B$ according to

$$\widetilde{y}_{tjb}\left(\lambda_b^L,\lambda_b^H\right)=\widetilde{\mu}_{tj}\left(\lambda_b^L\right)-\widetilde{\mu}_{tj}\left(\lambda_b^H\right)\quad\text{with}\quad\left\{\begin{array}{ll}\lambda_b^L= & \left[4\left(1-\cos\frac{2\pi}{b\cdot\delta}\right)^2\right]^{-1}\\ \lambda_b^H= & \left[4\left(1-\cos\frac{2\pi}{(b+1)\delta}\right)^2\right]^{-1}\end{array}\right., \tag{16}$$

where δ depends on the observation-frequency of y_t and always represents multiples of the lowest resolution frequency of observations of the J different y_t (and x_t) series. If the latter is, for example, annual, we are given with $\delta\in\{\delta^m=24;\delta^q=8;\delta^a=2\}$, where superscript m, q, and a denotes monthly, quarterly, and annual frequency of observation, respectively. For instance, for $B=4$, $\widetilde{y}_{tjb}$ retains cyclicalities with periodicity of 2-4 years (for $b=1$), 4-6 years (for $b=2$), 6-8 years (for $b=3$) and 8-10 years (for $b=4=B$), respectively. The only remaining parameter that needs to be chosen in advance and appropriately, i.e. for the observation-frequency of the underlying series, which is decomposed into band-components, is δ. We proceed analogously with all exogenous series at stake rendering $\widetilde{x}_{tjb}$ band-specific transforms.

3 A BSPR Application: Global Linkages

In the following three paragraphs, we briefly survey the recent literature on the theoretical rationale for and corresponding empirical evidence of the three core factors determining global linkages: trade linkages, financial integration, and policy coordination. The traditional theoretical view on global linkages rests on linkages induced by trade or financial integration of the *inter-industry* type. It is in the spirit of the popular Heckscher-Ohlin trade models (Baldwin, 2013) that are rooted in comparative advantage reasoning. The linchpin mechanism of these models and of rationalizations of corresponding empirical findings is the increasing specialization in production. The latter is supposedly due to trade linkages across diverse sectors implying decreasing—or, at least, a counteracting force to—co-movement. It results particularly in industry-specific technology shocks. See, among many others, Calderón et al. (2007); Inklaar et al. (2008); Kose and Yi (2001, 2006); Liao and Santacreu (2015).

A broader strand of literature and, in particular, the vast majority of the empirical literature ascribes the dominant role in global output-interdependencies to *intra-industry* linkages. It can be seen as originating from "New Trade Theory" (NTT) which is founded on the notion of increasing returns to scale (i.e. "external economies of scale"). Nations with similar relative factor endowments jointly develop and run an industry realizing economies of scale by producing large quantities at low average unit costs. According to this strand of literature, trade linkages within the same sector foster spillovers and ultimately output synchronization; see, among many others, Arkolakis and Ramanarayanan (2009); Artis and Okubo (2011); De Benedictis and Tajoli (2007); De Haan et al. (2008); Duval et al. (2016); Imbs (2007); Inklaar et al. (2008); Johnson (2014); Kose et al. (2003); Ng (2010). As in the case of advanced economies, especially countries with similar relative endowments of skilled labor, technology, and physical capital and engaged to a large extent in intra-industry trade, we expect their cyclical dynamics to be coupled.

However, the sectoral relative factor-intensity dimension is quite unclear in the EME-context, where major trading partners are made of both advanced as well as developing economies with diverse industry-structures. Thus, studies that take the heterogeneity of a country's trade partners into account when exploring the link between trade and bilateral output co-movement are rare. Recent exceptional studies are Karim and Stoyanov (2020) and Shrawan and Dubey (2022). It remains to be answered what type of intra-industry trade linkages (classified by factor intensity of sectors) promote business cycle synchronization in this context. Additionally, trade linkages of either type may also reinforce financial ties and promote financial linkages by stimulating international borrowings and foreign equity participation through FDI in outward-oriented industries; see Gawellek et al. (2016); Nachane and Dubey (2018); Rose and Spiegel (2009).

Strengthening of bilateral financial linkages can be seen as progressing financial globalization, i.e. progressing international cross-border asset trading. The consequence for global linkages is an unsettled issue known as the *financial globalization–real regionalization puzzle* emanating from the theoretical real business cycle (RBC) strand of literature: Absent major global financial shocks (setting international macroeconomic fluctuations into phase, i.e. synchronizing them exogenously), the international RBC model (Backus et al., 1995) and international RBC models incorporating financial globalization (Heathcote and Perri, 2004) predict real regionalization. That is decoupling rather than co-movement of macroeconomic dynamics with increasing global financial integration. In Heathcote and Perri (2004) financial globalization at first[5] induces a home bias in portfolios of investors. As imperfectly correlated stochastic shocks imply imperfectly correlated cross-border dividends, a domestic security bias in portfolios is the result in the presence of any non-zero cost (such as cost of information or shipping and/or opportunity cost) associated with foreign dividend income. Financial market deepening intrinsically increases equilibrium diversification by actually increasing the potential gains from international asset trade. Home biased portfolios put a strain on investors' portfolio structures as the correlation of dividends across countries is disturbed and, for instance, prevent a perfect or full hedge position. Hence, less international business cycle co-movement –or more real regionalization– results, going hand in hand with financial globalization.

Heathcote and Perri (2004) provide some evidence for the prerequisite of this mechanism in showing that the correlation of stochastic shocks hitting the countries of the industrialized world in the period from the mid-1980s to year 2000 has markedly fallen compared to the early 1970s to mid-1980s era. At the same time international trade in financial assets has sharply increased. They also show that a calibrated model economy with the above sketched mechanism at its heart succeeds in quantitatively capturing both of these phenomena. This viewpoint, however, is all but exclusive and uncontroversial. As Nachane and Dubey (2018) put it "much of the empirical evidence points otherwise" in that several recent studies find progressing financial globalization to be associated with more rather than less international output co-movement; see, among others, Artis and Okubo (2011); Böhm et al. (2022); Imbs (2007); Kose et al. (2012).

Corresponding rationalizations primarily come up with the relative dominance of global –or, at least, internationally contagious– financial shocks vis-à-vis idiosyncratic productivity shocks; see Kose et al. (2012); Mendoza and Quadrini (2010); Morgan et al. (2004)

[5] And in the presence of even just minor idiosyncrasies in productivity shocks across countries.

