Global Trade and GDP Co-movement*

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Abstract

We revisit the association between trade and GDP comovement for 135 countries from 1970 to 2009. Guided by a simple theory, we introduce two notions of trade linkages: (i) *direct* bilateral trade index and (ii) common exposure to third countries capturing the role of similarity in *trade networks*. Both measures are economically and statistically associated with GDP correlation, suggesting an additional channel through which GDP fluctuations propagate through trade linkages. Moreover, high income countries become more synchronized when the content of their trade is tilted toward inputs while trade in final goods is key for low income countries. Finally, we present evidence that the density of the international trade network is associated with an amplification of the association between global trade flows and bilateral GDP comovement, leading to a significant evolution of the trade comovement slope over the last two decades. This insight cautions against the view that there exist a single time-invariant "deep" value for the trade comovement slope.

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1 Introduction

Over the past decades, both import and export flows have increased much faster than GDP for almost all countries in the world. This march toward more open economies has been accompanied by a reorganisation of he world's production across different locations, with both trade in intermediate inputs and in final goods trade representing an increasing share of world GDP, now reaching around three times the share observed in the 1970s. In valued-added terms, trade increased at an average annual growth rate of more than 5 percent during the 1990-2009 period, with the share of trade in intermediate inputs roughly constant at around 70% of total trade. During the same period, the average GDP co-movement across all pairs of countries rose from 6% to 38%.

The general surge in trade-over-GDP also implies more complex patterns for international propagation: when two countries are increasingly connected to the same direct or indirect trade partners, the associated surge in "third country" exposure can create systemic interdependence that operates over and above direct trade linkages. The consequences of these changes in trade patterns for the synchronization of economic activity are an important issue because they can have implications for macroeconomic policies.[1] In light of these global trends, several questions arise: did the rise of Global Value Chains (GVCs) have a specific effect on the correlation of GDP and its association with both direct and indirect trade flows? Did the rise in production fragmentation have the same effect across income groups? Are *direct* trade linkages more important than common exposure to third markets? Did the sensitivity of GDP co-movement to an increase in bilateral trade flows evolve over time?

Since the seminal paper by Frankel and Rose (1998), hereafter FR, a large empirical literature has studied the determinants of cross-country business cycle co-movement, showing that bilateral trade is an important and robust element associated with changes in GDP correlation while measures of financial linkages or countries' sectoral similarity are not statistically associated with higher bilateral synchronization.[2] In this paper we re-assess the association between global trade and cross-country business cycle correlation using a large sample of 135 countries from 1970 to 2009, including high and low income countries. Using constructed panel data and controlling for both observed and unobserved heterogeneity between countries and over time, we estimate the *trade co-movement* slope (TC-slope) across different income groups and unveil a series of new

[1]For example, the extent to which the Euro Zone can be considered as an optimal currency area (and, therefore a common monetary policy could be optimal) largely depends on the synchrony of business cycles among the member countries.

[2]Among *many* others, see Frankel and Rose (1998), Clark and van Wincoop (2001), Imbs (2004), Baxter and Kouparitsas (2005), Calderon et al. (2007), Inklaar et al. (2008), Di Giovanni and Levchenko (2010), Ng (2010), Liao and Santacreu (2015), di Giovanni et al. (2016) and Duval et al. (2015). The literature mostly focused on high income countries, with the notable exception of Calderon et al. (2007), and set up estimation equations that unveil a single time-invariant value for the association between *bilateral* trade flows and business cycle correlation.

determinants of GDP co-movement, including the different role of the content of trade flows for each income group as well as the presence of network effects and how they interact with bilateral proximity. Moreover, we also uncover important time variations in the TC-slope, which suggests that the sensitivity of GDP correlation to changes in trade proximity is not akin to a time-invariant deep parameter but is a function of other elements that evolve over time.

Building on earlier literature, this paper makes several contributions. First, starting with the role of *bilateral* trade flows, we update previous analysis by separating trade flows into *trade in intermediate inputs* and *trade in final goods* and investigate separately their specific role for GDP synchronization for high and low income countries. As shown in de Soyres and Gaillard (2020) and confirmed in this paper, *trade in intermediate inputs* plays a particular role in the TC-slope for OECD countries. However, this finding is complemented and nuanced here by a novel insight regarding low income countries. Using only *within* country-pair variations and controlling for several factors including changes in the similarity of industrial structure across country pairs, we show that economies at the lower end of the income distribution experience an increase in the correlation of their GDP with their trade partners when the content of their trade flows is more tilted toward final goods trade. According to our simple model and in line with other networks model, this difference suggests that supply-side shocks are more important in high income countries, while demand shocks are more important in low income countries. Moreover, to better understand this difference, we use disaggregated trade data and show that country-pairs with a large TC-slope in intermediate inputs are also characterized by high proximity in the sectoral composition of their trade flows. All told, our analysis suggests that trade in inputs is associated with higher GDP correlation when countries have a similar industrial structure.[3]

Second, guided by recent debates on the role of Global Value Chains and the systemic interdependence that can arise from worldwide input-output linkages, we move beyond *bilateral* trade linkages and construct new indices of *network* proximity for all country pairs. We argue that changes in GDP synchronization between two countries can be the result of an increased common exposure to third markets, which can happen either at the first order when two countries have similar trade partners or at the second order when countries' direct partners have similar partners. On the whole, our results reveal that first order common exposure is particularly strong for high-income countries, while second-order proximity, a measure of more indirect propagation, is more prevalent for low income economies. Moreover, we show theoretically and empirically that the marginal increase in GDP comovement associated with the increase in any trade link is itself increasing in the overall *density* of the network. As such, this amplification aspect linked with overall network density helps rationalize the wide array of TC-slopes found in the literature since any estimate depends on both the time and country coverage. Interest-

[3]To the extend that such similarity is in turn associated with a higher degree of input specificity, then this finding is fully consistent with results in Barrot and Sauvagnat (2016).

ingly, this result challenges the usual assumption of a single time-invariant relationship between trade and GDP comovement. While the complementarity between network and bilateral trade could rationalize our finding that the TC-slope significantly increased in the last two decades, we cannot rule out the possibility that other factors weighed into this evolution. In particular, the growth of price distortion could have also have played a role.

Finally, we provide various robustness checks, using different controls, measures and sample selection. For instance, controlling for bilateral financial interconnection of the banking sector or foreign direct investment does not affect our main findings (although it reduces our sample due to data coverage). Overall, our results are robust to a wide range of specifications and trade indexes and highlight important disparities among country groups and over time.

Relationship to the literature. Starting with Frankel and Rose (1998), a large number of papers have studied and confirmed the positive association between trade and GDP comovement in the cross-section.[4] This paper is mostly related to a few recent contributions. First, di Giovanni et al. (2016) uses a *cross-section* of French firms and presents evidence that international input-output linkages at the micro level are an important driver of the value added comovement observed at the macro level. Their evidence is in line with the findings of this paper and supports the role of Global Value Chains in the synchronization of GDP fluctuations across countries.[5] Second, Liao and Santacreu (2015) is the first to study the importance of the extensive margin for GDP and TFP synchronization and shows that changes in the number of products traded across countries (rather than the average shipment per product) plays an important role in the synchronization of GDP. Third, Calderon et al. (2007) investigate the relationship between trade and business cycle comovement for both developed and developing countries. Based on cross sectional estimates, they find that the impact of trade integration on business cycles is higher for industrial countries than for developing countries. Fourth, our paper is related to a recent series of papers developing theoretical frameworks to measure GVC participation, including Bems et al. (2011) and others.

If the empirical association between bilateral trade and GDP comovement has long been known, the underlying economic mechanism leading to this relationship is still unclear. Using the workhorse IRBC with three countries, Kose and Yi (2006) have shown that the model can explain at most 10% of the *slope* between trade and business cycle synchronization, leading to what they called the *Trade Comovement Puzzle* (TCP). Since then, many papers including Johnson

[4]See papers cited for instance in footnote 2.

[5]Relatedly, Burstein et al. (2008) uses a cross section of trade flows between US multinationals and their affiliates as well as trade between the United States and Mexican maquiladoras to measure production-sharing trade and its link with the business cycle. Moreover, Ng (2010) uses cross-country data from 30 countries and shows that bilateral production fragmentation has a positive effect on business cycle comovement. The concept of bilateral production fragmentation used is different from this paper as it takes into account only a subset of trade in intermediates, namely imported inputs that are then further embodied in exports. Moreover, the cross-sectional nature of the analysis allows for neither dyadic nor time windows fixed effects.

(2014) or Duval et al. (2015), have refined the puzzle, highlighting different ingredients that could bridge the gap between the data and the predictions of standard models.[6] Our simple theoretical framework is closely related to previous analysis such as Long and Plosser (1983) and Acemoglu et al. (2012). Our contribution here simply consists of using existing tools to clarify the different channels linking global trade and bilateral GDP correlation. We then used insights regarding the role of inputs and final good trade, as well as the importance of network similarity, to guide our empirical exercise.

The rest of the paper is organized as follows. We first provide a simple trade network model in section 2, highlighting the role of trade in the global GDP-comovement. We then turn to our empirical contribution. Section 3 presents the data and the different constructed variables used throughout the paper. Section 4 investigates the global TC-slope not only across countries in different income groups, but also over time. We discuss the main implications of our results in section 5 and, in section 6, we test several possible explanations for some of the key differences between the results relative to high and low income countries. Finally, section 7 concludes.

2 A simple trade network model

To motivate our empirical work and formalize our intuition, we write a parsimonious static model of international trade with multiple countries and sectors, along the line of Long and Plosser (1983) and Acemoglu et al. (2012). We make strong assumptions in order to simplify the analysis. Our main goal is to illustrate through a series of example several mechanisms through which GDP in two countries can be correlated, which will then be tested empirically in the next section. In particular, we show that GDP comovement is the result of a combination of many factors, including the correlation structure of shocks hitting every country in the world, bilateral trade linkages between countries as well as their indirect exposure to the rest of the trade network, and the association between gross output and GDP which can be time varying.[7] For simplicity, our framework abstracts from other considerations such as the presence of financial linkages or the possibility of common (or coordinated) monetary policy. Note, however, that we will control for these and other elements in our empirical investigations in subsequent sections.

[6] For a quantitative solution to the Trade Comovement Puzzle, see de Soyres and Gaillard (2020), where it is shown that production linkages *alone* are not sufficient for a macro model to deliver a trade co-movement slope in line with the data.

[7] As discussed in Johnson (2014), comovement in intermediate input, and the resulting comovement in gross output, does not necessarily translate into real value-added comovement. Building on this insight, de Soyres and Gaillard (2020) shows that the introduction of markups and extensive margin adjustments can create a mechanical link between input correlation and GDP correlation. We simplify the discussion here by introducing a simple *ad hoc* proportional transformation between output and real value-added that illustrates the fact that the sensitivity of GDP comovement to trade proximity is a function of other elements – which could include the prevalence of markups for example.

2.1 Basic setup

Production and pricing. Consider a world with many countries ($i, j \in \{1, ..., N\}$) and many sectors ($s, s' \in \{1, ..., S\}$). In country i and sector s, gross output is the result of a Cobb Douglas combination of three main elements: (1) an exogenous technology shock ($Z_{i,s}$), (2) intermediate inputs from all other sector-countries in the world ($X_{i,s}^{j,s'}$), and (3) inelastic domestic factors of production ($L_{i,s}$).

$$Y_{i,s} = Z_{i,s} \cdot \left(\prod_{j,s'} (X_{i,s}^{j,s'})^{\alpha_{i,s}^{j,s'}} \right) \cdot L_{i,s}^{\gamma_{i,s}}, \tag{1}$$

with $\sum_{j,s'} \alpha_{i,s}^{j,s'} + \gamma_{i,s} = 1$. The production cost of a representative firm in each country i and sector s is a function of the price charged by its input suppliers and the suppliers of its suppliers. For simplicity we assume that there are no trade costs. Moreover, we also assume that firms' markups ($\mu_{i,s}$) are completely exogenous and independent of the destination market which further implies that prices are equal across all destination markets. Denoting $p_{i,s}$ the price of output produced by country-sector (i, s) and w_i the price of domestic factor in country i, standard cost minimization conditions imply that the price in (i, s) is given by:

$$p_{i,s} = \mu_{i,s} \cdot MC_{i,s} = \mu_{i,s} \cdot \frac{c_{i,s}}{Z_{i,s}} \times w_i^{\gamma_{i,s}} \cdot \prod_{j,s'} (p_{j,s'})^{\alpha_{i,s}^{j,s'}} \tag{2}$$

With $MC_{i,s}$ the marginal cost in (i, s) and $c_{i,s}$ a constant depending only on parameters.[8] As is usual in all models with input-output linkages, the price in a given sector-country is a direct function of all other prices in the economy. To simplify notation, we stack prices in all countries and sectors into an $(N \times S, 1)$ vector $\mathbf{P}$, where the first S rows contain the prices of all sectors in country 1, subsequent S rows contain all prices in country 2, etc... Taking the log and denoting by $\mathbf{\Omega}$ the cross-country input-output matrix of the economy, prices are the solution of a simple linear system:[9]

$$\log(\mathbf{P}) = (\mathcal{I}_{NS} - \mathbf{\Omega})^{-1} \begin{pmatrix} k_{1,1} - \log(Z_{1,1}) + \gamma_{1,1} \log(w_1) \\ \vdots \\ k_{N,S} - \log(Z_{N,S}) + \gamma_{N,S} \log(w_N) \end{pmatrix} \tag{3}$$

