Global Trade and GDP Co-movement*

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This version: August 2021

Abstract

This paper revisits the relationship between trade and cross-country GDP correlation for 134 countries from 1970 to 2009. We introduce two notions of trade linkages: (i) *direct* bilateral trade index and (ii) common exposure to "third" countries capturing the role of *trade networks*. Both are economically and statistically associated with GDP correlation, suggesting an indirect 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 lower income countries. Finally, we present evidence of an increase in the trade co-movement slope over the last two decades, which may reflect the increase of the density of the international trade network. This insight cautions against the view that there exist a single time-invariant "deep" value for the trade comovement slope at the heart of the so-called Trade-Comovement Puzzle.

Keywords: International Trade, International Business Cycle Comovement, Networks, Input-Output Linkages.

JEL Classification: F15, F44, F62

*We thank the 2020 World Development Report team as well as seminar and conference participants for helpful comments. The views in this paper are solely the responsibility of the authors and should not necessarily be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. We thank Henry Young for his superb research assistance.

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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 the world's production across different locations: as a share of world GDP, both trade in intermediate inputs and in final goods increased sharply, reaching in 2009 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 cross-country correlation of GDP – or GDP co-movement – rose from 6% to 38%.

The surge in trade-over-GDP, and increase in the overall density of the world trade network, suggests that complex patterns of international propagation could be at play: over and above direct trade linkages, two countries can be increasingly connected to the same direct or indirect trade partners, implying a higher "*third country*" exposure. 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: are *direct* trade linkages more important than common exposure through trade network? 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? 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. From a qualitative point of view, the vast majority of papers emphasize the role of bilateral international trade links as an important determinant of GDP comovement. That is, an increase in trade intensity is associated with an increase in cross-country GDP correlation. From a quantitative point of view, however, the strength of the association is very heterogeneous across papers. Using a sample of 100 low and high income countries from 1970 to 1995, Baxter and Kouparitsas (2005) shows that the association between bilateral trade intensities and GDP comovement is robust, but does not find a clear role of industrial similarity highlighted in Imbs (2004). Their point estimate imply that a doubling of trade is associated with a 1.5 to 3 percentage point increase in GDP correlation. Kose and Yi (2006) uses 21 OECD countries from 1970:2000 and shows that a doubling of total trade over

[1] For example, the extent to which currency zones such as the West African Economic and Monetary Union (WAEMU) can be considered as optimal currency areas (and, therefore a common monetary policy could be optimal) largely depends on the synchrony of business cycles among the member countries.

GDP is associated with a GDP comovement surge of about 6 percentage point. Calderon et al. (2007) is using a very comprehensive dataset containing 147 countries between 1960 and 1999. The authors highlight that trade intensity has smaller impact on business cycle correlation among low-income countries than among high-income ones. When trade over GDP is multiplied by two, the associated increase in GDP comovement ranges from just 1.0 to 6.5 percentage points respectively. With 21 OECD countries in the period 1970–2003, Inklaar et al. (2008) estimates a structural model to estimate the effect of trade intensity on output correlation. They find that doubling bilateral trade over GDP leads to increase of synchronization between 3.5 and 9 percentage points. Based on a panel of 55 countries and 28 sectors from 1970:1990, Di Giovanni and Levchenko (2010) show the importance of trade in intermediate inputs. In their estimation, doubling trade is associated with a 4 percentage point increase in output comovement, with an effect three times bigger for sector-pairs characterized by strong input-output links as measured by coefficients in the 1997 Input-Output matrix from the BEA. Using panel regressions, Duval et al. (2016) uses a mix of high and low countries from 1995 to 2013 and shows the importance of the measurement of value-added trade.[2] Finally, Liao and Santacreu (2015) uses a sample of 20 OECD countries and 10 developing countries from 1980Q1:2009Q4 and highlights the importance of the extensive margin of trade. In summary, the studies described above focus on *bilateral* linkages and reveal that the trade comovement slopes vary greatly as researchers vary the composition of their sample.[3]

Understanding the determinants of trade exposure is also theoretically challenging. As shown by Kose and Yi (2006), the workhorse IRBC 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 have refined the puzzle, highlighting different ingredients that could bridge the gap between the data and the predictions of standard models (Johnson (2014), Duval et al. (2016), and de Soyres and Gaillard (2021)).

Despite the important heterogeneity of the size of the *Trade Co-movement slope* (TC-slope) found in the literature, there is surprisingly little systematic empirical research on the association between trade linkages on GDP correlations. What is the respective role of direct trade versus common exposure to third countries? How does the TC-slope differ across different income groups but

[2]Relatedly, Ng (2010) uses cross-country data from 30 countries and shows that bilateral production fragmentation has a positive effect on business cycle comovement. di Giovanni et al. (2018) uses a cross-section of French firms and presents evidence that international I/O linkages at the micro level are an important driver of the value added comovement observed at the macro level. 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.

[3]Huo et al. (2019) uses a structural approach and proposes a perfectly competitive production framework to measure technology and non-technology shocks. In their setup, international transmission through trade accounts for a third of total comovement.

also over time, and depending on the composition of traded goods. The purpose of this paper is to estimate and decompose the relationship between (direct and indirect) trade linkages and GDP correlations for a large sample of 134 countries from 1970 to 2009, unraveling large heterogeneity among countries, over time, and among the type of goods that are traded. Using constructed panel data and controlling for both observed and unobserved heterogeneity between countries and over time, we estimate the TC-slope across different income groups and unveil a series of new determinants of GDP co-movement for each income group, including the different role of the content of trade flows and the presence of network effects. 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. This observation implies that using a single value of the TC-slope as a target for the international propagation properties quantitative macro model can be misleading.

Our first contribution is to decompose 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. We first confirm and update previous findings that total trade intensity is significantly associated with higher GDP correlation among all income groups, but the association is economically much stronger in high income countries. This result echos the one of Calderon et al. (2007) and Di Giovanni and Levchenko (2010) based on cross sectional estimates, who show that the relationship between trade integration on business cycles is higher for industrial countries than for developing countries. Moreover, as shown in de Soyres and Gaillard (2021) 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. A simple analytical framework suggests that one way to interpret this difference along income groups could be that supply-side shocks are more important in high income countries, while demand shocks are more important in lower income countries.[4]

Second, guided by recent debates on the role of Global Value Chains and the systemic interdependence that can arise from worldwide input-output (I/O) linkages (see Bems et al. (2011) and others), we move beyond *bilateral* trade linkages and construct new indices of *network* proximity

[4] The distinction between supply and demand shocks and their respective propagation patterns follows previous production network analysis such as Carvalho and Tahbaz-Salehi (2019).

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 the association between GDP synchronization and both first- and second- order common exposure are particularly strong for high-income countries, while their effects vanish for low income economies where second order proximity is unrelated to business cycle comovement. Moreover, we show theoretically and empirically that the marginal increase in GDP correlation associated with larger trade links is itself increasing in the overall *density* of the network. As such, the amplification of propagation through overall network density helps rationalize the wide array of TC-slopes found in the literature. Indeed, any estimate of the impact of a marginal change of trade linkages on GDP comovement depends on the overall network structure of the economy, which in turn depends on the countries present in a researcher's sample as well as the time period considered. While previous empirical research on the association between trade and GDP correlation does not *explicitly* state that there is only a single, immutable, TC-slope, the empirical specifications and associated quantitative exercises sometimes make such assumption *implicitly*. Our result challenges this implicit assumption and emphasises that there is no "deep" parameter for the TC-slope. This simple observation helps understand the variety of TC-slopes found in the literature.[5] Finally, most of our results are robust to the addition of different controls, measures and sample selection. and highlight important disparities among country groups and over time.

The rest of the paper is organized as follows. In section 2, we propose a simple trade framework along the line of Long and Plosser (1983) and Acemoglu et al. (2012) that highlights how global GDP-comovement is related to direct and indirect trade exposure, before turning to our main empirical contribution. Section 3 presents the data and describes the variables used throughout the paper. Section 4 investigates the global TC-slope across countries. We highlight important differences across income groups and present evidence of significant time variations, which we link to the evolution of the overall density of the world trade network. In section 5, we show that our results are robust to a variety of alternative specifications. Section 6 concludes.

[5]Our findings highlight that the TC-slope differs across country-pairs and over time. Hence, it is not surprising that papers using different data sample find different values for their estimated TC-slope. In this sense, unveiling the sensitivity of the slope to the sample country and time coverage helps rationalize the heterogeneity of estimates found in the literature.

2 A Simple Illustrative Model

This section motivates our empirical work in Section 4 by presenting a parsimonious static model of international trade with multiple countries, along the line of Long and Plosser (1983) and Acemoglu et al. (2012). Our objective is to clarify, through a series of example, the role of inputs and final goods trade as well as the role of common exposure to other countries in shaping global GDP correlations. We abstract 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.

2.1 A Basic IRBC setup

Consider a world with many countries ($i, j \in \{1, ..., N\}$). In country i, gross output is produced from a Cobb Douglas combination of (i) an exogenous technology shock (Z_i), (ii) intermediate inputs from all countries (X_i^j), and (ii) a domestic factor (L_i), such that $Y_i = Z_i \cdot \left(\prod_j (X_i^j)^{\alpha_i^j}\right) \cdot L_i^{\gamma_i}$ with $\sum_j \alpha_i^j + \gamma_i = 1$. The production cost of a representative firm in each country 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 and that firms' markups (μ_i) are exogenous and independent of the destination market which further implies that prices are equal across all destination markets. Denoting by p_i and w_i output price and domestic factor price in i, cost minimization implies that output price in i is given by:

$$p_i = \mu_{i,s} \cdot MC_i = \mu_i \cdot \frac{c_i}{Z_i} \cdot w_i^{\gamma_i} \cdot \prod_j (p_j)^{\alpha_i^j}, \tag{1}$$

with MC_i the marginal cost in i and $c_i = \gamma_i^{-\gamma_i} \prod_j \alpha_i^{j^{-\alpha_i^j}}$ a constant depending only on parameters. As usual with I/O linkages, the price in a given country is a function of all other prices in the economy.[6] We follow Helpman and Krugman (1987) and assume that nominal wages are fixed by an homogeneous outside good so that real wage movements are only driven by price fluctuations.

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

[6] With $\mathbf{P}$ the $(N,1)$ vector of prices, $\mathbf{P}$ solves the system: $\log(\mathbf{P}) = (\mathcal{I}_N - \mathbf{\Omega})^{-1} \begin{pmatrix} k_{1,1} - \log(Z_1) + \gamma_1 \log(w_1) \\ \vdots \\ k_N - \log(Z_N) + \gamma_N \log(w_N), \end{pmatrix}$, with $k_i = \log(\mu_i \cdot c_i)$ and the I/O matrix $\mathbf{\Omega}$ is simple defined by $(\Omega)_{i,j} = \alpha_i^j$.

in country j spends a fraction α_i^j on goods coming from i, so that:

$$p_i X_i^j = \alpha_i^j p_j Y_j \ , \qquad \text{for all } i, j. \tag{2}$$

Aggregate demand in each country j is denoted by D_j.[7] Country j addresses a fraction β_i^j of its total demand to country i, so that market clearing in the final goods market can be written as:

$$p_i y_i^j = \beta_i^j D_j \ , \qquad \text{for all } i, j, \tag{3}$$

where y_i^j is the amount of good produced in i that are absorbed as final demand in j. Finally, the resource constraint condition is given by: $Y_i = \sum_j y_i^j + \sum_j X_i^j$, for all i. We store all shares β_i^j into a (N, N) matrix $\mathbf{B}$, demand D_j in vector $\mathbf{D}$ and nominal input in vector $\mathbf{PY}$. Combining the resource constraint, (2) and (3), we can solve for nominal output in each country:

$$\mathbf{PY} = \underbrace{\left(\mathbf{I}_N - \left(\boldsymbol{\Omega}^T\right)\right)^{-1} \cdot \mathbf{B}}_{=\mathbf{T}} \cdot \mathbf{D} \tag{4}$$

Solving for gross output in each country amounts to jointly solving for prices (using (1)) and nominal output (using (4)).

