Global Trade and GDP Co-movement*

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Abstract

This paper revisits the relationship between trade and GDP co-movement for 135 countries from 1970 to 2009. Guided by a simple theory, we introduce two notions of trade linkages: (i) *direct* bilateral trade index and (ii) common exposure to "third" countries capturing the role of *trade networks*. Both are economically and statistically associated with GDP correlation, suggesting an additional channel through which GDP fluctuations propagate through trade linkages. Moreover, high income countries become more synchronized when the content of their trade is tilted toward inputs while trade in final goods is key for low income countries. Finally, we present evidence 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

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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, with both trade in intermediate inputs and trade in final goods representing an increasing share of world GDP, now reaching around three times the share observed in the 1970s. In valued-added terms, trade increased at an average annual growth rate of more than 5 percent during the 1990-2009 period, with the share of trade in intermediate inputs roughly constant at around 70% of total trade. During the same period, the average GDP co-movement across all pairs of countries rose from 6% to 38%.

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

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

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

[2] Among *many* others, see Frankel and Rose (1998), Clark and van Wincoop (2001), Imbs (2004), Baxter and Kouparitsas (2005), Calderon et al. (2007), Inklaar et al. (2008), Di Giovanni and Levchenko (2010), Ng (2010), Liao and Santacreu (2015), di Giovanni et al. (2018) and Duval et al. (2015). The literature mostly focused on high income countries, with the notable exception of Calderon et al. (2007), and set up estimation equations that unveil a single time-invariant value for the association between *bilateral* trade flows and business cycle correlation.

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

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

Second, guided by recent debates on the role of Global Value Chains and the systemic interdependence that can arise from worldwide input-output (IO) linkages, we move beyond *bilateral* trade linkages and construct new indices of *network* proximity for all country pairs. We argue that changes in GDP synchronization between two countries can be the result of an increased common exposure to third markets, which can happen either at the first order when two countries have similar trade partners or at the second order when countries' direct partners have similar partners. On the whole, our results reveal that first order common exposure is particularly strong for high-income countries, while second-order proximity, a measure of more indirect propagation, is more prevalent for low income economies. Moreover, we show theoretically and empirically that the marginal increase in GDP comovement associated with larger trade links is itself increasing in the overall *density* of the network. As such, this amplification aspect linked with overall network density helps rationalize the wide array of TC-slopes found in the literature since any estimate depends on both the time and country coverage. While previous empirical research on the trade-comovement slope does not *explicitly* state that there is only a single, immutable, trade-comovement slope, the empirical specifications used make such assumption *implicitly*. Our result challenges this implicit assumption and helps understand the time variations in the trade-comovement slope.

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

Relationship to the literature. Starting with Frankel and Rose (1998), a large number of papers have studied and confirmed the positive association between trade and GDP comovement in the cross-section.[3] This paper is mostly related to a few recent contributions. First, di Giovanni et al. (2018) uses a cross-section of French firms and presents evidence that international IO linkages at the micro level are an important driver of the value added comovement observed at the macro level. Using sector-level Input-Output table together with firm-level information, they show that firms that buy inputs from importers from a particular country are more correlated with that country. In their sample, the evidence on upstream linkages is more mixed. Our findings are in line with their evidence and supports the role of Global Value Chains in the synchronization of GDP fluctuations across countries.[4] However, our large sample, which includes developed and developing countries, suggests that both intermediate and final goods links could play a role, depending on the level of development of countries at play. Second, Calderon et al. (2007) investigate the relationship between trade and business cycle comovement for both developed and developing countries. Based on cross sectional estimates, they find that the impact of trade integration on business cycles is higher for industrial countries than for developing countries. Also related is Caselli et al. (2019), which shows that trade openness lowers income volatility because it allows countries to be exposed to several country-specific shocks and not only their own domestic shocks. While our paper focuses on GDP comovement, the reduction in volatility is consistent with the presence of propagation of shocks and the importance of diversification in trade partners. Third, Liao and Santacreu (2015) is the first to study the importance of the extensive margin for GDP and TFP synchronization and shows that changes in the number of products traded across countries (rather than the average shipment per product) plays an important role in the synchronization of GDP. Huo et al. (2019) uses a more structural approach and proposes a perfectly competitive production framework to measure technology and non-technology shocks. Given a model structure that focuses on supply shocks and assuming values for all elasticities, the authors structurally estimate supply-side shocks and analyzes their cross-sectional properties and the role of network propagation. In this setup, international transmission

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

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

through trade accounts for a third of total comovement. Fourth, our paper is related to a recent series of papers developing theoretical frameworks to measure GVC participation, including Bems et al. (2011) and others.

If the empirical association between bilateral trade and GDP comovement has long been known, the underlying economic mechanism leading to this relationship is still unclear. Using the workhorse IRBC with three countries, Kose and Yi (2006) have shown that the model can explain at most 10% of the *slope* between trade and business cycle synchronization, leading to what they called the *Trade Comovement Puzzle* (TCP). Since then, many papers including Johnson (2014) or Duval et al. (2015), have refined the puzzle, highlighting different ingredients that could bridge the gap between the data and the predictions of standard models.[5] Our simple theoretical framework is closely related to previous analysis such as Long and Plosser (1983), Acemoglu et al. (2012). The distinction between supply and demand shocks and their respective propagation patterns follows previous production network analysis such as Carvalho and Tahbaz-Salehi (2019). Compared to these papers, our contribution simply consists of using existing tools to clarify the different channels linking global trade and bilateral GDP correlation. We then used insights regarding the role of inputs and final good trade, as well as the importance of network similarity, to guide our empirical exercise.

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

2 Illustration using a simple trade network model

To motivate our empirical work and formalize our intuition, we write a parsimonious static model of international trade with multiple countries, along the line of Long and Plosser (1983) and Acemoglu et al. (2012). We make strong assumptions in order to simplify the analysis. Our main goal is to illustrate through a series of example several mechanisms through which GDP in two countries can be correlated, which will then be tested empirically in the next section. In particular, we show that GDP comovement is the result of a combination of many factors,

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

including the correlation structure of shocks hitting every country in the world, bilateral trade linkages between countries as well as their indirect exposure to the rest of the trade network, and the association between gross output and GDP which can be time varying.For simplicity, our framework abstracts from other considerations such as the presence of financial linkages or the possibility of common (or coordinated) monetary policy. Note, however, that we will control for these and other elements in our empirical investigations in subsequent sections.

2.1 Basic setup

Production and pricing. Consider a world with many countries ($i, j \in \{1, ..., N\}$). In country i, gross output is produced from a Cobb Douglas combination of (1) an exogenous technology shock (Z_i), (2) intermediate inputs from all countries (X_i^j), and (3) a domestic factor (L_i).

$$Y_i = Z_i \cdot \left(\prod_j (X_i^j)^{\alpha_i^j} \right) \cdot L_i^{\gamma_i}, \tag{1}$$

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. Moreover, we also assume 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:

$$p_i = \mu_{i,s} \cdot MC_i = \mu_i \cdot \frac{c_i}{Z_i} \cdot w_i^{\gamma_i} \cdot \prod_j (p_j)^{\alpha_i^j} \tag{2}$$

With MC_i the marginal cost in i and c_i a constant depending only on parameters.[6] As is usual in models with IO linkages, the price in a given country is a function of all other prices in the economy. To simplify notation, we stack prices in all countries into an $(N, 1)$ vector $\mathbf{P}$. Taking the log and denoting by $\mathbf{\Omega}$ the cross-country IO matrix of the economy, prices are the solution of a simple linear system:[7]

$$\log(\mathbf{P}) = (\mathcal{I}_N - \mathbf{\Omega})^{-1} \begin{pmatrix} k_{1,1} - \log(Z_1) + \gamma_1 \log(w_1) \\ \vdots \\ k_N - \log(Z_N) + \gamma_N \log(w_N) \end{pmatrix} \tag{3}$$

[6]The variable c_i is defined as: $c_i = \gamma_i^{-\gamma_i} \prod_j \alpha_i^{j\,-\alpha_i^j}$