[8]The variable $c_{i,s}$ is defined as: $c_{i,s} = \gamma_{i,s}^{-\gamma_{i,s}} \prod_{j,s'} \alpha_{i,s}^{j,s' - \alpha_{i,s}^{j,s'}}$

[9]For simplicity, we write $\log(\mathbf{P})$ the vector of log prices. We denote $k_{i,s} = \log(\mu_{i,s} \cdot c_{i,s})$ and the Input-Output matrix $\mathbf{\Omega}$ can be defined by block using country-pair input-output matrices $\Omega_{i,j}$ as:

$$\mathbf{\Omega} = \begin{pmatrix} \Omega_{1,1} & \Omega_{1,2} & \dots \\ \vdots & \vdots & \vdots \\ \Omega_{N,1} & \dots & \Omega_{N,N} \end{pmatrix}, \qquad \text{with } (\Omega_{i,j})_{s,s'} = \alpha_{i,s}^{j,s'}$$

Clearing conditions. Gross output is used both as an intermediate input in production and to produce a composite final good used by consumers. With Cobb Douglas production function, the representative firm in country j and sector s' spends a fraction $\alpha_{i,s}^{j,s'}$ on goods coming from (i,s), so that:

$$p_{i,s} X_{i,s}^{j,s'} = \alpha_{i,s}^{j,s'} p_{j,s'} Y_{j,s'} \quad , \qquad \text{for all } i,j,s,s' \tag{4}$$

Aggregate demand in each country j is denoted by D_j.[10] Country j addresses a fraction $\beta_{i,s}^{j}$ of its total demand to country-sector (i,s), so that market clearing in the final goods market can be written as:

$$p_{i,s} y_{i,s}^{j} = \beta_{i,s}^{j} D_j \quad , \qquad \text{for all } i,j,s \tag{5}$$

where $y_{i,s}^{j}$ is the amount of good produced in (i,s) that are absorbed as final demand in country j. We store all shares $\beta_{i,s}^{j}$ into a (NS, N) matrix $\mathbf{B}$ where each row corresponds to a sector-country (i,s) and the columns correspond to all countries.[11] Finally, the resource constraint condition is given by

$$Y_{i,s} = \sum_{j} y_{i,s}^{j} + \sum_{j,s'} X_{i,s}^{j,s'} \quad , \qquad \text{for all } i,s \tag{6}$$

Combining (4), (5) and (6), we can solve for nominal output in each country and sector:

$$\begin{pmatrix} p_{1,1} Y_{1,1} \\ \vdots \\ p_{N,S} Y_{N,S} \end{pmatrix} = \underbrace{\left(\mathbf{I}_{NS} - \left(\mathbf{\Omega}^{T}\right)\right)^{-1} \cdot \mathbf{B}}_{=\mathbf{T}} \cdot \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} \tag{7}$$

In this stylized framework, solving for gross output in each sector-country amounts to jointly solving for prices using (3) and nominal output using (7). The simplicity of the analysis follows from our strong assumption, in particular Cobb-Douglas production and demand aggregates, as well as essentially exogenous demand. Our main goal here is to propose a framework that is as simple as possible while guiding as well as providing intuition for our empirical investigations in the next section.

Defining Real Value Added. Measuring real value added in this framework is not straightforward. Statistical agencies measure real value added in each sector as the difference between

[10] A natural general equilibrium closing of the model would be to assume that total demand D_i equals total income of domestic production factor $w_i L_i$ as well as domestic profits. We keep things more general here and solve for gross output for any level of final demand, which makes it possible, in principle, to study both supply shocks (through shocks to technology $Z_{i,s}$) as well as demand shocks if were to introduce shocks to D_i.

[11] Matrix $\mathbf{B}$ is defined as:

$$\mathbf{B} = \begin{pmatrix} \beta_{1,1}^{1} & \beta_{1,1}^{2} & \cdots & \beta_{1,1}^{N} \\ \beta_{1,2}^{1} & \beta_{1,2}^{2} & \cdots & \beta_{1,2}^{N} \\ \vdots & \vdots & \vdots & \vdots \\ \beta_{N,S}^{1} & \beta_{N,S}^{2} & \cdots & \beta_{N,S}^{N} \end{pmatrix}$$

gross output and intermediate input, measured using base period prices. As discussed in Kehoe and Ruhl (2008) or in Johnson (2014), in a perfectly competitive setting, this procedure amounts to measuring changes in domestic factor supply (i.e. changes in labor $L_{i,s}$ in our model without capital). Hence, without markups, our assumption that domestic factors are completely inelastic would lead to constant *measured* real value added.

However, Basu and Fernald (2002), de Soyres and Gaillard (2020) and others note that things differ markedly when one introduces markups. By introducing a wedge between marginal cost and marginal revenue product of inputs, the presence of markups creates a proportional relationship between gross output and profits fluctuations. In such a case, even with inelastic domestic factor supply, real value added can still fluctuate owing to movements in profits.

We parsimoniously account for such a channel by positing a reduced form relationship between gross output $Y_i = \sum_s Y_{i,s}$ and *measured* real GDP, so that $RGDP_i = \sum_s L_{i,s} + \kappa_i Y_i$, with κ_i a constant. In a reduce form, κ_i accounts for the fact that, with constant markup, any change in gross output is associated with a proportional change in profits, which are measured as value added and are part of real GDP. As a result, in such a setup with fixed domestic factor supply, changes in real GDP come only from gross output fluctuations. Hence, when investigating real GDP comovement, we can actually focus on gross output ($Y_{i,s}$) comovement.

In the rest of this section, we show how correlation of gross output fluctuations can emerge from a variety of different channels, which we then formally test in the rest of the paper.

2.2 Propagation of shocks and global trade flows

Our framework is similar to previous network models and shares the same propagation properties. As noted in Acemoglu et al. (2016), theory predicts that TFP shocks propagate downstream while demand shocks propagate upstream.[12] We take this insight on-board and describe its consequences for the relationship between trade and GDP comovement.

In particular, trade in final good is not associated with cross-country propagation in a world with only supply-side shocks. However, with demand shocks, both intermediate input and final good trade are relevant. We illustrate this logic through a series of examples below.

2.2.1 Propagation of TFP shocks

When demand shifters are fixed and technology is the only source of shocks, equation (7) implies that nominal output is constant. The proportional change in real gross output in any country, $\widehat{Y}_i$, is a function of the vector of shocks and the Leontieff inverse. In matrix form, changes in output

[12] This result, already established in previous papers with Cobb-Douglas networks, simply follows from inspecting (3) and (7).

can be written as:

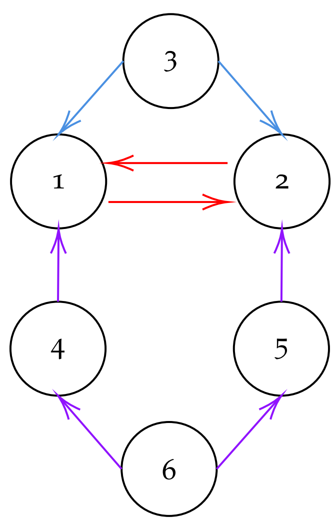
$$\widehat{\mathbf{Y}} = [\mathbf{I}_{NS} - \mathbf{\Omega}]^{-1}\,\widehat{\mathbf{Z}} \tag{8}$$

Note that the matrix $\mathbf{B}$, capturing final good trade, is not present in this equation. In the rest of this sub-section, we present stylized examples with specific Input-Output matrices to illustrate several determinants of bilateral comovement.

Consider a world with six countries and only one sector per country. We choose a specific structure of input-output linkages in order to show how (i) bilateral trade, (ii) direct common trade exposure, and (iii) indirect common trade exposure all play a role in bilateral output (and ultimately GDP) comovement. The structure is described in figure 1 and the associated $\mathbf{\Omega}$ matrix is given by:

$$\mathbf{\Omega} = \begin{pmatrix} 0 & \alpha_1^2 & \alpha_1^3 & \alpha_1^4 & 0 & 0 \\ \alpha_2^1 & 0 & \alpha_2^3 & 0 & \alpha_2^5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \alpha_4^6 \\ 0 & 0 & 0 & 0 & 0 & \alpha_5^6 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{9}$$

Figure 1. Network representation of input-output linkages as described in (9)



Using equation (8), we can write the proportional change in gross output in countries 1 and 2 as a function of all shocks and trade linkages:[13]

$$\widehat{Y_1} = \frac{1}{\mid \mathbf{\Omega} \mid}\left(\widehat{Z_1} + \alpha_1^2\widehat{Z_2} + (\alpha_1^3 + \alpha_1^2\alpha_2^3)\widehat{Z_3} + \alpha_1^4\widehat{Z_4} + \alpha_1^2\alpha_2^5\widehat{Z_5} + (\alpha_1^4\alpha_4^6 + \alpha_1^2\alpha_2^5\alpha_5^6)\widehat{Z_6}\right) \tag{10}$$

$$\widehat{Y_2} = \frac{1}{\mid \mathbf{\Omega} \mid}\left(\alpha_2^1\widehat{Z_1} + \widehat{Z_2} + (\alpha_2^3 + \alpha_2^1\alpha_1^3)\widehat{Z_3} + \alpha_2^1\alpha_1^4\widehat{Z_4} + \alpha_2^5\widehat{Z_5} + (\alpha_2^5\alpha_5^6 + \alpha_2^1\alpha_1^4\alpha_4^6)\widehat{Z_6}\right) \tag{11}$$

[13]The variable $\mid \mathbf{\Omega} \mid$ is the determinant of matrix $\mathbf{\Omega}$

where we recall that α_i^j is the spending share in country i on goods coming from country j.

We consider a case where technology shocks are uncorrelated, so that $\text{Cov}(Z_i, Z_j) = 0$ for all i and j.[14] In such a case, correlation between $\widehat{Y}_1$ and $\widehat{Y}_2$ is solely due to global trade linkages. Using equations (10) and (11), we can write a simple expression for $\text{corr}(\widehat{Y}_1, \widehat{Y}_2)$:[15]

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda \Big(\alpha_1^2 + \alpha_2^1 + (\alpha_1^3 + \alpha_1^2\alpha_2^3)(\alpha_2^3 + \alpha_2^1\alpha_1^3) + \alpha_2^1(\alpha_1^4)^2 + \alpha_1^2(\alpha_2^5)^2 \\ + (\alpha_1^4\alpha_4^6 + \alpha_1^2\alpha_2^5\alpha_5^6)(\alpha_2^5\alpha_5^6 + \alpha_2^1\alpha_1^4\alpha_4^6) \Big) \tag{12}$$

Equation (12) reveals that several types of trade linkages can give rise to endogenous output co-movement. We will now examine three cases that provide economic intuition for the empirical exercise we perform in the next sections.

1. *Bilateral trade*. Consider a situation where countries 1 and 2 both import inputs from one-another but do not trade with the rest of the world. In other words, α_1^2 and α_2^1 are strictly positive but all other input-output shares are zero. Following (12), the correlation between $\widehat{Y}_1$ and $\widehat{Y}_2$ is simply a function of bilateral trade shares:

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda \left(\alpha_1^2 + \alpha_2^1 \right) \tag{13}$$

   With TFP shocks as the sole source of fluctuation, only trade in input is relevant for the synchronization of economic activity.

2. *First order "third country" exposure*. This situation happens when countries 1 and 2 import intermediates from country 3 (meaning that α_1^3 and α_2^3 are strictly positive) but all other input-output shares are zero. This situation is interesting because neither country 1 nor country 2 exports any value added to each other. With uncorrelated technology shocks, the only reason countries 1 and 2 co-move is because they are commonly exposed to country 3. Using (12), we get a simple expression for bilateral correlation of output:

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda \left(\alpha_1^3\alpha_2^3 \right) \tag{14}$$

3. *Second order "third country" exposure*. In this case, the only trade flows are as follows: country 6 exports inputs to countries 4 and 5, which are used for production and further re-exported

[14] In our empirical analysis below, we control for time invariant shock correlation using country-pair fixed effects, while changes in the average correlation of shocks are captured using time windows fixed effects.

[15] where λ is defined by

$$\lambda = \left(| \boldsymbol{\Omega} |^2 \sqrt{\text{Var}(\widehat{Y}_1)\text{Var}(\widehat{Y}_2)} \right)^{-1}$$

to countries 1 and 2 respectively. In such a configuration, countries 1 and 2 have neither bilateral ties nor any first order network proximity since there is no overlap between their trade partners. However, they are both indirectly exposed to country 6. Equation (12) then yields the following expression of bilateral output correlation:

$$\operatorname{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda \left(\alpha_1^4 \alpha_4^6 \alpha_2^5 \alpha_5^6 \right) \tag{15}$$

For simplicity, we chose here a sparse and symmetric second order network exposure, but other types of indirect exposure will naturally arise in the data given the high density of the actual network of trade linkages. For instance, indirect exposure could arise if country 6 is both directly linked to country 1 and indirectly linked to country 2.[16]

An inspection of equations (13) to (15) reveals that GDP co-movement is the result of several type of linkages, including direct bilateral trade links (case 1) as well as common exposure to third countries using first- or second-order partners (cases 2 and 3, respectively).

