Fundamental Moments*

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Abstract

Global trade can give rise to global hubs, centers of activity whose influence on the global economy is large enough that local disturbances have consequences in the aggregate. This paper investigates the nature, existence, and rise of such hubs using the World Input-Output Tables (WIOT) to evaluate the importance of vertical trade in creating global hubs that significantly affect countries volatility and their co-movement. Our results suggest that the world has become more granular since 1995, with significant consequences on GDP volatility and co-movements especially in developed countries. These consequences are well explained by international trade.

Keywords: Aggregate volatility, GDP synchronization, global hubs, input-output linkages, World Input-Output Tables.

JEL Codes: E32, F44

1 Introduction

Microeconomic shocks have effects in the aggregate if the economy is populated by large firms or large sector, a property Gabaix (2011) calls "granularity". Then the law of large numbers does not hold in its strong form. The distribution of activity itself is an endogenous manifestation of vertical linkages as summarized by input-output tables. With the advent of global supply chains over the past decades, it is plausible that the

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patterns of specialization have altered significantly, at regional and global levels, giving rise to global hubs. If aggregate fluctuations have granular origins, then international trade is likely to affect aggregate moments at country, regional, and global levels, by changing the fundamental structure of the world economy. Here we investigate this possibility empirically.

We have known since Hulten (1978) that under some assumptions aggregate fluctuations can be represented by a weighted average of microeconomic shocks, for instance at sector level. The weights can be interpreted as the influence of each sector (Acemoglu et al., 2012), and influence vectors are in turn directly implied by input-output linkages, both purely domestic and across countries. We compute these influence vectors for all 40 countries covered by world input-output tables (WIOT) between 1995 and 2014. This provides a granular decomposition of aggregate fluctuations for most of the world economy. We verify whether the second moments of GDP in the panel formed by these countries correlate significantly with their *fundamental* (granular) determinants, implied by global input-output linkages. We focus on two of the most scrutinized moments of GDP fluctuations: their volatility and their international synchronization.

The main appeal of a granular decomposition of aggregate fluctuations grounded on WIOT is that the respective roles of domestic and international input-output linkages can readily be identified. WIOT comprises national input-output tables that form its block diagonale, to which international vertical linkages are appended for each pair of countries. Relative to conventional national tables, WIOT decomposes total trade for each country into the flows with each of its individual partner: All the exports from country c are broken down by country of destination, and all of its imports are broken down by country of origin.[1] Thus, it is possible to place every single country (or sector) in world trade provided it has coverage in WIOT. This opens the door for three interesting decompositions.

First, one can decompose WIOT into two matrices: one that embed only purely domestic input-output linkages, and one that focuses on international vertical trade. With this decomposition, one can assess whether the fundamental determinants of volatility and co-movements are associated with international trade. This decomposition does not purport to construct a counterfactual exercise characterizing what would have happened absent the rise in vertical trade. Rather, the exercise is performed as a decomposition, taking the patterns of trade as given by WIOT, i.e. implicitly given by a global distribution of productivities and trade costs. The patterns of trade observed in WIOT imply a worldwide distribution of influence vectors. And the influence vectors can, in turn,

[1] This of course does not go without simplifications. See for instance Dietzenbacher et al. (2013) for a detailed discussion of the construction of WIOT.

be decomposed into a domestic and an international component, which each map into aggregate volatility and co-movement.

Second, one can readily generate decompositions of WIOT omitting individual sectors. This exercise isolates the impact of a given activity on fundamental moments globally. Armed with such selected versions of WIOT, we evaluate empirically the consequences on volatility and co–movements of the existence and emergence of large sectors.

Third, one can focus on sub-sets of WIOT, characterized by large trade flows, where the intensity of vertical linkages is liable to create local hubs with sizeable consequence at the regional level. For instance did the deep economic integration within the European Union stimulate the emergence of local hubs? And did the developing world become more granular with the offshoring of manufacturing activities to China?[2]

The data paint a picture of increased granularity in the world economy, that seems largely due to international trade. The phenomenon is strongest in advanced economies, especially the European Union. Increased granularity translates in increased volatility of GDP: We find a large role for the fundamental explanations of aggregate volatility, at least on par with other conventional regressors. International trade, through its effect on granularity, increases aggregate volatility in the full sample of 40 countries. The result is most pronounced in rich countries, and corresponds to the emergence of a large financial and real estate sector, which has prevailed since the 2000's.

We also find a significant role for fundamental explanations of aggregate co-movements: Countries cycles are more synchronized when the same hubs exist in both economies. This is once again mostly true in advanced economies, but it is not exclusively explained by international trade. The fundamental drivers of co-movements have emerged in the 2000's, and they have intensified with the Great Financial Crisis of 2008. Once again, we find financial service and real estate to be a significant driver of this result.[3]

The possibility that microeconomic shocks have aggregate effects is not new (Jovanovic, 1987, Long and Plosser, 1987), but it has recently gone through a revival. Gabaix (2011) shows micro shocks can have aggregate effects in an economy populated by large firms or sectors. The intuition builds from Hulten (1978) who shows aggregate fluctuations can be decomposed into a weighted average of micro shocks, with weights

[2]These are not counter-factual exercises. Modifying the patterns of trade - increasing trade costs in one country, one sector, or one region - would have general equilibrium consequences on WIOT. Bosker and Westbrock (2015) propose counterfactual exercises about the welfare effects of changed trade costs in the world economy.

[3]No individual country is at the root of these results. We experimented on versions of WIOT from which the US, China, Germany, or other large advanced economies were omitted, but no results were altered significantly. We also experimented with subsets of countries, e.g. omitting Germany or the UK from the European Union, or China from developing economies. No results were significantly changed.

given by gross output shares (the "Domar" weights). When Domar weights are distributed with fat tails, micro shocks do not average out in the aggregate. Carvalho and Gabaix (2013) show the great moderation of the 1980's can be ascribed to a fall in the share of manufacturing in the US, while its undoing is due to the emergence of the financial sector. They confirm US aggregate volatility has sizeable fundamental origins. Our paper picks up from theirs, extending their analysis to more countries, and more aggregate moments.