The simplicity of this baseline framework follows from strong assumptions such as Cobb-Douglas production, exogenous demand shocks, and fixed labor supply. These restrictions allow us to easily derive results that provide guidance and intuitions for our empirical investigations.[8]

Defining Real Value Added. Measuring real value added in this framework is not straightforward. Statistical agencies measure real value added as the difference between 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 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 (2021) 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

[7] 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 to study both supply shocks (through shocks to technology $Z_{i,s}$) and demand shocks (through shocks to D_i).

[8] In appendix, we simulate a more sophisticated version of our model and show that our results regarding the importance of different trade channels on GDP comovement are preserved.

a proportional relationship between gross output and profits fluctuations. Even with inelastic domestic factor supply, real value added can still fluctuate owing to movements in profits.

We account for such a channel by positing a reduced form relationship between gross output Y_i and *measured* real GDP, so that $RGDP_i = L_i + \kappa_i Y_i$, with κ_i a constant. κ_i accounts for the fact that, with constant markups, profits are a fraction of gross output. Importantly, since profits are captured in statistical value added, any change in gross output is associated with a proportional change in profits which is then captured as a change in real GDP. As a result, in such a setup with fixed domestic factor supply, changes in real GDP come only from gross output fluctuations and gross output (Y_i) comovements are translated into real GDP comovements.

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

2.2 Propagation of shocks and global trade flows: the network effects

Our framework is similar to previous network models and shares the same propagation properties. As noted in Acemoglu et al. (2016) and Carvalho and Tahbaz-Salehi (2019), theory predicts that TFP shocks propagate downstream while demand shocks propagate upstream.[9] In both cases, we show that the link between bilateral GDP correlation and trade linkages can be expressed as:

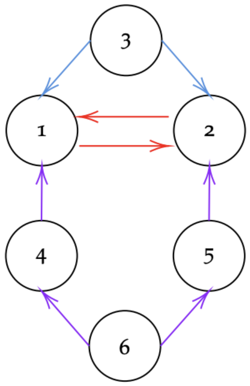
$$\begin{aligned} \text{corr GDP}_{i,j} \propto \;& \text{Bilateral trade exposure}_{i,j} \\ & + 1^{st} \text{ order trade network exposure}_{i,j} + \textit{Higher order} \text{ trade network exposure}_{i,j} \end{aligned} \tag{5}$$

TFP shocks. When demand shifters are fixed and there is only TFP shocks, equation (4) 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 and changes in output can be $\widehat{\mathbf{Y}} = \left[\mathbf{I}_N - \mathbf{\Omega}\right]^{-1} \widehat{\mathbf{Z}}$. Note that the matrix $\mathbf{B}$, which captures final good trade, is not present in this equation. Consider a world with six countries and the I/O structure $\mathbf{\Omega}$ described in figure 1.[10]

[9] This result, already established in previous papers with Cobb-Douglas networks, simply follows from inspecting the price system and (4). Although Acemoglu et al. (2016) employs a closed-economy multi-sector framework, the basic Cobb-Douglas structure is similar to ours so that countries and sectors are treated symmetrically: a shock to a particular country in a 6-country, 1-sector model has the same effect as a shock to a particular sector in a 1-country, 6-sector model, as long as both models have the same $\mathbf{\Omega}$ and $\mathbf{B}$ matrices.

[10] We chose this particular I/O structure in order to obtain intuitive and easy-to-interpret equations. Our main results extend to more complex I/O linkages, albeit at the expense of more complicated expressions.

Figure 1. Network representation of I/O linkages



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

With this structure, changes in gross output as a function of shocks and trade linkages are:

$$\widehat{Y}_1 = \frac{1}{\mid \mathbf{\Omega} \mid}\left(\widehat{Z}_1 + \alpha_1^2\widehat{Z}_2 + (\alpha_1^3 + \alpha_1^2\alpha_2^3)\widehat{Z}_3 + \alpha_1^4\widehat{Z}_4 + \alpha_1^2\alpha_2^5\widehat{Z}_5 + (\alpha_1^4\alpha_4^6 + \alpha_1^2\alpha_2^5\alpha_5^6)\widehat{Z}_6\right) \tag{6}$$

$$\widehat{Y}_2 = \frac{1}{\mid \mathbf{\Omega} \mid}\left(\alpha_2^1\widehat{Z}_1 + \widehat{Z}_2 + (\alpha_2^3 + \alpha_2^1\alpha_1^3)\widehat{Z}_3 + \alpha_2^1\alpha_1^4\widehat{Z}_4 + \alpha_2^5\widehat{Z}_5 + (\alpha_2^5\alpha_5^6 + \alpha_2^1\alpha_1^4\alpha_4^6)\widehat{Z}_6\right) \tag{7}$$

where α_i^j is the spending share in country i on goods coming from country j and $\mid \mathbf{\Omega} \mid$ is the determinant of matrix $\mathbf{\Omega}$. We consider a case where technology shocks are uncorrelated, so that $\text{Cov}(Z_i, Z_j) = 0$ for all i and j.[11] In such a case, correlation between $\widehat{Y}_1$ and $\widehat{Y}_2$ is solely due to global trade linkages. Using equations (6) and (7), we can write a simple expression for $\text{corr}(\widehat{Y}_1, \widehat{Y}_2)$:

$$\begin{aligned}\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\Bigg(& \underbrace{\alpha_1^2 + \alpha_2^1}_{\text{bilateral trade exposure}} + \underbrace{(\alpha_1^3 + \alpha_1^2\alpha_2^3)(\alpha_2^3 + \alpha_2^1\alpha_1^3)}_{\text{1st order networth exposure}} \\ & + \underbrace{\alpha_2^1(\alpha_1^4)^2 + \alpha_1^2(\alpha_2^5)^2 + (\alpha_1^4\alpha_4^6 + \alpha_1^2\alpha_2^5\alpha_5^6)(\alpha_2^5\alpha_5^6 + \alpha_2^1\alpha_1^4\alpha_4^6)}_{\text{2nd order network exposure}}\Bigg)\end{aligned} \tag{8}$$

where $\lambda = \left(\sqrt{\text{Var}(\widehat{Y}_1)\text{Var}(\widehat{Y}_2)}\right)^{-1}$. Equation (8) reveals that several types of trade linkages can give rise to endogenous output co-movement: direct trade in intermediate input, common exposure to a third country (first order network effect), and higher common order exposure to other countries (in our example, we simply show the second order network effect).

Notice that even if countries 1 and 2 do not export anything at all, the first order network effects (direct network exposure) generate GDP comovement between the two countries, as long as both countries are exposed to shocks emanating from the same country 3. In that case, we get

[11] 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.

that $\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\alpha_1^3\alpha_2^3\right)$. A similar intuition arises with the second order network effect (or indirect network exposure). Even if country 1 and 2 do not export anything at all and do not share a common direct partner ($\alpha_1^2 = \alpha_2^1 = \alpha_1^3 = \alpha_2^3 = 0$), they can be linked through second-order network effect, as long as their partners share common partners. In such case, $\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\alpha_1^4\alpha_4^6\alpha_2^5\alpha_5^6\right)$. These cases illustrate the conceptual difference between our analysis and the value-added perspective studied in Duval et al. (2016). Value-added trade between countries 1 and 2 takes *third country effect* into account only insofar that some value-added in produced in country 1 and ends up being absorbed in country 2, or vice versa. By construction, looking at value-added trade cannot account for cases where two countries do not exchange *any* value-added, either directly or indirectly, but have correlated GDP fluctuations due to their exposure to similar trade partners.

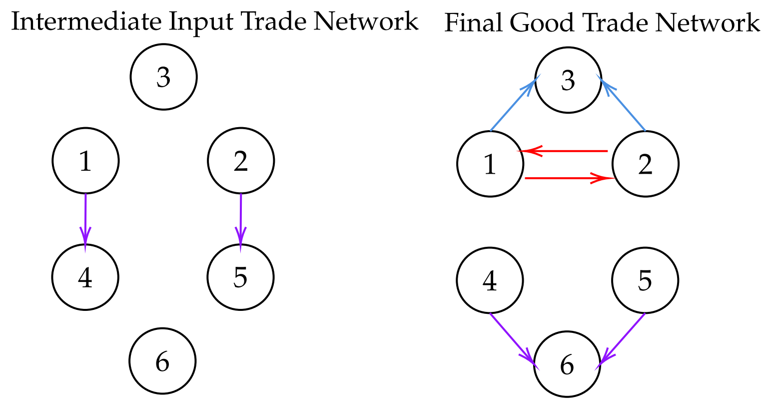
The mechanisms described above do not operate independently, and the density of the global trade network can act as a powerful amplification factor. From equation (8), the impact of common exposure is larger in presence of bilateral trade (i.e. when α_1^2 and α_2^1 are non zero). This simple observation implies that the strength of each channel increases with the presence of other linkages in the trade network. Hence, an increase in any given trade link in the sparse network of the 1970s is not expected to have the same effect as increasing a trade link in today's denser trade network. In section 4.4, we provide empirical support for this amplification channel.

Demand shocks. Consider now 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: $\widehat{\mathbf{Y}} \propto \left(\mathbf{I}_N - \left(\mathbf{\Omega}^T\right)\right)^{-1} \cdot \mathbf{B} \cdot \widehat{\mathbf{D}}$, which 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.

The I/O and demand shares matrices associated with this structure are given by:

$$\mathbf{\Omega} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_4^1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_5^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad \mathbf{B} = \begin{pmatrix} \beta_1^1 & \beta_1^2 & \beta_1^3 & 0 & 0 & 0 \\ \beta_2^1 & \beta_2^2 & \beta_2^3 & 0 & 0 & 0 \\ 0 & 0 & \beta_3^3 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_4^4 & 0 & \beta_4^6 \\ 0 & 0 & 0 & 0 & \beta_5^5 & \beta_5^6 \\ 0 & 0 & 0 & 0 & 0 & \beta_6^6 \end{pmatrix} \tag{9}$$

Figure 2. Network representation of both input and final good trade as described in (9)



Using equation (2.2) yields the proportional change in gross output in countries 1 and 2:

$$\widehat{Y_1} \propto \beta_1^1 \widehat{D_1} + \beta_1^2 \widehat{D_2} + \beta_1^3 \widehat{D_3} + \beta_4^4 \alpha_1^4 \widehat{D_4} + \beta_4^6 \alpha_1^4 \widehat{D_6} \tag{10}$$

$$\widehat{Y_2} \propto \beta_2^1 \widehat{D_1} + \beta_2^2 \widehat{D_2} + \beta_2^3 \widehat{D_3} + \beta_5^5 \alpha_2^5 \widehat{D_5} + \beta_5^6 \alpha_2^5 \widehat{D_6} \tag{11}$$

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:

$$\text{corr}(\widehat{Y_1}, \widehat{Y_2}) = \lambda \Bigg(\underbrace{\beta_1^1 \beta_2^1 + \beta_2^2 \beta_1^2}_{\text{bilateral trade exposure}} + \underbrace{\beta_1^3 \beta_2^3}_{\text{1st order network exposure}} + \underbrace{\beta_4^6 \beta_1^6 \alpha_1^4 \alpha_2^5}_{\text{2nd order network exposure}} \Bigg) \tag{12}$$

Similar to section 2.2, several types of trade linkages of final goods can give rise to endogenous output co-movement. The first term in equation (12) captures direct exposure to demand shocks through bilateral trade in final goods. Note that the absence of αs in this term simply reflects our assumption of no input trade between 1 and 2. The second term captures common exposure to demand shocks in country 3 due to the fact that both countries 1 and 2 export final goods to country 3. Finally, a third term arises because of common indirect trade network exposure to demand shocks in country 6. Indeed, a demand shock in country 6 triggers more exports of final goods from 4 and 5 to country 6. In turn, to produce these final goods, countries 4 and 5 import more intermediates from 1 and 2 which creates endogenous output correlation.