2.2.2 The role of network density

So far, we have considered situations where different types of linkages were analyzed in isolation from one another. In practice, these mechanisms do not operate independently, and the density of the global trade network can act as a powerful amplification factor. We illustrate this point by considering a situation where countries 1 and 2 trade with each-other (α_1^2 and α_2^1 are non-zero) and are also commonly exposed to country 3 (α_1^3 and α_2^3 are non-zero). Using equation (12), we can write bilateral output correlation as:

$$\operatorname{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda \left(\alpha_1^2 + \alpha_2^1 + (\alpha_1^3 + \alpha_1^2 \alpha_2^3)(\alpha_2^3 + \alpha_2^1 \alpha_1^3) \right) > \lambda \left(\alpha_1^2 + \alpha_2^1 + \alpha_1^3 \alpha_2^3 \right) \tag{16}$$

The inequality in equation (16) reveals that the correlation stemming from the combination of both bilateral trade and common exposure is larger than the sum of each channel individually. As such, it illustrates the complementarity that arises from these channels that amplify one another. The strength of each channel increases with the presence of other linkages in the trade network, which means that an increase in the overall density of the trade networks is expected to amplify each of the channel discussed above. Hence, one should not expect that the *marginal* effect of increasing any given link in the sparse network of the 1970s is the same as the effect of increasing a link in today's network. As a result, there is no such thing as a single "deep" parameter for the Trade Co-movement Slope. In the empirical exercise below, we test and provide support for such amplification through network density.

[16] Formally, this case happens when α_1^6, α_5^6 and α_2^5 are all strictly positive.

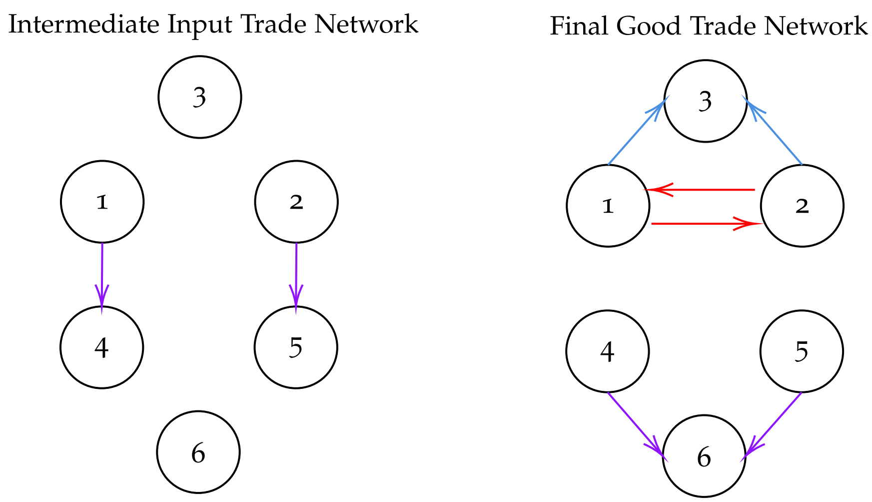
2.2.3 Propagation of Demand shocks

We now consider a world where technology is fixed and the only source of shocks are demand shifters $D_1, ..., D_N$. We take fluctuations in country-specific aggregate demand as exogenous for simplicity. In this case, since prices are fixed, changes in nominal and real output are proportional and we have:

$$\widehat{\mathbf{Y}} \propto \left(\mathbf{I}_{NS} - \left(\mathbf{\Omega}^T\right)\right)^{-1} \cdot \mathbf{B} \cdot \widehat{\mathbf{D}} \tag{17}$$

Equation (17) includes both $\mathbf{\Omega}$ and $\mathbf{B}$, revealing that propagation of demand shocks depends on the combination of both input and final good trade. We now illustrate the role of both links using the network structure described in figure 2, where some countries consume foreign final goods on top of their domestically produced good.

Figure 2. Network representation of both input and final good trade as described in (18)



The input-output and demand shares matrices associated with this structure are given by:

$$\mathbf{\Omega} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_4^1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_5^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad \mathbf{B} = \begin{pmatrix} \beta_1^1 & \beta_1^2 & \beta_1^3 & 0 & 0 & 0 \\ \beta_2^1 & \beta_2^2 & \beta_2^3 & 0 & 0 & 0 \\ 0 & 0 & \beta_3^3 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_4^4 & 0 & \beta_4^6 \\ 0 & 0 & 0 & 0 & \beta_5^5 & \beta_5^6 \\ 0 & 0 & 0 & 0 & 0 & \beta_6^6 \end{pmatrix} \tag{18}$$

Using equation (17) yields the proportional change in gross output in countries 1 and 2:

$$\widehat{Y_1} \propto \beta_1^1 \widehat{D_1} + \beta_1^2 \widehat{D_2} + \beta_1^3 \widehat{D_3} + \beta_4^4 \alpha_1^4 \widehat{D_4} + \beta_4^6 \alpha_1^4 \widehat{D_6} \tag{19}$$

$$\widehat{Y_2} \propto \beta_2^1 \widehat{D_1} + \beta_2^2 \widehat{D_2} + \beta_2^3 \widehat{D_3} + \beta_5^5 \alpha_2^5 \widehat{D_5} + \beta_5^6 \alpha_2^5 \widehat{D_6} \tag{20}$$

Assuming uncorrelated demand shocks, the only source of correlation between $\widehat{Y}_1$ and $\widehat{Y}_2$ is the combination of input and final goods trade, such that:[17]

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\beta_1^1\beta_2^1 + \beta_1^1\beta_2^1 + \beta_1^3\beta_2^3 + \beta_4^6\beta_1^6\alpha_1^4\alpha_2^5\right) \tag{21}$$

Similar to what we did in section 2.2.1, we now examine three cases that provide economic intuition for the empirical exercise we perform in the next section:

1. *Bilateral trade*. Consider a situation where only β_1^2 and β_2^1 are strictly positive but all other international demand shares are zero. Following (21), the correlation between $\widehat{Y}_1$ and $\widehat{Y}_2$ is simply a function of bilateral trade shares:

   $$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\beta_1^1\beta_2^1 + \beta_1^1\beta_2^1\right) \tag{22}$$

   With demand shocks as the sole source of fluctuation, trade in final goods becomes relevant for the synchronization of economic activity.

2. *First order "third country" exposure*. Consider a case where countries 1 and 2 export final goods to country 3. With β_1^3 and β_2^3 strictly positive and all other international demand shares zero, the only reason countries 1 and 2 co-move is that they are commonly exposed to demand shocks in country 3 and their bilateral correlation becomes:

   $$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\beta_1^3\beta_2^3\right) \tag{23}$$

3. *Second order "third country" exposure*. Consider a case where country 1 exports intermediates to country 4, which are then used in the production of final goods consumed in country 6. Similarly, country 2 exports intermediates to country 5, which are then re-exported as final goods to country 6. In such a configuration, countries 1 and 2 are commonly exposed to demand shocks in country 6 through their respective trade partners. Bilateral output correlation is given by:

   $$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\beta_4^6\beta_1^6\alpha_1^4\alpha_2^5\right) \tag{24}$$

From equations (22) to (24), it follows that demand shocks propagate across countries trough a combination of both trade in inputs and trade in final goods, with both direct and indirect exposure to common shocks increasing bilateral correlation.

[17] where λ is defined by

$$\lambda = \left(\sqrt{\text{Var}(\widehat{Y}_1)\text{Var}(\widehat{Y}_2)}\right)^{-1}$$

2.2.4 The role of sectoral composition

We slightly modify our setup and consider a world with only two countries and two sectors. To streamline the discussion, we also assume that there are no trade flows at all, implying that countries do not have any link with one another and technology shocks do not propagate across countries. Furthermore, technology shocks are sector specific and do not embed any country-specific component, in the sense that sectors s are hit by the same shock Z_s in both countries. This assumption creates a link between sectoral specialization and bilateral comovement even in the absence of any trade flows. We assume these shocks are uncorrelated across both sectors and follow a distribution with a common variance σ^2. Proportional changes in output in each country i and sector s are given by $\widehat{Y_{i,s}} = \widehat{Z_s}$.

Introducing $\pi_{i,s}$ as the share of sector s in country i's gross output, we can write the aggregate change in country i as a function of sectoral changes: $\widehat{Y}_i = \pi_{i,1}\widehat{Y_{i,1}} + \pi_{i,2}\widehat{Y_{i,2}} = \pi_{i,1}\widehat{Z_1} + \pi_{i,2}\widehat{Z_2}$. Using our assumptions on shocks orthogonality and the fact that $\pi_{i,2} = 1 - \pi_{i,1}$ for both countries, we can write the following:[18]

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \frac{\pi_{1,1}\pi_{2,1} + (1-\pi_{1,1})(1-\pi_{2,1})}{\sqrt{\pi_{1,1}^2 + (1-\pi_{1,1})^2} \cdot \sqrt{\pi_{2,1}^2 + (1-\pi_{2,1})^2}} \tag{25}$$

From equation (25), it is apparent that bilateral output correlation equals zero whenever countries are fully specialized in different sectors, while it equals one if and only if $\pi_{1,1} = \pi_{2,1}$. In other words: bilateral co-movement increases with countries' similarity in their sectoral composition.

2.3 Key Takeaways from the Model

To summarize, the model developed in this section gives rise to four testable predictions:

1. Bilateral GDP correlation increases with direct bilateral trade. Intermediate input trade is more important in the presence of supply-side shocks, while final good trade is important in presence of demand-side shocks.

2. Bilateral GDP correlation increases with common exposure to third countries through direct as well as indirect linkages. This prediction is what we call the *network* channel.

3. The previously mentioned channels complement one another in the sense that the marginal effect of increasing bilateral trade linkages or increasing common exposure to other countries depends on the *density* of the overall network of trade linkages. Hence, there is no

[18] Note that the (common) variance σ^2 disappears from this equation since it appears in both the numerator and the denominator.

such thing as a "deep parameter" for the Trade Co-movement Slope. Owing to increasing trade linkages over the past four decades, this result also implies that both trade- and network-comovement slopes are expected to increase over time.

4. Bilateral GDP correlation increases with the similarity of sectoral composition between two countries.

In the rest of the paper, we will test for the presence of all these channels in the data as well as other related aspects of the relationship between global trade and GDP correlation. It is worth noting that, on top of the forces discussed in the framework developed in this section, an obvious additional source of bilateral comovement is simply the correlation of country-specific shocks. Since this source is unlikely to be fully captured by our index of sectoral similarity discussed below, we will add country-pair fixed effects in our specification that effectively control for any time invariant factor affecting bilateral correlation.

3 Data sources and construction of our main variables

One of the objectives of this paper is to investigate the heterogeneity of the TC-slope across different levels of development as well as across different time periods. To be able to do so, we build on and expand previous studies by broadening both time and geographical coverage and we build a sample containing 40 years of data and a total of 135 countries, which accounts for almost the totality of world trade flows and world GDP. To investigate the role of income level in the determinants of bilateral GDP correlation, we create four types of country-pairs: (i) pairs where both countries belong to the OECD, (ii) pairs where both countries are high income (defined as *HH* pairs) according to the World Bank definition of income group, (iii) pairs where one country is high income and the other is not (defined as *HL* pairs), and (iv) pairs where no country is categorized as high income (defined as *LL*).[19] Note that for clarity of exposition we do not separate middle and low income countries, and only investigate the differences between high income and other countries. Moreover, the first sub-sample (constructed based on OECD membership) is not informed by income level but is designed to capture possible specificities related to being part of a coordinated club. Our analysis reveals that results in the *OECD* and *HH* sub-samples turn out to be qualitatively similar but quantitatively different.

As will be clear below, all of our specifications are designed to control for unobserved country-pair heterogeneity by using only within country-pair time series variations. Hence, we divide our 40 years of time coverage, stretching from 1970 to 2009, into four non-overlapping

[19] The classification of high, middle or low income countries is taken from the World Bank classification: http://databank.worldbank.org/data/download/site-content/OGHIST.xls.

time windows. In table 1, we report the share of total trade flows of each income group in our sample, relative to total world trade flows.

Table. 1. Trade flows in the different income groups [b]

Period	Total Flows [a]	Share of total trade (%) *OECD*	*HH*	*HL*	*LL*
1970:1979	303	60.7	65.2	32.4	2.1
1980:1989	881	64.5	70.6	29.4	1.9
1990:1999	1864	61.9	64.3	34.9	2.6
2000:2009	3972	48.1	47.8	46.5	6.2

[a] in billions of US dollars.

[b] selected income groups are not exclusive. Some countries among the *LL* group also appear in *OECD*. For instance, this is the case for Mexico.