Our approach allows for granularity to emerge from vertical trade. We closely follow Acemoglu et al. (2012) who construct a model in the spirit of Long and Plosser (1987) in which large sectors emerge because they are central in the network formed by input-output linkages. The Domar weights are then given by the influence vectors, capturing the existence and magnitude of hubs. Acemoglu et al. (2017) shows extreme events can occur in the aggregate simply because central sectors are exposed to fat-tailed idiosyncratic shocks. Using firm-level data, Bernard et al. (2019) document that the heterogeneity in Belgian firms can be ascribed to their place in the network of input-output linkages.

The literature has developed in three directions all introducing amendment to the classic Hulten result. First, with firm entry and exit, micro-dynamics can affect aggregate fluctuations through a different mechanism than Hulten's. The argument goes back to Hopenhayn (1992) and was more recently analyzed by Bilbiie et al. (2012), Clementi and Palazzo (2016), or Carvalho and Grassi (2019). Our paper works with sector-level data, and so abstracts from the extensive margin at firm level. Second, if micro shocks propagate throughout the economy, the simple Hulten arithmetic can be modified. Acemoglu et al. (2016) consider the propagation of shocks via input-output linkages. Carvalho et al. (2017) and Boehm et al. (2016) trace the global effects of shocks caused by natural disasters. Foerster et al. (2011) and Atalay (2017) control for propagation to identify separately "truly" idiosyncratic sector-level shocks. Our paper applies the Hulten arithmetic to sector-level shocks, which may or may not embed propagation mechanisms. In other words, we do not purport to identify "true" sector level disturbances: we take them as given and investigate their impact in the aggregate.[4] Third, Hulten's result requires efficient markets. With imperfections, Hulten's decomposition is augmented with second order effects. These can have large consequences, like in Baqaee (2018), Grassi (2018), or Bigio and La'O (2016). Baqaee and Farhi (2017) show how the Hulten decomposition must be amended to account for imperfections and inefficiencies in a general framework. Our paper focuses on first-order effects, if only because we follow

[4]In a companion paper, we propose a methodology to control for propagation mechanisms in a cross-country framework.

Acemoglu et al. (2012) and impose Cobb-Douglas production.

The question whether trade has consequences on aggregate moments is the object of a large literature. Johnson (2014) calibrates a model with final and intermediate goods trade to assess how the introduction of input-output linkages alter the trade-comovement puzzle. di Giovanni and Levchenko (2009) show sectors that are open to trade tend to display high volatility, which in turn affects aggregate volatility. di Giovanni and Levchenko (2010) show vertical trade between pairs of sectors tends to increase their co-movements, which in turn also affects aggregate co-movements. di Giovanni and Levchenko (2013) argue international trade increases the prevalence of fat tails in firm distributions, which in turn increases aggregate volatility. di Giovanni et al. (2014) argue firm-specific shocks affect aggregate volatility in France, because of fat-tailed firm distribution, and of domestic input-output linkages. di Giovanni et al. (2018) show French firms that trade with a country tend to co-move with the cycle there, which acts to increase significantly aggregate co-movements.

The rest of the paper is structured as follows. Section 2 describes our approach. Section 3 presents the results on volatility, on co-movements, and some robustness. Section 4 concludes.

2 Methodology

2.1 Empirical Implementation

Following Hulten (1978), Acemoglu et al (2012) show that, under perfect competition and Cobb Douglas production, aggregate fluctuations y_t can be written as a weighted average of micro-economic shocks, given by:

$$y_t = \sum_{i=1}^{n} \alpha_i \nu_{it} \varepsilon_{it} \tag{1}$$

where i indexes sectors, ε_{it} is a sector specific shock, α_i is the share of labor in sector i, and ν_{it} is the typical element of the influence vector ν_t. Acemoglu et al. (2012) show the influence vector is defined by

$$\nu_t' = \beta' \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t\right]^{-1}$$

where $\mathbf{I}$ is the identity matrix, β is a vector of sector-level final expenditure shares, $\mathbf{A}$ is a diagonal matrix of sector-level labor shares, and $\mathbf{W}_t$ reflects each economy's trade in intermediate goods. As such, $\mathbf{W}_t$ denotes each country's national input-output matrix, augmented with all elements in WIOT that capture the trade linkages of each country with the rest of the world. The decomposition of aggregate fluctuations necessitates therefore estimates of factor shares, expenditure shares, and empirical values for $(\mathbf{I}-\mathbf{A})\mathbf{W}_t$.

Information about $(\mathbf{I}-\mathbf{A})\mathbf{W}_t$ is directly available from WIOT, which reports $p_j x_{ij}$, the value of inputs from sector j used in the production of good i. Optimal choice of inputs guarantees that $p_j x_{ij} = (1-\alpha_i)\, p_i w_{ij} x_i$, where w_{ij} is a typical element of $\mathbf{W}_t$. Therefore,

$$w_{ij} = \frac{1}{1-\alpha_i}\frac{p_j x_{ij}}{p_i x_i}.$$

In other words, w_{ij} is given by a normalized version of WIOT, where the normalization is given by $(1-\alpha_i)\, p_i x_i$. By definition, a direct requirement matrix can be obtained by the normalization of the input-output matrix by total industry output, see Dietzenbacher et al. (2013). The typical element of a direct requirement matrix is therefore given by $\frac{p_j x_{ij}}{p_i x_i}$. It follows immediately that the typical element of the direct requirement matrix reported in WIOT can be written as $(1-\alpha_i)\, w_{ij}$. And thus it follows that $(\mathbf{I}-\mathbf{A})\mathbf{W}_t$ is exactly the direct requirement matrix reported in WIOT, with typical element $(1-\alpha_i)\, w_{ij}$. The direct requirement matrix in WIOT is therefore all that is needed to compute each industry's influence vector, across all countries.[5]

The factor shares α_i across sectors are directly obtained for each country from the direct requirement matrix in WIOT, using the definition

$$1-\alpha_i = \sum_j \frac{p_j x_{ij}}{p_i x_i}.$$

Finally, the expenditure shares on final goods β_i can be computed directly from WIOT as the sum of exports and domestic absorption net of final imports, expressed as a ratio of total value added in each sector i.[6]

2.2 The Role of Trade

Equation (1) defines an elasticity of GDP to sector-specific shocks that depends on the structure of vertical trade. Given the international structure of WIOT, it is possible to decompose the influence vectors into a part that corresponds to purely domestic input-output linkages, and one that reflects the international dimension of vertical trade. In particular, define $\mathbf{W}_t^{\mathrm{DOM}}$ as the block diagonale matrix formed by the domestic components of national input-output tables in WIOT, and $\mathbf{W}_t^{\mathrm{INT}}$ all the off-diagonale terms that reflect international vertical trade. Since $\mathbf{W}_t = \mathbf{W}_t^{\mathrm{DOM}} + \mathbf{W}_t^{\mathrm{INT}}$, the influence

[5] Here we differ from Acemoglu et al. (2012), who impose $\alpha_i = \alpha$, and need an empirical counterpart to $\mathbf{W}_t$. They obtain it by normalizing each entry in the US direct requirement matrix by $\sum_j p_j x_{ij}$, i.e., each column-wise sum.