From (12), it follows that demand shocks propagate across countries trough trade in inputs and trade in final goods, with both direct and indirect exposure to common shocks increasing bilateral correlation. Interestingly, trade in final goods is associated with the propagation of demand shocks but not supply shocks.

Both supply and demand shocks. In reality, both demand and supply shocks are likely to be important. As such, we now briefly consider a situation with only two countries trading both inputs ($\alpha_1^2, \alpha_2^1 \neq 0$) and final goods ($\beta_1^2, \beta_2^1 \neq 0$). With both supply and demand shocks, output correlation increases with total bilateral trade – a result that lends support for measures of trade linkages used in the literature previously. To see this, using the price system and (4), the proportional change in gross output in countries 1 and 2 can be written as:

$$\widehat{Y_1} = \widehat{p_1 Y_1} - \widehat{p_1} \propto (\beta_1^1 + \beta_2^1 \alpha_2^1)\widehat{D_1} + (\beta_1^2 + \beta_2^2 \alpha_2^1)\widehat{D_2} + \widehat{Z_1} + \alpha_1^2 \widehat{Z_2} \tag{13}$$

$$\widehat{Y_2} = \widehat{p_2 Y_2} - \widehat{p_2} \propto (\beta_2^1 + \beta_1^1 \alpha_1^2)\widehat{D_1} + (\beta_2^2 + \beta_1^2 \alpha_1^2)\widehat{D_2} + \widehat{Z_2} + \alpha_2^1 \widehat{Z_1} \tag{14}$$

With uncorrelated shocks, the correlation between $\widehat{Y_1}$ and $\widehat{Y_2}$ writes:

$$\text{corr}(\widehat{Y_1}, \widehat{Y_2}) = \lambda \Bigg(\underbrace{(\beta_1^1 + \beta_2^1 \alpha_2^1) \cdot (\beta_2^1 + \beta_1^1 \alpha_1^2) + (\beta_1^2 + \beta_2^2 \alpha_2^1) \cdot (\beta_2^2 + \beta_1^2 \alpha_1^2)}_{\text{Demand Shock propagation}} + \underbrace{\alpha_1^2 + \alpha_2^1}_{\substack{\text{Supply Shock} \\ \text{propagation}}} \Bigg) \tag{15}$$

In the above equation, it is clear that demand shocks in country 2 impact output in country 1 through two channels. First, a direct exposure arises if country 2 imports final goods from country 1 for its consumption. Second, indirect exposure arises if country 2 imports intermediate inputs from 1 which are used in production and ultimately absorbed in country 2. This observation underscores that both trade in inputs and in final goods can be vectors of propagation for demand shocks. Note that equation (15) was obtained without assuming any particular input-output structure or trade pattern between countries 1 and 2.

Trade indexes. Anticipating the need to construct empirical counterparts to trade indices, we note that one can utilize equations (2) and (3) to relate the αs and βs above to standard data. Denoting by $T^I_{i\to j}$ and $T^F_{i\to j}$ the trade flow in intermediate inputs and final goods from i to j respectively and using the fact that γ_j is the share of domestic value added in country j's gross output, we write:

$$\alpha_i^j = \frac{p_i X_i^j}{p_j Y_j} = \gamma_j \frac{T^I_{i\to j}}{GDP_j} \quad , \quad \beta_i^j = \frac{T^F_{i\to j}}{D_j} \approx \frac{T^F_{i\to j}}{GDP_j} \quad \text{and} \quad \beta_i^i \approx 1 - \sum_{k\neq i} \beta_k^i \,. \tag{16}$$

Bilateral trade and trade network exposures in equations (8), (12) and (15) are all composite functions of those specific indexes. In practice, most papers in the literature use a simplified proxy for bilateral trade exposure between two countries, simply expressed as the ratio between bilateral trade flows over the sum of GDPs of the two countries.[12] To be as close as possible to

[12] This simple expression of trade proximity, using total trade normalized by GDP, was introduced by Frankel and Rose (1998), and has been widely used since then, including by Di Giovanni and Levchenko (2010), Liao and Santacreu (2015) and others.

previous studies, we also use simple proxies for bilateral and network trade proximity in our baseline analysis in section 4, a choice that does not prevent us from investigating the role of different types of trade goods or the impact of overall network density in explaining the evolution of the TC-slope over time. We then examine the use of alternative indexes as sensitivity analysis.

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. We circumvent this issue by adding a number of controls and fixed effects that we discuss in the next section.

3 Data and measurement of trade linkages

We now turn to the main objectives of this paper and investigate the heterogeneity of the TC-slope across different levels of development and over time periods. Our sample contains a total of 134 countries for 40 years, which accounts for almost the totality of world trade flows and world GDP.

Data on trade flows come from from the Observatory of Economic Complexity (MIT), which 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. Annual GDP data come from the Word Development Indicators (WDI) of the World Bank, measured using constant 2010 prices in US dollars.[13] We classify countries mainly based on their income level by creating 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*).[14] We exclude countries whose share of oil rents represent more than 20% of GDP.[15] For clarity's sake, 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

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

[14] 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`. To avoid any time variation in the country composition of income groups, we fix the definition of income groups using the 2010 classification made. Stability in the identity of countries within each group is important since our identification of the TC-slope relies on within country-pair variations.

[15] In the World Development Indicators database, "oil rents" are the difference between the value of crude oil production at world prices and total costs of production. As shown in appendix, oil producers display very different structure of trade and business cycles. More than 70% of their trade comes from trade in primary goods, or commodities, which comprises goods sold for production or consumption just as they are found in nature; crude oil, coal, iron, and agricultural products like wheat or cotton. Oil producers business cycles are therefore substantially affected by fluctuations in the world crude oil prices. In section 5, we analyse the TC-slope within those countries in a sensitive analysis.

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 time windows. We also exclude country-pairs with less than two time-windows for which trade proximity and GDP are available. Our final sample counts 6374 unique country-pairs.

Identification strategy. 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, etc. Because those other factors can themselves be correlated with the index of trade proximity in the cross section, using cross-section identification could yield biased results. Indeed, in their seminal paper, Frankel and Rose (1998) uses 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. This limitation of cross sectional analysis has been also discussed by Imbs (2004), noting that bilateral trade intensity can be a proxy of country-pair similarity, and thus of correlated shocks. 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. Within each time window, we compute GDP correlation (Corr GDP) as well as the average trade intensities defined above.

Note that papers that use cross-sectional variations often instrument trade variables using a combination of time invariant variables such as distance, common border, former colonial ties, etc. Since our empirical strategy consists of using within country pair variations, such instruments are not useful in our case since any time invariant country-pair characteristic, in particular the *average* GDP correlation across all time windows, is absorbed by country-pair fixed effects. Moreover, adding TW_t controls for the recent rise of world GDP correlation since the 90s, which could be unrelated to trade intensity. Our approach is related to Di Giovanni and Levchenko (2010), which includes country pair fixed effects in a large *cross-section* of industry-level data to investigate the relationship between sectoral trade and gross output comovement at the industry level. Additionally, Duval et al. (2016) uses a quasi-correlation measure that can be computed for every year, which also allows for the inclusion of country pair and year fixed effects, and tests the importance of *value added* trade for GDP comovement.

3.1 Measurement: Trade Proximity and GDP-comovement

GDP. To extract the business cycle component from the trend, our main and benchmark filter is the Hodrick-Prescott (HP) filter with a yearly smoothing parameter of 100, which captures the standard business cycle fluctuations. We therefore mostly keep fluctuations that have a frequency between 8 and 32 quarters. In section 5, we provide robustness checks using a Baxter and King (BK) filter and a simple log-first difference.[16] For all country-pair (i, j), we compute the correlation of filtered GDP within each time-window t of 10 years, denoted Corr GDP_{ijt}. Figure 5 in appendix A.1 shows the evolution of GDP comovement of each pair of income group.

Bilateral Trade Proximity. Following the discussion in Section 2, we decompose our proxy for *bilateral* trade exposure into flows of type $d \in \{total, inter, final\}$ (for total trade flows, trade in intermediate inputs and trade in final goods respectively). For a country-pair (i, j) in a given time-window t, we define:

$$Trade^{d}_{ijt} = \frac{T^{d}_{i\leftrightarrow j,t}}{GDP_{it} + GDP_{jt}} \qquad \forall d \in \{total,\ inter,\ final\} \tag{17}$$

where $T^{d}_{i\leftrightarrow j,t} = T^{d}_{i\rightarrow j,t} + T^{d}_{j\rightarrow i,t}$ 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. To classify trade flows into final goods and intermediate inputs, we use a concordance table from SITC Rev. 2 to Broad Economic Categories (BEC) and aggregate trade flows in each category at the country-pair level.[17,18]

In the result tables below, we refer to Total$\equiv T^{total}$, Inter$\equiv T^{inter}$ and Final$\equiv T^{final}$ for simplicity. In all of our regressions, the intensity measures are averaged over each time window and their natural logs are used in estimation. In section 5 we will present results with alternative measures.

The trade proximity indices defined above are similar to earlier studies on the relationship between trade and GDP synchronization. Using such variables in an empirical setting ensures the comparability of our results to previous papers. As an alternative, we construct other bilateral trade measures derived from the theoretical framework in section 2 using the decomposition (15). We define "demand" and "supply" side of trade indices that respectively capture the strength of

[16] 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 filter.

[17] 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`.

[18] 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 in section 5. The main results remain unchanged.

propagation of different shocks as:

$$\text{Trade}_{\text{supply}} = (\beta_1^1 + \beta_2^1\alpha_2^1)\cdot(\beta_2^1 + \beta_1^1\alpha_1^2) + (\beta_1^2 + \beta_2^2\alpha_2^1)\cdot(\beta_2^2 + \beta_1^2\alpha_1^2)\,,\ \text{Trade}_{\text{demand}} = \alpha_1^2 + \alpha_2^1 \quad (18)$$

with input shares αs and demand shares βs obtained using (16).

***Network* exposure index.** In a world with many countries, the bilateral index of trade proximity is not a sufficient measure of trade linkages.[19] Following the discussion in section 2, we expect bilateal GDP comovement to be increasing in the similarity of countries i and j spending shares with respect to all other partners k. Accordingly, we propose a simple measure of *first-order* network proximity that proxies the similarity of trade shares across all other partners, normalized by overall openness to trade. Our *third country* index is then defined as:

$$network_{ijt}^{1st} = \left(1 - \frac{1}{2}\sum_k \left|\frac{T_{i\leftrightarrow k,t}}{T_{i,t|-j}} - \frac{T_{j\leftrightarrow k,t}}{T_{j,t|-i}}\right|\right) \quad (19)$$

where $T_{i\leftrightarrow k,t}$ represents total trade flows between countries i and k while $T_{i,t|-j}$ denotes the total trade flows of country i vis-a-vis all of its partners, except country j. This index aims to capture similarity in the geographical composition of trade shares between i and country j, normalized by trade openness. Pairs that exhibit similar trade partners have an index close to one while pairs with completely different partners have an index of zero.

