Value Added and Productivity Linkages Across Countries

Online Appendix (OA)

For Online Publication Only

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This appendix contains additional exercises on the empirical relationship between trade linkages (split into final goods and intermediate inputs) and cross-country GDP correlations. It also provides further information on the quantitative model and extensive robustness checks that compare the model to prior setups in the literature.

Contents

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OA1 Empirical Appendix

OA1.1 Data source

Trade Comovement Puzzle In this appendix, unless explicitly stated, the empirical analysis is performed on 40 OECD countries and major emerging markets, which account for around 90% of world GDP.[1] Our bilateral trade flows data come from Johnson and Noguera (2017) who separated between final and intermediate goods for 42 countries between 1970 and 2009. According to their data appendix A.2, they construct their data as follows. For bilateral goods trade, they use the NBER-UN Database for 1970-2000 and the CEPII BACI Database for 1995-2009. This data is reported on a commodity-basis. They assign commodities to end uses and industries using existing correspondences from the World Bank. To assign commodities to end uses, they use correspondences between SITC (Revision 2) 4-digit or HS (1996 Revision) 6-digit commodities and the BEC end use classifications. To assign commodities to industries, they use correspondences between SITC and HS categories and ISIC (Revision 2) industries. GDP data comes from the 9th Penn World Tables. We use the output-side real GDP at chained PPPs (variable *rgdpo*), to compare relative productive capacity across countries and over time.[2]

[1] The list of countries is: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, United States and Vietnam.

[2] We drop Romania and South Africa from their sample because of lack of GDP series in the Penn World Tables. Moreover, in Johnson and Noguera (2017)'s data for Russia starts only in 1990 while data for Estonia, Slovak

We also use OECD data and quarterly based price GDP data in some robustness checks. In total, we have 630 country-pairs appearing 4 times and 190 pairs appearing 2 times (both in the case of 10 years time windows), leading to a dataset with a total of 2900 observations.

The main paper focuses on a smaller sample of 35 countries in order to have a balance the panel and restrict to countries for which most variables are available. The restriction leads to the exclusion of some ex-URSS associated countries (Slovenia, Estonia, Russia, Hungary, Slovakia, Czech republic). In this appendix, we show that our empirical results are robust even after this change.

OA1.2 Summary statistics

Table 1 shows the summary statistics of the data used throughout the empirical investigations, either in the core paper or in this online appendix.

Table. 1. Summary statistics

Statistic	Min	Max	Mean	Pctl(25)	Median	Pctl(75)	N	St. Dev.
log_inx_tot_trade	−15.440	−2.412	−6.870	−7.685	−6.756	−5.878	2,380	1.653
log_inx_int_trade	−15.814	−2.851	−7.407	−8.229	−7.298	−6.415	2,380	1.682
log_inx_fin_trade	−16.647	−3.451	−7.875	−8.738	−7.716	−6.767	2,380	1.748
corr_GDP_HP	−0.933	0.964	0.265	−0.013	0.315	0.583	2,380	0.399
corr_GDP_BK	−0.928	0.961	0.263	−0.010	0.312	0.573	2,380	0.389
corr_GDP_FD	−0.976	0.978	0.245	−0.026	0.285	0.542	2,380	0.382
third_tot	0.123	0.942	0.538	0.411	0.544	0.674	2,380	0.172
sector_ex	0.023	0.722	0.304	0.208	0.291	0.387	2,380	0.134
index_C_claims_2	0.00000	1.431	0.039	0.001	0.003	0.012	874	0.130
index_TOT_FDI	−0.002	0.012	0.0004	0.00002	0.0001	0.0004	663	0.001
SITC_sector	0.081	0.798	0.441	0.336	0.438	0.542	2,380	0.143

OA1.3 Main Sensitivity Analysis of the Trade Comovement Slope

Table 2 provides various sensitivity analysis of our main empirical results regarding the trade-comovement slope. More details of those results are provided in the online appendix and a short summary of our investigation is reported here.

In the first series of robustness analysis, we ask how our results change when we restrict our sample in different ways. The first row simply restates our baseline results for reference. In the second row, we use 20 years time windows when computing GDP correlation. In the third and fourth row, we reduce our sample by excluding coutry pairs in the European Union

Republic, Slovenia and Czech Republic start only in 1993. All country-pairs involving one of those five countries appears only two times in the case of 10 years time-windows and cannot be used at all in the case of 20 years time-windows.

and the USSR respectively. In the fifth row, we restrict our sample to the first three time windows (from 1970 to 1999) so that our time coverage is in line with original Kose and Yi (2006) analysis. In all these cases, our main results are virtually unchanged.

A second series of analysis relates to the inclusion of alternative controls for sectoral decomposition. Recall that our regressions include controls for similarity in specialization patterns which could impact GDP synchronization over and beyond any trade effect. In rows six, seven and eight, we use different sector categorization and dis-aggregation to compute our sectoral proximity measure. These variations do not affect our empirical results.

A third series of robustness exercises relate to the definition of our trade proximity indices. In our main results, we construct, for each country-pair and time window, the average over all years in the time window of the log of bilateral trade divided by the sum of GDP. In row nine, we do not take the log of the trade over (bilateral) GDP ratios and instead use simply the levels. In row ten, we do not construct the average of log ratio, but instead use the log of the average ratio. Row eleven presents results where instead of using the ratio of bilateral trade over sum of GDP, we use the maximum of bilateral trade divided by each country in the pair. Finally, row twelve presents results where we change our database and use the Structural Analysis (STAN) database for the trade flows. Again, our main message are not altered by these variations.

The last set of sensitivity investigations relates to the definition of GDP as well as other robustness exercises. In our main results, we use annual data on real GDP at chained PPPs from the 9th Penn World Table. Rows thirteen and fourteen show the results when using the variable called "RGDPNA" which measures real GDP at constant 2011 national prices, when we use HP filter and first difference respectively. In rows fifteen and sixteen, we perform a weighted regression where each observation is weighted by the sum of GDP of both countries in the pair – hence giving relatively more weights to pairs containing at least one big country such as the US. As previously, our results are not materially affected by such changes. In row eighteen and nineteen, we come back to the role of measured productivity. In eighteen, we estimate the effect of trade on SR comovement using the Baxter nad King (BK) filter. Finally, we test in row nineteen whether adding bilateral Solow Residual correlation in specification (**??**) has a significant impact on the relation between real GDP co-movement and intermediate inputs trade. Once controlling for the cross-country correlation in measured productivity (SR), the coefficient associated to trade in intermediate inputs becomes insignificant, while still positive.