[6] In practice, the final expenditure shares are computed using gross value added given in WIOT, and using Leontief's decomposition when needed. See Section 2.3.

vector is given by

$$
\begin{aligned}
\nu_t' &= \beta' \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{DOM}} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{INT}} \right]^{-1} \\
&= \beta' \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{DOM}} \right]^{-1} + \nu_t' \left[(\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{INT}} \right] \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{DOM}} \right]^{-1}.
\end{aligned}
$$

In addition, the final expenditure shares can be decomposed into a purely domestic term, and one focused on exports: $\beta_i = \beta_i^{\mathrm{DOM}} + \beta_i^{\mathrm{INT}}$, with β_i^{DOM} domestic expenditures on domestic final good i, and β_i^{INT} foreign expenditures on domestic final good. And the influence vector decomposes naturally into

$$
\nu_t' = \nu_t^{\mathrm{DOM}\,\prime} + \nu_t^{\mathrm{INT}\,\prime},
$$

where $\nu_t^{\mathrm{DOM}\,\prime} = \beta^{\mathrm{DOM}\,\prime} \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{DOM}} \right]^{-1}$ reflects the purely domestic component of the influence, and

$$
\nu_t^{\mathrm{INT}\,\prime} = \beta^{\mathrm{INT}\,\prime} \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{DOM}} \right]^{-1} + \nu_t' \left[(\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{INT}} \right] \left[\mathbf{I} - (\mathbf{I} - \mathbf{A})\mathbf{W}_t^{\mathrm{DOM}} \right]^{-1}
$$

embeds the role of international trade, both in intermediate and final goods.

By definition, aggregate fluctuations are given by

$$
y_t = \sum_{i=1}^{n} \alpha_i \nu_{it}^{\mathrm{DOM}} \varepsilon_{it} + \sum_{i=1}^{n} \alpha_i \nu_{it}^{\mathrm{INT}} \varepsilon_{it} \tag{2}
$$

which identifies the sources of granular aggregate fluctuations that arise from purely domestic linkages, and those that are caused by international trade.

2.3 The Role of Hubs

The previous exercise performs a decomposition of WIOT that makes no use of its bilateral dimension. More refined decompositions are possible: we now select out the trade linkages associated with individual countries, regions, or sectors rather than trade as a whole.

We first compute the influence vector

$$
\nu_t'^{-r} = \beta' \left[\mathbf{I} - (\mathbf{I} - \mathbf{A}) \, \mathbf{W}_t{}^{-r} \right]^{-1},
$$

where $\mathbf{W}_t{}^{-r}$ denotes the world input-output matrix where all cells involving country r are omitted. The influence vector $\nu_t'^{-r}$ implies a decomposition of aggregate fluctuations that corresponds to world input-output linkages abstracting from country r. Comparing the decomposition of aggregate fluctuations implied by ν_t' versus $\nu_t'^{-r}$ quantifies the contribution of country r in the emergence of a global hub, with potential consequences on aggregate moments. The same exercise can be performed among sub-sets of countries, formed for instance by regional trade agreements, and the importance of a specific country in each region can then be assessed analogously.

The same logic can be used to assess the importance of a given sector for aggregate fluctuations. Define the influence vector

$$\nu_t'^{-i} = \beta' \left[\mathbf{I} - (\mathbf{I} - \mathbf{A}) \, \mathbf{W}_t{}^{-i} \right]^{-1},$$

where $\mathbf{W}_t{}^{-i}$ denotes the world intput-output matrix where all cells involving sector i are omitted. The vector $\nu_t'^{-i}$ implies a decomposition of aggregate fluctuations abstracting from sector i. A comparison between ν_t' and $\nu_t'^{-i}$ helps quantify the role of sector i as a global hub. Once again, this decomposition can be performed globally, or for sub-sets of countries, for instance constituting regional trade areas.

Both manipulations imply changed values for factor shares, expenditure shares, value added, and intermediate use. To incorporate these changes in our evaluations of alternative influence vectors $\nu_t'^{-r}$ or $\nu_t'^{-i}$, we identify the mapping between input-output linkages and sector-level value added y_{it}. This mapping, due to Leontief (1936), is a simple identity that writes:

$$y_{it} = V_{it} \, \text{TR}_{it} \, \text{FD}_{it}$$

where $V_{it} = \frac{y_{it}}{s_{it}}$ is the so-called value added coefficient, s_{it} denotes gross output in sector i, TR_{it} denotes the typical element of the total requirement matrix $\left[\mathbf{I} - \mathbf{W}_t(\mathbf{I} - \mathbf{A})\right]^{-1}$, and FD_{it} is the typical element of final demand in sector i, given by $\left[\mathbf{I} - \mathbf{W}_t(\mathbf{I} - \mathbf{A})\right] \mathbf{s}_t$. Leontief's decomposition can be expressed in matrix algebrae, with self-explanatory notation:

$$\mathbf{Y}_t = \mathbf{V}_t \, \mathbf{TR}_t \, \mathbf{FD}_t$$

where $\mathbf{V}_t$ is a diagonal matrix populated with the value added coefficients $\frac{y_{it}}{s_{it}}$. Leontief's decomposition gives the estimates of sector and country sources of value added for each sector's final good production. For given values of $\mathbf{W}_t$, along with the associated values of $\mathbf{A}$ and β, Leontief's decomposition computes value added at sector-level y_{it}.