[7]For simplicity, we write $\log(\mathbf{P})$ the vector of log prices. We denote $k_i = \log(\mu_i \cdot c_i)$ and the IO matrix $\mathbf{\Omega}$ is simple defined by $(\Omega)_{i,j} = \alpha_i^j$

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

$$p_i X_i^j = \alpha_i^j p_j Y_j \ , \qquad \text{for all } i,j \tag{4}$$

Aggregate demand in each country j is denoted by D_j.[8] 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:

$$p_i y_i^j = \beta_i^j D_j \ , \qquad \text{for all } i,j \tag{5}$$

where y_i^j is the amount of good produced in i that are absorbed as final demand in j. We store all shares β_i^j into a (N,N) matrix $\mathbf{B}$.[9] Finally, the resource constraint condition is given by:

$$Y_i = \sum_j y_i^j + \sum_j X_i^j \ , \qquad \text{for all } i \tag{6}$$

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

$$\begin{pmatrix} p_1 Y_1 \\ \vdots \\ p_N Y_N \end{pmatrix} = \underbrace{\left(\mathbf{I}_N - \left(\mathbf{\Omega}^T\right)\right)^{-1} \cdot \mathbf{B} \cdot}_{=\mathbf{T}} \begin{pmatrix} D_1 \\ \vdots \\ D_N \end{pmatrix} \tag{7}$$

Solving for gross output in each country amounts to jointly solving for prices using (3) and nominal output using (7). The simplicity of the analysis follows from our strong assumptions, in particular Cobb-Douglas production and demand aggregates and essentially exogenous demand. Our main goal is to propose a framework that is as simple as possible in order to provide guidance and intuitions for our empirical investigations in the next section.

Defining Real Value Added. Measuring real value added in this framework is not straightforward. Statistical agencies measure real value added 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.

[8] 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).

[9] Matrix $\mathbf{B}$ is defined as $(\mathbf{B})_{i,j} = \beta_i^j$

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

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

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

2.2 Propagation of shocks and global trade flows

Our framework is similar to previous network models and shares the same propagation properties. As noted in Acemoglu et al. (2016) and Carvalho and Tahbaz-Salehi (2019), theory predicts that TFP shocks propagate downstream while demand shocks propagate upstream.[10] We take this insight on-board and describe its consequences for the relationship between trade and GDP comovement.

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

2.2.1 Propagation of TFP shocks

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

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

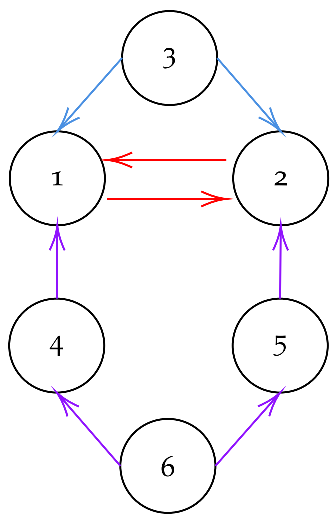
[10]This result, already established in previous papers with Cobb-Douglas networks, simply follows from inspecting (3) and (7). Although Acemoglu et al. (2016) employs a closed-economy multi-sector framework, the basic Cobb-Douglas structure is similar to ours so that countries and sectors are treated 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.

Note that the matrix **B**, capturing final good trade, is not present in this equation. In the rest of this sub-section, we present stylized examples with specific IO matrices to illustrate several determinants of bilateral comovement.

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

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

Figure 1. Network representation of IO linkages as described in (9)



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

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

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

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 (10) and (11), we can write a simple expression for $\text{corr}(\widehat{Y}_1, \widehat{Y}_2)$:[12]

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda \Bigg(\underbrace{\alpha_1^2 + \alpha_2^1}_{\text{bilateral trade exposure}} + \underbrace{(\alpha_1^3 + \alpha_1^2\alpha_2^3)(\alpha_2^3 + \alpha_2^1\alpha_1^3)}_{\text{1st order networth exposure}} \\ + \underbrace{\alpha_2^1(\alpha_1^4)^2 + \alpha_1^2(\alpha_2^5)^2 + (\alpha_1^4\alpha_4^6 + \alpha_1^2\alpha_2^5\alpha_5^6)(\alpha_2^5\alpha_5^6 + \alpha_2^1\alpha_1^4\alpha_4^6)}_{\text{2nd order network exposure}} \Bigg) \tag{12}$$

Equation (12) 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 generate GDP comovement between the two countries, as long as both countries are exposed to same country 3. In that case, we get 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. 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. In such case, $\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\alpha_1^4\alpha_4^6\alpha_2^5\alpha_5^6\right)$.

While bilateral linkages between countries have been shown to play a role since Kose and Yi (2006), little is known on the impact of common exposure through similarity of trade network. Our paper provides a first attempt towards this objective as we empirically test the importance of both bilateral trade and the network exposure in generating GDP co-movement across countries.

Finally, it is interesting to note that mechanisms above do not operate independently, and the density of the global trade network can act as a powerful amplification factor. Looking at equation (12), we can note that 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 imply that the strength of each channel increases with the presence of other linkages in the trade network. 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 trade network. In the empirical exercise, we provide support for the amplification through network density and show that the trade-comovement slope is indeed increasing over time. Our findings caution against specifications

[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.

[12] where λ is defined by $\lambda = \left(\sqrt{\text{Var}(\widehat{Y}_1)\text{Var}(\widehat{Y}_2)}\right)^{-1}$.

that implicitly assume a constant marginal effect of trade on GDP comovement while using long time periods.

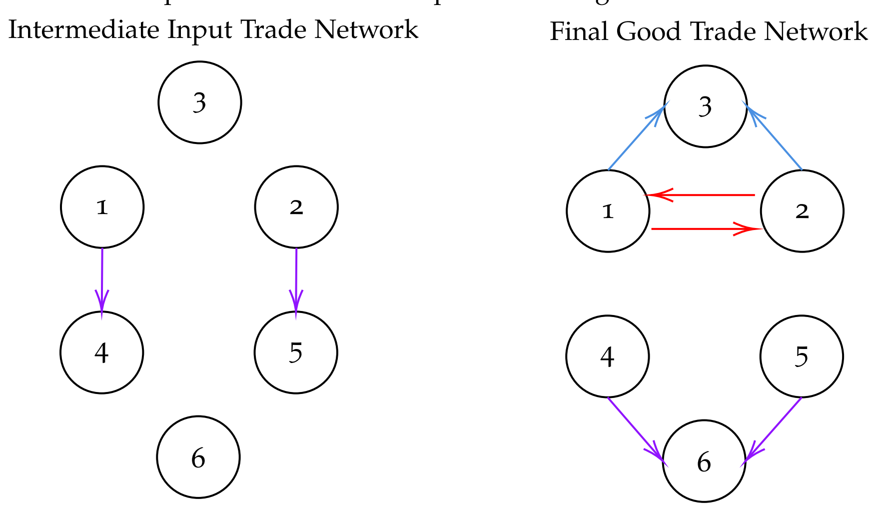
2.2.2 Propagation of Demand shocks

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 we have:

$$\widehat{\mathbf{Y}} \propto \left(\mathbf{I}_N - \left(\boldsymbol{\Omega}^T\right)\right)^{-1} \cdot \mathbf{B} \cdot \widehat{\mathbf{D}} \tag{13}$$

Equation (13) includes both $\boldsymbol{\Omega}$ and $\mathbf{B}$, revealing that propagation of demand shocks depends on the combination of both input and final good trade. We now illustrate the role of both links using the network structure described in figure 2, where some countries consume foreign final goods on top of their domestically produced good.