Table. 2. Robustness exercises on estimated Trade Comovement-slope in the data

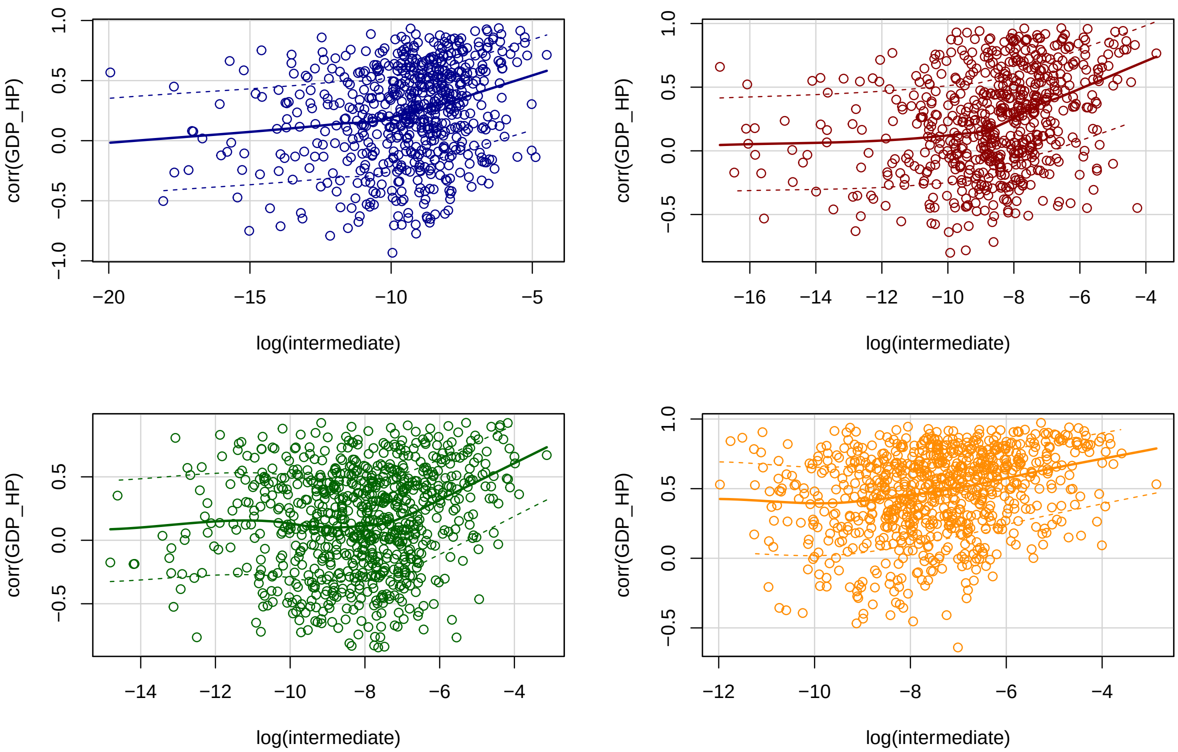
	Coeff. trade in inputs	Coeff. trade in final goods	GDP Filter	Countries ∣ Obs.	Period	TW	CP
Sample selection							
1. Whole Sample	0.060**	−0.038	HP	40 ∣ 2,900	1970-2009	Yes	Yes
1. 35 countries (cf. main paper)	0.063**	−0.023	HP	40 ∣ 2,380	1970-2009	Yes	Yes
2. 20 years TW	0.074**	−0.054	HP	40 ∣ 1,450	1970-2009	Yes	Yes
3. Excluding EU CP	0.056**	0.005	HP	40 ∣ 2,280	1970-2009	Yes	Yes
4. Excluding USSR	0.064**	−0.006	HP	34 ∣ 2,244	1970-2009	Yes	Yes
5. Alternative TW	0.081***	0.014	HP	34 ∣ 2,244	1970-1999	Yes	Yes
Alternative controls for sectoral composition							
6. 4Digits SITC	0.058**	−0.045*	HP	36 ∣ 2,520	1970-2009	Yes	Yes
7. ISIC classification	0.059**	−0.045*	HP	36 ∣ 2,520	1970-2009	Yes	Yes
8. 1Digit Agg. sectors	0.088	−0.044	HP	38 ∣ 1,291	1970-2009	Yes	Yes
Alternative indexes							
9. $level(trade)^a$	34,9*	−36.8	HP	40 ∣ 2,900	1970-2009	Yes	Yes
10. $\log(mean(trade))$	0.053**	−0.034	HP	40 ∣ 2,900	1970-2009	Yes	Yes
11. $\max\left(\frac{T_{i\leftrightarrow j}}{GDP_i}, \frac{T_{i\leftrightarrow j}}{GDP_j}\right)$	0.060**	−0.040*	HP	40 ∣ 2,900	1970-2009	Yes	Yes
12. STAN data	0.209**	−0.107	HP	20 ∣ 760	1995-2014	Yes	Yes
Other robustnesses							
13. RGDPNA measure	0.110***	−0.096***	HP	40 ∣ 2,900	1970-2009	Yes	Yes
14. RGDPNA measure	0.069***	−0.058***	FD	40 ∣ 2,900	1970-2009	Yes	Yes
15. Weighted GDP	0.048**	−0.046*	HP	40 ∣ 2,900	1970-2009	Yes	Yes
16. Weighted GDP	0.061**	−0.047*	FD	40 ∣ 2,900	1970-2009	Yes	Yes
17. Whole sample	0.036*	−0.020	BK	40 ∣ 2,900	1970-2009	Yes	Yes
18. SR-slope	0.055*	−0.033	BK	40 ∣ 2,367	1970-2009	Yes	Yes
19. With SR-corr. as control	0.023	−0.004	HP	40 ∣ 2,367	1970-2009	Yes	Yes

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs. TW stands for Time Windows Fixed Effects while CP stands Coutry-Pairs Fixed Effects, which are inluded in all our analysis.

OA1.4 Additional Analysis on the Trade-Comovement Slope

In this section, we conduct additional robustness checks and show that our main empirical results concerning the trade co-movement slope are robust to alternative specifications, sample selection and time period. We start by providing in Figure 1 scatter-plots relating GDP co-movomenets and trade intensity for each time windows. In each time-windows, their is a positive relationship between the two variables. Therefore, the main analysis consists in disentangling effects coming from unobserved heterogeneity (common borders, same language etc.) and specific time effect (the global rise in GDP correlation through time).

Figure 1. Bilateral trade intensity and GDP correlation (HP-filter) for the four time windows from 1970 to 2009. Blue: 1970-1979, Red: 1980-1989, Green: 1990-1999, Orange: 2000-2009.



OA1.4.1 Trade comovement slope with financial controls

We provide additional robustness of the trade comovement slope using financial controls. To this effect, we construct two additional variables capturing the financial interconnection between every country-pairs. First, we construct an index of financial integration (FI) using Foreign Direct Investment (FDI) data, as follows: $FI_{ijt} = \frac{FDI_{i \to j,t} + FDI_{j \to i,t}}{GDP_{it} + GDP_{jt}}$. Second, we use the total bilateral cross-border claims (including bank and non-bank sectors for all maturities) from the consolidated banking statistics from the Bank for International Settlement to construct an index of financial proximity (FP) between a country i and j: $FP_{ijt} = \frac{C_{i \to j,t} + C_{j \to i,t}}{GDP_{it} + GDP_{jt}}$, where here $C_{i \to j,t}$ refers to total cross-border claims from country i to country j.