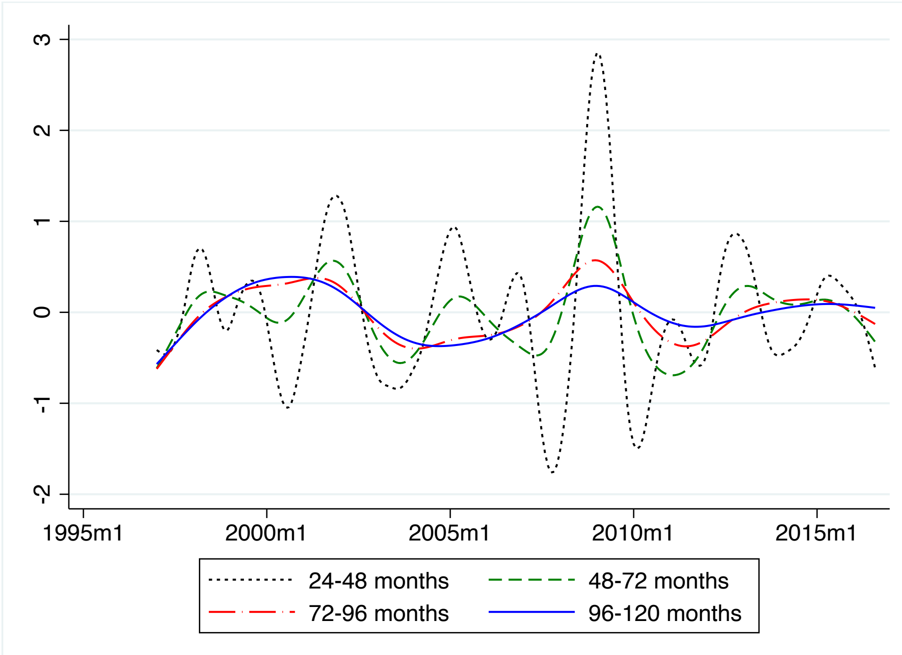
among others. This opposing viewpoint, which is backed up by both empirical evidence and models of financial contagion, together with its –from a theoretical and empirical perspective– no less quantitatively backed up alternative constitutes a central puzzle in the context of financial globalization. What the debate of this puzzling ambiguity so far seems to ignore is that the RBC viewpoint and the financial contagion viewpoint might be both correct as their line of reasoning concerns dynamics of different frequency bands. For example, the financial contagion perspective is rather restricted to cyclical dips or downturns and, due to the efficiency of financial markets and a direct rather than propagated shock impact, to higher frequency bands. The RBC productivity shocks rationalization, on the other hand, is more symmetric concerning up-swing as well as downturn phases, less transitory, and, hence, suggesting itself for cyclical dynamics of lower frequencies. We are, thus, confident that our BSPR approach will shed some light on this topical but unsolved puzzle.

Global linkages not only concern trade and financial markets but usually also imply repercussions on monetary and fiscal policy coordination. Currency in China has a trimillenary tradition. In its latest phase, that is, since the mid-1990s until 2005, China pegged the renminbi to the US dollar. Since 2005 the Chinese currency is subject to a managed float system effectively tying the renminbi to a weighted basket of international currencies and thereby restricting the scope of monetary and fiscal policy (Frankel and Rose, 1998; Imbs, 2007). Policy responses to shocks homogenize at the global level resulting in concerted action and co-movement. Technology spillovers, emanating from trade and financial linkages, additionally reinforce cross-country inflation synchronization, which in turn has the potential to determine business cycle synchronization (Ciccarelli and Mojon, 2010; Mumtaz et al., 2011). Not explicitly accounting for these determinants, i.e. monetary and fiscal policy coordination and inflation cohesion, of global linkages in quantitative analysis bears the risk of omitted variable bias. It would obscure the measurement of the impact of trade and financial linkages on international business cycles synchronization (Nachane and Dubey, 2018).

3.1 Data and descriptives

Our central dependent variables, comprised in y_{jb} in (9), are given by bilateral correlations between output series as proxied by an index of industrial production (IIP) across four different frequency bands for an initial set of 24 trading partner economies and for one supranational trading partner economy, i.e. the European Union (EU), and corresponding series for our reference economy, i.e. for China (see Table A.1 in the Appendix).

Figure 1: Frequency band components: monthly IIP for China



The underlying IIP series are obtained from the Thomson Reuters (TR) Datastream database and are given in monthly frequency. They mostly cover the period from January 1997 to August 2016. Exceptions are the economies of Russia, Indonesia, and Thailand that cover the period from January 2000 to August 2016.[6] They are decomposed into four different components using (16) and setting $\delta = \delta^m = 24$ corresponding to the four frequency bands with periodicity ranges of 2-4 years (for $b = 1$), 4-6 years (for $b = 2$), 6-8 years (for $b = 3$), and 8-10 years (for $b = 4$), respectively. An exemplary decomposition of this type for the underlying monthly Chinese IIP series is shown in Figure 1. Sample transformations of series with different observation-frequency can be found in Figure A.1 and Figure A.2 in the Appendix.

Figure 2 and Figure 3 show the bilateral IIP-correlations with respective Chinese IIP band-components across the four considered distinct frequency bands for a group of 13 advanced and a group of four EME countries, respectively. Figure 4 provides corresponding information for a sample of five developing countries. Correlations given in Figure 2

[6]The (mixed) observation-frequency of series underlying the measures and indicators described in this section is given along with some detail on construction in Table A.2 in the Appendix.

and Figure 3 widely confirm precursory descriptive work using chained quarterly GDP series for China and a sample of 23 OECD economies by Fidrmuc et al. (2013) in that "many countries show a relatively high correlation for some short-run frequencies" with corresponding Chinese macroeconomic dynamics. Apart from the case of Saudi Arabia (Figure 4), the bilateral IIP-correlation in the 2-4 years frequency band throughout, i.e. including non-OECD developing economies, exceeds a value of +0.2.