Figure 2. Network representation of both input and final good trade as described in (14)



The IO and demand shares matrices associated with this structure are given by:

$$\boldsymbol{\Omega} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \alpha_4^1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_5^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad \mathbf{B} = \begin{pmatrix} \beta_1^1 & \beta_1^2 & \beta_1^3 & 0 & 0 & 0 \\ \beta_2^1 & \beta_2^2 & \beta_2^3 & 0 & 0 & 0 \\ 0 & 0 & \beta_3^3 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_4^4 & 0 & \beta_4^6 \\ 0 & 0 & 0 & 0 & \beta_5^5 & \beta_5^6 \\ 0 & 0 & 0 & 0 & 0 & \beta_6^6 \end{pmatrix} \tag{14}$$

Using equation (13) yields the proportional change in gross output in countries 1 and 2:

$$\widehat{Y_1} \propto \beta_1^1 \widehat{D_1} + \beta_1^2 \widehat{D_2} + \beta_1^3 \widehat{D_3} + \beta_4^4 \alpha_1^4 \widehat{D_4} + \beta_4^6 \alpha_1^4 \widehat{D_6} \tag{15}$$

$$\widehat{Y_2} \propto \beta_2^1 \widehat{D_1} + \beta_2^2 \widehat{D_2} + \beta_2^3 \widehat{D_3} + \beta_5^5 \alpha_2^5 \widehat{D_5} + \beta_5^6 \alpha_2^5 \widehat{D_6} \tag{16}$$

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:

$$\text{corr}(\widehat{Y_1}, \widehat{Y_2}) = \lambda \left(\underbrace{\beta_1^1 \beta_2^1 + \beta_2^2 \beta_1^2}_{\text{bilateral trade exposure}} + \underbrace{\beta_1^3 \beta_2^3}_{\text{1st order network exposure}} + \underbrace{\beta_4^6 \beta_1^6 \alpha_1^4 \alpha_2^5}_{\text{2nd order network exposure}} \right) \tag{17}$$

Similar to section 2.2.1, several types of trade linkages of final goods can give rise to endogenous output co-movement. The first term in equation (17) 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. We consider a slightly more general case below and show that if country 1 exports intermediates to country 2 which are then consumed in 2,then such a link is a vector of demand shock propagation. The second term captures common exposure to demand shocks in country 2 due to the fact that both countries 1and 2export final goods to country 3. Finally, a third term arises because of common indirect 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 equation (17), it follows that demand shocks propagate across countries trough a combination of both trade in inputs and trade in final goods, with both direct and indirect exposure to common shocks increasing bilateral correlation. Interestingly, trade in final goods is associated with the propagation of demand shocks but not supply shocks.

2.2.3 Both supply and demand shocks

Finally, we 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, we combine (3) and (7) and note that proportional change in gross output in countries 1 and 2 can be written as:

$$\widehat{Y_1} = \widehat{p_1 Y_1} - \widehat{p_1} \propto (\beta_1^1 + \beta_2^1 \alpha_2^1) \widehat{D_1} + (\beta_1^2 + \beta_2^2 \alpha_2^1) \widehat{D_2} + \widehat{Z_1} + \alpha_1^2 \widehat{Z_2} \tag{18}$$

$$\widehat{Y_2} = \widehat{p_2 Y_2} - \widehat{p_2} \propto (\beta_2^1 + \beta_1^1 \alpha_1^2) \widehat{D_1} + (\beta_2^2 + \beta_1^2 \alpha_1^2) \widehat{D_2} + \widehat{Z_2} + \alpha_2^1 \widehat{Z_1} \tag{19}$$

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

$$\operatorname{corr}(\widehat{Y_1}, \widehat{Y_2}) = \lambda \Bigg(\underbrace{(\beta_1^1 + \beta_2^1 \alpha_2^1) \cdot (\beta_2^1 + \beta_1^1 \alpha_1^2) + (\beta_1^2 + \beta_2^2 \alpha_2^1) \cdot (\beta_2^2 + \beta_1^2 \alpha_1^2)}_{\text{Demand Shock propagation}} + \underbrace{\alpha_1^2 + \alpha_2^1}_{\text{Supply Shock propagation}} \Bigg) \tag{20}$$

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. Moreover, using equations (4) and (5), we can 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 can write:

$$\alpha_i^j = \frac{p_i X_i^j}{p_j Y_j} = \gamma_j \frac{T^I_{i \to j}}{GDP_j} \quad , \quad \beta_i^j = \frac{T^F_{i \to j}}{D_j} \approx \frac{T^F_{i \to j}}{GDP_j} \quad \text{and} \quad \beta_i^i \approx 1 - \sum_{k \neq i} \beta_k^i \tag{21}$$

In the rest of the paper, we empirically test for the relevance of these links for the relationship between global trade and GDP correlation. After presenting our data in section 3, we will start in section 4.1 by using measures of trade proximity that are similar to what have been studied in previous papers. From there, sections 4.2 to 4.5 introduce other trade proximity indices that are in line with the predictions of our framework. 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 sources and measurement of trade linkages

One of the objectives of this paper is to investigate the heterogeneity of the TC-slope across different levels of development as well as across different time periods. To be able to do so, we build on and expand previous studies by broadening both time and geographical coverage. Our sample contains a total of 135 countries, which accounts for almost the totality of world trade flows and world GDP, for 40 years of data. To our knowledge, this is the most comprehensive coverage of countries and years in this literature, thus far.

To investigate the role of income level in the determinants of bilateral GDP correlation, we create four types of country-pairs: (i) pairs where both countries belong to the OECD, (ii) pairs where both countries are high income (defined as *HH* pairs) according to the World Bank definition of income group, (iii) pairs where one country is high income and the other is not (defined as *HL* pairs), and (iv) pairs where no country is categorized as high income (defined as *LL*).[13] Note that for clarity of exposition we do not separate middle and low income countries, and only investigate the differences between high income and other countries. Moreover, the first sub-sample (constructed based on OECD membership) is not informed by income level but is designed to capture possible specificities related to being part of a coordinated club. Our analysis reveals that results in the *OECD* and *HH* sub-samples turn out to be qualitatively similar but quantitatively different. As will be clear below, all of our specifications are designed to control for unobserved country-pair heterogeneity by using only within country-pair time series variations. Hence, we divide our 40 years of time coverage, stretching from 1970 to 2009, into four non-overlapping time windows. In table 2, we report the share of total trade flows of each income group in our sample, relative to total world trade flows.

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

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

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

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. In an effort to separate the effect of trade linkages from other unobservable elements, we construct a

[13] 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.

panel dataset by creating four periods of ten years each. 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. (2015) 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 Trade Proximity and GDP-comovement

GDP. We use annual GDP data from the Word Development Indicators (WDI) of the World Bank, measured using constant 2010 prices in US dollars.[14] For our analysis, GDP series need to be filtered in order to extract the business cycle component from the trend. Our main and benchmark filter is the standard Hodrick-Prescott (HP) filter with a smoothing parameter of 100 which is consistent with the yearly frequency of our data. Such a transformation allows us to capture the standard business cycle fluctuations. With this setting, we mostly keep fluctuations that have a frequency between 8 and 32 quarters. In section 5, we provide robustness checks using a Baxter and King (BK) filter and a simple log-first difference.[15] With the filtered GDP, we compute the GDP correlation for each country-pair (i, j) within each time-window t of 10 years, denoted Corr GDP_{ijt}.

Bilateral Trade Proximity. We collect data on bilateral trade flows from the Observatory of Economic Complexity (MIT). This database covers 215 countries over the period 1962-2014. The data are classified according to the 4-digit Standard International Trade Classification (SITC), Revision

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

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

2. Only products and commodities are considered. To classify trade flows into final goods and intermediate inputs, we use a concordance table from SITC Rev. 2 to Broad Economic Categories (BEC).[16,17] Finally, we exclude country-pairs with less than two time-windows for which trade proximity is available. We aggregate trade flows in each category at the country-pair level and following the insights of section 2, we distinguish the type of flow $d \in \{total, inter, final\}$ (for total trade flows, trade in intermediate inputs and trade in final goods respectively).