Table 3 summarizes the results with financial controls. Except for the specification using correlation of first difference GDP together with financial proximity index, the results are shown to be robust to the inclusion of financial controls. Using a larger sample including high and low income countries, World Bank (2019) show consistent findings.

Table. 3. Trade - GDP correlation, Disaggregated trade, controls with financial variables

	Corr GDP$^{\text{HP filter}}$				Corr ΔGDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{Trade}^{\text{input}})$	0.170***	0.177***	0.298***	0.312***	0.067	0.074	0.202*	0.186*
	(0.065)	(0.063)	(0.097)	(0.095)	(0.075)	(0.074)	(0.104)	(0.098)
$\ln(\text{Trade}^{\text{final}})$	−0.006	−0.048	−0.367***	−0.351***	0.074	0.036	−0.340***	−0.316***
	(0.057)	(0.057)	(0.092)	(0.094)	(0.063)	(0.067)	(0.093)	(0.095)
$\ln(\text{FP})$		0.039**				0.027		
		(0.016)				(0.019)		
$\ln(\text{FI})$				−0.022				−0.036*
				(0.020)				(0.021)
$third_{country}$		0.322		−0.319		0.400		0.429
		(0.301)		(0.502)		(0.330)		(0.612)
Country-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Window FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
EU + USSR dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,030	1,030	728	728	1,030	1,030	728	728
R^2	0.425	0.432	0.440	0.443	0.343	0.347	0.350	0.355

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs.

OA1.4.2 Robustness: excluding EU and USSR country-pairs, alternative time windows and time periods

We conduct three sets of analysis concerning our main empirical findings that trade in intermediate inputs is associated with more GDP correlation while trade in final goods is not.

(i). In table 4, we first provides additional results of the main regressions ((1) and (2) in the main paper) with 20 years time windows and fixed effects. The results confirm the robustness of our findings under alternative time windows. Using this dataset, we find a significant trade in inputs co-movement slope using HP filter or first difference.

(ii). In table 5 we run the same empirical analysis with fixed effects but we exclude country-pairs with two countries in the 2000 European Union, while in table 6 we exclude USSR countries. This is motivated by the fact that the European Union (or trade unions) have made correlated policies to improve trade each other, which may influence the correlation between trade intensity and GDP correlation. Perhaps surprisingly, dropping country-pairs in the European Union from the sample increases the correlation between trade in intermediate goods and GDP comovement. We find a similar conclusion when excluding USSR countries.

(iii). In table 7, we focus only on the three first time windows that cover the period from 1970

Table. 4. Trade - GDP correlation using 20 years time windows

	Corr $GDP^{HP\ filter}$					Corr ΔGDP				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(Trade^{total})$	0.047***	0.019*				0.016**	0.017			
	(0.007)	(0.011)				(0.007)	(0.013)			
$\ln(Trade^{input})$			0.056*	0.074**	0.081**			0.070**	0.074**	0.079**
			(0.033)	(0.033)	(0.033)			(0.030)	(0.031)	(0.031)
$\ln(Trade^{final})$			−0.005	−0.054	−0.063*			−0.047*	−0.057*	−0.063**
			(0.029)	(0.034)	(0.034)			(0.026)	(0.031)	(0.031)
Country-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Time Window FE	No	Yes	No	Yes	No	Yes	No	Yes		
EU + URSS dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
N	1,450	1,450	1,450	1,450	1,450	1,450	1,450	1,450	1,450	1,450
R^2	0.058	0.068	0.061	0.075	0.103	0.009	0.009	0.017	0.017	0.032

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

to 1999. In that case, we still find a significant trade co-movement slope, with a larger effect of trade intensity on GDP comovement.[3]

Table. 5. Trade and GDP correlation with 10 years time windows - no EU country-pairs

	Corr $GDP^{HP\ filter}$				Corr ΔGDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(Trade^{input})$	0.056**	0.066***	0.067***	0.067***	0.049**	0.047*	0.048**	0.046*
	(0.026)	(0.025)	(0.026)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
$\ln(Trade^{final})$	0.005	−0.043*	−0.051**	−0.050*	−0.005	−0.020	−0.030	−0.028
	(0.023)	(0.025)	(0.026)	(0.026)	(0.021)	(0.024)	(0.024)	(0.024)
$sector_{prox}$				−0.107				−0.253
				(0.161)				(0.158)
$third_{country}$			0.326**	0.332**			0.354**	0.366**
			(0.161)	(0.162)			(0.147)	(0.147)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
URSS dum.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	2,280	2,280	2,280	2,280	2,280	2,280	2,280	2,280
R^2	0.044	0.173	0.178	0.178	0.022	0.143	0.149	0.150

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

OA1.4.3 Robustness: sector composition

In table 8 we show the results of an analysis where the index of similarity in sectoral composition is constructed using first the ISIC classification (columns (2) and (5)) and then using the

[3] Notice that findings for the points (ii) and (iii) are also valid using FD.

Table. 6. Trade and GDP correlation with 10 years time windows - no USSR countries

	Corr $GDP^{HP\ filter}$				Corr ΔGDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(Trade^{input})$	0.064**	0.066**	0.073***	0.072***	0.063***	0.055**	0.066***	0.061**
	(0.027)	(0.027)	(0.027)	(0.027)	(0.025)	(0.025)	(0.025)	(0.025)
$\ln(Trade^{final})$	−0.006	−0.020	−0.043	−0.042	−0.020	−0.007	−0.031	−0.026
	(0.024)	(0.027)	(0.027)	(0.027)	(0.022)	(0.025)	(0.026)	(0.026)
$sector_{prox}$				−0.064				−0.302*
				(0.160)				(0.154)
$third_{country}$			0.307*	0.310*			0.361**	0.374**
			(0.164)	(0.165)			(0.150)	(0.151)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
URSS dum.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	2,244	2,244	2,244	2,244	2,244	2,244	2,244	2,244
R^2	0.037	0.143	0.165	0.165	0.020	0.132	0.151	0.154
Notes:	*p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation.							

Table. 7. Trade and GDP correlation with 10 years time windows - first three time windows

	Corr $GDP^{HP\ filter}$				Corr ΔGDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(Trade^{input})$	0.081***	0.062**	0.071**	0.079***	0.067**	0.034	0.046	0.055*
	(0.030)	(0.028)	(0.028)	(0.028)	(0.030)	(0.029)	(0.029)	(0.029)
$\ln(Trade^{final})$	0.014	−0.034	−0.052*	−0.061**	0.001	−0.006	−0.025	−0.034
	(0.026)	(0.028)	(0.029)	(0.029)	(0.026)	(0.029)	(0.030)	(0.030)
$sector_{prox}$				0.677***				0.679***
				(0.170)				(0.173)
$third_{country}$			0.255	0.208			0.337*	0.289*
			(0.174)	(0.170)			(0.174)	(0.171)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
URSS dum.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	2,270	2,270	2,270	2,270	2,270	2,270	2,270	2,270
R^2	0.068	0.222	0.250	0.258	0.033	0.189	0.221	0.229
Notes:	*p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation.							