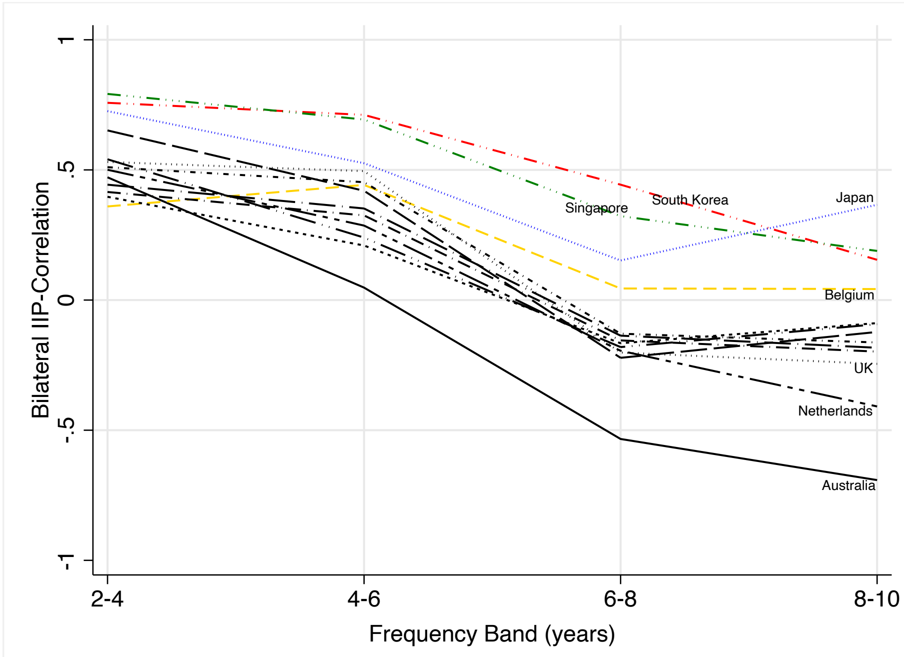
As can be seen from Figure 2, there are three trading partner economies, for which the IIP-correlation has positive support across all considered bands. These are the three Asian economies of Japan (dotted), Singapore, and South Korea (each of the latter two: dashed and dotted) and the European economy of Belgium (dashed). Interestingly, the least homogenous picture across bands is given for the bilateral IIP-correlations of developing countries. Obviously, there is no peaking of bilateral IIP-correlations at the 4-6 years band for this sub-sample, while a maximum is found in this frequency interval for India (Figure 3) and South Korea (Figure 2). A similar concave pattern, though peaking in the more long-run 6-8 years range, is given for the Philippines (Figure 4). In the group of developing economies, Saudi Arabia stands out in so far as its bilateral IIP-correlation increases with implied periodicities over the whole range.

Clearly convex patterns –with a decrease at the intermediate bands and an increase in the long-run frequencies– are given for Brazil, South Africa (Figure 3), and Malaysia (Figure 4). For the remaining majority of analyzed trading partner economies, we find a "hockey stick"-like shape with IIP-correlation peaking at the highest frequency band, decreasing up to the 6-8 years band, and than either stagnating or slightly increasing in the 8-10 years cyclical growth frequency band. Overall, there seems to be enough variation in bilateral IIP-correlations across economies and frequency bands to justify a more systematic inferential analysis applying the BSPR techniques proposed in Section 2.

3.2 Construction of explanatory indicator variables

Our first central block of explanatories, contained in x'_{jb} in representation (9) of the BSPR model outlined in Section 2, are trade linkages. As argued above, they can be of two general types: inter-industry and intra-industry trade linkages.

Figure 2: Bilateral IIP-correlations: advanced economies



The inter-industry trade linkage indicators that we consider are quite standard and frequently used in the empirical literature (Nachane and Dubey, 2013). We define them as average bilateral export intensity (ExI), import intensity (ImI), and total trade intensity or relative openness (TrI) with our reference economy China

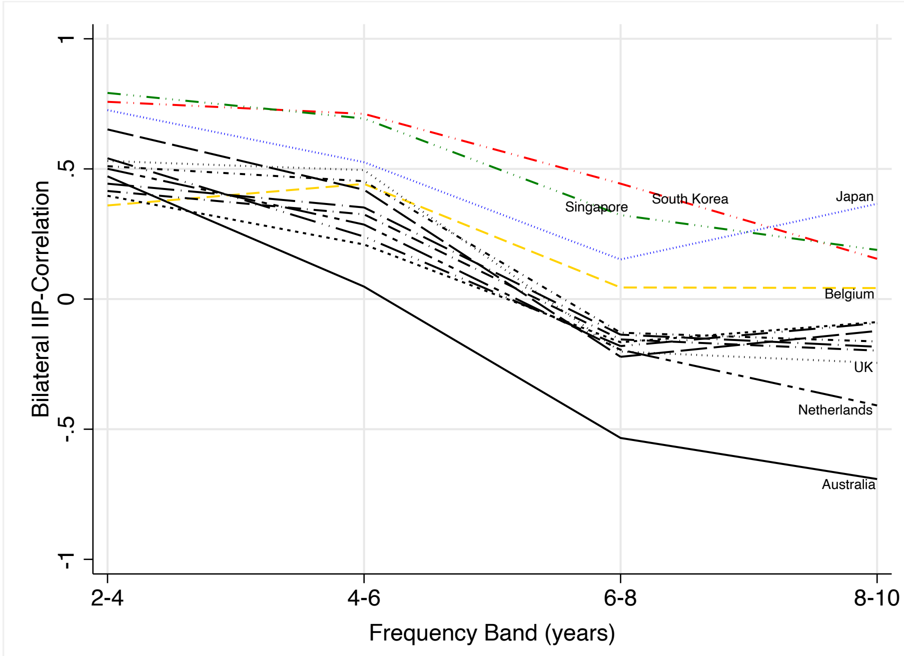
$$\text{Inter-industry } ExI_{jb} = \frac{1}{N}\sum_{t}^{N}\left(\frac{Ex_{C,j\ b\ t}}{Ex_{C\ b\ t} + Ex_{j\ b\ t}}\right) \tag{17}$$

$$\text{Inter-industry } ImI_{jb} = \frac{1}{N}\sum_{t}^{N}\left(\frac{Im_{C,j\ b\ t}}{Im_{C\ b\ t} + Im_{j\ b\ t}}\right) \tag{18}$$

$$\begin{aligned} \text{Inter-industry } TrI_{jb} &= \frac{1}{N}\sum_{t}^{N}\left(\frac{Tr_{C,j\ b\ t}}{Tr_{C\ b\ t} + Tr_{j\ b\ t}}\right) \\ &= \frac{1}{N}\sum_{t}^{N}\frac{Ex_{C,j\ b\ t} + Im_{C,j\ b\ t}}{(Ex_{C\ b\ t} + Im_{C\ b\ t}) + (Ex_{j\ b\ t} + Im_{j\ b\ t})}, \end{aligned} \tag{19}$$

where subscript b refers to the b-th frequency band deviation cycle component, C denotes China, and $j = 1, ..., J$ its major trading partners. $Ex_{C,j}$, $Im_{C,j}$, and $Tr_{C,j}$ denote total nominal exports from China to j, total nominal imports from j to China, and total trade (in nominal terms) between China and country j, respectively. All underlying Chinese series are available in monthly frequency and can be aggregated to lower resolution observation-frequency to obtain corresponding deviation cycle components and allowing for band-specific averages also in the mixed frequency case.