The extent to which countries have correlated GDP can be influenced by many factors beyond international trade, including correlated shocks, financial linkages, common monetary policies, and so on. Because those other factors can themselves be correlated with the index of trade proximity in the cross section, using cross-sectional identification could yield biased results. Indeed, in their seminal paper, FR use cross-sectional variations to evaluate whether bilateral trade intensity correlates with business cycle synchronization, but their specification does not rule out omitted variable bias such as, for example, the fact that neighboring countries have at the same time more correlated shocks and larger trade flows. By constructing a panel dataset and controlling for both country-pair and time windows fixed effects, this paper relates to recent studies that try to control for unobserved characteristics.[20] Therefore, in order to separate the effect of trade linkages from other unobservable elements, we construct a panel dataset by creating four periods of ten years each.[21] Within each time window, we compute GDP correlation as well as the average trade intensities defined below.

3.1 Trade Proximity and GDP-comovement

GDP. We use annual GDP data from the Word Development Indicators (WDI) of the World Bank, measured using constant 2010 prices in US dollars.[22] For our analysis, GDP series need to be filtered in order to extract the business cycle component from the trend. Our main and benchmark filter is the standard Hodrick-Prescott (HP) filter with a smoothing parameter of 100

[20] Di Giovanni and Levchenko (2010) includes country pair fixed effects in a large cross-section of industry-level data with 55 countries from 1970 to 1999 in order to test for the relationship between sectoral trade and *output* (not *value-added*) comovement at the industry level. Duval et al. (2015) includes country pair fixed and year effects in a panel of 63 countries from 1995 to 2013 and test the importance of *value added* trade in GDP comovement.

[21] Adding time windows fixed effects controls for the recent rise of world GDP correlation since the 1990s, which could be unrelated to trade intensity.

[22] We used the data series called "NY.GDP.MKTP.KD".

which is consistent with the yearly frequency of our data. Such a transformation allows us to capture the standard business cycle fluctuations. With this setting, we mostly keep fluctuations that have a frequency between 8 and 32 quarters. In section 6, we provide robustness checks using a Baxter and King (BK) filter and a simple log-first difference.[23] With the filtered GDP, we compute the GDP correlation for each country-pair (i, j) within each time-window t of 10 years, denoted Corr GDP$_{ijt}$.

Trade Proximity. We collect data on bilateral trade flows from the Observatory of Economic Complexity (MIT). This database covers 215 countries over the period 1962-2014. The data are classified according to the 4-digit Standard International Trade Classification (SITC), Revision 2. Only products and commodities are considered. To classify trade flows into final goods and intermediate inputs, we use a concordance table from SITC Rev. 2 to Broad Economic Categories (BEC).[24,25] Finally, we exclude country-pairs with less than two time-windows for which trade proximity is available.

We then aggregate trade flows in each category at the country-pair level. For each type of flow $d \in \{total, inter, final\}$ (for total trade flows, trade in intermediate inputs and trade in final goods respectively) we construct an index for *bilateral* trade proximity of a country-pair (i, j) in a given time-window t, as follows:

$$Trade^d_{ijt} = \frac{T^d_{i \leftrightarrow j,t}}{GDP_{it} + GDP_{jt}} \qquad \forall d \in \{total, I, F\} \tag{26}$$

where $T^d_{i \leftrightarrow j,t} = T^d_{i \to j,t} + T^d_{j \to i,t}$ is total trade flows between countries i and j, defined as the sum of exports from i to country j and exports from j to country i.[26] In the result tables below, we refer to Total$\equiv T^{total}$, Inter$\equiv T^{inter}$ and Final$\equiv T^{final}$ for simplicity.

3.2 Network Effects

A key contribution of this paper is to provide evidence that the association between GDP co-movement and trade linkage operates not only through bilateral trade intensity, but also through

[23]We use a Baxter and King (BK) filter with fluctuations between 32 and 200 quarters to isolate medium-term fluctuations in the spirit of Comin and Gertler (2006). A simple log-first difference is a more "agnostic" transformation that accounts for both the cyclical and the trend components embodied in any year-to-year fluctuation, but it is sometimes considered as less sensitive to researcher's assumptions and preferences regarding the parameters of the filtering method.

[24]The concordance table from SITC Rev2 to BEC can be found on the UN Trade Statistics webpage: https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp.

[25]We merge capital goods and intermediate inputs as a single bundle of intermediate inputs. Trade in capital goods is roughly 14% to 15% of total trade flows. For robustness, we also consider trade in capital goods separately. The main results remain unchanged.

[26]This specification is widely used in the literature. As a robustness check, we also adopt an alternative used index: $Trade^d_{ijt} = \max\left\{\frac{T^d_{i\to j,t}+T^d_{j\to i,t}}{GDP_{it}}, \frac{T^d_{i\to j,t}+T^d_{j\to i,t}}{GDP_{jt}}\right\}$.

common exposure to third countries, which we refer to as *network effects*.

First order *network* index. In a world with many countries, the bilateral index of trade proximity is not a sufficient measure of trade linkages.[27] We first complement the above co-variate with an index of *first order* network proximity that is constructed to reflect the fact that two countries might experience a surge in their GDP correlation if their exposure to a common third country increases. In other words, over and above changes in bilateral trade flows, two countries that are increasingly linked to similar partners are likely to become more synchronized. To account for such a common exposure mechanism, we construct a *third country* index aiming to capture the *first order* component of a trade network, such that:

$$network^{1st}_{ijt} = 1 - \frac{1}{2}\sum_k \left| \frac{T_{i\leftrightarrow k,t}}{T_{i,t}} - \frac{T_{j\leftrightarrow k,t}}{T_{j,t}} \right| \tag{27}$$

where $T_{i\leftrightarrow k,t}$ represents the total trade flows between country i and country k and $T_{i,t}$ denotes the total trade flows of country i vis-a-vis all of its partners. This index effectively measures the geographical overlap in two countries' trade partners. Note that country-pairs with very similar trade partners have an index close to one while two countries trading with completely different partners have an index of zero.

Second order *Network* effect. As a measure of 2nd order network proximity for any pair (i, j), we build an index measuring to what extend country i's partners are linked with country j's partners, weighted by the importance of the partners in terms of total trade flows of the two countries i and j:

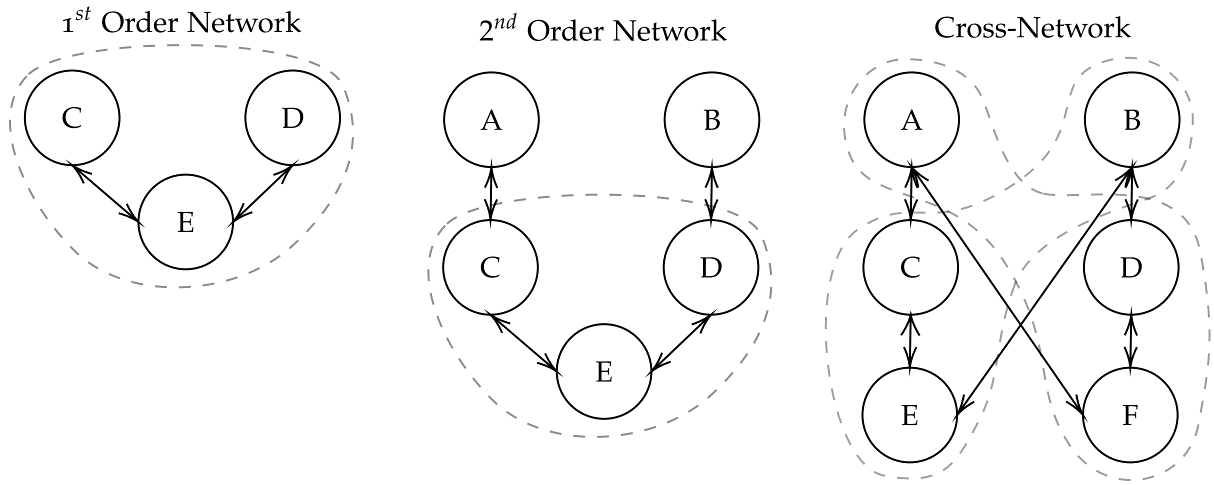
$$network^{2nd}_{ijt} = \frac{1}{4}\left(\sum_{z\in\mathcal{P}(i)} \sum_{y\in\mathcal{P}(j)} (w_t(i,z) + w_t(i,y) + w_t(j,z) + w_t(j,y)) * network_{zyt} \right) \tag{28}$$

where $w_t(i,z) = \frac{T_{i\leftrightarrow z,t}}{T_{i,t}}$. Under this specification, the more the partners of my partner are similar to my partners in terms of 1st order network, the higher the index $network^{2nd}_{ijt}$.

Cross-Network effect. In the robustness tests (section 6), we go a step further and construct another index capturing non-symmetric situations where a country's direct partners are linked with another country second order partners. We refer to this situation as a cross-network effect

[27] The importance of third country effect is also mentioned in Kose and Yi (2006) and Duval et al. (2015) analyzes the role of indirect trade linkages between two countries using a value-added approach. Our approach differs from Duval et al. (2015) because common exposure to third countries can happen even when two countries do not exchange any value added with one-another.

Figure 3. Illustration of first order, second order and cross network proximity indexes.



Note: dashed areas represent 1st order network. The second order effect and the cross-network effect can be represented as a combination of 1st order network effects.

of trade proximity, denoted ($cross\,network_{ijt}$) and defined as follows:

$$cross\,network_{ijt} = 1 - \frac{1}{4}\left(\sum_{z \in \mathcal{P}(j)} w_t(j,z) \sum_k \left| \frac{T_{i\leftrightarrow k,t}}{T_{i,t}} - \frac{T_{z\leftrightarrow k,t}}{T_{z,t}} \right| + \sum_{z \in \mathcal{P}(i)} w_t(i,z) \sum_k \left| \frac{T_{j\leftrightarrow k,t}}{T_{j,t}} - \frac{T_{z\leftrightarrow k,t}}{T_{z,t}} \right| \right)$$

$$= \frac{1}{2}\left(\sum_{z \in \mathcal{P}(j)} w_t(j,z) network_{izt} + \sum_{z \in \mathcal{P}(i)} w_t(i,z) network_{jzt} \right) \qquad (29)$$

where $w_t(i,z) = \frac{T_{i\leftrightarrow z,t}}{T_{i,t}}$. The index measures the extent to which a country i in the country-pair (i,j) is similar in terms of trade partners (i.e. in terms of direct *network* index) to all countries $z \in \mathcal{P}(j)$ trading with its partner j, weighted by the importance of z in the total trade of j.

As an illustration, we combine the three network representations in figure 3. Finally, we summarize in table 2 the evolution of our three *network* indexes in our sample. Interestingly, the first order network effect is much larger in *OECD* countries relative to the other group considered.

Table. 2. Network index in the different income groups [a]

	Network index *100											
	First order				Second order				Cross-network			
Period	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*
70:79	53.6	47.4	47.1	50.1	46.4	46.5	47.5	47.8	42.1	42.2	40.9	40.0
80:89	55.7	48.0	47.3	50.1	48.0	47.9	48.8	49.0	42.4	42.1	40.9	40.3
90:99	56.5	49.6	46.6	48.6	48.5	49.3	49.4	49.2	42.7	42.7	41.7	41.0
00:09	55.0	47.2	44.5	46.7	48.4	49.3	49.3	49.2	43.3	43.3	42.6	42.3

[a] Numbers reported are the average over all country-pairs.

3.3 Proximity in sectoral composition

As discussed in section 2, if shocks have a sectoral component then two countries with increasing similarity in sectoral specialization could experience a corresponding surge in business cycle co-movements even in the absence of any trade linkages. In order to account for such a mechanism, we build two bilateral indexes of *proximity in sectoral composition*. The first index is based on countries' proximity in terms of sector share in GDP while the second focuses on the proximity in traded goods, at the 4-digit SITC level or ISIC level, as proxy for domestic specialization in exported goods. Data for sector shares in GDP come from the World Bank's WDI. We use the share in value added of nine main sectors composed of service, agriculture and seven manufacturing sectors (textile, industry, machinery, chemical, high-tech, food and tabacco, and other).[28] Such an index is a direct measure of two countries' specialization, but its usefulness is somewhat limited by the high level of sectoral aggregation which allows us to capture only specialization in broad sectors. Moreover, data are available only for a subset of all countries.