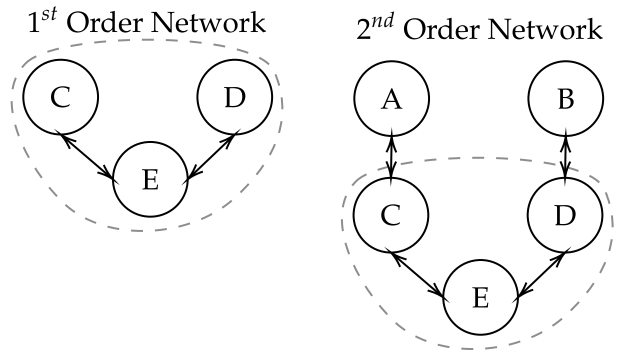
As a measure of 2^{nd} order network proximity for any pair (i,j), we build a proxy index measuring to what extend country i's partners are linked with country j's partners, weighted by the importance of the partners in terms of total trade flows of the two countries i, j:

$$network_{ijt}^{2nd} = \frac{1}{4}\left(\sum_{z\in\mathcal{P}(i)}\sum_{y\in\mathcal{P}(j)}\Big[w_t(z,i;j)\cdot w_t(y,j;i) + w_t(z,j;i)\cdot w_t(y,i;j)\Big]\cdot network_{zyt}^{1st}\right) \quad (20)$$

where $w_t(z,i;j) = \frac{T_{i\leftrightarrow z,t}}{T_{i,t|-j}}$. Under this specification, higher values for the $network_{ijt}^{2nd}$ index are associated with high proximity between i partner's partners and j partner's partners. Note that the pair (i,j) is second order connected whenever they trade with partners z and y that are themselves first order connected (i.e. $network_{zyt}^{1st} > 0$). The quantities $w_t(z,i;j)\cdot w_t(y,j;i)$ and $w_t(y,j;i)\cdot w_t(z,j;i)$ capture the importance of (z,y) for the country pair (i,j). If i does not trade with z but trade with

[19] The importance of third country effect is also mentioned in Kose and Yi (2006) and Duval et al. (2016) analyzes the role of indirect trade linkages between two countries using a value-added approach. Our approach differs from Duval et al. (2016) 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 and second order network proximity indexes.



Note: dashed areas represent 1st order network. In the left chart, countries C and D have a common exposure to country E, and hence have a non-zero 1st order network proximity. In the right chart, countries A and B do not have any trade partner in common, but their respective partners C and D have a common exposure to country E. Hence, countries A and B have a non-zero 2nd order proximity due to their indirect exposure to country E.

y, and j does not trade with y but trade with z, then (i, j) is 2^{nd} order connected through (z, j) since $w_t(z, j; i) \cdot w_t(y, i; j) > 0$. If instead both i and j trade only with y but not with z, then (i, j) is not 2^{nd} order connected through (z, j).[20] As an illustration, we compare our two indices in figure 3.

3.2 Additional controls

Trade unions. We introduce dummies for country-pairs among the USSR, the Euro area, the Organization of the Petroleum Exporting Countries (OPEC), the different waves of the European Union and in the North American Free Trade Agreement (NAFTA). Those dummies aim to capture specific trade environment and border effects as highlighted in Clark and van Wincoop (2001).

Proximity in trade composition. 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 a bilateral indexes of *proximity in trade composition*. The index is based on countries' proximity in terms traded goods, at the 4-digit SITC level or ISIC level, as proxy for domestic specialization.[21] We define the sectoral proximity index in terms of traded goods denoted

[20] In such a case, note that (i, j) common exposure to y is captured by our 1^{st} order network variable.

[21] In Appendix,we also show results using an index based on the similarity of sector share in GDP, using data for sector shares in GDP from the World Bank's WDI. However, data limitations imply that such an analysis can only be done for a limited number of countries.

$export^{prox}_{ijt}$ for a given country-pair (i, j) in time-window t as:

$$export^{prox}_{ijt} = 1 - \frac{1}{2} \sum_{s \in \mathcal{S}_{EX}} \left| \frac{EX_{i,t}(s)}{EX_{i,t}} - \frac{EX_{j,t}(s)}{EX_{j,t}} \right| \tag{21}$$

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). Country pairs with very similar trade composition have an index close to 1, while countries that export completely different sectors have an index of 0. 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 5.

3.3 Descriptive statistics

In Table 1, we present key descriptive statistics. Starting with general statistics, there is a large increase in overall GDP synchronisation over time, for all income groups (+20pp on average). This synchronisation is particularly substantial among OECD countries. It is also noticeable that final goods account for a relatively large share of traded goods for lower income countries, in particular when they are trading with other low income partners (i.e. for country-pairs in the *LL* group). However, this specificity is less pronounced in the last decade. Concerning trade proximity, there are larger bilateral links and first order network exposure among OECD and high income countries relative to low income countries. The second order network tend to be higher among low income countries, but the difference is small given the standard deviation of around 0.10 of this index in each country-pairs. Finally, the export proximity index, measuring similarity in sectoral composition of exported goods, is larger for *OECD* country-pairs and significantly increases over time for all country-pairs in different income groups. This reveals a convergence in terms of economic structure among all country-pairs.

Before turning to the regression analysis, it is useful to look at the unconditional correlations between our main variables. It is noticeable that the correlation between GDP synchronisation and bilateral trade is stronger among high income countries relative to developing countries. This correlation increases over time. Second, we note that correlation between GDP synchronisation and network exposures does increase over time, except for low income countries. Surprisingly, the 2^{nd} network exposure is negatively correlated with GDP comovement and other trade proximity indices. This, however, does not mean that 2^{nd} network exposure is negatively correlated with those variables over time within country-pair, which is the relevant dimension of our study. Indeed, given our specifications, we are most interested in *within* country-pair changes in business cycle synchronization and how it relates to time variations in trade linkages.

Turning to cross-correlation of explanatory variables, we note that the only pair of variables that is (unconditionally) highly correlated is first order network exposure and bilateral trade, meaning that countries trading more each other are more likely to be exposed to similar countries. This is likely to be the case if, for instance, those countries are part of the same trade union or share common border; a feature that our empirical strategy will control for using country-pair fixed effects.

Overall, these naive correlations tend to be in line with the main points we investigate more precisely below: the link between trade and GDP synchronization seems to be heterogeneous across income group, and tends to vary over time. Of course, those simple correlations do not control for the factors such as similarity in exported goods and sectors, trade unions, common borders, common exposure to global shocks etc, which is the purpose of the next sections.

Table. 1. Trade intensity and cycle synchronization: summary statistics of main variables [a]

	Selected countries and sample							
Period	Time Window: 1970:1979				Time Window: 2000:2009			
Country pairs	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*
I. General statistics								
− corr GDP (HP-filetered)*100	30.0	29.9	4.3	1.8	68.8	56.3	26.5	20.3
− Share of global trade flows	62.1	63.4	24.6	1.5	52.3	50.3	42.0	6.0
− Ratio final/intermediate good traded	0.27	0.29	0.32	0.48	0.28	0.26	0.26	0.31
II. Trade proximity statistics								
− log bilateral trade intensities	−8.4	−9.3	−10.5	−10.4	−6.7	−8.9	−10.9	−11.2
− 1^{st} order network	0.54	0.46	0.43	0.44	0.55	0.46	0.40	0.40
− 2^{nd} order network	0.93	0.95	0.96	0.97	0.95	0.97	0.99	1.0
− Supply trade index*100	0.10	0.13	0.07	0.04	0.36	0.29	0.14	0.12
− Demand trade index*100	0.21	0.28	0.17	0.07	0.78	0.81	1.33	0.53
III. Proximity in traded goods								
− Export proximity*100, 4-digit SITC	29.9	21.9	10.7	12.7	38.1	26.0	14.3	13.9
− Export proximity*100, ISIC	46.1	35.4	33.2	40.3	53.3	39.4	28.5	29.5
IV. Cross-sectional correlations								
− corr GDP – log bilateral trade	0.27	0.19	0.12	0.12	0.39	0.41	0.24	0.16
− corr GDP – 1^{st} order network	0.01	0.03	0.02	0.12	0.17	0.31	0.05	0.07
− corr GDP – 2^{nd} order network	−0.21	−0.33	−0.10	−0.09	−0.07	−0.08	−0.20	−0.19
− 1^{st} order network – log bilateral trade	0.59	0.63	0.48	0.43	0.69	0.60	0.55	0.62
− 1^{st} order network – 2^{nd} order network	−0.07	−0.17	−0.15	−0.25	0.14	0.00	−0.06	−0.15

[a] selected income groups are not exclusive. Some countries among the *LL* group also appear in *OECD*. The table excludes oil producers.

4 Results: the Global Trade-Comovement Slope

We now present our main analysis regarding the association of the association between global trade and GDP comovmenent. We proceed step-by-step and gradually investigate the TC-slope from multiple angles, decomposing the slope along different trade linkages, across income groups, type of traded goods, and over time.

4.1 The Role of Trade Linkages for different Income Groups

We first extend the FR results on the relationship between total trade intensity and cross-country GDP correlation. We use a panel estimation with country-pair (CP) and time-window (TW) fixed effects to exploit *within* country-pair time variations for the identification:[22]

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}, \tag{22}$$

where $\mathbf{X}_{ijt}$ is the vector of additional control variables, including trade unions and sectoral proximity of trade. Again, *CP* fixed effects control for time invariant factors that can influence GDP comovement between two countries, such as distance, common border, common language, etc. *TW* fixed effects capture aggregate changes in GDP comovement for all country-pairs in the world that could be due to, for instance, global aggregate shocks. In this specification as well as all subsequent analysis, standard errors are clustered 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:

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \tag{23}$$

In equation (23), $\textbf{network}_{ijt}$ defines a vector composed of the first and second order network measures discussed above. The results are gathered in table 2. Three main results emerge.

First, consistent with previous work, trade proximity using total trade flows is significantly associated with more GDP correlation, but the estimate for our sample of country is much smaller than the one reported in the literature. According to the second columns, a doubling in the trade intensity would only increase cross-country GDP correlation by 1.1pp, against 6pp in FR and 6.3pp for Kose and Yi (2006). This association is however very heterogeneous. Investigating the slope for different income groups reveals that doubling the trade intensity is associated with an increase

[22] 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.

Table. 2. Trade Comovement slope with total trade index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(Trade)	0.019***	0.017***	0.085***	0.105***	0.040***	0.032**	0.012***	0.011***	0.014**	0.015**
	(0.004)	(0.004)	(0.031)	(0.034)	(0.013)	(0.014)	(0.004)	(0.004)	(0.006)	(0.006)
network^{1st}		0.210***		0.947***		0.441***		0.202***		0.080
		(0.059)		(0.261)		(0.156)		(0.060)		(0.110)
network^{2nd}		0.086		1.476***		−0.183		0.123		0.261
		(0.086)		(0.391)		(0.241)		(0.083)		(0.162)
CP+TW FE, controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,814	16,814	1,292	1,292	2,584	2,584	16,698	16,698	5,942	5,942
Within R^2	0.008	0.010	0.077	0.100	0.044	0.050	0.002	0.004	0.002	0.003

Notes: Variable definitions and sources are described in detail in the text. The sample period is 1970–2009. Standard deviation in parenthesis and clustered at the country-pair level. *p<0.1; **p<0.05; ***p<0.01.

in GDP correlation of 7.2pp for OECD countries (much closer to the literature, mostly based on OECD countries), 3.2pp for the *HH* group, 0.8pp for *HL* group and 1.0 pp for the *LL* sub-sample. Alternatively, moving from the 25th to the 75th percentiles of log total trade is associated with an increase in GDP correlations up to 21.2 pp for *OECD* country pairs, 11.7 pp for pairs in the *HH* group, 3.7 pp for the *HL* group and 5.3 pp for the *LL* sub-sample.