We construct an index for *bilateral* trade proximity of a country-pair (i, j) in a given time-window t, as follows:

$$Trade^d_{ijt} = \frac{T^d_{i\leftrightarrow j,t}}{GDP_{it} + GDP_{jt}} \qquad \forall d \in \{total, I, F\} \tag{22}$$

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.[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 our accounting framework in section 2, parameters α^j_i and β^j_i measure total spending of country i in intermediate and final goods from country j, as a share of gross output and gross consumption respectively. However, the indices $Trade^d_{ijt}$ defined here are normalized by value added and not by gross output, and hence they should be interpreted as a scaled version of the spending shares.

Table. 2. Trade ratio between final and intermediate goods

	OECD	*HH*	*HL*	*LL*
Avg ratio Final/Inputs (%)	27.2	25.8	27.0	38.0

"Supply" and "Demand" bilateral links. 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. We also go one step further and construct novel bilateral trade measures that are more closely related to the theoretical framework in section 2. To this end, we build "supply" and "demand" indices based on the expressions in equation (20), with input shares αs and demand shares βs obtained using (21). Table 3 summarizes the evolution of those indexes by income group.

[16]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.

[17]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 5.3. The main results remain unchanged.

[18]This specification for trade proximity using total trade normalized by GDP is widely used in the literature, including Frankel and Rose (1998), Di Giovanni and Levchenko (2010) and others. As a robustness check, we also adopt an alternative used index: $Trade^d_{ijt} = \max\left\{\frac{T^d_{i\rightarrow j,t}+T^d_{j\rightarrow i,t}}{GDP_{it}}, \frac{T^d_{i\rightarrow j,t}+T^d_{j\rightarrow i,t}}{GDP_{jt}}\right\}$.

Table. 3. Trade flows in the different income groups [a]

	Supply shock index *100				Demand shock index *100			
Period	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*
1970:1979	0.10	0.14	0.08	0.05	0.20	0.28	0.18	0.09
1980:1989	0.19	0.24	0.14	0.08	0.39	0.56	0.31	0.15
1990:1999	0.26	0.27	0.14	0.09	0.59	0.67	0.34	0.19
2000:2009	0.34	0.30	0.18	0.18	0.73	0.75	0.38	0.32

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

First order *network* 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 captures the similarity of trade shares across all other partners, normalized by overall openness to trade. Our *third country* index is then defined as:

$$network^{1st}_{ijt} = \left(1 - \frac{1}{2}\sum_k \left|\frac{T_{i\leftrightarrow k,t}}{T_{i,t|-j}} - \frac{T_{j\leftrightarrow k,t}}{T_{j,t|-i}}\right|\right) \tag{23}$$

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. The first term captures similarity in the geographical composition of trade shares between i and country j: pairs that exhibit similar trade partners have an index close to one while pairs with completely different partners have an index of zero. The second term normalizes the index by trade openness.

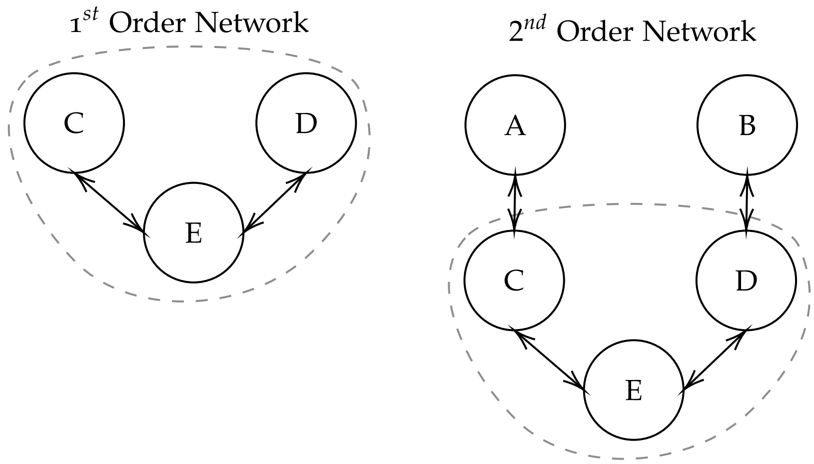
Second order *Network* effect. As a measure of 2^{nd} order network proximity for any pair (i, j), we build an index measuring to what extend country i's partners are linked with country j's partners, weighted by the importance of the partners in terms of total trade flows of the two countries i and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

$$network^{2nd}_{ijt} = \frac{1}{4}\left(\sum_{z\in\mathcal{P}(i)}\sum_{y\in\mathcal{P}(j)}\Big[w_t(z,i;j)\cdot w_t(y,j;i) + w_t(z,j;i)\cdot w_t(y,i;j)\Big]\cdot network^{1st}_{zyt}\right) \tag{24}$$

where $w_t(z,i;j) = \frac{T_{i\leftrightarrow z,t}}{T_{i,t|-j}}$. Under this specification, higher values for the $network^{2nd}_{ijt}$ 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

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

Figure 3. Illustration of first order 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.

themselves first order connected (i.e. $network^{1st}_{zyt} > 0$). 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 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 OPEC and the different waves of the European Union. We also control for country-pairs in the North American Free Trade Agreement (NAFTA).

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

[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

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

$$export^{prox}_{ijt} = 1 - \frac{1}{2} \sum_{s \in \mathcal{S}_{EX}} \left| \frac{EX_{i,t}(s)}{EX_{i,t}} - \frac{EX_{j,t}(s)}{EX_{j,t}} \right| \tag{25}$$

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. We provide in table 4 the evolution of export proximity over time for the income groups considered. *OECD* country-pairs are significantly more similar than those in other groups. Moreover, the time evolution of these indices also reveals a higher convergence, in terms of economic structure, among *OECD* countries compared with other sub-samples. 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.

Table. 4. Export proximity index in the different income groups [a]

	Export proximity*100							
	4-digit SITC				ISIC [b]			
Period	*OECD*	*HH*	*HL*	*LL*	*OECD*	*HH*	*HL*	*LL*
70:79	29.9	21.9	11.3	14.2	46.1	35.4	28.7	36.8
80:89	32.6	21.2	12.0	15.0	48.4	34.6	26.8	33.7
90:99	37.3	24.5	14.0	15.6	52.6	38.6	26.8	30.0
00:09	38.1	26.0	16.1	17.1	53.3	39.4	28.7	30.7

[a] Number reported is the average over all country-pairs.

[b] We classify goods and products at the ISIC level following the correspondence table https://unstats.un.org/unsd/tradekb/Knowledgebase/50054/Correlation-between-ISIC-and-SITC-codes-or-Commodity-and-Industry.

4 The Global Trade-Comovement Slope

This section revisits the seminal FR analysis and extend the analysis to additional variables defined in the previous section. We proceed step-by-step and gradually introduce our variables and additional controls that may interact with the Trade-Comovement Slope.

4.1 The initial Frankel and Rose (1998) specification revisited

We first extend the FR results to a large sample of countries separated into different income groups. As already specified before, we estimate a panel with country-pair (CP) and time-

done for a limited number of countries.

window (TW) fixed effects with the following specification:[22]

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}, \tag{26}$$

where $\mathbf{X}_{ijt}$ is a vector of additional control variables that includes dummies for USSR countries, the Euro area, NAFTA countries and the different waves of the European Union, and proximity in the composition of trade. On the one hand, the introduction of CP fixed effects means that we are using only *within* country-pair time variations for the identification. These dummies effectively control for time invariant factors that can influence GDP comovement between two countries, such as distance, common border, common language, etc. On the other hand, TW fixed effects capture aggregate changes in GDP comovement for all country-pairs in the world that could be due to aggregate shocks. In this specification as well as all subsequent analysis, standard errors are 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:

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \boldsymbol{\gamma}\, \mathbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \tag{27}$$

In equation (27), $\mathbf{network}_{ijt}$ defines a vector composed of the first and second order network measures discussed above. The results are gathered in table 5. Three main results emerge.