We define the sectoral proximity index in terms of traded goods denoted $export^{prox}_{ijt}$ for a given country-pair (i, j) in time-window t as:

$$export^{prox}_{ijt} = 1 - \frac{1}{2} \sum_{s \in \mathcal{S}_{EX}} \left| \frac{EX_{i,t}(s)}{EX_{i,t}} - \frac{EX_{j,t}(s)}{EX_{j,t}} \right| \tag{30}$$

where $EX_{i,t}(s)$ refers to total export of country i in sector $s \in \mathcal{S}_{EX}$, with $\mathcal{S}_{EX}$ being the set of sectors (each 4-digit SITC code or ISIC code, depending on the definition adopted). We define the sectoral proximity index in terms of sector shares in GDP, denoted $sector^{prox}_{ijt}$, for a given country-pair (i, j) in time-window t as:

$$sector^{prox}_{ijt} = 1 - \frac{1}{2} \sum_{s \in \mathcal{S}} \left| \frac{Y_{i,t}(s)}{Y_{i,t}} - \frac{Y_{j,t}(s)}{Y_{j,t}} \right| \tag{31}$$

where $Y_{i,t}(s)$ refers to total value-added of country i in sector $s \in \mathcal{S}$, with $\mathcal{S}$ being the set of sectors. For both indexes, country pairs with very similar sectoral/trade composition have an index close to 1, while countries that completely specialize in different sectors have an index of 0. We provide in table 3 the evolution of sectoral proximity and export proximity over time for the income groups considered. In section 4, we use the export proximity constructed at the 4-digit SITC level and leave the ISIC specification as a robustness exercise in section 6.

Looking at indices based on exports as well as GDP, we note that country-pairs in the *OECD* are significantly more similar than those in other groups. Moreover, the time evolution of these indices also reveals a higher convergence, in terms of economic structure, among *OECD* countries

[28] Data are available here: https://databank.worldbank.org/data/source/.

Table. 3. Sectoral and export proximity index in the different income groups [a]

	Export proximity*100								Sectoral proximity*100			
	4-digit SITC				ISIC [b]				WDI [c]			
Period	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*
70:79	29.9	21.9	11.3	14.2	46.1	35.4	28.7	36.8	85.2	83.3	75.3	78.4
80:89	32.6	21.2	12.0	15.0	48.4	34.6	26.8	33.7	88.8	84.5	78.6	81.5
90:99	37.3	24.5	14.0	15.6	52.6	38.6	26.8	30.0	89.5	88.1	78.8	81.6
00:09	38.1	26.0	16.1	17.1	53.3	39.4	28.7	30.7	89.6	83.5	75.5	78.2

[a] Number reported is the average over all country-pairs.
[b] We classify goods and products at the ISIC level following the correspondence table https://unstats.un.org/unsd/tradekb/Knowledgebase/50054/Correlation-between-ISIC-and-SITC-codes-or-Commodity-and-Industry.
[c] WDI refers to sectoral proximity in terms of share of WDI sectors GDP in total GDP. Data is available here: https://databank.worldbank.org/data/source/.

compared with other sub-samples.

4 The Global Trade-Comovement Slope

In this section, we revisit the seminal FR analysis and use all variables defined in the previous section as well as additional controls to investigate the determinants of business cycle correlation for different income groups and time periods. We proceed step-by-step and gradually introduce our variables.

4.1 The initial Frankel and Rose (1998) specification

We first review the FR results by extending the analysis to a large sample of countries separated into different income groups. Following the more recent literature, we use a panel fixed effect in order to control for unobserved heterogeneity between country-pairs, as well as changes in economic conditions over time that are not related to trade.[29] As a first step, we estimate a panel with country-pair (CP) and time-window (TW) fixed effects with the following specification:

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}, \tag{32}$$

where $\mathbf{X}_{ijt}$ is a vector of additional control variables that includes dummies for URSS countries, the euro area, and the different waves of the European Union. On the one hand, the introduction of CP fixed effects means that we are using only *within* country-pair time variations for

[29]In order to discriminate between fixed or random effects, we run a Hausman test which display a significant difference ($p < 0.001$), and we therefore reject the random effect model.

the identification. These dummies effectively control for time invariant factors that can influence GDP comovement between two countries, such as distance, common border, common language, etc. On the other hand, TW fixed effects capture aggregate changes in GDP comovement for all country-pairs in the world that could be due to aggregate shocks. In this specification as well as all subsequent analysis, standard errors are robust to clustering at the country-pair level, which accounts for serial correlation across time. That is, we allow for the error term to have a fixed country-pair component common to all (i, j) observations.

In a second step, we introduce our network indexes (first and second order), which aim to capture the *network effect* of trade on GDP comovement stemming from both direct and indirect exposure to third countries. For this exercise, we use the following specification:

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \tag{33}$$

In equation (33), $\textbf{network}_{ijt}$ defines a vector composed of the first and second order network measures discussed above. The results are gathered in table 4.

Two main results emerge. First, as previously highlighted in the literature, trade proximity using total trade flows is significantly associated with more GDP correlation, for all considered groups. However, the strength of this association is very heterogeneous. Using the point estimate obtained with all country pairs, we find that moving from the 25th to the 75th percentiles of log total trade is associated with an increase in GDP correlation of 5.0 percentage points. The same number increases up to 16.7 percentage points for *OECD* country pairs, 7.1 percentage points for pairs in the *HH* group, 5.9 percentage points for the *HL* group and 9.3 percentage for the *LL* sub-sample.

Second, the effect of trade through the *network effect* is high and significant. According to our point estimate, moving from the 25th to the 75th quantiles of the direct network index implies an increase in GDP correlation of about 7.3 percentage points for all country-pairs, again with stark differences across sub-samples. For pairs in the OECD group, moving from the 25th to the 75th percentiles is associated with an impressive 30.9 percentage point increase in bilateral GDP correlation, while it is 14.6 percentage point for pairs in the *HH* group and only 6.2 percentage points for pairs in *HL*. Interestingly, the strength of a marginal increase in the direct network indexes is decreasing as the sample includes countries at the lower end of the income distribution, with the latter effect becoming statistically insignificant for the *LL* group.

Interestingly, the second order network index also plays a significant role for GDP comovement when using the whole sample. Concerning the classification in terms of income group, the point estimates increase as we move to the low income group. For example, for the *LL* group, when moving from the 25th to the 75th quantiles of this index, GDP-correlation increases 8.8%, while the first order network effect is insignificantly correlated with more GDP-comovement. This result highlights the possible strong dependence of those country-pairs to the global network as opposed to their more direct bilateral network. When focusing on the particular *OECD* group, we find the second order network effect is particularly high, with an increase in GDP correlation of 21.3% when moving from the first to the last quartiles.

All told, this first exercise reveals a subtle association between trade and GDP co-movement. While previous investigations highlighted the role of either direct or indirect bilateral trade, the economic and statistical significance of our network indices sheds light on an additional channel stemming from increasing exposure to other countries. As we will show below, the strength of this new channel is increasing over time, which makes it all the more relevant for understanding recent and future changes in cross-country business cycle synchronization.

Table. 4. Trade Comovement slope with total trade index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(Trade)	0.023***	0.021***	0.083***	0.090***	0.038***	0.028*	0.024***	0.023***	0.032***	0.038***
	(0.005)	(0.006)	(0.030)	(0.033)	(0.013)	(0.015)	(0.006)	(0.006)	(0.012)	(0.006)
network^{1st}		0.293***		1.082***		0.540***		0.254***		−0.044
		(0.067)		(0.262)		(0.163)		(0.073)		(0.073)
network^{2nd}		0.457**		2.914***		−0.201		0.567**		1.143***
		(0.221)		(0.913)		(0.555)		(0.243)		(0.243)
CP+TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
R^2	0.006	0.009	0.068	0.094	0.033	0.039	0.002	0.005	0.005	0.009

Notes: *p<0.1; **p<0.05; ***p<0.01.

4.2 Accounting for trade in intermediate inputs and final goods

Expanding on our results using total trade flows, we now refine the analysis and decompose total trade flows into two sub-categories: *trade in intermediate inputs* and *trade in final goods*. As discussed in de Soyres and Gaillard (2020) for the case of high income countries, trade in intermediate inputs is significantly correlated with GDP comovement, while trade in final goods is not.[30] In this section, we test the differential relationship between business cycle synchronization and both trade in intermediate inputs and trade in final goods in a larger sample covering different income groups.

[30] In de Soyres and Gaillard (2020), we also show theoretically how international input-output linkages, coupled with market power and extensive margin adjustments, can quantitatively generate a strong link between trade in intermediate inputs and GDP-comovement, resolving the *Trade-Comovement Puzzle*

We run the following specification (with and without network effects), where we disaggregate total trade flows ($\text{Trade}_{ijt}^{total}$) into trade in intermediate inputs ($\text{Trade}_{ijt}^{inter}$) and trade in final goods ($\text{Trade}_{ijt}^{final}$):

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \tag{34}$$

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \boldsymbol{\gamma}\, \mathbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \tag{35}$$

The results are shown in table 5. When focusing on country-pairs in *OECD* and *HH*, we see that the TC slope is significantly driven by trade in intermediate inputs as opposed to trade in final goods[31] Turning to country-pairs in the *HL* and *LL* groups, we find an opposite result: the TC slope is significantly related to more trade in final goods while trade in intermediate inputs is not significantly associated with higher GDP comovement. These findings are also strongly economically significant: according to the point estimate obtained when controlling for network effects, moving from the 25th to the 75th quantiles of log trade in intermediate inputs is associated with a 21.7 percentage points increase in GDP correlation for pairs in the *OECD* group and a 12.9 percentage point increase for pairs in the *HH* group. For pairs in the *HL* and *LL* groups, moving from the 25th to the 75th quantile of log trade in final goods increases respectively GDP comovement by 4.9 and 5.1 percentage points respectively.

According to our theoretical framework, and in line with observations in previous papers such as Acemoglu et al. (2016), we note that supply-side shocks propagate downstream whereas demand-side shocks propagate downstream. Hence, our results suggest that higher income countries are prominently subject to TFP shocks while lower income ones are mostly subject to demand shocks. In section 6, we show these results are robust to a number of alternative specifications, including financial controls (FDI and constructed financial interconnection BIS indexes), different GDP filters and different measures of trade intensities.

4.3 The role of sectoral proximity and export proximity

We complement the analysis with additional controls that aim to capture the proximity in terms of sectoral composition. As shown in section 2, if two countries have similar sectors, they are more likely to experience GDP comovement. We test this prediction using two measures of proximity: (i) proximity in terms of exported goods using our index $\text{export}_{ijt}^{prox}$ and (ii) proximity in terms of GDP sector shares captured by the index $\text{sector}_{ijt}^{prox}$. While $\text{export}_{ijt}^{prox}$ is available for all considered country-pairs, $\text{sector}_{ijt}^{prox}$ is constrained by data availability. We run the following

[31]Notice that we combine trade in capital goods with trade in intermediate inputs. Separating those flows to the regression provides similar results as shown in the sensitive analysis.

Table. 5. Trade Comovement slope with disaggregated trade index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(inter)	0.011^{**}	0.009	0.106^{***}	0.103^{***}	0.043^{***}	0.034^{**}	0.008	0.007	0.014	0.018^{***}
	(0.005)	(0.005)	(0.030)	(0.030)	(0.013)	(0.014)	(0.006)	(0.006)	(0.011)	(0.006)
ln(final)	0.012^{***}	0.012^{**}	-0.023	-0.009	-0.011	-0.009	0.017^{***}	0.016^{***}	0.015	0.017^{***}
	(0.005)	(0.005)	(0.024)	(0.025)	(0.012)	(0.012)	(0.005)	(0.005)	(0.010)	(0.005)
network^{1st}		0.305^{***}		1.046^{***}		0.521^{***}		0.264^{***}		-0.040
		(0.067)		(0.259)		(0.163)		(0.073)		(0.073)
network^{2nd}		0.416^{*}		2.906^{***}		-0.170		0.518^{**}		1.076^{***}
		(0.221)		(0.938)		(0.550)		(0.243)		(0.243)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
R^2	0.006	0.009	0.074	0.099	0.035	0.040	0.003	0.005	0.004	0.008
Notes:								*p<0.1; **p<0.05; ***p<0.01.		

two specifications:

$$\begin{aligned}\text{Corr GDP}_{ijt} &= \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \alpha_1 \text{ export}_{ijt}^{prox} \\ &\quad + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{36}$$

$$\begin{aligned}\text{Corr GDP}_{ijt} &= \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \alpha_1 \text{ export}_{ijt}^{prox} \\ &\quad + \alpha_2 \text{ sector}_{ijt}^{prox} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{37}$$

The results are gathered in table 6. On the one hand, focusing on the first five columns, we find that similarity in the type of traded goods has a surprisingly negative effect on GDP-comovement, which is the opposite of what is predicted by our simple model in section 2. This result could be explained by the possible substitutability between traded goods, which implies that a positive technology shock in one country decreases the market share of producers in other countries, leading to fluctuations in the opposite direction when they trade similar goods. On the other hand, other estimated coefficients are not sensitive to the addition of $\text{export}_{ijt}^{prox}$. Turning to the effect of sectoral proximity (last five columns) on the sub-sample for which data are available, we do not find a statistically significant effect of $\text{sector}_{ijt}^{prox}$ on GDP-comovement.