Second, our results provide new insights regarding the role of common exposure to third countries through our first and second order network indices, and how this channel varies across income groups. The effect of trade through the *1st order network effect* is high and significant for most income groups. 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 4.3 pp for all country-pairs, 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 27.0 pp increase in bilateral GDP correlation, while it is 10.9 pp for pairs in the *HH* group and only 4.0 pp 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.

Our 2nd order network index is more ambiguous and presents again noticeable difference across income groups. The index is only statistically significant for pairs in the OECD group. For those countries, moving from the 25th to the 75th quantiles of the 2nd order network index implies an increase in GDP correlation of about 20 pp. However, we find no statistical significance for other groups of countries, hinting that going beyond the first order network effect only marginally improves our understanding of the effect of trade on GDP correlation for these countries.

While previous investigations highlighted the role of either direct bilateral gross trade or bilateral value added trade links, the economic and statistical significance of our network indices sheds light on an additional channel stemming from increasing exposure to other countries.[23]

4.2 Decomposing the Role of the Type of Traded Goods

We now refine the analysis and decompose total trade flows into two sub-categories: *trade in intermediate inputs* ($\text{Trade}_{ijt}^{inter}$) and *trade in final goods* ($\text{Trade}_{ijt}^{final}$). In de Soyres and Gaillard (2021), we use a sample of high income countries and show that trade in intermediate inputs is significantly correlated with GDP comovement, while trade in final goods is not.[24] However, as discussed in section 2, both trade in final or intermediate inputs can be associated with GDP co-movement depending on whether the underlying propagated shock comes from a demand or a supply (TFP) shocks.[25] To test this, we estimate the following specification with and without network effects and its decomposition into final and intermediate goods:

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \boldsymbol{\gamma}\,\mathbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \quad (24)$$

Results are shown in table 3. When focusing on country-pairs in *OECD* and *HH*, the TC slope is significantly driven by trade in intermediate inputs as opposed to trade in final goods.[26] Turning to country-pairs in the *HL* and *LL*, 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 disaggregated network effects, moving from the 25th to the 75th quantiles of log trade in intermediate inputs is associated with a 16.8 pp increase in GDP correlation for pairs in the *OECD* group and a 9.1 pp increase for pairs in the *HH* group. For pairs in the *HL* and *LL*, moving from the 25th to the 75th quantile of log trade in final goods increases respectively GDP comovement by 4.5 pp and 5.0 pp.

[23] See for example Duval et al. (2016) for an investigation using trade proximity indices based on value added linkages, such that country *i*'s exports to destination *j* includes both the value added directly exported as well as value added exported through third country but ends up absorbed by *j*. Note that this measure is conceptually very different from our "common exposure" index, since it is still a bilateral measure of trade: for example, it does not account for cases where two countries are importing goods from the same partner.

[24] In de Soyres and Gaillard (2021), we also show theoretically how international I/O 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*

[25] In section 5, we use more direct measures that directly map the propagation channels of supply and demand shocks in light of section 2.

[26] 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.

The distinction between network indexes between final and intermediate goods reflect a strong role for the I/O linkages through trade in intermediate goods for all group of countries, with the exception of the *LL*. In particular, common exposure to third countries *via* intermediate inputs is statistically significantly associated with GDP comovement, while common exposure *via* final good trade is not. As income decreases, the role of the network intermediate index decreases markedly. Those results suggest that it is particularly important to distinguish between the type of traded goods empirically, but also theoretically.

Table. 3. Trade Comovement slope with disaggregated trade index

	corr GDP											
	OECD	*OECD*	*OECD*	*HH*	*HH*	*HH*	*HL*	*HL*	*HL*	*LL*	*LL*	*LL*
ln(inter)	0.105***	0.109***	0.080**	0.032***	0.025**	0.022*	−0.000	−0.001	−0.001	0.002	0.003	0.003
	(0.031)	(0.031)	(0.032)	(0.012)	(0.012)	(0.012)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
ln(final)	−0.020	−0.003	0.006	0.004	0.004	−0.000	0.012***	0.012***	0.012***	0.012**	0.012**	0.013**
	(0.025)	(0.025)	(0.025)	(0.012)	(0.012)	(0.012)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
network^{1st}		0.911***			0.445***			0.212***			0.078	
		(0.260)			(0.156)			(0.060)			(0.111)	
network^{2nd}		1.445***	1.317***		−0.213	−0.250		0.086	0.073		0.195	0.169
		(0.397)	(0.404)		(0.235)	(0.236)		(0.083)	(0.083)		(0.162)	(0.159)
network inter^{1st}			1.638***			0.541***			0.129**			0.046
			(0.318)			(0.144)			(0.056)			(0.096)
network final^{1st}			−0.243			0.206			0.079			−0.122
			(0.250)			(0.142)			(0.051)			(0.091)
CP+TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,292	1,292	1,292	2,575	2,575	2,575	16,480	16,480	16,480	5,820	5,820	5,820
Within R^2	0.082	0.104	0.121	0.044	0.050	0.055	0.003	0.004	0.004	0.003	0.004	0.004

Notes: Variable definitions and sources are described in detail in the text. The sample period is 1970–2009. Standard deviation in parenthesis and clustered at the country-pair level. *p<0.1; **p<0.05; ***p<0.01.

A possible interpretation for the above results might be related to our theoretical framework, and in line with observations in previous papers such as Acemoglu et al. (2016). Supply-side shocks propagate downstream whereas demand-side shocks propagate downstream. This implies that trade in final good is a vector of propagation for demand shocks only. Hence, our finding that the association between final good trade and GDP synchronization becomes more important as income decreases suggests that lower income countries may be more subject to demand shocks. An alternative reason might be related to the broad specialization of trade flows, despite the fact that we control for export proximity. In particular, low income countries' trade flows tend to be more specialized toward final goods relative to countries in the high income group (see Table 1).

4.3 The evolution of the TC Slope from 1970 to 2009

We now investigate the potential time evolution of the association between trade linkages and GDP correlation, across income groups and type of traded goods. To this end, 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.[27] Formally, we now test:

$$\begin{aligned}\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}^{total}_{ijt}) + \beta_2\, LTW_t \times \ln(\text{Trade}^{total}_{ijt}) + \gamma_1\, \text{network}^{1st}_{ijt} \\ + \gamma_2\, LTW_t \times \text{network}^{1st}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}\end{aligned} \tag{25}$$

where $\mathbf{X}_{ijt}$ refers again to controls (including the second order network index). By adding these interaction terms, we specify that coefficients β_2 and γ_2 indicate whether the TC slope estimated with respect to trade and the coefficients associated with the first order network effects in the period 1990-2009 are different from the coefficients estimated using the period 1970-1989.[28]

Table 4 summarizes our findings and prompts a few observations. We find evidence that the TC-slope is stronger in recent decades, but again with noticeable heterogeneity. Among OECD countries, the effect of bilateral trade proximity increased in recent decades. In contrast, among the high income group, we surprisingly find that the slope was not significant during the period 1970-1989 but turned positive and significant in the last two decades. Among the *HL* and the *LL* groups, we do not find any statistically significant increase of the bilateral trade slope over time. Below, we decompose again the evolution and show that the distinction in the type of traded goods can explain this dichotomy. Looking at our first order trade network indices, results indicate that the effect of common exposure to third countries increased significantly over time for all income groups except the OECD group, where the slope associated to network proximity was already very high even in earlier time windows.

We then investigate the role of the evolution of trade on GDP comovement when we decompose trade into final and intermediate goods. We run the following specification, where β_2, β_4 and

[27] 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 are time variations within the *late* sub-sample.

[28] Note that adding a time window for the second order network effect do not change the results. Hence, we focus the analysis of time evolution of the TC-slope on the first order and bilateral trade linkages.

Table. 4. Evolution of the TC-slope with total trade index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(total)	0.003	0.008	0.076^{**}	0.076^{**}	-0.013	-0.009	0.007	0.012^{**}	0.020^{**}	0.027^{***}
	(0.005)	(0.005)	(0.036)	(0.036)	(0.015)	(0.015)	(0.005)	(0.006)	(0.009)	(0.010)
LTW*ln(total)	0.018^{***}	0.010^{***}	0.065^{***}	0.064^{***}	0.047^{***}	0.037^{***}	0.014^{***}	0.006	0.004	-0.007
	(0.003)	(0.004)	(0.021)	(0.025)	(0.007)	(0.007)	(0.004)	(0.004)	(0.008)	(0.009)
network^{1st}	0.232^{***}	0.091	0.833^{***}	0.831^{***}	0.632^{***}	0.457^{***}	0.181^{***}	0.047	-0.011	-0.201
	(0.059)	(0.066)	(0.257)	(0.267)	(0.156)	(0.171)	(0.065)	(0.074)	(0.122)	(0.144)
LTW*network^{1st}		0.245^{***}		0.005		0.340^{***}		0.221^{***}		0.295^{**}
		(0.055)		(0.161)		(0.119)		(0.062)		(0.128)
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	16,814	16,814	1,292	1,292	2,584	2,584	14,230	14,230	5,174	5,174
R^2	0.014	0.015	0.119	0.119	0.071	0.075	0.008	0.009	0.005	0.007

Notes: Variable definitions and sources are described in detail in the text. The sample period is 1970–2009. Standard deviation in parenthesis and clustered at the country-pair level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

γ_2 are the coefficients of interests similar to those of equation (26):

$$\begin{aligned} \text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2\, LTW_t \times \ln(\text{Trade}_{ijt}^{inter}) + \beta_3 \ln(\text{Trade}_{ijt}^{final}) \\ & + \beta_4\, LTW_t \times \ln(\text{Trade}_{ijt}^{final}) + \gamma_1\, \text{network}_{ijt}^{1st} + \gamma_2\, LTW_t \times \text{network}_{ijt}^{1st} \\ & + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{26}$$

Table 5 displays our results. We find an increasing role of trade in intermediate inputs for the OECD group and the *HH* group, which is consistent with earlier results. The evolution of the TC-slope for intermediate goods might be the result of the recent increase in the international trade linkages and the associated increase in global value chain. Our result shows also that countries among the *HL* and *LL* group do not, at least for the moment, display any association between bilateral trade in intermediate goods and GDP correlation. In the future, in might be interesting to verify whether developing countries display a higher association of trade in intermediate goods and GDP synchronisation, showing the possible transition stage of the TC-slope.

Altogether, the association between international trade linkages and GDP correlation increased over time, either directly (through bilateral trade) or via common exposure to other countries (as measured by our trade network index). This finding helps again understand different values of the TC-slope found in the literature, which rely on different geographic and time coverage. Moreover, it shows that increasing either direct or indirect trade proximity between two countries has a larger impact on their business cycle comovement than what was observed 40 years ago, in particular for countries trading intermediate goods. Overall, the heterogeneity unveiled here hints that unpacking the effect of trade in different types of goods across several time windows and income groups is a promising research avenue for improving our understanding of global business cycle correlation.

Table. 5. Evolution of the TC slope with disagregated trade flows

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(inter)	-0.002	0.058^{*}	0.001	0.000	0.006
	(0.005)	(0.035)	(0.015)	(0.005)	(0.010)
LTW*ln(inter)	0.007	0.098^{***}	0.023^{**}	0.003	0.007
	(0.005)	(0.031)	(0.011)	(0.005)	(0.010)
ln(final)	0.008^{*}	0.018	-0.018	0.010^{**}	0.020^{***}
	(0.004)	(0.028)	(0.013)	(0.005)	(0.007)
LTW*ln(final)	0.003	-0.043	0.013	0.005	-0.012
	(0.004)	(0.032)	(0.011)	(0.005)	(0.008)
network^{1st}	0.107	0.759^{***}	0.471^{***}	0.059	-0.183
	(0.067)	(0.264)	(0.171)	(0.074)	(0.145)
LTW*network^{1st}	0.242^{***}	0.036	0.346^{***}	0.216^{***}	0.293^{**}
	(0.055)	(0.168)	(0.118)	(0.062)	(0.130)
CP+TW FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	16,629	1,292	2,575	14,054	5,076
R^2	0.016	0.126	0.075	0.009	0.008

Notes: Variable definitions and sources are described in detail in the text. The sample period is 1970–2009. Standard deviation in parenthesis and clustered at the country-pair level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The results include second order network interacted with the variable LTW_t.