Now when we replace $\mathbf{W}_t$ with $\mathbf{W}_t{}^{-r}$ or $\mathbf{W}_t{}^{-i}$, the change evidently affects directly the definition of the direct requirement matrix $\mathbf{W}_t$. Simultaneously, it also modifies the matrix of value added $\mathbf{Y}_t$, for given observed gross output s_t. These two modifications jointly define changed values for $\mathbf{Y}_t$, $\mathbf{A}$, β, and ultimately the influence vector ν_t'.

3 Empirics

3.1 A first look at the data

Gabaix (2011) and Acemoglu et al. (2012) show that, if the empirical distribution of activity can be approximated by a power law with tail parameter $\eta \in (1,2)$, then aggregate volatility decays at a rate slower than $n^{-2(\eta-1)/\eta}$, where n is the number of sectors. The smaller the estimates of the tail η, the lower the rate of decay in aggregate moments as n increases. Put differently, the lower η, the more we are likely to find a systematic relation between the second moments of GDP and the specialization of the economy, as captured by the influence vector. As a first description of the data, we now present some tail estimates of these distributions across the economies covered by WIOT.

A conventional procedure to estimate the tails of a distribution is due to Clauset et al. (2009), which also provides an estimation of the threshold value $x_{\min}$ above which x follows a power distribution. The value of this threshold is important, for the estimation focuses on observations above it. For small values of n, an issue of finite sample bias is frequent in this procedure, resulting in an unduly high estimate of $x_{\min}$. This in turn results in tail parameters being estimated on few observations. Clauset et al. (2009) recommends truncating the search over $x_{\min}$ to relatively low values, which introduces a degree of arbitrariness in the resulting estimates. The approach is not palatable for small samples with $n < 50$.[7]

Here we follow instead Pesaran and Yang (2016), who introduce an estimator directly applicable to the production network structure in WIOT. The approach uses the distribution of outdegrees d_i, defined as the share of a sector's output used as intermediate input by all other sectors in the economy. The outdegree of each sector is simply given by the column-wise sum of the entries in $\mathbf{W}_t$. Pesaran and Yang (2016) introduce the notion of dominance $0 \leq \delta_i \leq 1$, defined as the speed at which the outdegree in sector i increases with n:

$$d_i = \kappa n^{\delta_i}$$

with κ a constant independent of n. Absent any dominant sector, $\delta_i = 0$ for all i; strong dominance implies $\delta_i = 1$, and values between 0 and 1 imply weak dominance. For microeconomic shocks to have aggregate effects at least one sector i must be dominant with at least $\delta_i > 1/2$. In fact, Pesaran and Yang (2016) show that the limiting behavior of $\nu_t' \nu_t$, i.e. fundamental aggregate variance, is determined by $n^{2(\delta_{\max}-1)}$, where $\delta_{\max} = \max(\delta_1, \ldots, \delta_n)$. The effects of sector-specific shocks on aggregate volatility only exist

[7] An alternative is a regression of the (log) rank on the (log) size of microeonomic units. This approach can also suffer from a small sample bias, as discussed in Gabaix and Ibragimov (2011), which disqualifies it for the present purpose. Log-rank regressions also famously have low power in rejecting power law distributions.

in finite sample for $\delta_{\max} > 1/2$.[8] Pesaran and Yang (2016) show formally that $\delta_{\max}$ maps into the (inverse of the) shape parameter η of the power law distribution of the production network, so that an estimate of $\delta_{\max}$ characterizes the power law.

It is possible to estimate $\delta_{\max}$ non-parametrically. For each sector, we have

$$\log d_i = \log \kappa + \delta_i \log n + \varepsilon_i.$$

Summing across sectors, this implies that

$$\log \kappa = \frac{1}{n} \sum_i \log d_i,$$

since $\frac{\log n}{n} \sum_i \delta_i$ and $\frac{1}{n} \sum_i \varepsilon_i$ both tend to 0 in the limit. It follows that

$$\delta_{\max} = \frac{\log d_{\max} - \frac{1}{n} \sum_i \log d_i}{\log n}$$

which provides an estimate of $\delta_{\max}$ given directly observable outdegrees d_i and their maximum value $d_{\max}$. Since the tail of the distribution η is given by the inverse of $\delta_{\max}$, this characterizes the distribution.

To gain in precision, we implement the estimation over panel data, as recommended by Pesaran and Yang (2016) in small samples. We separate the available sample into two periods around the Great Recession of 2007/2008, first from 1995 to 2007, and then from 2008 to 2014. Standard errors for $\delta_{\max}$ are computed following Section 7.2.1 and 7.2.2 in Pesaran and Yang (2016) and the standard error of η is obtained using the Delta method. The non-parametric approach also makes it possible to identify all dominant units in WIOT, and in particular to document what sectors are dominant and whether their identities have changed over time.

WIOT covers 40 developed and developing countries, and provides annual data from 1995 to 2014.[9] The covered countries account for approximately 85% of world GDP. The input-output data are available for 31 industries for each country and each year. The data is in millions of U.S. dollars at current prices. Dietzenbacher et al. (2013) details the methodology used to construct these data.[10]

We estimate η for four large economies and for relevant groupings of countries such

[8] And they only survive for $n \to \infty$ if there is at least one strongly dominant sector.

[9] See http://www.wiod.org/database/iot.html

[10] We merge two releases of WIOT. The 2013 release contains input-output data for 40 countries and 35 industries (ISIC Rev. 3) spanning from 1995 – 2011. The 2016 release contains 43 countries and 56 industries (ISIC Rev. 4) spanning from 2000 – 2014. We use the 2013 release from 1995 – 1999 and the 2016 release from 2000 – 2014. We match all industries according to the ISIC Rev. 3 definitions which results in 31 industries and 40 countries.

as the European Union. We also provide estimates for the whole world, and for versions that omit the US or China. To do so, we aggregate all the relevant elements in WIOT across countries: we select the elements in WIOT that summarize each country's production and exports in each sector, and sum them across all relevant countries. Given this synthetic aggregate matrix, we compute the outdegrees and their maximum values. Finally, we identify the impact of international trade by aggregating the elements of WIOT that pertain to purely domestic production in each sector across all relevant countries, and compute the outdegrees accordingly.