SITC 4-digits classification (columns (3) and (6)). The sample size is not exactly similar as in the main text but results are robust to this specification.

Table. 8. Trade - GDP correlation with controls for sectoral composition

	Corr $GDP^{HP\ filter}$			Corr ΔGDP		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(Trade^{input})$	0.057**	0.059**	0.058**	0.044*	0.043*	0.043*
	(0.026)	(0.026)	(0.026)	(0.024)	(0.024)	(0.024)
$\ln(Trade^{final})$	−0.036	−0.045*	−0.045*	−0.018	−0.025	−0.027
	(0.025)	(0.026)	(0.026)	(0.024)	(0.024)	(0.024)
$sector_{prox}$		0.042	−0.058		−0.376**	−0.219**
		(0.181)	(0.115)		(0.175)	(0.110)
$third_{country}$		0.272*	0.282*		0.369**	0.391***
		(0.154)	(0.156)		(0.144)	(0.146)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes
EU + URSS dum.	Yes	Yes	Yes	Yes	Yes	Yes
N	2,520	2,520	2,520	2,520	2,520	2,520
R^2	0.143	0.144	0.145	0.126	0.132	0.132

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

We then use the data from the World Development Indicators (WDI) of the World Bank to construct our index of proximity in sectoral composition. We use the share in value added of main sectors: service and agricultural sectors and we decompose manufacturing sectors into 7 main sub-sectors.[4] We then compute the following index:

$$index\_sector_{ij} = 1 - \frac{1}{2} \sum_k \left| share\_GDP_i^k - share\_GDP_j^k \right| \tag{1}$$

where k refers to a particular sector. Pairs of country with very similar sectoral composition have an index close to 1, while countries that completely specialize in different sectors would have an index of 0.

Results are gathered in table 9 and show a positive relationship between trade intensity in inputs and GDP comovement, with a similar magnitude when controlling for third index and sectoral composition. Note that the sample size is drastically reduced when using this data. Results are not significant with this sub-sample using HP-filtered data.

[4] This includes textile, industry, machinery, chemical, high-tech, food and tabacco, other. Data are available here: https://databank.worldbank.org/data/source/.

Table. 9. Trade - GDP correlation with controls for sectoral composition using World Bank data

	Corr $GDP^{\text{HP filter}}$			Corr ΔGDP		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\text{Trade}^{\text{input}})$	0.090	0.092	0.088	0.158***	0.164***	0.167***
	(0.059)	(0.060)	(0.056)	(0.055)	(0.054)	(0.053)
$\ln(\text{Trade}^{\text{final}})$	0.046	−0.019	−0.044	−0.086*	−0.127**	−0.142***
	(0.047)	(0.049)	(0.047)	(0.046)	(0.052)	(0.052)
$sector_{prox}$			1.587***			0.393
			(0.432)			(0.459)
$third_{country}$			0.954**			0.796*
			(0.422)			(0.469)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes
EU + URSS dum.	Yes	Yes	Yes	Yes	Yes	Yes
N	1,291	1,291	1,291	1,291	1,291	1,291
R^2	0.253	0.292	0.314	0.233	0.283	0.289
Notes:	*p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation.					

OA1.4.4 Robustness: log(mean) regressions

In the main text, we constructed the index of trade proximity by taking, for each time window, the average of the log-proximity observed every year. Alternatively, instead of taking the "*mean of log proximity*", we could take the "*log of mean proximity*". We show in table 10 the results using the log transformation on the average trade intensities within each time-windows. As compared to results in the paper, the R^2 is slightly lowered. Moreover, notice that given the median increase in trade intensities in intermediate inputs of 5.76 and the estimates reported in column (2), the implied increase in GDP correlation is $log(5.76) * 0.052 = 0.091$, very similar to the case with "*mean of log proximity*" reported in the core paper.

OA1.4.5 Robustness: alternative bilateral trade data

We also use the STAN Bilateral Trade Database by Industry and End-Use data (BTDIxE).[5] BTDIxE consists of values of imports and exports of goods, broken down by end-use categories. Estimates are expressed in nominal terms, in current US dollars for all OECD member countries. The trade flows are divided into capital goods, intermediate inputs and consumption. For the sake of comparison with the results in the main text, we first group the capital and intermediate goods together and create the index of trade proximity as explained in the main text. Due to data availability, we use the data from 1995 to 2014 which allows us to create four

[5] See at http://www.oecd.org/trade/bilateraltradeingoodsbyindustryandend-usecategory.htm.

Table. 10. Trade and GDP correlation with 10 years time windows - Trade Proximity constructed as log(mean) (*as opposed to mean(log)*)

	Corr GDP$^{\text{HP filter}}$				Corr ΔGDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(\text{Trade}^{\text{input}})$	0.044*	0.052**	0.051**	0.052**	0.028	0.036*	0.036*	0.034
	(0.023)	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)
$\ln(\text{Trade}^{\text{final}})$	−0.027	−0.034	−0.044*	−0.044*	−0.010	−0.017	−0.029	−0.027
	(0.022)	(0.023)	(0.023)	(0.023)	(0.021)	(0.022)	(0.022)	(0.022)
$sector_{prox}$				0.086				−0.251*
				(0.146)				(0.139)
$third_{country}$			0.337**	0.334**			0.442***	0.450***
			(0.149)	(0.150)			(0.141)	(0.141)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
URSS + EU dum.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	2,900	2,900	2,900	2,900	2,900	2,900	2,900	2,900
R^2	0.153	0.166	0.169	0.169	0.139	0.151	0.156	0.157
Notes:	*p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation.							

time windows of 5 years each (tables 11 and 12). With 20 countries, the dataset contains 190 pairs, for a total of 760 observations with four time windows. The tables below present the robustness results using both the HP filter (for business cycle frequencies) and then the Baxter and King filter (for medium term frequencies).

Table. 11. Trade and HP-Filtered GDP - STAN database (1995 to 2014)

	dependent variable: corr(GDP_i^{HP},GDP_j^{HP})					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Trade)	0.064***		-0.009		0.103	
	(5.94)		(-0.14)		(1.53)	
$\ln(\text{Trade}^{\text{input}})$		0.044*		0.146*		0.209**
		(1.88)		(1.77)		(2.59)
$\ln(\text{Trade}^{\text{final}})$		0.021		-0.152*		-0.107
		(1.06)		(-2.04)		(-1.39)
Country-Pair FE	no	no	yes	yes	yes	yes
Time Trend	no	no	no	no	yes	yes
N	760	760	760	760	760	760

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs.

OA1.5 Trade and GDP components

To better understand the source of the positive association between GDP comovement and trade, we now propose a simple refinement to the empirical analysis performed so far.