Figure 3: Bilateral IIP-correlations: EME countries



For intra-industry trade linkages (TL) our baseline bilateral measure is the observation period average of the also frequently used indicator by Grubel and Lloyd (1975):

$$\text{Intra-industry } TL_{jb} = \frac{1}{N} \sum\nolimits_t^N \left(1 - \frac{\sum_s |Ex_{C,j\ s\ t} - Im_{C,j\ s\ t}|}{\sum_s |Ex_{C,j\ s\ t} + Im_{C,j\ s\ t}|}\right), \tag{20}$$

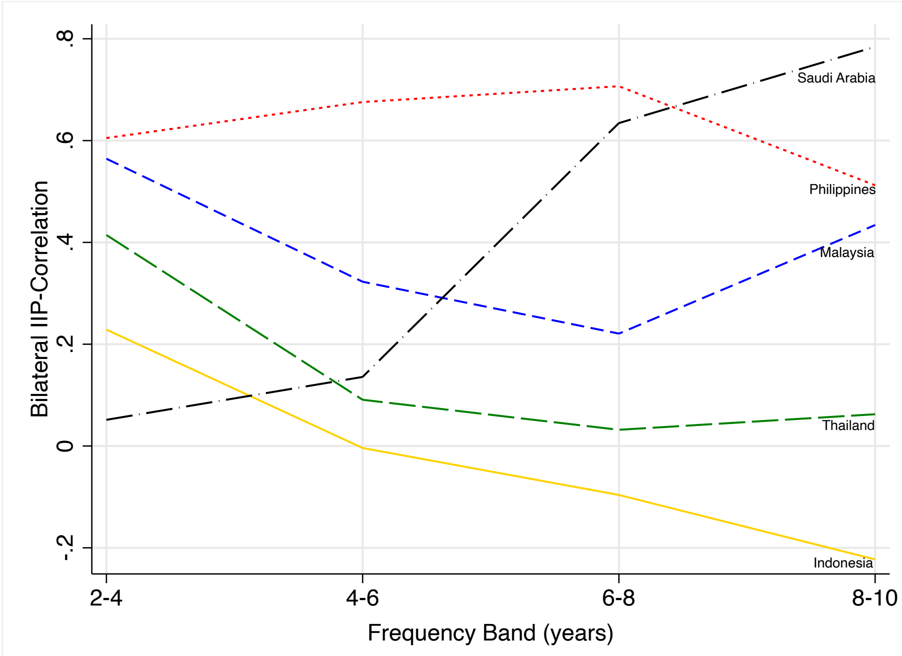
where $s = 1, ..., S$ denotes considered sectors or commodities. It is bound to the $(0, 1)$ interval. Both export and import quantities are aggregated over industries (see Section 3.3 for detail). We also construct and use the indicator as an industry-specific measure, which is given for each sector s by

$$\text{Intra-industry } TL_{jbs} = \frac{1}{N} \sum\nolimits_t^N \left(1 - \frac{|Ex_{C,j\ s\ t} - Im_{C,j\ s\ t}|}{|Ex_{C,j\ s\ t} + Im_{C,j\ s\ t}|}\right). \tag{21}$$

How industries s are exactly defined and which sectoral quantities we actually use in the BSPR estimates is detailed in 3.3.

Similar to our bilateral dependent variable, IIP-correlation, the remaining explanatories represent bilateral correlations. We consider two measures of financial integration. First, bilateral correlations of some measure of financial openness, that is, of M2/GDP ratios, across respective band-specific deviation cycle components b of the M2/GDP se-

Figure 4: Bilateral IIP-correlations: developing countries



ries of country j with its analogue Chinese component-series.[7] We refer to this measure as Financial Integration (FI) I. Secondly, we consider bilateral correlations of respective stock price index series that we dissect into frequency band component series before band-wisely computing correlations. A summary of underlying stock market index series and corresponding sources is given in Table A.4 in the Appendix. Henceforth, we refer to this indicator as FI II.

Analogously, we construct bilateral measures for monetary policy coordination based on pair-wise and band-specific M2 growth rate correlations and for fiscal policy coordination based on pair-wise and band-specific public deficit, i.e. government surplus to GDP ratio, growth rate correlations.

Finally, we compute a band-specific indicator of inflation co-movement using bilateral correlations of deviation cycle components of respective CPI series (levels).

[7]As M2 is a relatively liquid monetary aggregate including short-term assets held by non-banks, it is a frequently used proxy in this context (Nachane and Dubey, 2018, p. 11).

3.3 The sectoral dimension of intra-industry linkages

As argued at the beginning of Section 3, factor intensity as a defining property of sectors is assessed crucial for intra-industry trade linkages in predicting international business cycle co-movement at different frequencies in the literature. We, thus, consider sectors classified by factor intensity also in our BSPR analysis. Our primary dataset for the respective series is the General Administration of Customs of the P.R. China (GACC, henceforth 'China Customs'), from which we retrieve a total of 968 monthly series. Half of these refer to import quantities, the other half to export quantities, respectively. They are compiled at the two-digit China Harmonized Commodity Description and Coding System (HS) code level comprising 22 commodities for 22 out of our 25 considered major trading partner economies of China.[8] The factor intensity classification is done on the basis of the UNCTAD/WTO International Trade Center classification using the standard industrial trade classification (SITC) 'rev. 2 codes' and distinguishing five main groups of sectors at the three-digit level following the scheme of the Empirical Trade Analysis Center (ETA) of Erasmus University Rotterdam. A summary of the applied scheme is given in Table 1.