Table 1 reports our estimates for the whole period from 1995 to 2014, and pre / post-2008. The left panel uses all the elements in WIOT, the right panel focuses on the entries corresponding to purely domestic input trade. Worldwide estimates of η are 1.925 over the full period, and displays a slight increase over the period, from 1.917 to 1.939, suggesting the world diversifies slightly. This result survives if one abstracts from the US, but it is reversed if it is China that is omitted. In other words, it is because of the emergence of China in the global economy that the world has become more diversified: Even though large sectors are emerging in China, they are sufficiently specific to China that the world is diversifying. We can see this from Table A1 in the appendix, where we list the three most pervasive sectors for each region and country, as defined by the three largest values of δ_i. The dominant sectors in China (in the sense of $\delta_{\max}$) are equipment goods, chemicals, and agriculture. But the dominant sectors globally are "Renting and Other Business Services" and financial intermediation.[11], [12]

Table 1's lower panel presents estimates for individual countries and the European Union (EU). Over the full period, Germany is the most specialized economy ($\eta = 1.447$), followed by the US ($\eta = 1.488$), China ($\eta = 1.575$), and the EU ($\eta = 1.646$). But these countries are on diverging trends: China is strongly diversifying its economy over the period, η increasing from 1.510 to 1.710 since 1995. The US and the EU are going the other way, with estimates of η that are actually significantly lower than China's over the most recent period 2008-2014. This is likely reflecting the industrialisation of a country initially specialized in agricultural production, and the de-industrialization of countries producing mostly in services. The data in Table A1 support this interpretation: China's dominant sectors included agriculture betwen 1995 and 2007, but that was replaced by petrol after 2008. The EU's dominant sectors included equipment goods between 1995 and 2007, but that was replaced by utilities after 2008.

[11]"Renting and Other Business Services" is short for Renting of Machinery & Equipment and Other Business Services industry, K71 to K74 of the ISIC Rev. 3.)

[12]This is akin to what Grazzini and Spelta (2015) document: peripheral sectors in 1995 became important by 2011.

Table 1: Tail estimations (η)

Country/Region	With Trade 95 – 14	With Trade 95 – 07	With Trade 08 – 14	Without Trade 95 – 14	Without Trade 95 – 07	Without Trade 08 – 14
World	1.925	1.917	1.939	1.886	1.875	1.907
	(0.05)	(0.06)	(0.02)	(0.04)	(0.06)	(0.02)
World w/o USA	2.109	2.098	2.129	2.059	2.040	2.094
	(0.06)	(0.09)	(0.02)	(0.06)	(0.08)	(0.03)
World w/o China	1.835	1.854	1.800	1.785	1.805	1.750
	(0.04)	(0.06)	(0.01)	(0.04)	(0.06)	(0.01)
Germany	1.447	1.436	1.469	1.518	1.511	1.531
	(0.04)	(0.05)	(0.03)	(0.06)	(0.06)	(0.07)
USA	1.488	1.512	1.443	1.473	1.501	1.424
	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)
China	1.575	1.510	1.710	2.205	2.067	2.415
	(0.08)	(0.08)	(0.09)	(0.13)	(0.15)	(0.06)
EU15	1.646	1.675	1.595	1.583	1.607	1.540
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)

Notes: The tail estimates of η are the inverse of the estimator of $\delta_{\max}$ proposed by Pesaran and Yang (2016). The approach is based on the distribution of the outdegree of sectors. Standard errors are in parentheses.

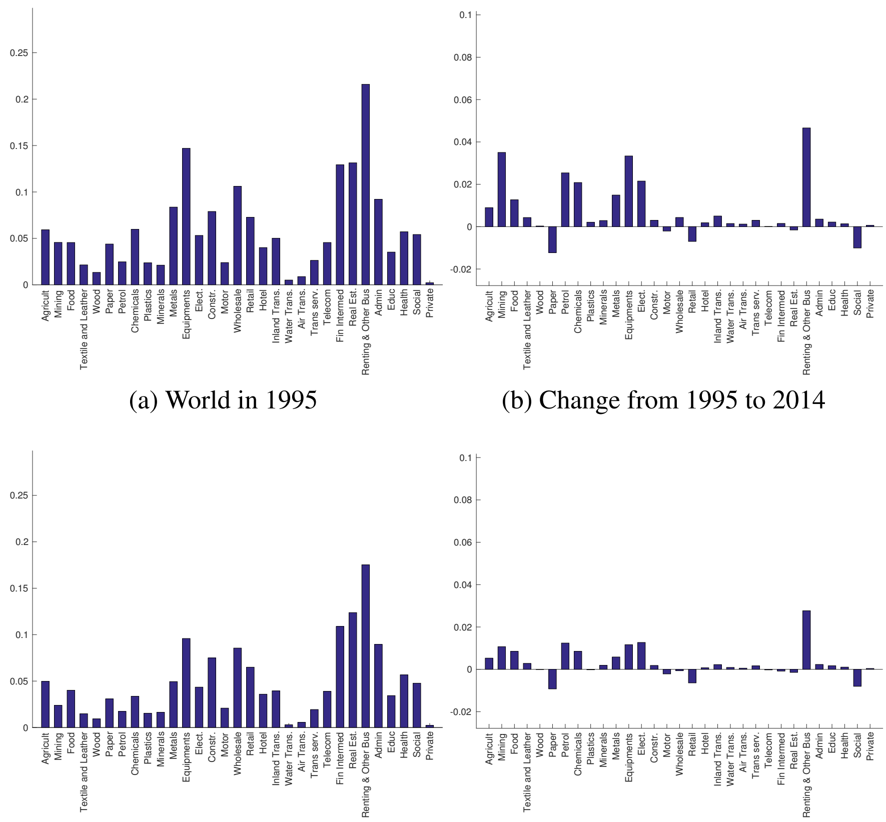
Germany constitutes an exception here, as its specialization fell slightly (but significantly), presumably because Germany did not de-industrialize much in the recent period. In fact, Germany's dominant sectors remain unchanged over the period: including Renting and Other Business Services, equipment goods, and transportation services.

How much of these trends are related with international trade? The right panel of Table 1 begins to answer this question with estimates of η abstracting from trade. First, China is estimated to be much more diversified abstracting from trade with estimates of η significantly above 2.[13] China, however, is still estimated to diversify from 1995 to 2014 even in the absence of international trade. The same can be said of Germany, although the magnitudes are much smaller: without trade Germany appears more diversified, and specializes slightly but not significantly. The EU displays the opposite pattern: without trade, the region is more specialized (1.583 vs. 1.646), and it specializes over time. The trends in the US are similar but not significant. Table A2 in the Appendix reports tail estimates for all 40 countries in the sample. The same conclusions emerge: the average country specializes, and it tends to happen because of international trade.