We decompose GDP fluctuations into changes in factor supply (labor and capital) and

Table. 12. Trade and BK-Filtered GDP - STAN database (1995 to 2014)

	dependent variable: corr(GDP_i^{BK},GDP_j^{BK})					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Trade)	0.075***		0.433***		0.397**	
	(5.23)		(3.86)		(3.16)	
ln($\text{Trade}^{\text{input}}$)		0.115***		0.562***		0.538***
		(3.71)		(3.71)		(3.60)
ln($\text{Trade}^{\text{final}}$)		-0.036		-0.106		-0.122
		(-1.32)		(-0.76)		(-0.83)
Country-Pair FE	no	no	yes	yes	yes	yes
Time Trend	no	no	no	no	yes	yes
N	760	760	760	760	760	760

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs.

variations of the Solow Residual (SR). A natural question to ask is: if trade is associated with higher GDP correlation, is it also associated with higher synchronization of labor and/or capital movements? This is an important question because its answer should guide our theoretical construction. For example, Johnson (2014) notes that, in a perfectly competitive framework with constant returns to scale, "*real value added depends on productivity and factor inputs alone*". In his framework, when the correlation of technology shocks across countries is independent of trade, then the trade-GDP comovement slope can only be generated by an increased correlation of factor supply.

However, in a framework where the Solow Residual does not only fluctuate due to changes in technology, one should not only focus on the comovement in factor supply. Indeed, as discussed in the core paper, a key element in solving the Trade Comovement Puzzle lies in our recognition that real GDP fluctuations are not restricted to movements in technology, labor and capital.

We examine this issue by running two sets of regressions. We first investigate the relationship between trade and factor supply synchronization. Denoting Corr L_{ijt} and Corr I_{ijt} the correlation of labor and investment between countries i and j at time t, we estimate:

$$\text{Corr L}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{\text{input}}) + \beta_2 \ln(\text{Trade}_{ijt}^{\text{final}}) + \text{controls}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \quad (2)$$

$$\text{Corr I}_{ijt} = \beta_1 \ln(\text{Trade}_{ijt}^{\text{input}}) + \beta_2 \ln(\text{Trade}_{ijt}^{\text{final}}) + \text{controls}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \quad (3)$$

Second, we construct the Solow Residual for each country as: $SR_{it} = log(RGDP_{it}) - \alpha log(K_{it}) - (1-\alpha)\, log(L_{it})$, with $\alpha = 1/3$. We then compute all country-pair correlations of

Solow Residuals for each time window.[6] In line with previous specifications, we estimate:

$$\text{Corr SR}_{ijt} \quad = \beta_1 \ln(\text{Trade}_{ijt}^{\text{input}}) + \beta_2 \ln(\text{Trade}_{ijt}^{\text{final}}) + \text{controls}_{ijt} + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \qquad (4)$$

Table. 13. Trade and SR, K and L correlation with 10 years time windows

	Corr $SR^{\text{HP filter}}$	Corr $I^{\text{HP filter}}$	Corr $L^{\text{HP filter}}$
	(1)	(2)	(3)
$\ln(\text{Trade}^{\text{input}})$	0.059**	0.057**	0.022
	(0.026)	(0.026)	(0.026)
$\ln(\text{Trade}^{\text{final}})$	−0.034	−0.114***	−0.056**
	(0.025)	(0.027)	(0.027)
CP + TW FE + Third country + URSS + EU dum.	Yes	Yes	Yes
N	2,367	2,367	2,367
R^2	0.212	0.262	0.114

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs. SR is computed using PWT 9.1, with $SR = log(rgdpna) - \alpha log(rkna) - (1-\alpha) log(emp)$ and $\alpha = 0.33$. Results are robust to the use of *rnna* and various values of α. Investment I is computed using PWT 9.1 using capital investment in structure, machinery, transport and other investment. We deflate investments using their corresponding price index.

Results in table 16 reveal two key insights for the relationship between trade and real GDP synchronization. First, looking at columns (3), we note that higher trade integration in intermediate inputs is not associated with an increase in labor comovement. We acknowledge that using total employment as a proxy for labor supply is subject to a number of limitations, with issues regarding differences in skills and un-observable hours worked for example. However, this absence of increase in total employment correlation for country-pairs increasing their trade links suggests that models where GDP synchronization is achieved by inducing a strong labor supply reaction to a foreign shock is likely to be at odds with the data. Second, looking at columns (1) to (2), we note that trade in intermediate inputs is significantly associated with the synchronization of Solow Residual and capital stocks.

Once again, it is important to remember that our panel specifications are not intended to use information about the *level* of GDP comovement across countries, but rather to account for the *change* in GDP comovement when countries are more integrated through trade. Hence, although the *level* of factor supply synchronization is high in the data (as discussed in appendix OA3.3), this synchronization does not seem to systematically increase with trade proximity. As a result, we argue that an important part of the high value of the observed trade-comovement slope comes from an increase in the synchronization of the Solow Residual, which can arise

[6] Capital stock and labor are measured using the variable *rkna* and *emp* in the PWT 9.1.

from a synchronization of aggregate profits.

OA1.6 Alternative measure of SR correlation

In this robustness, the Solow Residual in the data is constructed using the PWT9.1 using the variables of real GDP (*rgdpo*), real capital stock (*rnna*), total employment (*emp*) and the index of human capital per employee (*hc*), such that: $SR_{ij} = log(rgdpo) - \alpha log(rnna) - (1 - \alpha)log(emp * hc)$, with $\alpha = 1/3$. With this method, we can compute the SR for up to 592 country-pairs over 4 time-windows. Complete results of the trade-SR comovement slope are shown in table 14, where point estimates are positive and significant for intermediate inputs. Results hold for both HP-filter and first difference.

Table. 14. Trade and SR correlation with 10 years time windows, alternative measure

	Corr $SR^{HP\ filter}$			Corr ΔSR		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(Trade^{total})$	0.010			0.013		
	(0.012)			(0.012)		
$\ln(Trade^{input})$		0.055**	0.066***		0.054**	0.064***
		(0.025)	(0.025)		(0.025)	(0.024)
$\ln(Trade^{final})$		−0.044*	−0.044*		−0.040*	−0.040*
		(0.024)	(0.024)		(0.024)	(0.024)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes
URSS + EU dum.	No	No	Yes	No	No	Yes
N	2,367	2,367	2,367	2,367	2,367	2,367
R^2	0.213	0.215	0.235	0.208	0.210	0.228

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs.

Finally, table 15 shows that our results concerning the slope with respect to SR, I and L are somewhat robust to the use of first difference and the use of BK filter. We point out however that the slope with respect to investment and trade in intermediate inputs turns to be not significant using those two filtering procedures.