Table 1: Sectors calssified by factor intensity for sectoral intra-industry TL computation

Factor Intensity Classification (ETA product group)	Commodity HS industry codes
Primary products (A)	I, II, II, IV
Natural-resoure intensive products (B)	V, VIII, IX, XV, XIV
Unskilled-labor intensive products (C)	XI, XII, XIII, XX
Technology intensive products (D)	VI, XVI, XVIII, XIX, XVII
Human-capital intensive products (E)	X, XXI, XXI, XXII

Note: For detail on HS classification industry code and sources see Table A.3 in the Appendix.

Besides considering (21) for the above listed five sectors by factor intensity as explanatory, we also compute (20) for all $S = 22$ in China Customs available and in the subtractive part of (20) aggregated commodities and respective export and import quantities. We refer to it as overall intra-industry linkages in our BSPR estimates.

[8]Due to data issues and problems, which can hardly be taken care of or corrected for, this led us to abstract from series from Taiwan, Hong Kong, and the EU.

3.4 BSPR estimates and interpretation

The columns of Table 2 labeled Model I, II, and III reflect how we proceed in identifying the determinants of bilateral global linkages for our reference economy China. The three considered core models might be represented in an extension of baseline BSPR model (9). It reads

$$y_{jb} = \alpha_b + x'_{jb}\beta + x'_{jbs}\beta_s + z'_{jb}\beta_b + z'_{jbs}\beta_{bs} + \nu_j + \varepsilon_{jb} \tag{22}$$

with $E(\varepsilon_{jb}|\alpha_b, \nu_j, \mathbf{x}, \mathbf{z}) = 0$, where $\mathbf{x} = \{x_{jb}; x_{jbs}\} \wedge \mathbf{z} = \{z_{jb}; z_{jbs}\}$ with $s = 1, ..., S$ denoting sectors classified by factor intensity, we estimate –besides band-fixed and country-fixed effects, α_b and ν_j– general β effects, effects referring to quantities of particular sectors β_s, to band-specific effects β_b of certain indicators, and to band-specific effects referring to variables of particular sectors β_{bs}, respectively. As the set of $\mathbf{z}$ variables is technically generated by band-(specific-)interaction terms, leaving out as reference band the 2-4 years periodicity interval, $\mathbf{z} \supsetneq \mathbf{x}$, i.e., $\mathbf{x}$ is a real sub-set of $\mathbf{z}$. A fully interacted model allowing for $\mathbf{z} \supseteq \mathbf{x}$ would boil down to single-equation estimations.

In Table 2, beginning with the second column down to line 'Trade Intensity' general β effects are given. The following 'Intra-Industry' block displays estimated effect sizes referring to sectoral quantities β_s. The proceeding row labeled 'Band Effects' together with the top row ('Constant') depict band-fixed effects, followed by the band-industry effects β_{bs} and finally some band-specific effects β_b ('Band-Inter-Industry,' 'Band-IC,' and 'Band-FI II') that have to be interpreted in conjunction with its reference β effects at the top of Table 2. The model types I to III vary with considered band-specific effects β_b: While Model I considers intra-industry trade linkages as sole band-specific determinants, Model II additionally considers inter-industry measures of bilateral exports, imports, and trade band-wisely. Finally, Model III on top of this specifies band-specific inflation co-movement and band-specific financial integration measured by indicator FI II, which come out fairly sizable and clearly significantly different from zero in our estimates.

In contrast, both macro-policy accordance indicators for monetary policy (MP) and fiscal policy (FP) –as well as bilateral M2/GDP ratio correlates captured by FI I– are not estimated as statistically different from zero if interacted with frequency band identifiers in extensions of our models (not shown in Table 2). Nevertheless, we keep them in the x_{jb}-part of the empirical model as, at least, non-interacted FP is estimated with a negative coefficient ($-.152$) statistically significant at a ten percent level in model III.The negative relationship might be rationalized by the fact that the synchronized creation of public deficits does not necessarily embody the information for what the respective economies used these means. Using deficits for consumptive or investive governmental spendings, debt service or combinations of it can have quite idiosyncratic effects on output dynamics. This led us to abstract from frequency-band-interacted versions of these regressors in the $z'_{jb}\beta_b$-parts ensuring $\mathbf{z} \supsetneq \mathbf{x}$.

In terms of information criteria and other values of fit to data, Model III seems an adequate choice.[9] However, it is worth to assess it also against the other two specifications. This becomes evident when looking at the estimated coefficient values of the general β effects block in the top rows of Table 2. As mentioned above, policy coordination indicators of either monetary or fiscal nature are nearly throughout not significantly associated with bilateral global linkages across specifications.

Inflation comovement (IC) seems negatively related to global linkages; see, at first, the corresponding coefficient estimates in the columns referring to Model I and II, respectively. As specification III shows in the penultimate row of coefficient estimates, this seems to have its origin at low frequencies as both the estimated BSPR coefficient for IC without band-interaction (referring to the 2-4 years band) amounting to 0.202 and the one referring to the 4-6 years periodicity ($-.054$) are insignificant, while there are indications for a significant negative association in the 6-8 years and 8-10 years band, respectively. According to Wang and Wen (2007) and Ciccarelli and Mojon (2010), it is an empirical fact that global co-movement in inflation is higher than the one in cyclical output dynamics. It is rationalized in a variety of New Keynesian two-country models by Wang and Wen (2007). The latter study also justifies IC as exogenous or, at least, not as endogenous. It shows that, at least, in the context of New Keynesian open-economy models, international spill-overs are not the origin of IC. In our results, though only for higher periodicity dynamics, the stylized fact that global inflation co-movement is higher than cyclical output dynamics is captured by the significant negative coefficients for IC in the 6-8 years ($-.344$) and 8-10 years ($-.628$) range in the column of Table 2 referring to Model III.