The elasticity of aggregate fluctuations to sector-level shocks is given by each element of the influence vector ν_{it}. For asymmetric distributions of ν_{it}, sector-level disturbances will not cancel out in the aggregate: It is of independent interest to document the

[13] In fact, aggregate moments do not exist for $\eta > 2$. It is reassuring that such estimates only arise in artificial constructs, abstracting from trade, or from a country.

empirical distributions of influence by sector. Figures 1 to 3 do so, first for the world economy as a whole, and then for three large economies, Germany, the US, and China. Each figure reports the initial distribution estimates in 1995, the change in each sector's influence between 1995 and 2014, and the estimates corresponding to a version of WIOT focused on domestic trade only.



(a) World in 1995

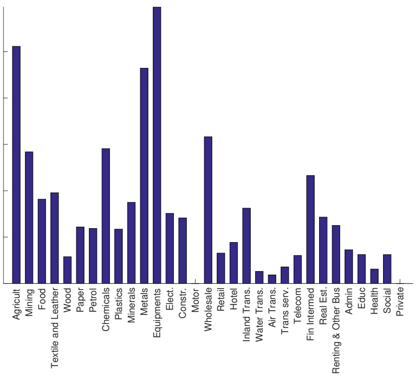
(b) Change from 1995 to 2014

(c) World in 1995 – Domestic

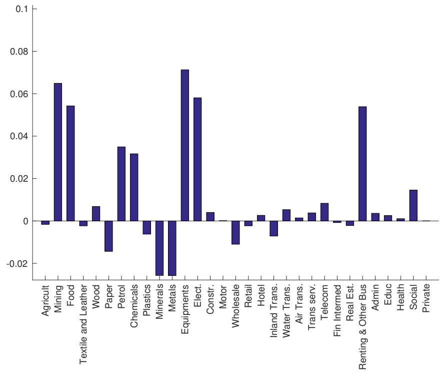
(d) Change from 1995 to 2014

Figure 1: Influence vectors for the world economy.

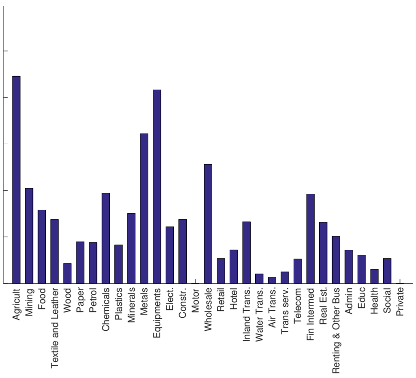
Figure 1 documents a bi-modal distribution for the worldwide influence vector in 1995: A first mode contains services, namely Renting and other business services, financial intermediation, real estate (FIRE), and wholesale, and a second one contains heavy manufacturing, namely equipments and metals. Interestingly, the 20 years since 1995 have witnessed an increase in already influent sectors: the largest increase occurred in the most influent sector, Renting and other business services. The second largest occurred in equipment goods, followed by mining. This is consistent with the world becoming more granular over the period, in the sense that the aggregate influence of a few sectors has risen. Abstracting from trade in the lower panel shows that a large part of the influence of manufactures originates from international trade: equipment goods, in particular are much less influent abstracting from trade. Renting and business services is still increasing the fastest between 1995 and 2014, even without the effect of trade.



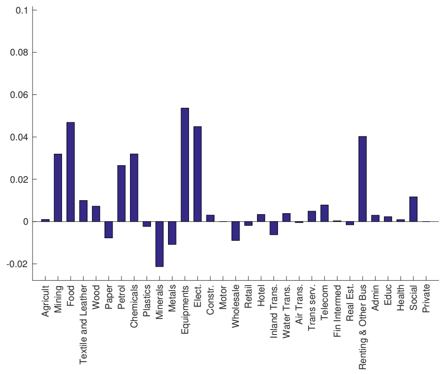
(a) China 1995



(b) Change from 1995 to 2014



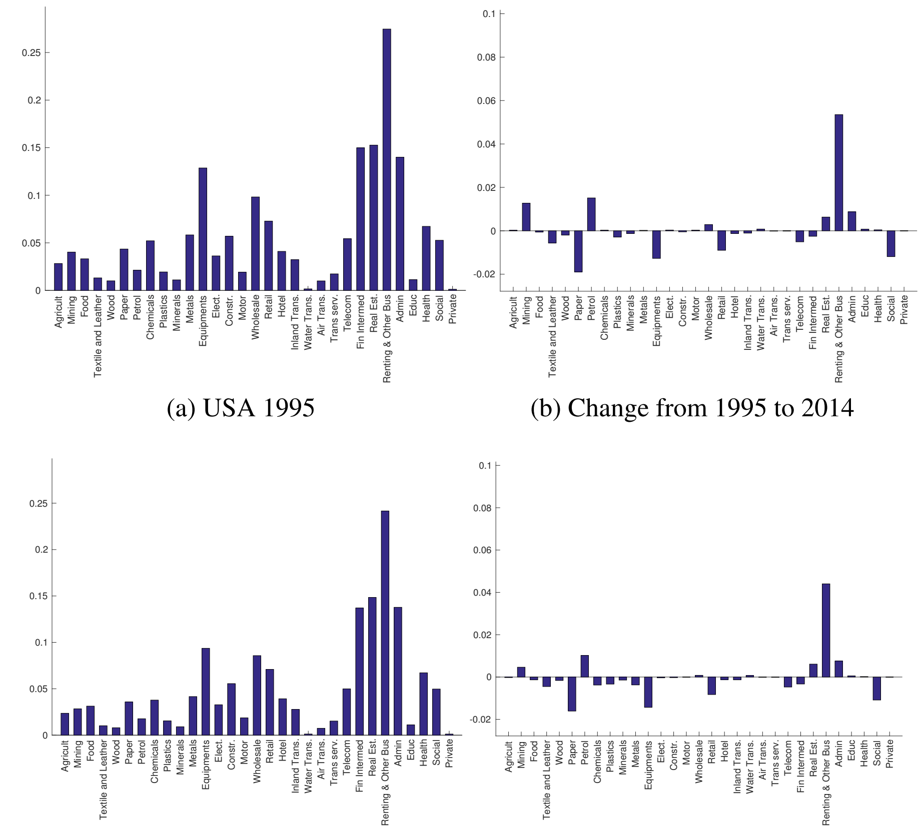
(c) China 1995 – Domestic



(d) Change from 1995 to 2014

Figure 2: Influence vectors for China.