OA1.7 The Role of the Extensive Margin

OA1.7.1 EM-IM decomposition using firm-level data

We now use the Exporter Dynamics Database (EDD) from the World Bank and test whether a change in the number of exporters (EM) and a change in the average value added per exporter (IM) are correlated with changes in real GDP comovement. This database provides measures of micro-characteristics of the export sector; number of exporters (their size and

Table. 15. Trade and SR, I and L correlation with 10 years time windows - Disaggregated trade

	Corr ΔSR	Corr ΔI	Corr ΔL	Corr $SR^{BK\ filter}$	Corr $I^{BK\ filter}$	Corr $L^{BK\ filter}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\text{Trade}^{\text{input}})$	0.044*	0.024	0.001	0.049*	0.009	0.010
	(0.024)	(0.028)	(0.024)	(0.027)	(0.034)	(0.025)
$\ln(\text{Trade}^{\text{final}})$	−0.025	−0.140***	−0.011	−0.034	−0.101***	−0.039
	(0.022)	(0.029)	(0.025)	(0.025)	(0.033)	(0.027)
CP + TW FE	Yes	Yes	Yes	Yes	Yes	Yes
Third country	Yes	Yes	Yes	Yes	Yes	Yes
URSS + EU dum.	Yes	Yes	Yes	Yes	Yes	Yes
N	2,367	2,367	2,367	2,367	2,367	2,367
R^2	0.196	0.159	0.132	0.213	0.187	0.125

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs.

growth), their dynamics in terms of entry, exit and survival, and the average unit prices of the products they trade, across 70 countries from 1997 to 2014. Over this time period, we average real GDP (transformed with log and HP-filter) correlations between country-pairs at quarterly frequency over 3 time-windows of 5 years, starting in 1997-Q1.[7] Due to the lack of coverage of the EDD, we use the only reported information of a reference country within a country-pair as direct measure for the EM and the IM.[8] Unfortunately, it is not possible to distinguish trade in intermediate goods and trade in final goods.

We measure the EM using the number of new exporters net of exiting firms between country i and country j, normalized by the total number of exporters. For the IM, we use the natural logarithm of the average value added per exporter. We test:

$$\text{Corr GDP}_{ijt} = \beta_1 \left[\frac{\text{Entry - Exit}}{\text{Nb Exp}}\right]_{ijt} + \beta_2 \ln\left(\left[\frac{\text{value}}{\text{exporter}}\right]_{ijt}\right) + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \tag{5}$$

Table **??**, column (Avg.), summarizes the results. Point estimates imply that an increase of 1% of the number of new net exporters is associated with an increase in real GDP correlation of about 3.5%. On the contrary, we find that the relationship between the IM and GDP correlation is not statistically significant. We then investigate in column (Std.) whether more variability along the extensive and intensive margins are associated with more real GDP correlation

[7] Unfortunately, OECD real GDP at quarterly frequency is not available for all the countries. We therefore reduce the sample. Further details regarding our sample are provided in the online appendix A.1 and robustness exercises are conducted in the online appendix A.4.

[8] For instance, the database contains information about exports from Belgium to many destinations, but there is no information about Belgium's imports. It is therefore not possible to compute symmetric measures.

within the considered time-windows. We test:

$$\text{Corr GDP}_{ijt} = \beta_1 \ln(\text{std nb exp}_{ijt}) + \beta_2 \ln\left(\left[\text{std } \frac{\text{value}}{\text{exporter}}\right]_{ijt}\right) + \text{CP}_{ij} + \text{TW}_t + \epsilon_{ijt} \quad (6)$$

Results feature a positive and significant relationship between variations in the number of exporters and GDP correlation, while variations along the intensive margin is negatively correlated with GDP comovement.

Table. 16. Cross-country GDP correlations and the margins of trade.

	Corr GDP$^{\text{HP filter}}$	
	(Avg.) specification	(Std.) specification
EM measure	3.480***	0.109*
	(1.285)	(0.065)
IM measure	−0.038	−0.022
	(0.163)	(0.043)
CP + TW FE	Yes	Yes
N	135	135
R^2	0.586	0.558

Notes: *p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs. We use EDD data from 1997 to 2014.
Avg. refers to specifications where we assess the link between GDP comovement and the average of each margin. Std. refers to specifications where we assess the link between GDP comovement and the volatility (standard deviation) of each margin in each configuration.

OA1.7.2 Robustness: HK decomposition using HS6 classification

In table 17, we provide the results of the estimation performed in section 6 of the paper using the Hummels and Klenow (2005) (HK) decomposition with the HS6 classification. It turns out that our results are consistent with this alternative specification (i.e. the slope is positive with respect to EM and negative with respect to IM). Only results with volatility of the EM measures is statistically significant. This could be due to the fact that we are not able to identify enough variation in the data with only two time windows, since our sample with the HS6 classification started from 1995 to 2006.

OA1.8 Markups, Terms of Trade and real GDP fluctuations

We used two different markup index estimates. We first used aggregated micro markups from De Loecker and Eeckhout (2018), who estimate aggregate markups using a cost-based approach in 134 countries from 1980 to 2016. This method defines markups as the ratio

Table. 17. Extensive and Intensive margins and GDP correlation with 5 years time windows using HS6

	Corr $GDP^{HP\ filter}$		Corr ΔGDP	
	(1)	(2)	(3)	(4)
ln(EM)	0.057		0.059	
	(0.087)		(0.098)	
ln(IM)	-0.103^{**}		-0.204^{***}	
	(0.051)		(0.059)	
ln(std(EM))		0.050^{**}		0.031
		(0.024)		(0.027)
ln(std(IM))		-0.034^{*}		-0.123^{***}
		(0.017)		(0.019)
Country-Pair FE	Yes	Yes	Yes	Yes
Time Window FE	No	Yes	No	Yes
N	1,122	1,122	1,122	1,122
R^2	0.238	0.239	0.209	0.066

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

of the output price to the marginal costs, and therefore relies solely on information from the financial statements of firms (sales value and cost of goods sold). Aggregating all firms specific markups for each country, De Loecker and Eeckhout (2018) provide a detailed and comparable measure of market power between countries. The sample that we use from their estimates includes 29 countries from 1980 to 2016.[9]

Second, we use Price Cost Margin (PCM) as an estimate of markups within each industry using data from 22 countries from 1971 to 2010.[10] Widely used in the literature, PCM is the difference between revenue and variable cost (the sum of labor and material expenditures, over revenue): $PCM = \frac{\text{Sales}-\text{Labor exp.}-\text{Material exp.}}{\text{Sales}}$. Data at the industry level come from the OECD STAN database, an unbalanced panel covering 107 sectors for 34 countries between 1970 and 2010. Due to missing data for many countries in the earliest years, we restrict the analysis for 22 countries. We compute PCM for each industry-country-year and then construct an average of PCM within each country-year by taking the sales-weighted average of PCM over each industry. Finally, the average PCM for a given time window is simply the mean of country-year PCM over all time periods.

[9]The list of countries is: Austria, Belgium, Canada, Colombia, Denmark, Finland, France, Germany, Greece, Ireland, Iceland, Indonesia India, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, Turkey, the United-Kingdom and the United-States.

[10]The list of countries is: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Iceland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, Portugal, Spain, Sweden, the United-Kingdom and the United-States.