Specification III is also highly instructive in explaining the *financial globalization–real regionalization vs. real contagion puzzle*. As we have argued above, what the debate of the

[9]In general, the overall R-squares calculated as squared correlations between predicted and actual dependent values are reasonably high lying between about 30 and approximately 40 percent. As all three specifications represent fixed-effects regressions maximizing within-R-squares, corresponding values by far outnumber the respective R-squared between values.

puzzle so far ignores is that the RBC viewpoint (FI promoting regionalization/decoupling) and the financial contagion viewpoint (FI promoting synchronization) might be both correct as their line of reasoning concerns dynamics of different frequency bands. The positive and highly significant FI II coefficient estimate at high frequencies (1.171) ad hoc speaks in favor of the financial contagion perspective, which seems bound to cyclical downturns and, due to the notorious efficiency of international financial markets and a direct rather than propagated shock impact, to higher frequency bands. On the other hand, the highly significant, and in terms of size even outnumbering, negative coefficient estimates for the 6-8 years band (-1.275) and the 8-10 years band (-1.585) can be seen as parallel evidence in favor of the RBC productivity shocks rationalization. The latter is from its nature more symmetric, less transitory, and, according to our estimates, a better fit for the explanation of cyclical dynamics at lower frequencies.

With regard to trade intensity across industries in our context of bilateral cyclical output co-movement, we find some evidence in favor of Heckscher-Ohlin-type specialization effects due to comparative advantage, though only for relative openness (TrI) subsuming relative bilateral exports and imports with the Chinese economy. It is indicated by significant negative coefficient estimates in specifications II and III with corresponding coefficient estimates $-.674$ and -2.356. However, this inter-industry decoupling is given for the two highest and for the top-low frequency band only as for the 6-8 years band it is netted out by a significant interaction term for TrI amounting to 4.909.

Assessing NTT-spillovers, possibly due to external economies of scale, intra-industry-specific quantities interpreted in combination with BSPR-coefficient estimates of their frequency-band-interacted expressions our estimates can be read as follows. We particularly find support for a positive net association in favor of overall external economies of scale for (a) low frequencies and (b) labor intensive sectors, where in terms of size unskilled labor intensive sectors are clearly outnumbering the effect of human capital (labor) intensive industries by nearly a quintuple with interaction term coefficients in specification III amounting to 2.515 and 0.586, respectively. Additionally, model III finds intra-industry trade linkages in technology-intensive production sectors to represent sizable, significant (at least, at a five percent level) determinants of bilateral output co-movement with a corresponding coefficient estimate of 1.139. This association is not short and medium run frequency band specific and is intensified only in the lowest, i.e. the cyclical growth, frequency band of 8-10 years. It is indicated by an interaction term coefficient of 1.272 that is significant at a ten percent level.

Table 2: Band spectral panel regression models: estimates

	Model I			Model II			Model III		
Constant		1.052***			1.019***			-0.158	
		(0.175)			(0.195)			(0.242)	
Monetary Policy		0.008			-0.342			-0.037	
		(0.429)			(0.416)			(0.369)	
Inflation Comovement (IC)		-0.514**			-0.556***			0.202	
		(0.180)			(0.194)			(0.234)	
Fiscal Policy		0.009			0.163			-0.152*	
		(0.130)			(0.161)			(0.074)	
Financial Int (FI) I		-0.111			-0.376			-0.077	
		(0.171)			(0.272)			(0.212)	
Financial Int (FI) II		-0.548***			-0.431***			1.171***	
		(0.140)			(0.103)			(0.256)	
Inter-Industry									
Exp Intensity (ExI)		-0.138**			-0.175			-0.924	
		(0.063)			(0.111)			(0.384)	
Imp Intensity (ImI)		0.234**			0.275*			0.051	
		(0.110)			(0.137)			(0.059)	
Trade Intensity (TrI)		-0.230			-0.674*			-2.356***	
		(0.726)			(0.834)			(0.699)	
Intra-Industry									
Overall		1.677			1.663			-2.053	
		(1.759)			(2.235)			(1.387)	
Primary		0.309			0.501			0.239	
		(0.557)			(0.400)			(0.372)	
Natural Resources		-0.895			-0.549			0.374	
		(0.705)			(0.738)			(0.476)	
Unskilled		-0.381*			-0.463*			-0.165	
		(0.199)			(0.235)			(0.186)	
Technology		0.149			-0.211			1.139**	
		(0.846)			(0.631)			(0.522)	
Human Capital		0.449			0.351			-0.143	
		(0.336)			(0.251)			(0.140)	
Band Effects									
Band	4-6 years	6-8 years	8-10 years	4-6 years	6-8 years	8-10 years	4-6 years	6-8 years	8-10 years
	-0.254**	-0.744***	-0.477***	-0.280**	-0.691***	-0.679***	0.427	0.347	0.761***
	(0.096)	(0.164)	(0.120)	(0.124)	(0.148)	(0.149)	(0.254)	(0.229)	(0.198)
Band-Intra-Industry									
Overall	-1.130	-1.765	-5.778*	-1.761	-3.061	-5.219*	1.262	0.464	-3.539*
	(1.484)	(2.747)	(2.848)	(1.690)	(2.266)	(2.556)	(1.233)	(1.687)	(1.720)
Primary	-0.691	-0.332	0.022	-0.928***	-0.497	-0.347	-0.291	-0.007	-0.793
	(0.474)	(0.609)	(0.684)	(0.299)	(0.350)	(0.573)	(0.359)	(0.347)	(0.463)
Natural Resources	1.113	1.156	1.899*	0.273	0.710	0.784	-1.138*	-0.787	0.413
	(0.929)	(0.898)	(0.992)	(0.667)	(0.747)	(1.007)	(0.608)	(0.558)	(0.634)
Unskilled	0.711**	-0.065	1.573*	0.664***	-0.251	0.407	-0.197	-0.287	2.515***
	(0.297)	(0.481)	(0.852)	(0.213)	(0.476)	(1.023)	(0.253)	(0.509)	(0.776)
Technology	0.054	-0.256	1.533	0.909	0.730	1.248	-0.715	-0.995	1.272*
	(0.851)	(1.587)	(1.289)	(0.825)	(1.231)	(0.991)	(0.570)	(0.798)	(0.749)
Human Capital	-0.425	-0.516	-0.062	-0.343	-0.407	-0.013	0.425*	0.256	0.586***
	(0.341)	(0.360)	(0.291)	(0.359)	(0.284)	(0.299)	(0.238)	(0.210)	(0.177)
Band-Inter-Industry									
Exp Intensity (ExI)				0.087	-0.405	0.125	0.004	-0.947***	0.319**
				(0.122)	(0.435)	(0.179)	(0.124)	(0.296)	(0.128)
Imp Intensity (ImI)				-0.193	-0.872	0.137	0.078	0.127	0.016
				(0.182)	(0.683)	(0.682)	(0.099)	(0.4317)	(0.348)
Trade Intensity (TrI)				1.556	4.107*	5.627**	1.673*	4.909***	0.768
				(1.004)	(2.837)	(2.120)	(0.949)	(1.422)	(1.183)
Band-IC							-0.054	-0.344***	-0.628***
							(0.104)	(0.113)	(0.116)
Band-FI II							-0.924**	-1.275***	-1.585***
							(0.384)	(0.242)	(0.219)
N obs		88			88			88	
Log L		67.811			90.033			136.394	
AIC		-93.621			-138.067			-230.786	
BIC		-41.597			-86.042			-178.763	
R-squared	Within	Between	Overall	Within	Between	Overall	Within	Between	Overall
	0.8250	0.0002	0.2999	0.8940	0.0002	0.2997	0.9632	0.0358	0.3921
Number of country		22			22			22	