Table. 5. Trade Comovement slope with total trade index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(Trade)	**0.025*****	**0.022*****	**0.082*****	**0.101*****	**0.042*****	**0.032****	**0.026*****	**0.023*****	**0.032*****	**0.035*****
	(0.005)	(0.006)	(0.031)	(0.033)	(0.014)	(0.015)	(0.006)	(0.006)	(0.012)	(0.012)
network^{1st}		**0.309*****		**1.014*****		**0.444*****		**0.276*****		−0.016
		(0.067)		(0.269)		(0.162)		(0.074)		(0.159)
network^{2nd}		0.118		**1.524*****		−0.137		0.135		0.268
		(0.092)		(0.405)		(0.233)		(0.100)		(0.216)
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	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
Within R^2	0.009	0.012	0.076	0.101	0.043	0.047	0.004	0.007	0.006	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.

[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.

First, as previously highlighted in the literature, trade proximity using total trade flows is significantly associated with more GDP correlation, for all considered groups. However, the strength of this association is very heterogeneous. Using the point estimate obtained with all country pairs, we find that moving from the 25th to the 75th percentiles of log total trade is associated with an increase in GDP correlation of 6.5 percentage points (pp). The same number increases up to 20.3 pp for *OECD* country pairs, 10.0 pp for pairs in the *HH* group, 6.4 pp for the *HL* group and 9.9 pp for the *LL* sub-sample.

Second, the effect of trade through the *first 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 6.3 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 29.0 pp increase in bilateral GDP correlation, while it is 10.9 pp for pairs in the *HH* group and only 5.5 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.

Third, our 2^{nd} order network index is more ambiguous and presents noticeable difference across income groups. The index is statistically significant for pairs in the OECD group. For those countries, moving from the 25th to the 75th quantiles of the 2^{nd} 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.

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

4.2 Accounting for trade in intermediate inputs and final goods

Expanding on our results using total trade flows, we now refine the analysis and decompose total trade flows into two sub-categories: *trade in intermediate inputs* and *trade in final goods*. As discussed in de Soyres and Gaillard (2020) for the case of high income countries, trade in intermediate inputs is significantly correlated with GDP comovement, while trade in final goods is not.[23] 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. More precisely, trade in final goods appears to be relevant only in the case of demand shock, while trade in intermediate inputs is relevant for both demand and supply shocks.[24] We therefore test the differential relationship between business cycle synchronization and trade in intermediate inputs and in final goods in a larger sample covering different income groups. We run the following specification (with and without network effects and its decomposition into final and intermediate goods), where we disaggregate total trade flows ($\text{Trade}_{ijt}^{total}$) into trade in intermediate inputs ($\text{Trade}_{ijt}^{inter}$) and trade in final goods ($\text{Trade}_{ijt}^{final}$):

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2 \ln(\text{Trade}_{ijt}^{final}) + \boldsymbol{\gamma}\, \textbf{network}_{ijt} + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \quad (28)$$

Results are shown in table 6. 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[25] Turning to country-pairs in the *HL*, 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. Concerning the *LL* group, the distinction between final and intermediate goods does not provide additional information, trade in intermediate inputs and final goods have a positive association with GDP comovement but very weak statistical significance. 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 6.7 pp increase in GDP correlation for pairs in the *OECD* group and a 5.4 pp increase for pairs in the *HH* group. For pairs in the *HL*, moving from the 25th to the 75th quantile of log trade in final goods increases respectively GDP comovement by 2.4 pp.

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 much more important than common exposure sue to final good trade. Moreover, as income decreases, the role of the network intermediate index decreases markedly.

According to our theoretical framework, and in line with observations in previous papers

[23]In de Soyres and Gaillard (2020), we also show theoretically how international IO 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*

[24]In section 4.5, we use more direct measures that directly map the propagation channels of supply and demand shocks in light of section 2.

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

Table. 6. Trade Comovement slope with disaggregated trade index

	corr GDP											
	OECD	*OECD*	*OECD*	*HH*	*HH*	*HH*	*HL*	*HL*	*HL*	*LL*	*LL*	*LL*
ln(inter)	**0.103*****	**0.107*****	**0.078****	**0.046*****	**0.037*****	**0.035****	0.009	0.007	0.007	0.015	0.016	0.017
	(0.030)	(0.030)	(0.031)	(0.013)	(0.014)	(0.014)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.011)
ln(final)	−0.020	−0.002	0.007	−0.009	−0.007	−0.013	**0.018*****	**0.017*****	**0.018*****	0.015	0.016	0.016
	(0.024)	(0.025)	(0.025)	(0.012)	(0.013)	(0.013)	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)
network^{1st}		**0.984*****			**0.428*****			**0.283*****			−0.016	
		(0.266)			(0.163)			(0.074)			(0.160)	
network^{2nd}		**1.521*****	**1.386*****		−0.132	−0.180		0.119	0.105		0.237	0.220
		(0.416)	(0.422)		(0.230)	(0.230)		(0.100)	(0.100)		(0.216)	(0.213)
network inter^{1st}			**1.699*****			**0.470*****			**0.198*****			0.061
			(0.320)			(0.156)			(0.070)			(0.142)
network final^{1st}			−0.209			**0.308****			0.051			−0.198
			(0.253)			(0.144)			(0.063)			(0.126)
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	1,224	1,224	1,224	2,541	2,541	2,541	10,538	10,538	10,538	2,745	2,745	2,745
Within R^2	0.081	0.106	0.123	0.045	0.049	0.053	0.005	0.007	0.006	0.004	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.

such as Acemoglu et al. (2016), supply-side shocks propagate downstream whereas demand-side shocks propagate downstream implying 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 are mostly subject to demand shocks. In section 5, we show these results are robust to a number of alternative specifications, including financial controls, different GDP filters and different measures of trade intensities.

4.3 The evolution of the TC Slope from 1970 to 2009

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

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.[26] Formally, we now test the change in the slope using the following specifications:

$$\begin{aligned}\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \beta_2\, LTW_t \times \ln(\text{Trade}_{ijt}^{total}) + \boldsymbol{\gamma} \times LTW_t \mathbf{network}_{ijt} \\ + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt}\end{aligned} \tag{29}$$

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

Table 7 summarizes our findings and prompts a few observations. First, by using the standard trade intensity measure used in the literature, we find that the Trade-Comovement slope is significantly higher in the period 1990-2009 relative to the period 1970-1989. This evidence is the strongest among OECD countries. For the high income group, we surprisingly find that the slope was not significant during the period 1970-1989 but turned to be positive and significant in the last two decades. Among the *HL* group, the slope was also increasing while we find no evidence of an increase among the *LL* group. Second, looking at the role of similarity in trade networks, results indicate that the effect of common network among the OECD was increasing and significant, while we do find evidence that network was less important in the last two decades for the *HH*. In contrast, we find that the second-order measure of network turns to be significantly associated with more GDP comovement for countries in the latter group. A similar observation is made for countries in the *HL* group, while the *LL* group is characterized by relatively little effect of the trade network.

Our main take from this analysis is that the marginal effect of an increase in trade on GDP synchronization appear to be changing over time. For most income groups, increasing bilateral trade in recent decades has a larger marginal impact on GDP comovement than in the past. Note that this claim can have important consequences: the conjunction of an increasing marginal effect

[26]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.

of trade and an increasing level of trade among most countries in the world implies an important role for trade links the surge in international business cycle correlation.