4.4 Network density as an amplification channel

The density of the global trade network can act as a powerful amplification factor beyond the direct bilateral trade between two countries. This can be illustrated using the framework in section 2. Consider 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 (8), we can write bilateral output correlation as:

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\alpha_1^2 + \alpha_2^1 + (\alpha_1^3 + \alpha_1^2\alpha_2^3)(\alpha_2^3 + \alpha_2^1\alpha_1^3)\right) > \lambda\left(\alpha_1^2 + \alpha_2^1 + \alpha_1^3\alpha_2^3\right) \tag{27}$$

The inequality in equation (27) 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. In the left hand side, the presence of the "$\alpha_1^2\alpha_2^3$" and "$\alpha_2^1\alpha_1^3$" terms show that the marginal increase in comovement associated with an increase in α_1^2 or α_2^1 (i.e. bilateral trade) is larger in presence of other linkages in the trade network. In other words, an increase in the overall density of the trade networks is expected to amplify each of the channel discussed above. This is particularly important since the average trade flow over GDP has more than tripled since the 1970s. 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.

We test this 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 $Network\,Density_{ijt} = \frac{\sum_{z \in \mathcal{P}(i)_{-j}} T_{i \leftrightarrow z,t} + \sum_{z \in \mathcal{P}(j)_{-i}} T_{j \leftrightarrow z,t}}{GDP_i + GDP_j}$, where $\mathcal{P}(i)_{-j}$ defines the set of i-partners except the country j. 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. With this variable, we test the following specification:

$$\begin{aligned} \text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \beta_2\, \text{density}_{ijt} \times \ln(\text{Trade}_{ijt}^{total}) + \boldsymbol{\gamma}_1\, \mathbf{network}_{ijt} \\ + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{28}$$

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.[29]

Table 6 summarizes our findings. Looking at the whole sample in the first column, the interaction between our bilateral measure of density and total bilateral trade intensity is statistically significant and positive: country-pairs that are more connected to the rest of the world feature a higher marginal effect of bilateral trade intensity, consistent with our theoretical prediction. We then find that the interaction between bilateral trade and bilateral density exhibits varying patterns in different sub-samples: density acts as an amplifier for the *OECD*, *HH* and *HL* groups, while we find no statistically significant role in the *LL* group.

Overall, our results imply that the TC-slope usually measured in the literature is a function of

[29] 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 4.3 in the sense that there is a worldwide increase in the association between global trade and bilateral GDP co-movement.

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 the rest of the world. In turn, this observation can help understand our previous result regarding the increase in the TC-slope in recent decades.

Table. 6. TC slope and interaction with network density.

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(total)	-0.002	0.086**	-0.001	-0.002	0.009
	(0.005)	(0.035)	(0.016)	(0.005)	(0.008)
Density*ln(total)	0.017***	0.052**	0.023***	0.012***	0.006
	(0.003)	(0.021)	(0.004)	(0.003)	(0.006)
network^{1st}	0.211***	0.815***	0.495***	0.204***	0.078
	(0.059)	(0.265)	(0.156)	(0.060)	(0.110)
Density	0.148***	0.371***	0.188***	0.111***	0.086
	(0.023)	(0.121)	(0.039)	(0.025)	(0.056)
CP+TW FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	16,814	1,292	2,584	16,698	5,942
Within R^2	0.014	0.107	0.057	0.006	0.004

Notes: Variable definitions and sources are described in detail in the text. The sample period is 1970–2009. Standard deviation in parenthesis and clustered at the country-pair level. $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The results include second order network measure.

4.5 Summary of empirical evidence

Guided by our simple framework, the empirical section offered novel insights on the complex association between global trade flows and bilateral GDP comovement:

1. *TC-slopes are very heterogeneous across income groups and type of traded goods.* 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 in these countries. Trade in final goods is significantly correlated with higher business cycle synchronization for the low income groups, which may partly reflect their specialization in terms of traded good.

2. *The role of common exposure as measured by our first order network index is large for high income country-pairs, but decay with country-pairs including low income countries. The second order network effects are only significant among the OECD group.* Overall, direct trade proximity and first order network indices capture most of the relationship between trade and business cycle synchronization for other country groups.

3. *The association between GDP comovement and bilateral trade in intermediate goods and first order network effects increased in recent decades.* As suggested by our simple model and supported by our empirical analysis, this increase can be rationalized by a surge of trade network density which amplifies the association between global trade and bilateral comovement. This may suggest an increasing role for Global Value Chains in over the past few decades.

These insights caution against the view that there exist a single time-invariant "deep" value for the trade comovement slope. The magnitude and the composition of the TC-slope significantly differs at different development stage, over time, and by type of traded goods. As such, quantitative IRBC models aimed at replicating a single value for the TC-slope can be misleading.

5 Robustness and Additional Exercises

We now evaluate the robustness of our results through a series of alternative specifications. We first focus on three refinements: (i) how do "Supply" and "Demand" side bilateral trade indexes, defined following our theoretical framework, impact GDP comovement across different income groups. (ii) how do the distinction between intermediate goods and capital goods, and (iii) cross network effects as another measure of second order linkage, affect our results. Those results are gathered in Table 7. Then, we provide sensitivity analysis with respect to additional controls, alternative measurement, sets of countries, and time periods.[30]

Table. 7. Alternative Specification

Model		corr GDP			
		OECD	*HH*	*HL*	*LL*
Demand/supply bilateral indexes	ln(trade $_{\text{Supply}}$)	0.132^{**}	-0.003	0.008	-0.010
	ln(trade $_{\text{Demand}}$)	-0.055	0.020	0.001	0.036^{**}
Distinguishing capital/inter goods	ln(inter)	0.131^{***}	0.036^{***}	0.016^{***}	0.019^{**}
	ln(capital)	-0.019	0.022^{**}	-0.011^{***}	-0.004
	ln(final)	0.004	-0.027^{**}	0.020^{***}	0.026^{***}
Adding cross network effects	ln(inter)	0.082^{**}	0.026^{*}	0.006	0.015^{*}
	ln(final)	0.003	-0.016	0.014^{***}	0.018^{**}
	$\text{network}^{1st}_{inter}$	1.690^{***}	0.531^{***}	0.054	-0.051
	$\text{network}^{1st}_{final}$	-0.202	0.301^{**}	0.068	-0.140

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

"Supply" and "Demand" side bilateral trade indexes. We first use the "supply" and "demand"

[30] We also provide additional robustness in Appendix using controls for financial linkages and for sectoral proximity. However, the samples are much smaller due to data limitation.

bilateral trade measures introduced in equation (18) and run the following specification:

$$\begin{aligned}\text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{trade}_{\text{supply}})_{ijt} + \beta_2 \ln(\text{trade}_{\text{demand}})_{ijt} + \boldsymbol{\gamma}\, \textbf{network}_{ijt} \\ & + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}\,.\end{aligned} \tag{29}$$

Results are mixed overall but reflect an interesting pattern. Looking at the entire sample, neither of the theory-driven bilateral indices is significantly associated with GDP comovement, leaving all the statistical association to our first order network variable. However, we notice that the "supply" bilateral trade link is large and significant for OECD countries, while the "demand" bilateral link is significant for the *LL* group. While we interpret this result cautiously, it may reflect that supply-side shocks are more important for richer countries, while demand-side shocks are more prevalent in lower income ones. It is also consistent with previous findings, as trade in intermediate inputs should be relevant only under the use of the supply sided bilateral index.

Separating capital and intermediate inputs. We further disaggregates trade in intermediate inputs into two subcomponent: trade in capital goods and trade in intermediate inputs. We first notice that some countries have extremely low (and sometimes zero) trade in capital goods, which leads to a smaller sample for each group. Results are quite similar for the *OECD*. For the *HH* group, trade in capital goods seem to be an important part of intermediate inputs that generate a positive slope between GDP comovement and trade, while we find no significant relationship for the *HL* and *LL* groups. Surprisingly, when disentangling capital and intermediate goods, we find the last two groups display a positive and significant association between bilateral trade in intermediate inputs and GDP comovement.[31]

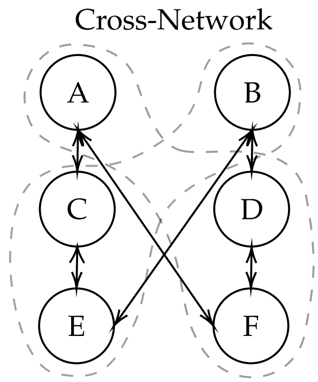
Cross network effects. In the baseline specification, we have estimated two different network effects: a first order network effect and a second order network effect. We now construct another cross-network, denoted ($cross\ network_{ijt}$), capturing non-symmetric situations where a country's direct partners are linked with another country second order partners. We illustrate this index in Figure 4 and define:

$$cross\ network_{ijt} = \frac{1}{2}\left(\sum_{z\in\mathcal{P}(j)} w_t(z,j;i)\cdot network^{1st}_{izt} + \sum_{z\in\mathcal{P}(i)} w_t(z,i;j)\cdot network^{1st}_{jzt}\right) \tag{30}$$

The index measures the extent to which a country i in the country-pair (i,j) is similar in terms of

[31] As shown in Table 9 in appendix, this may also reflects the fact that low income countries tend to trade commodities which are classified as intermediate goods.

Figure 4. Illustration of the cross network proximity indexes.



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

trade partners (i.e. in terms of first order *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.[32]

The introduction of the cross-network index does not change the estimated coefficients regarding bilateral trade flows and first order network effects.

5.1 Other robustness exercises

Our results are robust to a number of other alternative specifications. We first confirm that among non-OECD pairs, trade in final goods is significantly associated with more GDP-comovement. When considering the sample of oil producers (which is defined as country-pairs with at least one country with a share of oil rents to GDP greater than 15%, and that we excluded from the main analysis), we find no statistical significant relationship between trade intensities and GDP comovement.

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. We also confirm the general pattern using three additional analysis: (i) an alternative measure using the max operator when computing the trade intensities: $\ln(\text{Trade}) = \max\left(T_{i\leftrightarrow j}/GDP_i, T_{i\leftrightarrow j}/GDP_j\right)$, (ii) BK filtered GDP instead of HP filtered GDP,[33] (iii) 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

[32]This index is derived using the fact that: $\mathit{cross\,network}_{ijt} = 1 - \frac{1}{4}\left(\sum_{z\in\mathcal{P}(j)} w_t(j,z)\sum_k \left|\frac{T_{i\leftrightarrow k,t}}{T_{i,t|-z}} - \frac{T_{z\leftrightarrow k,t}}{T_{z,t|-i}}\right| + \sum_{z\in\mathcal{P}(i)} w_t(i,z)\sum_k \left|\frac{T_{j\leftrightarrow k,t}}{T_{j,t|-z}} - \frac{T_{z\leftrightarrow k,t}}{T_{z,t|-j}}\right|\right) \times \left(\frac{T_{i,t|-j}+T_{j,t|-i}}{GDP_{it}+GDP_{it}}\right)$.

[33]In the spirit of Comin and Gertler (2006), we keep fluctuations between 32 and 200 quarters to capture medium term business cycles.

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 turns out to be positive and significant.