4.4 The evolution of the TC Slope from 1970 to 2009

Having established the link between global trade flows and GDP comovement for different income groups, we now turn to the issue of the potential time evolution of the association between

Table. 6. The role of sectoral proximity and export proximity

	corr GDP									
	All	*OECD*	*HH*	*HL*	*LL*	*All*	*OECD*	*HH*	*HL*	*LL*
ln(inter)	0.010*	0.102***	0.037***	0.008	0.018	0.010	0.142*	0.089**	0.009	0.044**
	(0.005)	(0.030)	(0.014)	(0.006)	(0.011)	(0.014)	(0.082)	(0.040)	(0.014)	(0.022)
ln(final)	0.013***	−0.008	−0.007	0.017***	0.017*	−0.002	−0.046	−0.189***	0.013	−0.010
	(0.005)	(0.025)	(0.013)	(0.005)	(0.010)	(0.012)	(0.050)	(0.042)	(0.013)	(0.021)
network^{1st}	0.307***	0.967***	0.445***	0.271***	−0.027	0.321	0.703	0.287	0.324	−0.345
	(0.066)	(0.269)	(0.162)	(0.073)	(0.156)	(0.201)	(0.660)	(0.504)	(0.221)	(0.368)
network^{2nd}	0.446**	2.745***	−0.302	0.554**	1.081**	2.103***	3.216*	−1.107	2.471***	2.396**
	(0.221)	(0.955)	(0.550)	(0.243)	(0.469)	(0.607)	(1.885)	(1.544)	(0.656)	(0.976)
export^{prox}	−0.394***	−0.381	−0.754***	−0.318***	−0.075	−0.091	0.916*	−0.928**	0.024	0.333
	(0.083)	(0.237)	(0.182)	(0.092)	(0.146)	(0.188)	(0.473)	(0.439)	(0.206)	(0.295)
sector^{prox}						0.296	−0.249	0.430	0.172	−0.235
						(0.189)	(0.705)	(0.430)	(0.213)	(0.409)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	1,224	2,541	10,538	2,745	4,499	655	893	3,606	1,091
R^2	0.012	0.101	0.049	0.007	0.008	0.025	0.165	0.166	0.017	0.022

Notes: *p<0.1; **p<0.05; ***p<0.01.

a marginal increase in trade and business cycle synchronization. More precisely, we provide evidence regarding a noticeable evolution of the TC slope between 1970 and 2009. This evidence is of particular importance since GDP-comovement surged between 1990 and 2009, for many countries, including those in the low income groups. Moreover, establishing that the association between trade and business cycle synchronization not only varies by income group but is also time varying yields two additional benefits. First it helps reconcile different values of the TC-slope that are found in the literature and which rely on different geographic and time coverages. Second, it would lend support to the hypothesis that the marginal effect of increasing (either direct or indirect) trade flows between two countries changes with economic conditions. Such a hypothesis can then be investigated further in order to uncover what are the factors that enable and amplify the relationship between trade and GDP comovement.

We introduce a dummy variable LTW_t which equals to 1 for the last two time-windows in our sample – that is for the periods 1990:1999 and 2000:2009 – and 0 otherwise. This "Late Time Window" dummy is then interacted with the determinants of GDP comovement, allowing us to formally test for the difference between the TC-slope in earlier time windows and the slope observed toward the end of the time coverage.[32] Formally, we now test the change in the slope

[32]Note that with CP fixed effects we are only using within country-pair time variations in trade proximity and GDP correlation. Hence, it is important for our *Late Time Window* dummy to cover (at least) two time-windows so that there

using the following specifications:

$$\begin{aligned} \text{Corr GDP}_{ijt} = &\ \beta_1 \ln(\text{Trade}^{inter}_{ijt}) + \beta_2\, LTW_t \times \ln(\text{Trade}^{inter}_{ijt}) + \beta_3 \ln(\text{Trade}^{final}_{ijt}) \\ &+ \beta_4\, LTW_t \times \ln(\text{Trade}^{final}_{ijt}) + \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{38}$$

$$\begin{aligned} \text{Corr GDP}_{ijt} = &\ \beta_1 \ln(\text{Trade}^{inter}_{ijt}) + \beta_2\, LTW_t \times \ln(\text{Trade}^{inter}_{ijt}) + \beta_3 \ln(\text{Trade}^{final}_{ijt}) \\ &+ \beta_4\, LTW_t \times \ln(\text{Trade}^{final}_{ijt}) + \boldsymbol{\gamma_1}\, \textbf{network}_{ijt} + \boldsymbol{\gamma_2}\, LTW_t \times \textbf{network}_{ijt} \\ &+ \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{39}$$

where $\mathbf{X}_{ijt}$ refers again to controls. By adding these interaction terms, we specify that coefficients β_2, β_4 and $\boldsymbol{\gamma_2}$ indicate whether the TC slope estimated with respect to trade in intermediate inputs and final goods and the coefficients associated with network effects in the period 1990-2009 are different from the coefficients estimated using the period 1970-1989.

We present our results in table 7. Looking at non-interacted point estimates, we see that the findings are consistent with previous specifications, with trade in intermediate inputs being significantly correlated with more GDP comovement for country pairs in the *OECD* and *HH* sub-sample, while pairs in the other groupings feature a more prominent role for trade in final goods.

Looking at the time evolution, the results show that the TC slope in intermediate inputs significantly increased over time among developed countries (that is, in the *OECD* and *HH* groups). Between 1970 and 1989, the estimates indicate a significant TC-slope of about 0.06 for country-pairs among the *OECD* group, while it rises to 0.156 for the period 1990 to 2009. In terms of magnitude, moving from the 25th to the 75th percentile of log trade in intermediate inputs (for all time-windows) would have implied an increase in GDP comovement of about 13.0 percentage point from 1970 to 1989, which is much lower than the 31.2 percentage point increase corresponding to the slope estimated using the 1990 to 2009 period.

We also note that the TC-slope in final goods increased over time for the *HL* group, implying that an increase in final goods trade between high and low income countries is associated with a stronger increase in GDP comovement in recent time windows. Finally, as regards the time evolution of the association between network proximity and GDP comovement, we find a significant positive increase in the *network-comovement* slope in the period 1990 to 2009 relative to the period 1970 to 1989 for almost all sub-samples. The high point estimates of these interacted terms reveal that the surge in the association between trade network and business cycle synchronization is very large.

are time variations within the *late* sub-sample.

Altogether, these findings show that the association between international trade linkages and GDP correlation experienced a strong increase over time, either directly (through bilateral trade) or indirectly (via the network effect).

Table. 7. Time evolution of the Trade Comovement slope

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(inter)	0.002	0.004	0.074^{**}	0.066^{**}	0.013	0.008	0.003	0.005	0.012	0.015^{**}
	(0.006)	(0.006)	(0.033)	(0.033)	(0.016)	(0.016)	(0.007)	(0.007)	(0.013)	(0.007)
LTW*ln(inter)	0.010^{**}	0.006	0.074^{**}	0.090^{***}	0.028^{***}	0.025^{**}	0.006	0.002	0.012	0.007
	(0.005)	(0.005)	(0.029)	(0.031)	(0.011)	(0.011)	(0.006)	(0.006)	(0.013)	(0.006)
ln(final)	0.007	0.008	0.019	0.019	−0.021	−0.022	0.011^{*}	0.011^{*}	0.019^{*}	0.020^{***}
	(0.006)	(0.006)	(0.028)	(0.028)	(0.014)	(0.014)	(0.006)	(0.006)	(0.011)	(0.006)
LTW*ln(final)	0.008	0.007	−0.034	−0.045	0.009	0.004	0.010^{*}	0.010^{*}	−0.006	−0.009
	(0.005)	(0.005)	(0.032)	(0.033)	(0.011)	(0.011)	(0.006)	(0.006)	(0.012)	(0.006)
network^{1st}	0.317^{***}	0.211^{***}	0.800^{***}	0.699^{**}	0.608^{***}	0.482^{***}	0.273^{***}	0.189^{**}	−0.033	−0.133
	(0.066)	(0.073)	(0.269)	(0.273)	(0.165)	(0.176)	(0.073)	(0.082)	(0.156)	(0.082)
network^{2nd}	0.375^{*}	−0.030	2.830^{***}	1.944^{*}	−0.637	-1.154^{**}	0.509^{**}	0.102	1.101^{**}	1.302^{***}
	(0.221)	(0.227)	(0.984)	(1.012)	(0.552)	(0.553)	(0.244)	(0.252)	(0.469)	(0.252)
LTW*network^{1st}		0.236^{***}		0.211		0.369^{***}		0.180^{***}		0.154^{**}
		(0.058)		(0.158)		(0.117)		(0.068)		(0.068)
LTW*network^{2nd}		0.661^{***}		1.056^{***}		0.846^{***}		0.643^{***}		−0.157
		(0.129)		(0.404)		(0.246)		(0.150)		(0.150)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
R^2	0.015	0.019	0.110	0.121	0.062	0.071	0.010	0.013	0.008	0.009

Notes: *p<0.1; **p<0.05; ***p<0.01.

4.5 Network density as an amplification channel

In section 2, we discussed a mechanism that could explain the recent increase in the strength of the association between global trade and business cycle synchronization – namely, the role of overall network density. Our model highlights how network density interacts with the channels discussed above and strengthens the connection between individual links and bilateral GDP comovement.

To show the change in network density over time, we first display in table 8 the evolution of the ratio of total worldwide trade flows over total worldwide GDP in each of our four time windows, where we normalize with respect to the value in the first time window. Since the

1970s, the average trade flow over GDP has more than tripled. As a result of such an increase in network density, we expect a corresponding surge in the correlation between trade and GDP comovement.

Table. 8. Total trade flows over worldwide GDP
Value normalized in the first time window.

Period	70:79	80:89	90:99	00:09
Trade flows / GDP	1.0	1.81	2.13	3.10

We then move on to formally testing our intuition and construct a *bilateral* measure of network connectivity that reflects how much countries in a given country-pair are connected to the rest of the trade network. We compute the average bilateral network density for a given country-pair, as follows:

$$Network\,Density_{ijt} = \frac{\left(w(i,j)\sum_{z\in\mathcal{P}(i)_{-j}} Trade^{tot}_{i\leftrightarrow z,t} + w(j,i)\sum_{z\in\mathcal{P}(j)_{-i}} Trade^{tot}_{i\leftrightarrow z,t}\right)}{w(i,j)+w(j,i)} \tag{40}$$

where $\mathcal{P}(i)_{-j}$ defines the set of i-partners except the country j and $w_t(i,j) = \frac{T_{i\leftrightarrow j,t}}{T_{i,t}}$. This index measures the average trade volume over GDP of the two countries within the country-pair (i,j) when bilateral trade flows are not taken into account, and it aims to measure the connectivity of two countries to the rest of the network. In this sense, it should be interpreted not as a measure of overall network density, but rather as a measure of trade proximity between the pair at hand and the rest of the world. Table 9 presents the time evolution of this measure for each sub-sample.

Table. 9. Evolution of our *bilateral* measure of network density[a]

	Income Group				
Period	*All*	*OECD*	*HH*	*HL*	*LL*
70:79	0.3	0.5	0.5	0.3	0.2
80:89	0.7	1.0	1.0	0.7	0.4
90:99	1.0	1.6	1.5	0.9	0.6
00:09	1.6	2.4	2.2	1.4	1.0

[a] Reported numbers are average over all country-pairs.

We test the following specification:

$$\begin{aligned}\text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{Trade}^{inter}_{ijt}) + \beta_2 \ln(\text{Trade}^{final}_{ijt}) + \beta_3\,\text{density}_{ijt} \times \ln(\text{Trade}^{inter}_{ijt}) \\ & + \beta_4\,\text{density}_{ijt} \times \ln(\text{Trade}^{final}_{ijt}) + \boldsymbol{\gamma}_1\,\mathbf{network}_{ijt} + \boldsymbol{\gamma}_2\,\text{density}_{ijt} \times \mathbf{network}_{ijt} \\ & + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}\end{aligned} \tag{41}$$

Notice that our measure of bilateral density is directly linked to the first order network index as the later measures the intensive margin of the first order trade network, while the former can be interpreted as measuring similarity in the first order trade network.[33] Table 10 summarizes the findings.

The results present interesting differences across income groups. Regarding the first column of table 10 which presents the results using the whole sample, the interaction between our bilateral measure of density and trade network effects is positive, suggesting that country-pairs that are more connected to the rest of the world feature a higher marginal effect of network proximity. We also find that the interaction between bilateral trade and bilateral density is significant with different patterns in different sub-samples: bilateral density acts as an amplifier of intermediate trade proximity for the OECD and HH groups, while it strengthens the role of final goods trade in the HL group. Overall, our findings imply that the TC-slope usually measured in the literature is a function of overall connectivity between a country-pair and the rest of the world. In other words, bilateral trade flows have a higher marginal effect on GDP-comovement when two countries trade more with each other.

4.6 Summary of empirical evidence

The preceding sections provided empirical support for the theoretical results discussed in section 2 and offered novel insights on the complex association between global trade flows and bilateral GDP comovement. In particular, our findings can be summed up as follows:

1. The correlation between trade in intermediate inputs and GDP comovement is significant and positive for countries in the *OECD* and *HH* groups, suggesting a specific role for Global Value Chains and the prevalence of supply-side shocks in these countries. Interestingly, trade in final goods is significantly correlated with higher business cycle synchronization for the low income groups, which points towards the importance of demand-side shocks in this group.

2. Common exposure to third countries, measured using our network indices is significantly positively correlated with more GDP comovement. First order network effects decay as we move to low income group while second order network effects increase for those in the lowest income group.