Table. 7. Evolution of the TC-slope with total trade index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(total)	**0.013****	0.010	**0.093*****	**0.073*****	-0.000	-0.008	**0.015****	0.014*	**0.035*****	**0.035*****
	(0.006)	(0.036)	(0.016)	(0.007)	(0.014)	(0.017)	(0.007)	(0.007)	(0.013)	(0.013)
LTW*ln(total)	**0.009****	0.013	**0.025*****	**0.065*****	0.024*	**0.032*****	0.008	**0.012****	0.000	-0.001
	(0.004)	(0.026)	(0.008)	(0.005)	(0.013)	(0.009)	(0.005)	(0.005)	(0.012)	(0.012)
network^{1st}	**0.174****	0.203	**0.820*****	**0.875*****	**0.370****	**0.420****	0.163*	**0.188****	-0.086	-0.073
	(0.073)	(0.276)	(0.176)	(0.083)	(0.182)	(0.177)	(0.084)	(0.084)	(0.181)	(0.181)
LTW*network^{1st}	0.030	-0.120	**1.197*****	**0.883*****	-0.530^{*}	$-$**0.697*****	0.077	-0.061	0.282	0.473*
	(0.095)	(0.440)	(0.239)	(0.104)	(0.282)	(0.253)	(0.102)	(0.110)	(0.221)	(0.278)
network^{2nd}	**0.247*****	0.227	0.224*	0.027	**0.425*****	**0.403*****	**0.187*****	**0.169****	0.104	0.076
	(0.057)	(0.164)	(0.118)	(0.067)	(0.161)	(0.129)	(0.069)	(0.069)	(0.158)	(0.160)
LTW*network^{2nd}		0.280		**0.764*****		**0.424*****		**0.246*****		-0.221
		(0.209)		(0.069)		(0.136)		(0.074)		(0.196)
CP+TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
Within R^2	0.016	0.018	0.108	0.119	0.066	0.071	0.009	0.011	0.007	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.

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 $\boldsymbol{\gamma_2}$ are the coefficients of interests similar to those of equation (30):

$$\begin{aligned} \text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{Trade}_{ijt}^{inter}) + \beta_2\, LTW_t \times \ln(\text{Trade}_{ijt}^{inter}) + \beta_3 \ln(\text{Trade}_{ijt}^{final}) \\ & + \beta_4\, LTW_t \times \ln(\text{Trade}_{ijt}^{final}) + \boldsymbol{\gamma_1}\, \mathbf{network}_{ijt} + \boldsymbol{\gamma_2}\, LTW_t \times \mathbf{network}_{ijt} \\ & + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{30}$$

Table 8 displays the results. We find an increasing role of trade in intermediate inputs for the OECD group and the *HH* group, consistent with earlier results. We find however little evidence for an increase in the network effect of intermediate inputs. Interestingly, we find an increasing role for common exposure to third countries through final goods linkages over the last two decades, except for the *OECD* group. This is suggestive of an rising role of demand shocks, especially for lower income countries. Finally, notice that countries in the *LL* display no significant relationship between trade in input or final goods and GDP comovement.

Altogether, these findings show that the association between international trade linkages and GDP correlation increased over time, either directly (through bilateral trade) or indirectly (via the network effect) among the *OECD*, *HH* and *HL* groups.[27] As such, 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.

Table. 8. Evolution of the TC slope with disagregated trade flows

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(inter)	0.000	0.052	−0.007	0.004	0.018
	(0.006)	(0.035)	(0.015)	(0.007)	(0.014)
LTW*ln(inter)	0.007	**0.067****	**0.030****	0.003	−0.003
	(0.005)	(0.032)	(0.012)	(0.006)	(0.014)
ln(final)	0.009	0.011	−0.021	0.012*	0.016
	(0.006)	(0.027)	(0.014)	(0.006)	(0.011)
LTW*ln(final)	0.005	−0.026	−0.005	0.008	−0.004
	(0.005)	(0.033)	(0.013)	(0.006)	(0.012)
network inter^{1st}	**0.321*****	**1.582*****	**0.648*****	**0.252*****	−0.209
	(0.076)	(0.350)	(0.173)	(0.086)	(0.185)
LTW*network inter^{1st}	−0.076	0.036	−0.162	−0.078	0.408*
	(0.078)	(0.293)	(0.179)	(0.090)	(0.212)
network final^{1st}	−0.060	−0.242	0.037	−0.067	−0.002
	(0.068)	(0.269)	(0.150)	(0.075)	(0.164)
LTW*network final^{1st}	**0.327*****	−0.008	**0.605*****	**0.259*****	−0.309*
	(0.082)	(0.289)	(0.180)	(0.091)	(0.187)
CP+TW FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13,079	1,224	2,541	10,538	2,745
Within R^2	0.019	0.144	0.078	0.012	0.010

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

As mentioned in section 2, the density of the global trade network can act as a powerful amplification factor beyond the direct bilateral trade between two countries. We illustrate this point again by considering a situation where countries 1 and 2 trade with each-other (α_1^2 and α_2^1 are non-zero) and are also commonly exposed to country 3 (α_1^3 and α_2^3 are non-zero). Using equation (12), we can write bilateral output correlation as:

$$\text{corr}(\widehat{Y}_1, \widehat{Y}_2) = \lambda\left(\alpha_1^2 + \alpha_2^1 + (\alpha_1^3 + \alpha_1^2\alpha_2^3)(\alpha_2^3 + \alpha_2^1\alpha_1^3)\right) > \lambda\left(\alpha_1^2 + \alpha_2^1 + \alpha_1^3\alpha_2^3\right) \tag{31}$$

[27]In de Soyres and Gaillard (2020), we show that the rising market power could lead to an increasing role of trade on GDP comovement.

The inequality in equation (31) 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. Hence, one should not expect that the *marginal* effect of increasing any given link in the sparse network of the 1970s is the same as the effect of increasing a link in today's network. As a result, there is no such thing as a single "deep" parameter for the Trade Co-movement Slope.

Table 9 displays the time evolution of the ratio of total worldwide trade flows over total worldwide GDP in each of our four time windows, where we normalize with respect to the value in the first time window. Since the 1970s, the average trade flow over GDP has more than tripled. As a result of such an increase in network density, we expect a corresponding surge in the correlation between trade and GDP comovement.

Table. 9. Total trade flows over worldwide GDP
Value normalized in the first time window.

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

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

$$Network\,Density_{ijt} = \frac{\sum_{z\in\mathcal{P}(i)_{-j}} T_{i\leftrightarrow z,t} + \sum_{z\in\mathcal{P}(j)_{-i}} T_{j\leftrightarrow z,t}}{GDP_i + GDP_j} \tag{32}$$

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:

$$\begin{aligned} \text{Corr GDP}_{ijt} = {} & \beta_1 \ln(\text{Trade}_{ijt}^{total}) + \beta_2\, \text{density}_{ijt} \times \ln(\text{Trade}_{ijt}^{total}) + \boldsymbol{\gamma}_1\, \textbf{network}_{ijt} \\ & + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \end{aligned} \tag{33}$$

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.[28]

Table 10 summarizes the findings. Regarding the first column which presents the results using the whole sample, the interaction between our bilateral measure of density and total bilateral trade intensity is positive, suggesting that 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 is significant with different patterns in different sub-samples: density acts as an amplifier for the *OECD*, *HH* and *HL* groups, while we find no role in the *LL* group.

Overall, our findings imply that the TC-slope usually measured in the literature is a function of overall connectivity between a country-pair and the rest of the world. In other words, bilateral trade flows have a higher marginal effect on GDP-comovement when two countries trade more with 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. 10. TC slope and interaction with network density.

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(total)	0.004	**0.081****	0.002	0.007	**0.034****
	(0.007)	(0.035)	(0.017)	(0.007)	(0.014)
Density*ln(total)	**0.015*****	**0.049****	**0.018*****	**0.014*****	-0.001
	(0.003)	(0.020)	(0.004)	(0.003)	(0.008)
network^{1st}	**0.310*****	**0.881*****	**0.477*****	**0.276*****	-0.013
	(0.067)	(0.272)	(0.162)	(0.074)	(0.159)
Density	**0.122*****	**0.348*****	**0.135*****	**0.116*****	0.037
	(0.024)	(0.117)	(0.038)	(0.029)	(0.070)
CP+TW FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13,079	1,224	2,541	10,538	2,745
Within R^2	0.015	0.109	0.052	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 measure.

[28] 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.