Our model predicts that markups play an important role to make GDP react to foreign shocks. We now present additional empirical support and external validation for the role of markups in generating a link between terms of trade and real GDP fluctuations. We test the following hypothesis: countries where markups are high experience a larger decrease in real GDP when experiencing an increase in their terms-of-trade. For this, we compute the correlation of real GDP with the terms of trade and regress this correlation on markups estimates, such that:

$$\text{Corr(GDP , ToT)}_{it} = \beta\,\text{Markup.Index}_{it} + \text{Country}_i + \text{TW}_t + \epsilon_{it} \tag{7}$$

Table 18 gathers our findings.[11] We first show the results of pooled cross-section analysis and then perform fixed effect regression and add time dummies to control for time-window specific factors that might affect the correlation of GDP and terms-of-trade. We also run the exact same regression with the model generated data using $\frac{\sigma_i}{\sigma_i - 1}$ as markup index and using variations in σ_i. Regressions performed on model-generated data show that countries with higher markups also experience a larger decrease in their GDP when the relative price of their imports rises, consistent with what we observe in the data.

Table. 18. Markups and GDP-Terms of Trade correlation

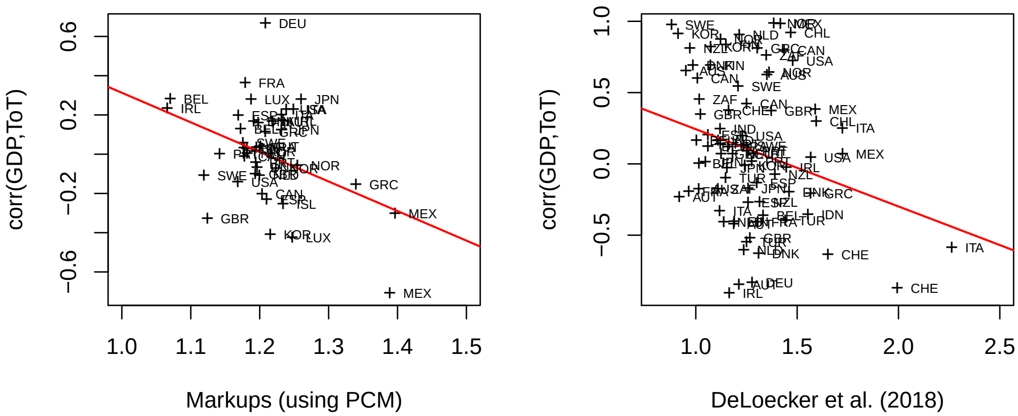
	$\text{Corr}(\ln(GDP_i^{HP}),\ln(ToT_i^{HP}))$				
	Data				Model
Markup measure	PCM [a]		De Loecker and Eeckhout (2018) [b]		
Markup index	-1.151 (0.967)	-2.650** (0.911)	-0.756*** (0.187)	-0.495* (0.289)	-0.262*** (0.019)
Country FE	Yes	Yes	Yes	Yes	Yes
Time windows FE	No	Yes	No	Yes	-
N	43	43	80	80	112
R^2	0.066	0.322	0.132	0.232	0.790

*p<0.1; **p<0.05; ***p<0.01. In parenthesis: std. deviation. SE clustered on country-pairs.
[a]We use two time-windows from 1971-2010 over 22 countries reported in appendix.
[b]We use three time-windows from 1980-2009 for 29 countries reported in appendix.

Figure 2 displays the relationship between $corr(GDP, ToT)$ and markups, measured as PCM (left panel) and using estimates in De Loecker and Eeckhout (2018) (right panel).

[11]Data on real GDP and terms of trade at the annual frequency are both taken from the OECD database and are HP filtered to capture business cycle frequencies. We also use first difference data and results are consistent with our findings using HP-filter, as shown in the online appendix A.5.2.

Figure 2. Markups and correlation GDP and Terms-of-trade.



OA2 An Economy Without Imported Inputs

In order to clarify the importance of international input-output linkages in generating a link between foreign shocks and domestic productivity, we review the intuitions presented in the paper in a situation with no imported input. In such a case, we show that markups(μ_{nt}) impact the measurement of GDP fluctuations only insofar that they vary over time. In other words, constant markups do not introduce any link between foreign shocks and domestic productivity.

Basic Setup In absence of imported inputs, the production function in country n at time t is directly expressed in value added terms as:

$$Y_{nt} = Z_{nt} K_{nt}^{\alpha} L_{nt}^{1-\alpha}$$

where Y_{nt} is the quantity of goods produced, K_{nt} and L_{nt} are the capital and labor inputs and Z_t is a measure of a country's efficiency at transforming inputs into output. Real GDP change between $t-1$ and t is constructed using previous period prices as base period prices, such that:

$$\widehat{GDP}_{nt} = \frac{P_{nt-1} \Delta Y_{nt}}{P_{nt-1} Y_{nt-1}} = \widehat{Y}_{nt} \approx \widehat{Z}_{nt} + \alpha \widehat{K}_{nt} + (1-\alpha) \widehat{L}_{nt} \tag{8}$$

Equation (8) illustrates that without international input-output linkages, the presence of markups in the base period prices used in RGDP construction does not introduce a term that creates a link between foreign goods and real GDP fluctuation. Keeping the TFP as an exogenous variable, this means that any endogenous change in real GDP in response to a foreign shocks comes from a change in factor supply ($\widehat{K}_{nt}$ or $\widehat{L}_{nt}$). If foreign goods and domestic inputs are complement, domestic real GDP can increase as a response to a positive foreign shock. However, this response is disciplined by the elasticity of factor supply.

Productivity Based on equation (8), we can construct proportional changes in the Solow Residual $\widehat{SR}_{nt}$ as:

$$\widehat{SR}_{nt} = \widehat{GDP}_{nt} - \alpha\widehat{K}_{nt} - (1-\alpha)\widehat{L}_{nt} = \widehat{Z}_{nt}$$

Without international input-output linkages, the negative result from Kehoe and Ruhl (2008) holds both with and without markups: domestic productivity is only driven by domestic technology and does not react to foreign shocks. Note however that despite the fact that μ_{nt} does not appear directly in equation (8), the presence of *variable* markups would have an impact on real GDP through its impact on labor and capital supply.

OA3 Quantitative Appendix

OA3.1 Detailed parameter values

Table 19 reports the parameter values used throughout the quantitative analysis.

OA3.2 SR measurement and attenuation bias

A possible concern when evaluating the trade-productivity slope is whether the Solow Residual (SR) is properly measured. As is standard, we defined SR such that it captures the change in real GDP ($RGDP$) that are not explained by movements of Labor and Capital. However, Huo et al. (2020) highlighted that such an approach is not perfect, as standard measures of factor inputs might be biased due to the presence of unobserved elements. As discussed in their paper, effective labor used in production might include a level of "unobserved effort" which implies that measures such as hours worked, which is available in standard database, do not accurately describe the effective level of labor input.