3. Similarity in exported goods composition is significantly negatively correlated with GDP

[33] As a robustness, we also used total trade flows over worldwide GDP as a measure of network density and interacted it our first order network effect. Results are similar in this case, although the logic of the estimation differs markedly: using world trade over world GDP as a measure of density means means the index is not bilateral and mostly measure an increasing trend for the whole sample. We see this exercise as confirming the findings in section 4.4 in the sense that there is a worldwide increase in the association between global trade and bilateral GDP co-movement.

Table. 10. Network density and Trade Comovement Slope

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(inter)	0.004	0.033	0.005	0.009	0.015
	(0.006)	(0.035)	(0.017)	(0.007)	(0.014)
ln(final)	0.003	0.042	-0.007	0.003	0.024^{**}
	(0.006)	(0.031)	(0.015)	(0.006)	(0.012)
density*ln(inter)	0.004	0.095^{***}	0.030^{***}	-0.006	-0.005
	(0.004)	(0.021)	(0.008)	(0.005)	(0.013)
density*ln(final)	0.011^{***}	-0.030^{*}	0.000	0.016^{***}	-0.020
	(0.004)	(0.017)	(0.007)	(0.004)	(0.012)
network^{1st}	0.230^{***}	0.931^{***}	0.506^{***}	0.165^{*}	-0.212
	(0.075)	(0.298)	(0.173)	(0.085)	(0.175)
network^{2nd}	0.213	2.588^{***}	-0.671	0.302	1.480^{***}
	(0.228)	(0.999)	(0.573)	(0.250)	(0.499)
density*1st net.	0.085^{**}	-0.076	0.003	0.106^{**}	0.244^{**}
	(0.035)	(0.093)	(0.061)	(0.044)	(0.104)
density*2nd net.	0.162^{**}	0.607^{**}	0.272^{***}	0.158^{*}	-0.582^{**}
	(0.063)	(0.260)	(0.099)	(0.083)	(0.233)
CP + TW FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13,079	1,224	2,541	10,538	2,745
R^2	0.016	0.122	0.066	0.012	0.016
Notes:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.		

comovement while there is no statistically significant effect of sectoral composition on GDP-comovement.

4. The correlation between GDP comovement and both bilateral trade and network effects tends to increase over-time. As suggested by our simple model, this increase could be rationalized by a surge of trade network density which can amplify the association between global trade and bilateral comovement. Overall, this insight cautions against the view that there exist a single time-invariant "deep" value for the trade comovement slope.
In the next section, we also discuss a complementary channel that could rationalize the time evolution of point estimates – namely, an increase in the sensitivity of GDP to foreign shocks due to higher markups.

5 Discussion

We now dig further into two particular findings: (1) the differential role of sector versus trade proximity, and (2) the time evolution of the marginal association between trade and GDP comovement. First, we show that the association between trade and business cycle correlation strongly depends on the sectoral composition of the economy, which creates another link between our explanatory variables. Second, we show that market powers have substantially risen in the 1090s, with the possible implication that international shock transmission could have strengthened even in the absence of increased trade flows.

5.1 Global Value Chain and Sectoral Composition

A number of studies document the strong influence of global value chain (GVC) in transmitting shocks across countries. Indeed, to the extent that inputs tend to be more customized and less substitutable than final goods, bilateral production fragmentation can be associated with higher complementarity between production factors, which would then lead to higher GDP comovement. Conversely, when two countries trade final goods while producing very similar goods, they can be seen as competing in the same market, which implies that a positive supply side shock (such as a technology innovation) in one country leads to an increase in this country's market share at the expanse of its trade partner, leading to opposite GDP movements.

In this section, we test the hypothesis that two economies with similar sectors and similar exported goods are more likely to comove when trade in intermediate inputs is high, and that they are less likely to comove when trade in final goods is high. To do so, we run the following two specifications:

$$\begin{aligned}\text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \beta_3 \, \text{export}_{ijt}^{prox} \\ & + \beta_4 \, \text{export}_{ijt}^{prox} \times \ln(\text{Trade}_{ijt}^{inter}) + \beta_5 \, \text{export}_{ijt}^{prox} \times \ln(\text{Trade}_{ijt}^{final}) \\ & + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{42}$$

$$\begin{aligned}\text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \beta_3 \, \text{sector}_{ijt}^{prox} \\ & + \beta_4 \, \text{sector}_{ijt}^{prox} \times \ln(\text{Trade}_{ijt}^{inter}) + \beta_5 \, \text{sector}_{ijt}^{prox} \times \ln(\text{Trade}_{ijt}^{final}) \\ & + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{43}$$

where $\mathbf{X}_{ijt}$ refers to controls, including first and second order network indices. The results are shown in table 11 and can be stated as follows. Country-pairs with similar export composition co-move more when they trade more in intermediate inputs and co-move less when they trade more final goods. Given the mean export proximity index in table 3 and the estimates in table 11, moving from the 25th to the 75th quantiles of the log trade index in intermediate inputs would imply an increase in GDP comovement of 0.20 for the *HH* group against 0.012 for the *HL* group. On the opposite side, moving from the 25th to the 75th quantiles of the log trade index in final goods would imply an increase in GDP comovement of negative 0.01 for the *HH* group against 0.05 for the *HL* group.

Table. 11. The role of sectoral composition as an amplifier of intermediate input's role

	corr GDP									
	All	*OECD*	*HH*	*HL*	*LL*	*All*	*OECD*	*HH*	*HL*	*LL*
ln(inter)	−0.012	0.044	−0.007	−0.012	−0.007	−0.059	-1.025^{*}	0.247	−0.082	−0.025
	(0.008)	(0.062)	(0.019)	(0.008)	(0.017)	(0.081)	(0.545)	(0.255)	(0.088)	(0.160)
ln(inter)*export^{prox}	0.155^{***}	0.227	0.266^{***}	0.131^{**}	0.147^{**}					
	(0.044)	(0.176)	(0.070)	(0.052)	(0.073)					
ln(inter)*sector^{prox}						0.085	1.324^{**}	−0.210	0.109	0.082
						(0.097)	(0.614)	(0.294)	(0.106)	(0.188)
ln(final)	0.023^{***}	0.026	0.029^{*}	0.020^{***}	0.035^{**}	0.006	1.705^{***}	0.143	−0.053	−0.035
	(0.007)	(0.051)	(0.017)	(0.008)	(0.014)	(0.082)	(0.578)	(0.314)	(0.088)	(0.174)
ln(final)*export^{prox}	-0.084^{**}	−0.094	-0.229^{***}	−0.037	−0.112					
	(0.042)	(0.161)	(0.066)	(0.048)	(0.073)					
ln(final)*sector^{prox}						−0.010	-1.998^{***}	−0.355	0.082	0.027
						(0.102)	(0.650)	(0.347)	(0.110)	(0.209)
export^{prox}	0.135	0.462	−0.775	0.489^{*}	0.074					
	(0.249)	(0.765)	(0.487)	(0.287)	(0.566)					
sector^{prox}						0.979	-8.253^{***}	-4.987^{*}	2.124^{**}	0.856
						(0.953)	(2.859)	(2.936)	(1.021)	(1.723)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	1,224	2,541	10,538	2,745	4,499	655	893	3,606	1,091
R^2	0.015	0.105	0.054	0.011	0.012	0.025	0.194	0.180	0.020	0.021

Notes: *p<0.1; **p<0.05; ***p<0.01.

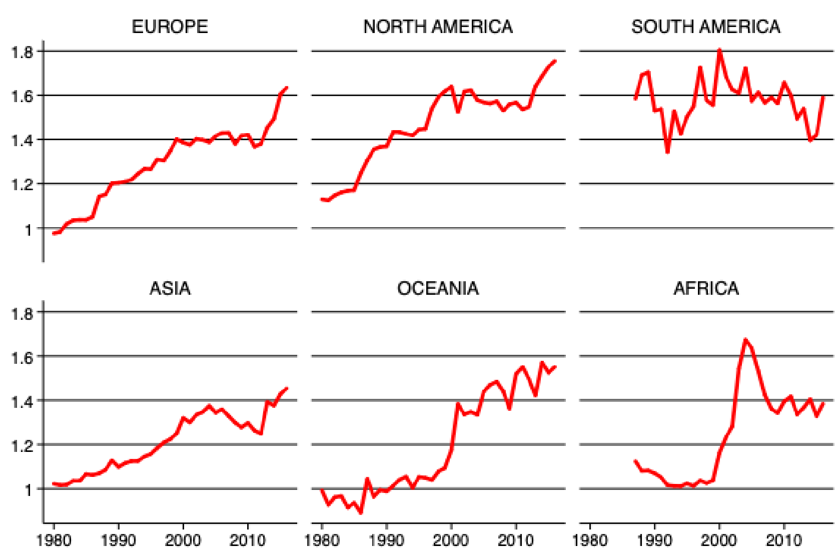
Regarding the similarity in GDP sector shares, the results are significant and consistent for *OECD* group only. For this sub-sample, given the mean sectoral proximity index, moving from the 25th to the 75th percentiles of the log intermediate inputs (respectively final goods) distribution would lead to an increase in GDP comovement of 0.29 (respectively negative 0.11). Notice, however, that moving from the 25th to the 75th quartile of the sectoral composition index would imply an average decrease in GDP comovement of 0.23.

5.2 Market Power

In de Soyres and Gaillard (2020), we argued that the rise in market power (and hence a greater share of profits in overall GDP) can help solve for the *Trade Comovement Puzzle* by generating a disconnect between movements in production factors (capital and labor) and GDP. The mechanism can be stated as follows: firms that charge a markup have a disconnect between the marginal cost and the marginal revenue product of their inputs (which are partly imported). The difference between these two is accounted as value added in the form of profits. Therefore, any change in input usage leading to a change in profits triggers a change in value added. Since higher markups are associated with higher profit shares in GDP (ceteris paribus), the higher the market power, the larger the association between foreign shocks and domestic GDP movements.

Since 1980, market powers have been increased substantially. For instance, Diez et al. (2018) and De Loecker and Eeckhout (2018) have shown that market powers have considerably increased over time in almost all developed countries. Figure 4 shows that markups have increased over time in Europe, North America, Asia and Oceania, while they seem to have been more subdued in Africa and South America. This evolution suggests that countries that experienced higher markup increases over time should also have experienced surges in the sensitivity of their GDP to foreign shocks. Admittedly, this phenomenon could also contribute to the time evolution of the TC-slope uncovered in the previous section, though studying this mechanism is beyond the scope of this paper.

Figure 4. Global Market Powers.



Source: figure 3 in De Loecker and Eeckhout (2018).

6 Robustness and additional exercises

This section provides additional results corroborating the findings that there is a significant correlation between bilateral trade and the trade network with GDP-comovement. We first investigate if the addition of financial integration (FI), such as FDI and flows of assets significantly affects our results. We then separate intermediate inputs and capital trade flows and then include cross network effects. Finally, we provide sensitive results with respect to additional controls, alternative measures, sets of countries, and time periods.

6.1 Financial Integration: role of FDI and flows of assets

Previous studies found that financial interconnection is significantly (and *negatively*) associated with GDP comovements. Kalemli-Ozcan et al. (2013) identifies a strong negative effect of banking integration on output synchronization, conditional on global shocks and country-pair heterogeneity. Such a result is consistent with a *resource shifting hypothesis* where an integration of capital market between two countries means that global savings are invested in the countries with the highest marginal productivity of capital – at the expense of investment in the rest of the world.[34]

Bilateral data on financial integration (FI) is scarce for pairs with two low income countries, but it is relatively widespread for other pairs. Hence, we focus our attention on the *OECD* and the *HL* groups for this exercise and account for the role of financial flows by using the consolidated banking statistics from the Bank for International Settlement and construct an index of financial proximity (FP).[35] We use the total bilateral cross-border claims (including bank and non-bank sectors for all maturities) between countries i and j to construct an index of financial proximity (FP), such that $FP_{ijt} = \frac{C_{i\to j,t}+C_{j\to i,t}}{GDP_{it}+GDP_{jt}}$, where here $C_{i\to j,t}$ refers to total cross-border claims from country i to country j in period t. Additionally, we control for FDI which might affect GDP comovement independently of trade proximity.[36] We use up-to-date and systematic FDI data for 206 economies around the world from the UNCTAD's Bilateral FDI Statistics, covering inflows, outflows, inward stock and outward stock by region and economy.[37] We use the inflows and outflows in order to construct a bilateral financial integration (FI) controls, such that: $FI_{ijt} = \frac{FDI_{i\to j,t}+FDI_{j\to i,t}}{GDP_{it}+GDP_{jt}}$, where here $FDI_{i\to j,t}$ refers to total FDI from country i to country j in period t. For

[34] In other words, if savings can be allocated across borders, a positive technology shock in one country relative to its partners creates an inflow of capital into this country at the expense of other economies.

[35] The dataset is available here: https://stats.bis.org/.

[36] According to Fontagné (1999), trade and FDI are positively correlated, which implies that failing to control for FDI is likely to bias our estimates of the relationship between trade and GDP correlation.