4.5 Alternative measures using "Supply" and "Demand" bilateral trade indexes

We finally use the "supply" and "demand" bilateral trade measures introduced above and that more closely linked to our theoretical framework. We use this decomposition as a way to try to disentangle the role of supply versus demand shocks in propagating international shocks through trade linkages. In particular, we run the following specification:

$$\begin{aligned} \text{Corr GDP}_{ijt} &= \beta_1 \ln(\text{trade}_{\text{supply}})_{ijt} + \beta_2 \ln(\text{trade}_{\text{demand}})_{ijt} + \boldsymbol{\gamma}\, \textbf{network}_{ijt} \\ &\quad + \mathbf{X}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \,. \end{aligned} \tag{34}$$

Results presented in table 11 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, once we start looking atdifferent incomegroups, 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 could again suggest that supply-side shocks are more important for richer countries, while demand-side shocks are more prevalent in lower income ones. .

Table. 11. Trade Comovement slope with total trade index

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
$\ln(\text{trade}_{\text{Supply}})$	−0.007	0.127**	−0.004	−0.006	−0.036*
	(0.008)	(0.058)	(0.018)	(0.009)	(0.020)
$\ln(\text{trade}_{\text{Demand}})$	0.015	−0.053	0.026	0.015	0.051**
	(0.009)	(0.059)	(0.018)	(0.010)	(0.022)
network^{1st}	0.340***	1.105***	0.464***	0.308***	−0.002
	(0.067)	(0.268)	(0.159)	(0.074)	(0.160)
network^{2nd}	0.059	1.339***	−0.186	0.076	0.168
	(0.092)	(0.389)	(0.227)	(0.100)	(0.217)
CP+TW FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	13,027	1,224	2,540	10,487	2,724
R^2	0.010	0.101	0.046	0.005	0.005

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

4.6 Summary of empirical evidence

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

1. The correlation between trade in intermediate inputs and GDP comovement is significant and positive for countries in the *OECD* and *HH* groups, suggesting a specific role for Global Value Chains in these countries. Interestingly, trade in final goods is significantly correlated with higher business cycle synchronization for the low income groups, which may partly reflects their specialization in terms of traded good.

2. Common exposure to third countries, measured using our network indices is significantly positively correlated with more GDP comovement. First order network effects decay as we move to low income group while second order network effects is only significant among the *OECD* group.

3. The correlation between GDP comovement and both bilateral trade and network effects tends to increase over-time. As suggested by our simple model, this increase could be rationalized by a surge of trade network density which can amplify the association between global trade and bilateral comovement. Indeed, interactions between our network density index and bilateral trade linkages provides support for this hypothesis.

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, and over time. The literature provide little insights on how one could rationalize those findings, and future research is needed in that direction.

5 Robustness and additional exercises

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

5.1 Financial Integration: role of FDI and flows of assets

Previous studies found that financial interconnection is significantly (and *negatively*) associated with GDP comovements. Kalemli-Ozcan et al. (2013) identifies a strong negative effect of banking integration on output synchronization, conditional on global shocks and country-pair heterogeneity. Such a result is consistent with a *resource shifting hypothesis* where 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.[29]

Bilateral data on financial integration (FI) is scarce for pairs with two low income countries, but it is relatively widespread for other pairs. Hence, we focus our attention on the *OECD* and the *HL* groups for this exercise and account for the role of financial flows by using the consolidated banking statistics from the Bank for International Settlement and construct an index of financial proximity (FP).[30] We use the total bilateral cross-border claims (including bank and non-bank sectors for all maturities) between countries i and j to construct an index of financial proximity (FP), such that $FP_{ijt} = \frac{C_{i\to j,t}+C_{j\to i,t}}{GDP_{it}+GDP_{jt}}$, where here $C_{i\to j,t}$ refers to total cross-border claims from country i to country j in period t. Additionally, we control for FDI which might affect GDP comovement independently of trade proximity.[31] 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.[32] We use the inflows and outflows in order to construct a bilateral financial integration (FI) controls, such that: $FI_{ijt} = \frac{FDI_{i\to j,t}+FDI_{j\to i,t}}{GDP_{it}+GDP_{jt}}$, where here $FDI_{i\to j,t}$ refers to total FDI from country i to country j in period t. For this measure, we report only the effect of including this control for the whole sample.

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

5.2 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 go a step further and construct another index capturing non-symmetric situations where a country's direct partners are linked with an-

[29]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.

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

[31]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.

[32]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.

Table. 12. Effect of financial integration

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

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

other country second order partners. We refer to this situation as a cross-network effect of trade proximity, denoted ($cross\,network_{ijt}$) and defined as follows:

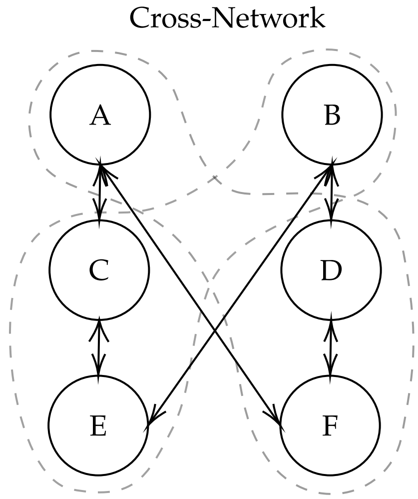
$$cross\,network_{ijt} = \frac{1}{2}\left(\sum_{z\in\mathcal{P}(j)} w_t(z,j;i)\cdot network^{1st}_{izt} + \sum_{z\in\mathcal{P}(i)} w_t(z,i;j)\cdot network^{1st}_{jzt} \right) \tag{35}$$

The index measures the extent to which a country i in the country-pair (i,j) is similar in terms of trade partners (i.e. in terms of direct *network* index) to all countries $z \in \mathcal{P}(j)$ trading with its partner j, weighted by the importance of z in the total trade of j.[33] As an illustration, we represent our index in figure 4.

Table 13 provides the results. The introduction of the cross-network index does not change the estimated coefficients regarding bilateral trade flows and first order network effects. However, it influences point estimates associated with the second order network measure, which is likely to be the case, as those two indexes measure trade network effects taking place further down in the trade network.

[33] Note that the index is derived using the fact that: $1-\frac{1}{4}\left(\sum_{z\in\mathcal{P}(j)} w_t(j,z)\sum_k \left|\frac{T_{i\leftrightarrow k,t}}{T_{i,t|-z}} - \frac{T_{z\leftrightarrow k,t}}{T_{z,t|-i}}\right| + \sum_{z\in\mathcal{P}(i)} w_t(i,z)\sum_k \left|\frac{T_{j\leftrightarrow k,t}}{T_{j,t|-z}} - \frac{T_{z\leftrightarrow k,t}}{T_{z,t|-j}}\right|\right) \times \left(\frac{T_{i,t|-j}+T_{j,t|-i}}{GDP_{it}+GDP_{it}}\right) = \frac{1}{2}\left(\sum_{z\in\mathcal{P}(j)} w_t(z,j;i)\cdot network^{1st}_{izt} + \sum_{z\in\mathcal{P}(i)} w_t(z,i;j)\cdot network^{1st}_{jzt}\right.$.

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.

5.3 Separating capital and intermediate inputs

Table 14 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* and the *HL* group. 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 the reverse for the *HL* group.

5.4 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).[34] Such an index is a direct measure of two countries' specialization, but its usefulness is somewhat limited by the high level of sectoral aggregation which allows us to capture only specialization in broad sectors. Moreover, data are available only for a subset of all countries.