Note: Fixed-effects (within) regression; group variable: country; robust standard errors in parentheses ; *** p<0.01, ** p<0.05, * p<0.1

4 Conclusion

In this paper, we introduced the technique of band spectral panel regression (BSPR) to analyze global linkages across sectors and frequency bands. Methodologically, the BSPR relies on dissecting time series –allowably measured in mixed frequency– into "deviation cycle" dynamics by frequency band (Artis et al., 2004). It computes measures of real co-movement, trade linkage, financial market integration, and policy coordination by frequency. It represents a panel version of the more general band spectral regression model (Engle, 1974). Its panel structure consists in entities, referring e.g. to economies, and frequency bands, referring to periodicities of cyclical dynamics, rather than entities and time as in standard panel models. BSPR models are flexible in allowing for band-specific fixed effects and band-industry-specific interaction terms, which both are of high relevance in the study of global linkages. Technically, BSPR models can control for unobserved heterogeneity across cross-sectional entities and frequency bands. They have the potential to remove omitted variable bias problems if omitted regressors are cross-sectional and frequency band invariant.

In our BSPR application on bilateral output co-movement of the Chinese economy with its major trading partner economies, we find evidence for the association of both inter-industry trade intensities and intra-industry trade linkages with international output co-movement. In particular, we find support for Heckscher-Ohlin inter-industry decoupling due to specialization –that can be rationalized with comparative advantage arguments– for top-high as well as for top-low frequency bands. Evidence for *New Trade Theory* intra-industry "external economies of scale" is found for (a) relatively low frequencies and (b) sectors with high labor intensity. Spillovers in technology intensive industries are not frequency-specific in the short and medium run. If at all, they are only intensified in the cyclical growth related frequency band of 8-10 years periodicities.

Furthermore, we find no convincing evidence for policy coordination indicators of either monetary or fiscal nature to be associated with bilateral global linkages. We also confirm the well-documented and theoretically rationalized empirical fact that global inflation co-movement is higher than co-movement in cyclical output dynamics by estimating a negative association between bilateral output linkages and inflation co-movement. However, we find it to be only significant in the relatively low frequency bands.

Finally, our BSPR estimates are most helpful in explaining the *financial globalization*–

real regionalization vs. real contagion puzzle. Against the backdrop of our findings, both the RBC view, which sees financial integration fostering regionalization of output dynamics, and the financial contagion perspective, which suggests the opposite (i.e. fostering synchronization), can be justified at different frequency bands. Our BSPR estimates find indications of the first in low frequency bands and indications of the latter in the highest frequency band. We attribute this to the RBC rationalization being more symmetric, less transitory, and resting rather on propagated than direct impacts of shocks. The opposite applies to models of financial contagion.

For future work, we see a wide array of applications for the proposed BSPR methodology within the realms of possibility. It comprises determinants of political and/or partisan business cycles and their synchronization, e.g. across federal states, relatively low frequency-contingent financial cycles and their co-movement, e.g. across different comodities and markets, as well as cycles in capital formation, labor demand or migration flows and their synchronicity at the regional or international level. However, it also remains a future task to thoroughly study and analyze the statistical properties and assumptions of the BSPR model. This includes to possibly generalize it to multivariate –as opposed to combined bivariate (bilateral)– applications.

Statement: During the preparation of this work the authors used no generative AI and/or AI-assisted technologies.

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Appendix

Table A.1: Selection of considered 25 major trading partner economies of China

1	Australia	6	France	11	Italy	16	Russia	21	Spain
2	Belgium	7	Germany	12	Japan	17	Saudi Arabia	22	Taiwan
3	Brazil	8	Hong Kong	13	Malaysia	18	Singapore	23	Thailand
4	Canada	9	India	14	Netherlands	19	South Africa	24	UK
5	EU	10	Indonesia	15	Philippines	20	South Korea	25	USA

Note: In alphabetical order; throughout, the reference economy is China.

Table A.2: Indicator variables and underlying time series

Indicator	**Series**			
	frequency	exceptions	coverage	exceptions
Bilateral IIP Correlation	monthly		Jan 1997 - Aug 2016	Russia, Indonesia, Thailand: Jan 2000 - Aug 2016
Inter-Industry	monthly	Saudia Arabia: quarterly	Jan 1997 - Aug 2016	Saudi Arabia: Q4 1996 - Q3 2016
Intra-Industry	monthly		Jan 1997 - Aug 2016	
FI I	quarterly	Saudia Arabia: yearly	Q4 1996 - Q3 2016	Saudi Arabia: 1996-2016
FI II	monthly		Jan 1997 - Aug 2016	Spain, Russia: Sep 1997 - Aug 2016 Saudi Arabia: Jan 1998 - Aug 2016
MP	monthly		Jan 1997 - Aug 2016	Spain: Sep 1997 - Aug 2016 Belgium: Jan 1999 - Aug 2016
FP	quarterly	Saudi Arabia: yearly	Q4 1996 - Q3 2016	Saudi Arabia: 1996-2016
IC	monthly		Jan 1997 - Aug 2016	

Notes: IIP–index of industrial production; indicators as defined in text: Inter-industry–inter-industry trade linkages, Intra-industry–intra-industry trade linkages, FI I–index of financial integration I, FI II–index of financial integration II, MP–monetary policy coordination index, FP–fiscal policy coordination index, IC–inflation cohesion. For Saudi Arabia (South Africa) IIP refers to non-durable manufacturing, petroleum and coal, and crude petroleum sectors (manufacturing sector) only, for Philippines FI II monthly data is obtained from aggregating daily figures; seasonal adjustment: X-12 ARIMA (where appropriate). Data sources: TR Datastream; China Customs