[37] Data are in principle collected from national sources. In order to cover the entire world, where data are not available from national sources, data from partner countries (also called mirror data) as well as from other international organizations have also been used. Data can be downloaded on the UNCTAD website.

this measure, we report only the effect of including this control for the whole sample.

The results of the benchmark specification with additional controls are shown in table 12. The bilateral trade comovement slope and the trade network comovement slope are not affected by the inclusion of financial variables, suggesting that the link between trade and GDP comovement remains unaffected by the inclusion of these controls.

Table. 12. Effect of financial integration

	corr GDP							
	All	*All*	*All*	*All*	*OECD*	*OECD*	*HL*	*HL*
ln(inter)	0.169**	0.164**	−0.006	−0.006	0.405***	0.402***	−0.013	−0.015
	(0.078)	(0.078)	(0.018)	(0.018)	(0.093)	(0.094)	(0.023)	(0.023)
ln(final)	−0.091*	−0.088	0.008	0.007	−0.059	−0.054	0.023	0.021
	(0.054)	(0.054)	(0.015)	(0.015)	(0.046)	(0.047)	(0.018)	(0.018)
network^{1st}	0.802	0.832	0.855***	0.855***	−0.558	−0.573	0.941***	0.942***
	(0.634)	(0.636)	(0.189)	(0.189)	(0.807)	(0.804)	(0.218)	(0.218)
network^{2nd}	−1.620	−1.650	−0.112	−0.111	−0.616	−0.681	0.404	0.378
	(1.735)	(1.731)	(0.568)	(0.569)	(1.936)	(1.876)	(0.650)	(0.649)
BIS index		−23.453						
		(27.939)						
FDI index				0.531		−6.283		15.823**
				(3.573)		(5.380)		(6.547)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	846	846	2,947	2,947	492	492	2,030	2,030
R^2	0.098	0.099	0.026	0.026	0.229	0.233	0.021	0.024

Notes: *p<0.1; **p<0.05; ***p<0.01. Note that column 1 shows the results using the sub-sample containing data on the BIS index while column 3 shows the result using only country-pairs with data on the FDI index.

6.2 Separating capital and intermediate inputs

We combined in our benchmark specification trade in intermediate inputs and trade in capital goods. We now relax this assumption and test separately the effect of bilateral trade in capital goods and in intermediate inputs. Trade in capital goods account for only around 15% of total trade, and some country-pairs do not trade capital goods. We construct the index relative to capital goods $\text{Trade}_{ijt}^{capital}$ as we did in section 3. We then test the following specification:

$$\begin{aligned} \text{Corr GDP}_{ijt} &= \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{capital}) + \beta_3 \ln(\text{Trade}_{ijt}^{final}) \\ &+ \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{44}$$

The results are gathered in table 13, where we also show the benchmark specification without separating trade flows. Overall, our previous results are still valid except that now intermediate inputs seem to also play a role for *HL* pairs. Trade in capital goods is, however, not significant for the *OECD* and *LL* groups. Interestingly, trade in capital goods seems to be positively correlated with more GDP comovement for *HH*, while we find the opposite for *HL*, suggesting again possible heterogeneity in the effect of bilateral trade flows along the development stage for capital goods.

Table. 13. Trade Comovement slope with disaggregated trade index and capital flows

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(inter)	0.009		0.103^{***}		0.034^{**}		0.007		0.018^{***}	
	(0.005)		(0.030)		(0.014)		(0.006)		(0.006)	
ln(inter)		0.014^{**}		0.117^{***}		0.026^{**}		0.016^{***}		0.017
		(0.006)		(0.031)		(0.013)		(0.006)		(0.012)
ln(capital)		-0.010^{***}		-0.006		0.028^{***}		-0.015^{***}		-0.012
		(0.004)		(0.019)		(0.009)		(0.004)		(0.008)
ln(final)	0.012^{**}	0.016^{***}	-0.009	-0.013	-0.009	-0.010	0.016^{***}	0.021^{***}	0.017^{***}	0.024^{**}
	(0.005)	(0.005)	(0.025)	(0.024)	(0.012)	(0.013)	(0.005)	(0.005)	(0.005)	(0.011)
network^{1st}	0.305^{***}	0.349^{***}	1.046^{***}	1.026^{***}	0.521^{***}	0.603^{***}	0.264^{***}	0.301^{***}	-0.040	0.034
	(0.067)	(0.069)	(0.259)	(0.258)	(0.163)	(0.163)	(0.073)	(0.076)	(0.073)	(0.159)
network^{2nd}	0.416^{*}	0.490^{**}	2.906^{***}	2.971^{***}	-0.170	0.119	0.518^{**}	0.613^{**}	1.076^{***}	1.199^{**}
	(0.221)	(0.226)	(0.938)	(0.938)	(0.550)	(0.556)	(0.243)	(0.249)	(0.243)	(0.492)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	12,702	1,224	1,222	2,541	2,508	10,538	10,194	2,745	2,614
R^2	0.009	0.011	0.099	0.103	0.040	0.047	0.005	0.009	0.008	0.009
Notes:							*p<0.1; **p<0.05; ***p<0.01.			

6.3 Cross network effects

In the baseline specification, we have estimated two different network effects: a first order network effect and a second order network effect. We now test the implication of a third network index which aims to capture how a country i is similar in terms of trade partners to the partners of a country j. This measure is described in section 3, and table 14 provides the results and show that the inclusion of such a measure does not change the estimated coefficients regarding bilateral trade flows and first order network effects. However, it influences point estimates associated with the second order network measure, which is likely to be the case, as those two indexes measure trade network effects taking place further down in the trade network.

Table. 14. Trade Comovement Slope with cross network effects

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(inter)	0.009	0.008	0.103***	0.107***	0.034**	0.035**	0.007	0.006	0.018***	0.017
	(0.005)	(0.005)	(0.030)	(0.031)	(0.014)	(0.014)	(0.006)	(0.006)	(0.006)	(0.011)
ln(final)	0.012**	0.012**	−0.009	−0.009	−0.009	−0.009	0.016***	0.016***	0.017***	0.017*
	(0.005)	(0.005)	(0.025)	(0.025)	(0.012)	(0.012)	(0.005)	(0.005)	(0.005)	(0.010)
network^{1st}	0.305***	0.294***	1.046***	1.084***	0.521***	0.523***	0.264***	0.246***	−0.040	−0.035
	(0.067)	(0.067)	(0.259)	(0.264)	(0.163)	(0.165)	(0.073)	(0.074)	(0.073)	(0.153)
network^{2nd}	0.416*	0.364*	2.906***	3.019***	−0.170	−0.160	0.518**	0.432*	1.076***	0.866*
	(0.221)	(0.221)	(0.938)	(0.961)	(0.550)	(0.554)	(0.243)	(0.242)	(0.243)	(0.504)
network^{cross}		0.166		−0.330		−0.056		0.245*		0.343
		(0.115)		(0.409)		(0.258)		(0.126)		(0.279)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
R^2	0.009	0.009	0.099	0.099	0.040	0.040	0.005	0.006	0.008	0.009
Notes:								*p<0.1; **p<0.05; ***p<0.01.		

6.4 Other robustness exercises

Our results are robust to a number of other alternative specifications that we gather in table 15. We first confirm that among non-OECD pairs, trade in final goods is significantly associated with more GDP-comovement. When considering only the last two time windows, we find consistent results except for sub-samples with the lowest number of observations (the *LL* and *HH* groups), for which bilateral trade flows turn out to be statistically insignificant. Network effects, however, are in line with previous results.

We then find that under alternative sectoral proximity indexes, the results remain very similar when using ISIC export proximity or SITC 2-digit export proximity.

Finally, we confirm the general pattern using three additional analysis: (i) an alternative measure of trade proximity built using the mean of log trade intensities instead of the log of the mean trade intensities within time-windows, (ii) an alternative measure using the max operator when computing the trade intensities: $\ln(\text{Trade}) = \max\left(T_{i\leftrightarrow j}/GDP_i, T_{i\leftrightarrow j}/GDP_j\right)$, (iii) BK filtered GDP instead of HP filtered GDP,[38] (iv) First difference instead of HP-filtered GDP. For the alternative bilateral trade measures using the max operator or the mean log, the results are very close to the benchmark specification. With the alternative filters, all results are consistent except for the *LL* group for which the correlation between trade in intermediate inputs and GDP-comovement

[38] In this exercise, we keep fluctuations between 32 and 200 quarters.

turns out to be positive and significant in the case of BK-filtered GDP.

Table. 15. Sensitive analysis: Trade and GDP-comovement

	Estimated coefficient					
	ln(input)	ln(final)	$network^{1st}$	$network^{2nd}$	Sample	Pairs | Obs.
(i) Sample selection						
Alternative Group	0.007	0.012**	0.25***	0.23	*Non-OECD*	4094 | 11830
Period (1990:2009)	0.206***	-0.107*	1.38*	1.93	*OECD*	316 | 616
Period (1990:2009)	0.025	0.018	0.98**	0.56	*HH*	754 | 1434
Period (1990:2009)	0.044***	0.034***	0.49***	3.80***	*HL*	3598 | 6582
Period (1990:2009)	0.027	0.004	0.64***	4.09***	*LL*	1140 | 1972
(ii) Alternative controls						
SITC 2-digit $export^{prox}$	0.097***	-0.007	0.96***	2.75***	*OECD*	320 | 1224
SITC 2-digit $export^{prox}$	0.036***	-0.008	0.53***	-0.30	*HH*	764 | 2533
SITC 2-digit $export^{prox}$	0.009	0.017***	0.27***	0.49**	*HL*	3650 | 10521
SITC 2-digit $export^{prox}$	0.018*	0.017*	-0.01	1.08**	*LL*	1165 | 2744
ISIC $export^{prox}$	0.103***	-0.010	1.02***	2.77***	*OECD*	320 | 1224
ISIC $export^{prox}$	0.038***	-0.011	0.56***	-0.29	*HH*	764 | 2533
ISIC $export^{prox}$	0.008	0.016***	0.28***	0.49**	*HL*	3650 | 10521
ISIC $export^{prox}$	0.018	0.017*	-0.02	1.09**	*LL*	1165 | 2744
(iii) Alternative Measures						
mean $\ln(index)$	0.111***	-0.034	1.05***	2.68***	*OECD*	320 | 1224
mean $\ln(index)$	0.037***	-0.016	0.58***	-0.28	*HH*	764 | 2533
mean $\ln(index)$	0.007	0.016***	0.26***	0.45*	*HL*	3650 | 10521
mean $\ln(index)$	0.017	0.016*	-0.04	1.03***	*LL*	1165 | 2744
Max trade index [c]	0.103***	-0.013	1.06***	2.92***	*OECD*	320 | 1224
Max trade index [c]	0.038***	-0.011	0.57***	-0.18	*HH*	764 | 2533
Max trade index [c]	0.009	0.018***	0.26***	0.47*	*HL*	3650 | 10521
Max trade index [c]	0.018	0.017*	-0.05	1.12**	*LL*	1165 | 2744
BK filter	0.115***	-0.010	1.05***	3.24***	*OECD*	324 | 1260
BK filter	0.047***	-0.017	0.57***	-0.10	*HH*	320 | 1224
BK filter	0.010*	0.014***	0.26***	0.52**	*HL*	3650 | 10521
BK filter	0.026**	0.015	-0.05	1.11***	*LL*	1165 | 2744
First difference	0.078***	0.004	0.67**	2.74***	*OECD*	320 | 1224
First difference	0.017	-0.025*	0.59***	-0.38	*HH*	764 | 2533
First difference	0.009	0.023**	0.25***	0.62**	*HL*	3650 | 10521
First difference	0.021**	0.020**	0.14	1.03**	*LL*	1165 | 2744

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation.
[a] We provide the results using EU and USSR dummies since adding those controls substantially reduce the significance of trade in final goods.
[b] FDI and BIS are mostly available for *OECD* and *HH* groups. We report only the robustness with those two groups.
[c] We define max trade index as the measure using $\max\left(T_{i\leftrightarrow j}/GDP_i, T_{i\leftrightarrow j}/GDP_j\right)$.

7 Conclusion

This paper takes a fresh look into an old question: what is the association between trade flows and GDP comovement at business cycle frequencies? Guided by a simple theory, we provide novel evidence on the role of both bilateral and global trade flows and emphasize the strong interaction arising between bilateral linkages and the global trade network, which implies that the previously studied Trade-Comovement slope should not be – and indeed is not – constant over time. Taking a closer look at different income groups, we also present new facts on the role of sectoral composition and on the type of trade that seems to be associated with GDP correlation.

Looking ahead, we believe the paper provides interesting scope for future research. According to our model, the reason why the TC-slope seems to be mostly driven by trade in intermediate inputs in developed countries, while it is mostly driven by trade in final goods in developing countries, suggests that these countries are mostly hit by different shocks: supply-side in high income countries, demand-side in lower income group. We believe this insight can be investigated further. Moreover, the TC-slope has significantly increased over time. While the literature has documented the possible role of the global rise of markups, it seems important to investigate further the channels that could explain this pattern.

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