We define the sectoral proximity index in terms of sector shares in GDP, denoted $sector_{ijt}^{prox}$,

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

Table. 13. Addition of the "Cross-Network" index

	corr GDP									
	All	*All*	*OECD*	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(total)	**0.019*****		**0.100*****		0.028*		**0.020*****		**0.034*****	
	(0.006)		(0.034)		(0.014)		(0.006)		(0.012)	
network^{1st}	**0.293*****		**1.137*****		**0.531*****		**0.246*****		-0.027	
	(0.067)		(0.264)		(0.165)		(0.074)		(0.157)	
ln(inter)		0.006		**0.079****		**0.032****		0.004		0.016
		(0.005)		(0.033)		(0.014)		(0.006)		(0.011)
ln(final)		**0.012****		0.004		-0.015		**0.017*****		0.017*
		(0.005)		(0.025)		(0.013)		(0.005)		(0.010)
$\text{network}^{1st}_{inter}$		**0.252*****		**1.748*****		**0.519*****		**0.181*****		0.075
		(0.064)		(0.318)		(0.159)		(0.070)		(0.142)
$\text{network}^{1st}_{final}$		0.068		-0.166		**0.337****		0.032		-0.202
		(0.058)		(0.264)		(0.148)		(0.063)		(0.125)
network^{2nd}	0.104	0.073	**1.515*****	**1.386*****	-0.128	-0.178	0.116	0.087	0.197	0.151
	(0.092)	(0.091)	(0.411)	(0.427)	(0.236)	(0.233)	(0.099)	(0.099)	(0.222)	(0.217)
network^{cross}	0.189*	0.223*	-0.100	-0.018	-0.106	-0.097	**0.271****	**0.311****	0.416	0.442*
	(0.115)	(0.114)	(0.410)	(0.420)	(0.254)	(0.258)	(0.126)	(0.126)	(0.268)	(0.269)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,079	13,079	1,224	1,224	2,541	2,541	10,538	10,538	2,745	2,745
Within R^2	0.009	0.009	0.097	0.120	0.039	0.045	0.005	0.005	0.008	0.009

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.

for a given country-pair (i, j) in time-window t as:

$$sector^{prox}_{ijt} = 1 - \frac{1}{2}\sum_{s\in\mathcal{S}}\left|\frac{Y_{i,t}(s)}{Y_{i,t}} - \frac{Y_{j,t}(s)}{Y_{j,t}}\right| \tag{36}$$

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.

We then run the following specification:

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

The results are gathered in table 15. For the sub-sample for which data is available, we do not find a statistically significant effect of $\text{sector}^{prox}_{ijt}$ on GDP-comovement.

Table. 14. TC slope with further disaggregation

	corr GDP							
	OECD	*OECD*	*HH*	*HH*	*HL*	*HL*	*LL*	*LL*
ln(inter)	**0.112*****	**0.083****	**0.030****	0.024*	**0.018*****	**0.015****	0.012	0.015
	(0.032)	(0.033)	(0.013)	(0.013)	(0.006)	(0.006)	(0.012)	(0.012)
ln(capital)	−0.002	0.003	**0.032*****	**0.030*****	**−0.015*****	**−0.015*****	−0.010	−0.010
	(0.020)	(0.020)	(0.009)	(0.009)	(0.004)	(0.004)	(0.008)	(0.008)
ln(final)	−0.025	0.001	−0.010	−0.014	**0.023*****	**0.023*****	**0.022****	**0.023****
	(0.024)	(0.024)	(0.013)	(0.014)	(0.005)	(0.006)	(0.011)	(0.011)
network inter^{1st}		**1.675*****		**0.502*****		**0.229*****		0.111
		(0.325)		(0.156)		(0.073)		(0.147)
network final^{1st}		−0.186		**0.359****		0.041		−0.193
		(0.258)		(0.145)		(0.066)		(0.134)
network^{2nd}		**1.417*****		−0.062		0.132		0.253
		(0.422)		(0.230)		(0.102)		(0.224)
CP+TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,222	1,222	2,508	2,508	10,194	10,194	2,614	2,614
Within R^2	0.085	0.127	0.050	0.060	0.007	0.009	0.005	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.

5.5 Other robustness exercises

Our results are robust to a number of other alternative specifications that we gather in table 16. We first confirm that among non-OECD pairs, trade in final goods is significantly associated with more GDP-comovement. When considering only the last two time windows, we find consistent results except for sub-samples with the lowest number of observations (the *LL* and *HH* groups), for which bilateral trade flows turn out to be statistically insignificant. Network effects, however, are in line with previous results.

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

Finally, we confirm the general pattern using three additional analysis: (i) an alternative measure of trade proximity built using the mean of log trade intensities instead of the log of the mean trade intensities within time-windows, (ii) an alternative measure using the max operator when computing the trade intensities: $\ln(\text{Trade}) = \max\left(T_{i\leftrightarrow j}/GDP_i, T_{i\leftrightarrow j}/GDP_j\right)$, (iii) BK filtered GDP instead of HP filtered GDP,[35] (iv) First difference instead of HP-filtered GDP. For the alternative bilateral trade measures using the max operator or the mean log, the results are very close to the benchmark specification. With the alternative filters, all results are consistent except for the *LL* group for which the correlation between trade in intermediate inputs and GDP-comovement turns out to be positive and significant in the case of BK-filtered GDP.

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

Table. 15. The absence of role for sectoral proximity in addition to export proximity

	corr GDP				
	All	*OECD*	*HH*	*HL*	*LL*
ln(inter)	0.010	0.142*	**0.089****	0.009	**0.044****
	(0.014)	(0.082)	(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.

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

Table. 16. Sensitive analysis: Trade and GDP-comovement

	Estimated coefficient					
	ln(input)	ln(final)	$network^{1st}$	$network^{2nd}$	Sample	Pairs | Obs.
(i) Sample selection						
Alternative Group	0.006	0.012**	0.25***	0.01	*Non-OECD*	4094 | 11830
Period (1990:2009)	0.216***	-0.100	1.38*	1.24	*OECD*	316 | 616
Period (1990:2009)	0.022	0.018	0.98**	0.08	*HH*	754 | 1434
Period (1990:2009)	0.038***	0.031***	0.59***	1.08***	*HL*	3598 | 6582
Period (1990:2009)	0.020	-0.001	0.71***	1.17***	*LL*	1140 | 1972
(ii) Alternative controls						
SITC 2-digit $export^{prox}$	0.102***	0.001	0.99***	1.60***	*OECD*	320 | 1224
SITC 2-digit $export^{prox}$	0.033**	-0.007	0.45***	-0.11	*HH*	764 | 2533
SITC 2-digit $export^{prox}$	0.008	0.016***	0.28***	0.11	*HL*	3650 | 10521
SITC 2-digit $export^{prox}$	0.017	0.016*	0.00	0.24	*LL*	1165 | 2744
ISIC $export^{prox}$	0.109***	-0.004	1.06***	1.54***	*OECD*	320 | 1224
ISIC $export^{prox}$	0.036***	-0.011	0.48***	-0.11	*HH*	764 | 2533
ISIC $export^{prox}$	0.007	0.016***	0.29***	0.12	*HL*	3650 | 10521
ISIC $export^{prox}$	0.016	0.016*	-0.01	-0.11	*LL*	1165 | 2744
(iii) Alternative Measures						
mean ln($index$)	0.114***	-0.029	1.09***	1.39***	*OECD*	320 | 1224
mean ln($index$)	0.035***	-0.015	0.50***	-0.14	*HH*	764 | 2533
mean ln($index$)	0.006	0.016***	0.27***	0.10	*HL*	3650 | 10521
mean ln($index$)	0.016	0.016*	-0.03	0.23	*LL*	1165 | 2744
Max trade index [c]	0.107***	-0.009	1.11***	1.48***	*OECD*	320 | 1224
Max trade index [c]	0.036***	-0.010	0.50***	-0.10	*HH*	764 | 2533
Max trade index [c]	0.007	0.017***	0.27***	0.11	*HL*	3650 | 10521
Max trade index [c]	0.016	0.016*	-0.03	0.26	*LL*	1165 | 2744
BK filter	0.119***	-0.006	1.10***	1.58***	*OECD*	324 | 1260
BK filter	0.045***	-0.016	0.50***	0.04	*HH*	320 | 1224
BK filter	0.009	0.014***	0.28***	0.11	*HL*	3650 | 10521
BK filter	0.024**	0.014	-0.04	0.26	*LL*	1165 | 2744
First difference	0.078***	0.004	0.72***	1.11***	*OECD*	320 | 1224
First difference	0.015	-0.024*	0.55***	-0.12	*HH*	764 | 2533
First difference	0.008	0.023***	0.27***	0.20**	*HL*	3650 | 10521
First difference	0.020*	0.020**	0.16	0.32	*LL*	1165 | 2744

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

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