Finally, our main analysis follows the literature and uses a standard log specification which leads to the omission of country-pairs with a trade proximity of zero. In the last rows of table 8, we present two other robustness checks that include zeros in trade. First, we specify a mixture model in which the trade intensity effect is estimated following $\beta \log(\text{Trade}^d_{ijt})\mathbb{1}_{\text{Trade}^d_{ijt}>0} + \delta\mathbb{1}_{\text{Trade}^d_{ijt}=0}$, where δ measures the effect of a zero trade flow and β measures the effect of a positive trade flow.[34] Using this specification, the magnitude and the significance of our main results are confirmed. To complement this analysis, we also use an estimated Box-Cox transformation of the original trade level data that account for zero trade flows (see Box and Cox (1964)). While not directly interpretable, our results are again confirmed.

6 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 theoretical framework, 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, could be linked to the nature of shocks hitting different countries. We believe this insight can be investigated further. Another important aspect of the TC-slope is its evolution over time. While our work suggests that this increase is linked to the higher density of the world trade network, other elements could be investigated further, including the possible role of surging markups or changing specialization patterns.

[34] This is motivated by the fact that for trade flows, there can be a discrete spike at zero which can be associated with the sensitivity of the measurements and true zero trade flows.

Table. 8. Sensitive analysis: Trade and GDP-comovement

	Estimated coefficient				
	ln(input)	ln(final)	*network*^{1st}	*network*^{2nd}	Sample
(i) Sample selection					
Non-OECD Group	-0.002	0.010***	0.20***	0.01	*Non-OECD*
Oil producers (oil rent >15% GDP)	-0.009	0.001	0.34***	-0.00	*Oil producers*
(ii) Alternative controls					
SITC 2-digit export^{prox}	0.104***	0.000	0.92***	1.52***	*OECD*
SITC 2-digit export^{prox}	0.023**	0.002	0.48***	-0.20	*HH*
SITC 2-digit export^{prox}	0.005	0.012***	0.18***	0.07	*HL*
SITC 2-digit export^{prox}	0.011*	0.013**	0.03	0.05	*LL*
ISIC export^{prox}	0.110***	-0.005	0.99***	1.44***	*OECD*
ISIC export^{prox}	0.024**	0.000	0.49***	-0.22	*HH*
ISIC export^{prox}	0.003	0.012***	0.18***	0.07	*HL*
ISIC export^{prox}	0.011*	0.013**	0.01	0.07	*LL*
(iii) Alternative Measures					
Max trade index [a]	0.109***	-0.010	1.03***	1.39***	*OECD*
Max trade index [a]	0.025**	0.002	0.50***	-0.19	*HH*
Max trade index [a]	0.002	0.011***	0.17***	0.07	*HL*
Max trade index [a]	0.008	0.012**	-0.01	0.07	*LL*
BK filter	0.119***	-0.007	1.05***	1.45***	*OECD*
BK filter	0.029**	-0.003	0.52***	-0.12	*HH*
BK filter	0.005	0.010***	0.18***	0.05	*HL*
BK filter	0.014**	0.011**	-0.01	0.03	*LL*
First difference	0.074***	0.007	0.70***	1.00**	*OECD*
First difference	0.010	-0.024*	0.39**	-0.12	*HH*
First difference	0.005	0.015***	0.12***	0.05	*HL*
First difference	0.015**	0.009*	0.09	0.02	*LL*
Mixture model	0.109***	-0.003	0.91***	1.44***	*OECD*
Mixture model	0.030***	-0.006	0.29**	-0.11	*HH*
Mixture model	0.002	0.011***	0.12***	0.10	*HL*
Mixture model	0.003	0.012***	-0.00	0.05	*LL*
Box-Cox transform	0.489***	-0.046	0.81***	1.38***	*OECD*
Box-Cox transform	0.040***	-0.018	0.29**	-0.07	*HH*
Box-Cox transform	-0.000	-0.000***	0.13***	0.09	*HL*
Box-Cox transform	-0.000	-0.000***	0.00	0.03	*LL*

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation.

[a] We define max trade index as the measure using $\max\left(T_{i\leftrightarrow j}/GDP_i, T_{i\leftrightarrow j}/GDP_j\right)$.

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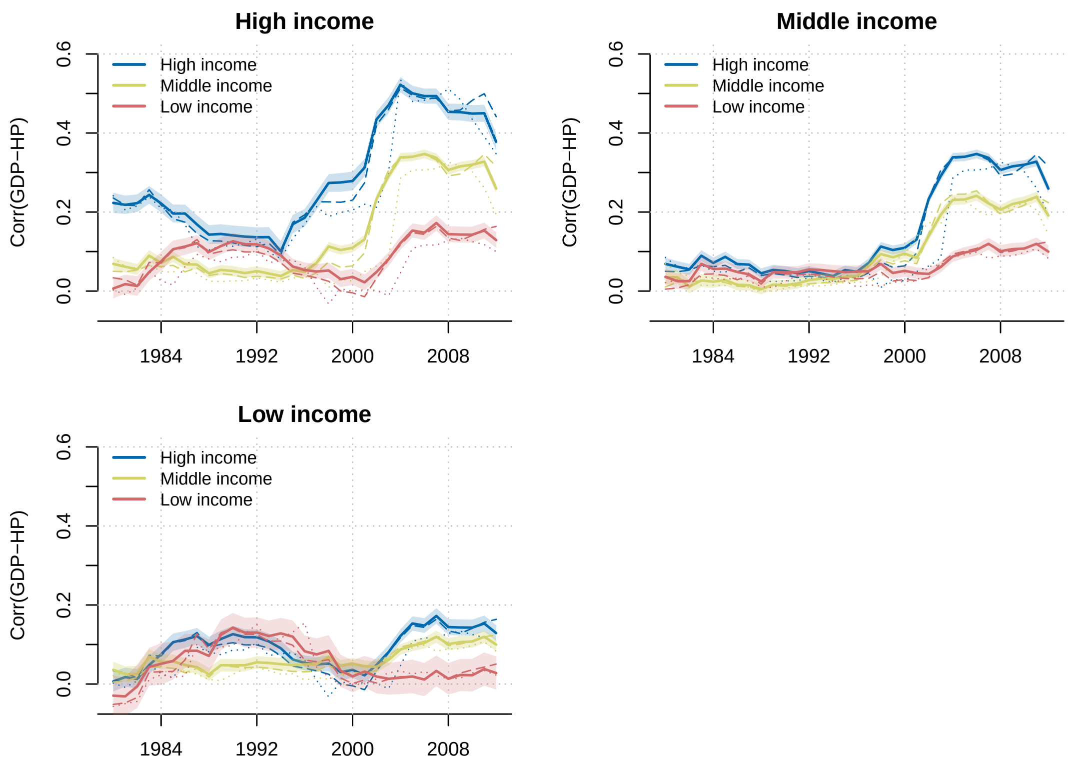
A Data Appendix

A.1 Evolution of GDP cross-correlation

Figure 5 displays the evolution of the GDP cross-country correlation over time for each income groups. To build these charts, we use a 10-year moving window and compute the correlation for all pairs of country. We then take the average of bilateral correlation across income groups. With 3 groups (high, middle and low income countries), this results in a total of 9 pairs of income groups which are depicted in thee charts. As shown in the top left chart, it is clear that high-income countries have experienced a large surge of their GDP co-movement since the 2000s.

Figure 5. Average GDP cross-correlation in selected income group.



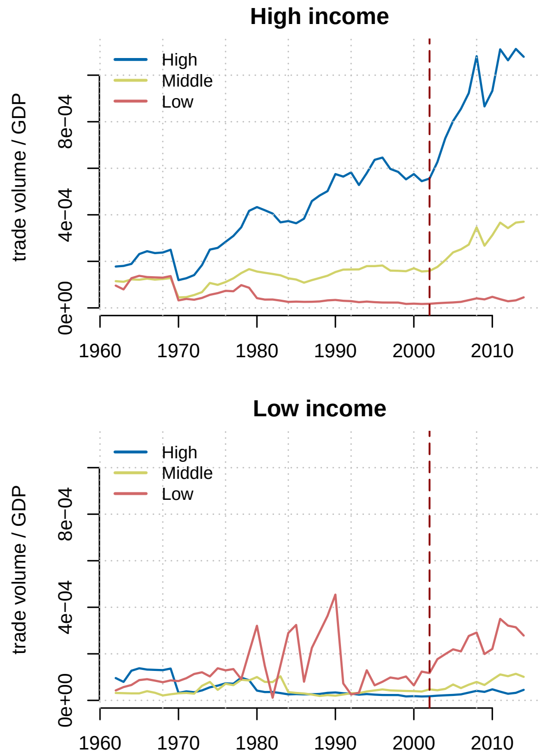
Note: the solid line refers to HP filtered data. The dashed and dotted lines refer to alternative filtering, namely first difference and BK-filter respectively. Shaded area are the 95% confidence interval.

Figure 6 displays the evolution of trade intensity from a given income group to another income group. All told, total trade intensity increased significantly since 1960.

A.2 Oil producers

Our main analysis exclude country-pairs with at least one country among the oil producers, defined as countries with a share of oil rents to GDP greater than 15%. This is motivated by the fact

Figure 6. Average trade intensity over GDP in selected income group.



Note: the dashed line refers to the period at which international GDP cross-correlation substantially raised.

that those countries have a very different economic and trade structure. Table 9 presents the share of commodity traded among countries pairs in the different income groups. It is clear that oil producers trade mostly commodities, i.e. crude oil, which makes those countries especially sensitive to the world crude oil price.

Table. 9. Average trade ratio of primary goods (commodity) relative to total trade

Period	Country-pairs in				
	OECD	*HH*	*HL*	*LL*	*Oil*
1970:1979	0.11	0.11	0.29	0.23	0.72
1980:1989	0.12	0.10	0.22	0.20	0.59
1990:1999	0.08	0.08	0.15	0.19	0.61
2000:2009	0.09	0.09	0.18	0.19	0.62

A.3 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 capital market integration means that global savings are invested in the most productive countries – at the expense of investment in the rest of the world.[35]

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 (BIS) and construct an index of financial proximity (FP).[36] We use the total bilateral cross-border claims $C_{i\to j,t}$, including bank and non-bank sectors for all maturities, between countries i and j in period t with $FP_{ijt} = \frac{C_{i\to j,t}+C_{j\to i,t}}{GDP_{it}+GDP_{jt}}$. Due to data limitation, we report only the effect of including this control for the whole sample. Additionally, we control for FDI which might affect GDP co-movement independently of trade proximity.[37] 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.[38] 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.

Table 10 shows that 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 financial linkages.

A.4 Proximity in sectoral composition

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. To account for such a mechanism, we define an index is based on countries' proximity in terms of sector share in GDP. 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).[39] Such an index is a direct measure of two countries'

[35] 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.

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

[37] 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.

[38] 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.

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

Table. 10. Effect of financial integration

	corr GDP							
	All	*All*	*All*	*All*	*OECD*	*OECD*	*HL*	*HL*
ln(inter)	0.170**	0.171**	−0.009	−0.009	0.430***	0.428***	0.002	0.000
	(0.077)	(0.077)	(0.018)	(0.018)	(0.089)	(0.090)	(0.027)	(0.027)
ln(final)	−0.074	−0.075	0.003	0.002	−0.037	−0.033	0.011	0.010
	(0.054)	(0.055)	(0.015)	(0.015)	(0.048)	(0.048)	(0.020)	(0.020)
network^{1st}	1.022*	1.014	0.882***	0.883***	−0.751	−0.760	0.827***	0.830***
	(0.619)	(0.618)	(0.185)	(0.185)	(0.759)	(0.757)	(0.238)	(0.238)
FP		5.684						
		(33.280)						
FI				0.868		−6.329		12.839***
				(3.590)		(5.113)		(4.808)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	955	955	3,112	3,112	530	530	1,934	1,934
Within R^2	0.095	0.095	0.026	0.026	0.235	0.240	0.016	0.018

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.