To better understand how measurement error can affect our results, we use our model as a data generating process. In particular, we assume that labor input effectively used in production is the combination of an observed factor $\widetilde{L}_{it}$ (for instance, total employment), and an unobserved factor u_{it} (for instance, labor utilization), so that $L_{it} = \widetilde{L}_{it} * u_{it}$. To investigate how the presence of unobserved factors impact our results, we define the "true" and the "mis-measured" Solow Residuals as follows:

$$\text{"True" SR}: \quad SR_{it} \quad = \log(RGDP_{it}) - \alpha \log(L_{it}) - (1-\alpha) * \log(K_{it}) \tag{9}$$

$$\text{"Mis-measured" SR}: \quad SR_{it}^{measured} \quad = \log(RGDP_{it}) - \alpha \log(\widetilde{L}_{it}) - (1-\alpha) * \log(K_{it}) \tag{10}$$

We model the unobserved part of labor input u_{it} as a stochastic variable and assume that it is positively synchronized with technology $Z_{i,t}$, i.e. $cov(Z_{it}, u_{it}) > 0$. This assumption captures the intuition that unobserved labor utilization (or effort level) is likely to co-move with the state of the aggregate economy. An econometrician only observes $\widetilde{L}_{it}$ and hence takes $SR_{it}^{measured}$ as a definition of the Solow Residual, even though it is not an exact measure of SR_{it}. The higher the variance of the unobserved factor u_{it}, the higher the generated measurement error in the evaluation of SR_{it}.

We investigate the consequences of measurement errors due to the presence of an unobserved factor on our results by setting $u_{it} = v_{it} + \mu\epsilon_{it}$, with ϵ_{it} the innovation used in the AR(1) generation of Z_{it} and $v_{it} \sim \mathcal{N}(\bar{v}, \sigma_v^2)$. The parameter μ captures the correlation between the unobserved factor with the aggregate TFP shock and v_{it} introduces additional movements in the unobserved factor that are not linked to the TFP shock. We set $\sigma_v = 0.032$, $\mu = 0.833$ and $\overline{v} = 0.17$. Table 20 provides the results and compares the result of using "true" and "mis-measured" SR in our regressions.

As expected, because L is not used directly in the definition of $RGDP$, the trade-comovement slope with respect to $RGDP$ is not affected by the presence of measurement error, as shown in the first row. More importantly, the presence of a measurement error in labor supply has consequences on both the SR-trade slope (second row) and the $RGDP$-trade slope once controlling for $corr(SR)$ (third row). First, the SR-slope is positive and significant for trade intensity in intermediate inputs, but the point estimate associated with a "mis-measured" SR is lower than its counterpart using the "true" value for SR. This is intuitive: "mis-measured" SR is more noisy than its "true" counterpart, and the cross-country correlation of the SR is lower. As a result, the explanatory power associated with trade in intermediate inputs is reduced. Second, in the third row, we look at the inclusion of $corr(SR)$ as a control in the regression of $corr(RGDP)$ on trade intensity. When $corr(SR)$ is properly measured, its inclusion as a control brings the input-trade slope close to zero. However, when $corr(SR)$ is mis-measured, the input-trade slope is reduced but still remains at 0.01, ten times higher than the point estimate of 0.001 obtained when using "true" $corr(SR)$ as a control. The presence of measurement error generates an attenuation bias which reduces the estimated association between $corr(RGDP)$ and $corr(SR)$. This, in turn, increases the point estimate for input trade. Overall, this analysis highlights that the presence of measurement error can explain why, in our empirical investigation, the inclusion of $corr(SR)$ as a control does not bring the trade slope to zero.

Table. 20. SR-trade comovement with measurement error, using model simulations

	"True" value for SR		With measurement error	
	Input	*Final*	*Input*	*Final*
$corr(RGDP)$ - trade slope	0.056***	0.006***	0.056***	0.006***
$corr(SR)$ - trade slope	0.051***	0.003***	0.045***	0.005***
$corr(RGDP)$ - trade slope, controlling for $corr(SR)$	0.001***	0.003***	0.010***	0.001***

*p<0.1; **p<0.05; ***p<0.01. SE clustered by country-pairs. Note that the simulations used here are based on a calibration with 15 countries among the set of 35 countries in the baseline model of the core paper.

OA3.3 Business cycle properties

In an effort to place our framework within the larger body of literature on international business cycles, we present the business cycle characteristics in Table 21. The model shares several characteristics of the standard IRBC model, including a strong correlation between C, I, and L with contemporaneous RGDP and a higher cross-country correlation of C compared to RGDP.

Table. 21. Business Cycle Statistics: Data and Models.[a]

	$\overline{std}^{RGDP}$	Avg. $\frac{std^X}{std^{RGDP}}$			Cross-country corr.				Corr. with $RGDP$			
		C	I	L	Y	C	I	L	Y_{-1}	C	I	L
Data[b] (average)	2.04	1.20	3.66	0.58	0.28	0.23	0.24	0.20	0.75	0.70	0.73	0.43
Model	1.97	0.60	3.88	0.34	0.32	0.48	0.47	0.47	0.75	0.96	0.96	0.96

[a] All model-based and observed statistics are computed using log transformation and HP-filter.

[b] Quarterly data for volatility are taken from Aguiar and Gopinath (2007) with a sample of 13 developed and 13 developing countries. Labor volatility is computed from the Penn World Table (PWT) and its model counterpart is annualized. Data for cross-country correlation and correlation with respect to RGDP uses the PWT.

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Table. 19. Parameter values

ISO	γ_i	f_i^E / f_{US}^E	$\sigma_i / (\sigma_i - 1)$	L_i^{ss}
ARG	0.29	4.38	1.56	13.60
AUS	0.31	0.45	1.19	8.90
AUT	0.30	3.93	1.16	3.76
BEL	0.24	0.71	1.23	4.12
BRA	0.33	14.93	1.59	68.13
CAN	0.35	0.98	1.28	14.95
CHE	0.31	1.79	1.72	3.93
CHL	0.29	1.34	1.58	5.54
CHN	0.10	5.25	1.31	735.72
DEU	0.32	2.59	1.20	39.60
DNK	0.31	1.07	1.47	2.76
ESP	0.30	2.50	1.23	16.61
FIN	0.27	3.04	1.17	2.31
FRA	0.33	0.80	1.21	25.63
GBR	0.33	1.07	1.33	27.38
GRC	0.44	2.32	1.20	4.45
IDN	0.34	9.38	1.48	91.55
IND	0.31	6.25	1.12	409.25
IRL	0.22	1.07	1.36	1.69
ISR	0.29	2.32	1.33	2.63
ITA	0.28	1.16	1.77	22.92
JPN	0.36	2.00	1.18	65.92
KOR	0.15	0.71	1.11	21.44
MEX	0.42	1.50	1.57	37.88
NLD	0.30	0.62	1.23	8.20
NOR	0.38	0.89	1.35	2.32
NZL	0.29	0.09	1.23	1.82
POL	0.26	6.61	1.33	14.48
PRT	0.30	1.07	1.19	5.08
SWE	0.29	2.86	1.16	694.76
THA	0.29	5.27	1.38	4.31
TUR	0.30	1.96	1.20	31.47
USA	0.43	1.00	1.47	20.09
VNM	0.29	6.07	1.33	138.64
ZAF	0.29	8.21	1.20	37.05
RoW	0.29	2.56	1.33	13.83
Mean	**0.30**	**3.02**	**1.33**	**72.30**