Figure 2 focuses on China, whose distribution is very different from the world's. In 1995, China's most influent sectors are equipment goods, agriculture, metals, and wholesale. Influence in China comes from heavy manufacturing sectors, and agriculture – very little from services. Since 1995, equipment goods, electricity, mining and food have become more influent, whereas metals, minerals, small manufacturing (like paper or plastics), and agriculture have all become less influent. This is consistent with the result that China's tail estimates have increased since 1995, since newly large sectors have emerged. The distribution of influence abstracting from trade, presented in the lower panel, is similar to the rest of Figure 2 trade does affect the influence of Chinese sectors, but it does so in a relatively homogeneous fashion across sectors.



(a) USA 1995

(b) Change from 1995 to 2014

(c) USA 1995 – Domestic

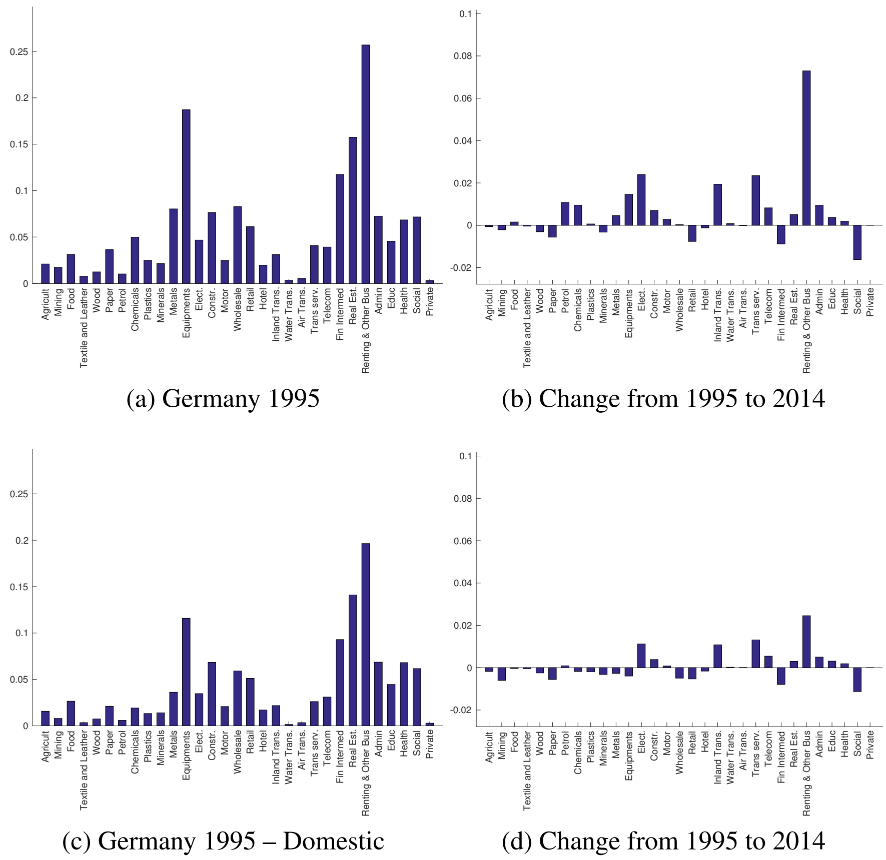
(d) Change from 1995 to 2014

Figure 3: Influence vectors for USA.

Figures 3 and 4 presents distribution estimates for the US and Germany. Both countries are predominantly service economies, with Renting and other business services the most influent sector, along with FIRE and administrative services. Equipment goods are the second most influent sector in Germany, and the fifth one in the US. In both countries, Renting and other business services has seen the fastest rate of increase in the 20 years since 1995, but Germany also experienced a sustained increase in the influence of several manufacturing sectors (equipments, electricity, petrol, and chemicals). This explains the fall in the US tail estimate, and the somewhat muted fall in the German estimate. The increase in the influence of Renting and other business services is largely due to international trade in both countries, with muted changes in that sector once international trade is abstracted from subfigures (c), (d), (g) and (h). This confirms the specialization of both economies can be ascribed to trade.

3.2 Fundamental Volatility

This Section presents evidence on the consequences of microeconomic disturbances on aggregate volatility. The key contribution is to extend existing results to the interna-



(a) Germany 1995 (b) Change from 1995 to 2014

(c) Germany 1995 – Domestic (d) Change from 1995 to 2014

Figure 4: Influence vectors for Germany

tional dimension, which makes it possible to isolate the role of international trade. We investigate whether the rate of decay in aggregate volatility is sufficiently low that we actually observe a systematic relationship between the observed volatility in GDP and its fundamental counterpart, implied by the sector specialization of the economy, given by

$$\sum_{i=1}^{n} \left(\alpha_i \nu_{i,t}\right)^2 \sigma_i^2$$

where σ_i^2 denotes the volatility of sector shocks.[14] We estimate the following panel model

$$V_{c,t} = \alpha_c + \gamma_t + \alpha \sum_{i=1}^{n} \left(\alpha_i \nu_{i,t}\right)^2 + \beta \mathbf{Z}_{c.t} + \xi_{c,t}, \tag{3}$$

where $V_{c,t}$ is the volatility of GDP in country c and at time t, and $\sum_{i=1}^{n} \left(\alpha_i \nu_{i,t}\right)^2$ is a Herfindahl index of sector influence that is theoretically relevant for aggregate volatility in country c. The sector-level variance σ_i^2 is omitted from the regression, since the

[14] A key assumption here is that the sector-level disturbances ε_{it} have time-invariant variance that is constant across countries. We test this assumption in the robustness section.

assumption that $\sigma^2_{i,c,t} = \sigma^2_i$ (for all c and t) implies that the variance of sector-level idiosyncratic shocks does not vary in the country-time dimension of the panel.[15] α_c is a country-specific intercept, γ_t is a year effect, and $\mathbf{Z}_{c.t}$ includes additional controls for the patterns of aggregate volatility. Positive and significant estimates of α would confirm across countries the evidence focused on the US that can be found in Carvalho and Gabaix (2013) or Acemoglu et al. (2012). Given the presence of country-specific intercepts, estimates of α are to be interpreted as changes in the fundamental specialization of the economy that over time tend to translate into changes in the volatility of GDP.