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. As an additional control variable, we define the sectoral proximity index in terms of sector shares in GDP for a given country-pair (i, j) in time-window t as: $sector^{prox}_{ijt} = 1 - \frac{1}{2}\sum_{s\in\mathcal{S}} \left|\frac{Y_{i,t}(s)}{Y_{i,t}} - \frac{Y_{j,t}(s)}{Y_{j,t}}\right|$, 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. The results are gathered in table 11. For the sub-sample for which data is available, we do not find a statistically significant effect of $\text{sector}^{prox}_{ijt}$.

Table. 11. The absence of role for sectoral proximity in addition to export proximity

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(inter)	0.010	0.140**	0.089**	0.009	0.044**
	(0.014)	(0.061)	(0.040)	(0.014)	(0.022)
ln(final)	−0.002	−0.046	−0.189***	0.013	−0.010
	(0.012)	(0.050)	(0.042)	(0.013)	(0.021)
network^{1st}	0.321	0.703	0.287	0.324	−0.345
	(0.201)	(0.660)	(0.504)	(0.221)	(0.368)
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
Controls	Yes	Yes	Yes	Yes	Yes
Observations	4,499	655	893	3,606	1,091
Within R^2	0.025	0.165	0.166	0.017	0.022

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

B Theory Appendix – extension with endogenous labor supply

We present here a version of our theoretical framework with endogenous labor supply. While this prevents us from deriving closed form solution, we can use simulations to investigate the model's properties. In each country, households have a static utility defined in (31), where consumption $C_{i,t}$ is a Cobb Douglas bundle of goods produced in all countries, using the country-specific demand shares in matrix **B**.

$$U_{i,t} = \frac{1}{1-\sigma}\left(C_{i,t} - \psi \frac{L_{i,t}^{1+\nu}}{1+\nu}\right)^{1-\sigma} \tag{31}$$

Households maximize their utility subject to their budget constraint defined as: $w_{i,t}L_{i,t} = p_{i,t}C_{i,t}$. Standard first order conditions lead to

$$\frac{\partial U_{i,t}}{\partial L_{i,t}} = \frac{w_{it}}{p_{i,t}} \frac{\partial U_{i,t}}{\partial C_{i,t}} \tag{32}$$

With GHH utility, equation (32) can be simply written as:

$$\psi L_{i,t}^{\nu} = \frac{w_{it}}{p_{i,t}} \tag{33}$$

Note that, as in the main text, we do not impose final demand to be equal to households' revenues, which allows for the introduction of exogenous demand shifters. We keep the model as simple as possible and assume that total demand $D_{i,t}$ addressed by country i to all firms serving its market is an exogenous shock. Moreover, with Cobb Douglas production, firms spend a fraction γ_i on labor so that labor demand writes:

$$w_{i,t}L_{i,t} = \gamma_i p_{i,t} Y_{i,t} \tag{34}$$

Hat Algebra Equilibrium. For any value of TFP shocks **Z** and demand shocks **D**, the equilibrium can be simply expressed in proportional as the solution of 4 systems of equations, expressed in matrix form below:

- Using (1) and gathering all wages in matrix **W** as well as labor shares in matrix **Γ**, proportional change in prices can be written as:

$$\widehat{\mathbf{P}} = (\mathcal{I}_N - \mathbf{\Omega})^{-1}\left(\mathbf{\Gamma}\cdot\widehat{\mathbf{W}} - \widehat{\mathbf{Z}}\right) \tag{35}$$

- Using (4), changes in nominal output is gven by:

$$\widehat{\mathbf{P}} + \widehat{\mathbf{Y}} = \left(\mathcal{I}_N - \left(\boldsymbol{\Omega}^T\right)\right)^{-1} \cdot \mathbf{B} \cdot \widehat{\mathbf{D}} \tag{36}$$

- Labor supply (33) and labor demand (34) respectively lead to:

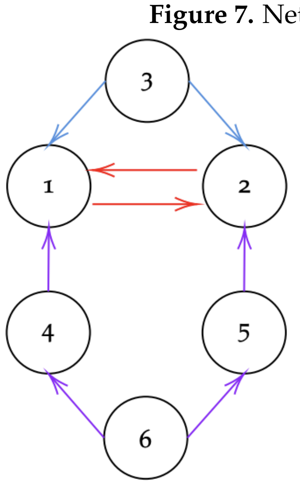
$$\nu \widehat{\mathbf{L}} = \widehat{\mathbf{w}} - \widehat{\mathbf{P}} \tag{37}$$

$$\widehat{\mathbf{w}} + \widehat{\mathbf{L}} = \widehat{\mathbf{P}} + \widehat{\mathbf{Y}} \tag{38}$$

We can then solve for changes in prices ($\widehat{\mathbf{P}}$), wages ($\widehat{\mathbf{W}}$), Labor ($\widehat{\mathbf{L}}$) and gross output ($\widehat{\mathbf{Y}}$) by solving equations (35) to (38). In the rest of this section, we use the input-output structures described in the main text and use simulations to show that our closed-form results obtained in a simplified model still hold in a slightly framework.

TFP shocks. We consider the cross-country input linkages described in figure 7, in which the strength of trade links depend on three parameters. First, $t_1 = \alpha_1^2 = \alpha_2^1$ captures the strength of direct intermediate input trade between countries 1 and 2. Second, $t_2 = \alpha_1^3 = \alpha_2^3$ captures the strength of first order network exposure to supply shocks to a common input supplier, country 3. Third, t_3 captures the strength of second order network exposure to supply shocks to a common (indirect) input supplier, country 6. Because the second order network effect is typically smaller than bilateral trade or first order proximity (as shown in equation (8), this effect appears with trade shares αs to the power 3 or above), we parametrize it as $t_3 = \alpha_1^4/2 = \alpha_2^5/2 = \alpha_4^6/2 = \alpha_5^6/2$ so that a change in t_3 has more pronounced effect on GDP comovement. Finally, note that in absence of final good trade, we simply have $\mathbf{B} = \mathcal{I}_6$.

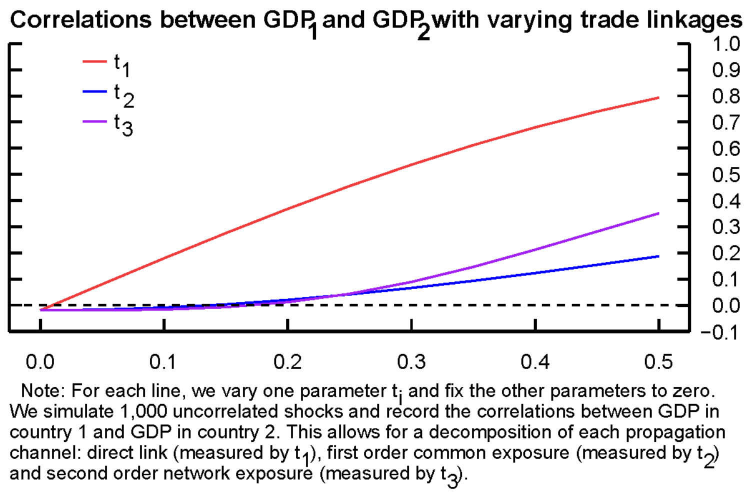
Figure 7. Network representation of I/O linkages



$$\boldsymbol{\Omega} = \begin{pmatrix} 0 & t_1 & t_2 & 2 \cdot t_3 & 0 & 0 \\ t_1 & 0 & t_2 & 0 & 2 \cdot t_3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 \cdot t_3 \\ 0 & 0 & 0 & 0 & 0 & 2 \cdot t_3 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Varying one-by-one parameters t_1, t_2 and t_3 while leaving the others to zero, we showcase the importance of each of the channel described in section 2.2. To do so, we simulate 1,000 random and uncorrelated TFP shocks ($\widehat{\mathbf{Z}}$) and record the correlation between country 1 and country 2's GDPs. Results are presented in figure 8.

Figure 8. Tracking GDP correlation as Trade Links vary – TFP shocks.



Note: The correlation is on the vertical axis and the value of t_i on the horizontal axis.

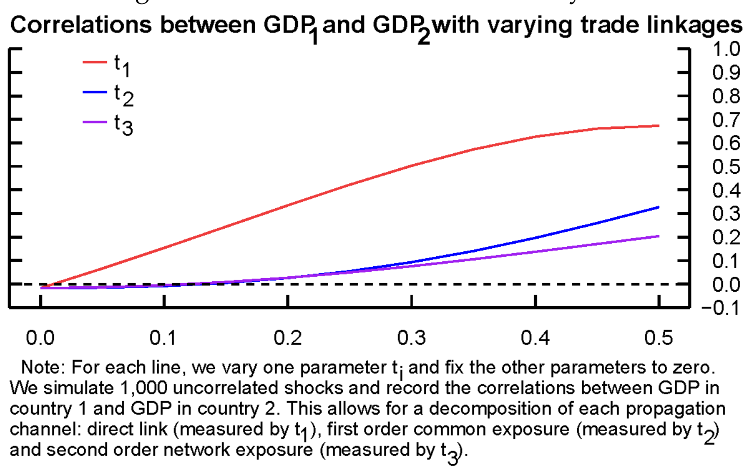
As expected, a more general version of the model yields results in line with our findings in section 2.2. First, bilateral correlation increases with direct trade linkages as embodied in parameter t_1. Second, even when countries 1 and 2 do not export anything at all, the first order network effects generate GDP comovement between the two countries, as long as both countries are exposed to same country 3, as measured by the parameter t_2. Third, a similar intuition arises with the second order network effect. Even if country 1 and 2 do not export at all and do not share a common direct partner ($\alpha_1^2 = \alpha_2^1 = \alpha_1^3 = \alpha_2^3 = 0$), they can be linked through second-order network effect, as long as their partners share common partners, as captured by parameter t_3. All told, adding endogenous labor supply to our model does not alter our predictions.

Demand shocks. Following our analysis in section 2.2, we now consider the structure presented in figure 2 and which we parametrize as in equation (39). Note that we fix the values of $\alpha_{4,1}$ and $\alpha_{5,2}$ to 0.5 which means that countries 4 and 5 are sourcing inputs from countries 1 and 2 respectively. As parameter t_3 increases, countries 4 and 5 become more and more exposed to demand shocks in their common partner (country 6) which in turn trickles down to their input suppliers and generate a positive comovement between countries 1 and 2.

$$\mathbf{\Omega} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}, \mathbf{B} = \begin{pmatrix} 1-t_1-t_2 & t_1 & t_2 & 0 & 0 & 0 \\ t_1 & 1-t_1-t_2 & t_2 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1-2\cdot t_3 & 0 & 2\cdot t_3 \\ 0 & 0 & 0 & 0 & 1-2\cdot t_3 & 2\cdot t_3 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{39}$$

We follow the same procedure as above and vary one-by-one parameters t_1, t_2 and t_3 while leaving the others to zero. Using a sequence of 1,000 uncorrelated demand shocks, we confirm the insight presented in section 2.2. Results are shown in figure 9.

Figure 9. Tracking GDP correlation as Trade Links vary – Demand shocks.



Note: The correlation is on the vertical axis and the value of t_i on the horizontal axis.

First, simulations with $t_1 > 0$ capture direct exposure to demand shocks through bilateral trade in final goods. Second, common exposure to demand shocks due to the fact that both countries 1 and 2 export final goods to country 3 (1^{st} order network) is captured in simulations with $t_2 > 0$. Finally, common indirect exposure to demand shocks in country 6 (2^{nd} order network) appears in simulations with $t_3 > 0$. All told, our results confirm that demand shocks propagate across countries trough a mix of trade in inputs and trade in final goods, with all three channels (indexed by t_1, t_2 and t_3) playing a role in the transmission of shocks across countries.