Table A.3: Sectors calssified by factor intensity for sectoral intra-industry TL computation

Factor Intensity Classification (ETA group)	China Customs: commodity (HS code)
Primary products (A)	Live animals / animal products (I)
	Vegetable products (II)
	Animal / vegetable oils and fats (III)
	Food, beverages, and tobacco (IV)
Natural-resoure intensive products (B)	Mineral products (V)
	Leather and related products (VIII)
	Wood, charcoal and related products (IX)
	Base metal and related products (XV)
	Pearls and (semi-)precious stones (XIV)
Unskilled-labor intensive products (C)	Textiles and textile articles (XI)
	Footwear, head gear and related products (XII)
	Stone, ceramics, and glass (XIII)
	Miscellanous manufactured articles (XX)
Technology intensive products (D)	Chemicals and allied industries (VI)
	Rubbers and plastics (VII)
	Machinery, electrical/electronic equipment (XVI)
	Precision/musical instruments and clocks (XVIII)
	Arms and ammunition (XIX)
	Vehicles, aircraft, and transportation (XVII)
Human-capital intensive products (E)	Pulp, paper, and related products (X)
	Artwork and antiques (XXI)
	Articles of special trade (XXII)

Note: HS classification industry code as provided by Export-to-China (ETCN, China Customs); Factor intensity classification (FIC) from Empirical Trade Analysis Center (ETA)

Source: China Customs (series); FIC-ETA: www2.econ.uu.nl/users/marrewijk/eta/intensity.htm

Table A.4: Stock market index series by country: codes and sources

Country	**Source**	**Code**	**Index Name**
Australia	Reserve Bank of Australia	AUSHRPRCF	S&P/ASX 200
Belgium	Euronex Brussels	BGSHRPRCF	BXS, Brussels Stock Exchange Cash Market Return Index
Brazil	Reuters	BRSHRPRCF	The Bovespa Index(Indice Bovespa)
Canada	Reuters	CNSHRPRCF	S&P/TSX, Toronto Stock Exchange Composite Share Price Index
China	National Bureau of Statistics of China	CHSHRPRCF	Shanghai Stock Exchange Composite Index China
EU	Thomson Reuters	EMSHRPRCF	Datastream EURO Share Price Index (Euro Zone)
France	Main Economic Indicators	FRSHRPRCF	SBF250
Germany	Reuters	BDSHRPRCF	Deutsche Boerse, DAX 30
Hongkong	Census and Statistics Department, Hong Kong	HKSHRPRCF	Hong Kong Heng Seng Share Price Index
India	Central Statistical Organisation, India	INSHRPRCF	Bombay Stock Exchange National 100 Share Price Index
Indonesia	Reuters	IDSHRPRCF	Jakarta Stock Exchange Index (JSX)
Italy	Borsa Italiana	ITSHRPRCF	Milan COMIT General Share Price Index
Japan	Reuters	JPSHRPRCF	Tokyo SE, TOPIX Index
Malaysia	Reuters	MYSHRPRCF	Financial Times Stock Exchange Bursa Malaysia KLCI
Netherlands	Statistics Netherlands	NLSHRPRCF	Amsterdam SE All Share Stock Price Index
Philippines	Central Bank Philippines	PSECOMP	PSEI Index, derived from daily series by me
Russia	Reuters	RSSHRPRCF	MICEX Share Price Index
Saudi Arabia	Saudi Arabian Monetary Agency	SISHRPRCF	Tadawul All Share Index (TASI)
Singapore	Thomson Reuters	SPSTDSCAF	Singapore STRAITS T.DS, Datastream
South Africa	Datastream	SASHRPRCF	Total Stock Market Stock Price Index
South Korea	Reuters	KOSHRPRCF	Korea Composite Stock Price Index (KOSPI)
Spain	Ministry of the Economy and Finance, Spain	ESSHRPRCF	Madrid SE General Index
Taiwan	Reuters	TWSHRPRCF	TSE Capitalization Weighed Stock Index (TAIEX)
Thailand	Reuters	THSHRPRCF	SET Index, Bangkok SE Price Index
UK	Reuters	UKSHRPRCF	Financial Times All Share Index
USA	Reuters	USSHRPRCF	Dow Jones Industrial Share Price Index

Figure A.1: Sample band components: quarterly M2 series for Germany

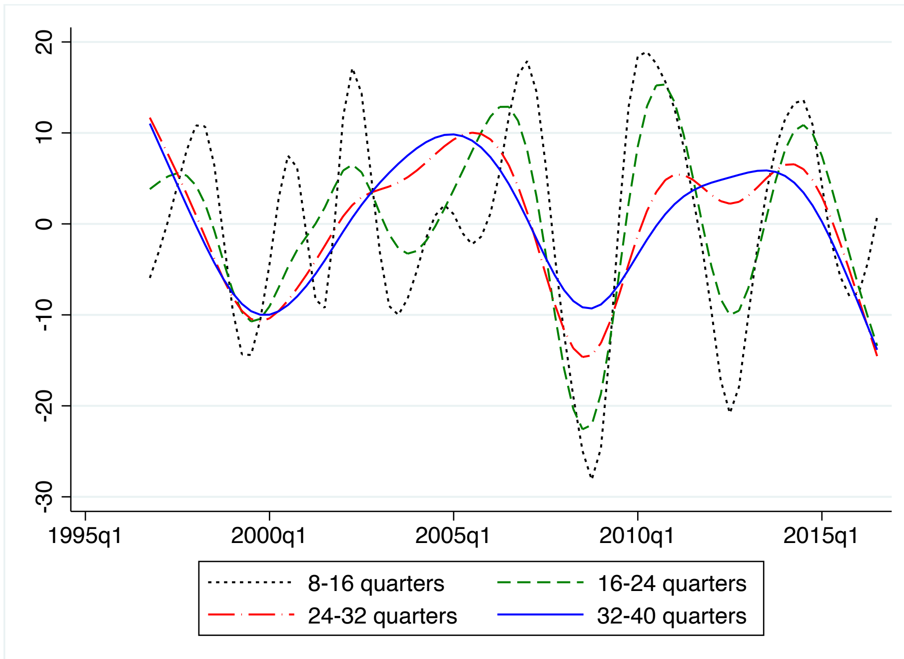

Figure A.2: Sample band components: Annual GDP series for Saudi Arabia