The decomposition of input-output linkages into purely domestic elements and those arising from international trade has an immediate application to the definition of fundamental volatility, which can decompose into

$$\sum_{i=1}^{n} {\alpha_i}^2 \, {\nu_{i,t}^{\mathrm{DOM}}}^2 \, {\sigma_i}^2 + \sum_{i=1}^{n} {\alpha_i}^2 \, \nu_{i,t}^{\mathrm{TRADE}} \, {\sigma_i}^2$$

where $\nu_{i,t}^{\mathrm{TRADE}} = {\nu_{i,t}^{\mathrm{INT}}}^2 + 2\nu_{i,t}^{\mathrm{DOM}}\nu_{i,t}^{\mathrm{INT}}$. It follows that equation (3) can be readily amended to evaluate the importance of international trade for the fundamental determinant of aggregate volatility:

$$V_{c,t} = \alpha_c + \gamma_t + \alpha_1 \sum_{i=1}^{n} \left(\alpha_i \nu_{i,t}^{\mathrm{DOM}}\right)^2 + \alpha_2 \sum_{i=1}^{n} {\alpha_i}^2 \, \nu_{i,t}^{\mathrm{TRADE}} + \beta \mathbf{Z}_{c.t} + \xi_{c,t}, \qquad (4)$$

The estimates of α_1 and α_2 decompose the sources of fundamental volatility between those arising from purely domestic input-output linkages, and those arising from international trade, respectively.

The influence vector ${\nu'_t}^{-j}$ can be used to assess the global importance of a given sector for aggregate volatility. We estimate

$$V_{c,t} = \alpha_c + \gamma_t + \alpha \sum_{i=1, i\neq j}^{n} \left(\alpha_i \nu_{i,t}\right)^2 + \beta \mathbf{Z}_{c.t} + \xi_{c,t}^{-j}, \qquad (5)$$

where the influence vector is now computed abstracting from input-output linkages that involve sector j. Equation (5) can help pinpoint the emergence of a large sector as a cause for a rise in aggregate volatility across countries.

Analogously, the influence vectors ${\nu'_t}^{-r}$ can readily be used to evaluate the contri-

[15]This is confirmed in the robustness section.

bution of a given country to aggregate volatility. In particular, we estimate

$$V_{c,t}^{-r} = \alpha_c^{-r} + \gamma_t + \alpha \sum_{i=1}^{n} \left(\alpha_i \nu_{i,t}^{-r} \right)^2 + \beta \mathbf{Z}_{c,t}^{-r} + \xi_{c,t}^{-r}, \tag{6}$$

where the subscript $-r$ denotes the exclusion of country r from the panel. The decomposition can be implemented to address the role of an emerging China in world trade, or the increasing fragmentation of the value chain across the US, Asia, and Europe.

In what follows, we present the results associated with the estimations of equations (3) to (6) on the sample formed by the 40 countries with WIOT coverage. Measures of $V_{c,t}$ are obtained from the annual growth rates of real GDP in 2005 PPP dollars, as reported by the Penn World Tables (version 9.0). The panel runs from 1986 to 2014, and $V_{c,t}$ is the volatility of GDP growth measured over 10-year rolling windows centered on year t.[16] Table 2 presents estimates of equations (3) and (4), including controls $\mathbf{Z}_{c.t}$ in specifications (3) and (4). We let volatility depend on financial and banking crises, as mesured by Laeven and Valencia (2013), and on per capita GDP, following Koren and Tenreyro (2007).

Table 2: Volatility of GDP

	(1)	(2)	(3)	(4)
$\sum_i^n (\alpha_i \nu_{i,t})^2$	13.3	5.84		
	(3.36)	(2.85)		
$\sum_i^n (\alpha_i \nu_{i,t}^{\text{DOM}})^2$			2.68	-2.96
			(5.55)	(4.83)
$\sum_i^n \alpha_i^2 \nu_{i,t}^{\text{TRADE}}$			18.14	9.99
			(4.33)	(3.08)
Crisis		0.02		0.02
		(0.03)		(0.03)
Real GDP p.c.		-0.73		-0.72
		(0.18)		(0.18)
R^2	0.16	0.30	0.17	0.31
$N \times T$	800	800	800	800

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are autocorrelation and heteroskedasticity robust, with a Bartlett Kernel to account for the 10 years rolling windows used to estimate the volatility of GDP. All regressions include time-dummies and country fixed-effects.

[16] The standard errors are corrected for the serial correlation induced by the computation of volatility in overlapping rolling windows using the standard Bartlett correction.

Table 2 suggests that granular volatility prevails in the sample formed by 40 countries. Interestingly, the granularity that is related with international trade, $\sum_{i=1}^{n} {\alpha_i}^2\ \nu_{i,t}^{\mathrm{TRADE}}$, is always correlated significantly with aggregate volatility. The same is not true of the granularity implied by the purely domestic component of WIOD. This is indicative of the fact that international trade tends to exacerbate the granularity of the countries in our sample, presumably through the specialization of the economy.

Table 3: Volatility of GDP cycles in regions

Region	OECD-19		EU-15		EU-27		DVC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum_i^n(\alpha_i\nu_{i,t})^2$	7.33		7.19		-0.13		0.84	
	(2.53)		(2.69)		(0.09)		(3.01)	
$\sum_i^n(\alpha_i\nu_{i,t}^{\mathrm{DOM}})^2$		6.30		6.97		-1.94		-1.70
		(3.03)		(3.39)		(3.40)		(2.77)
$\sum_i^n \alpha_i^2\nu_{i,t}^{\mathrm{TRADE}}$		8.30		7.65		-0.11		42.6
		(2.24)		(3.50)		(0.09)		(19.3)
Crisis	0.04	0.04	0.06	0.06	0.12	0.12	-0.004	-0.02
	(0.02)	(0.02)	(0.04)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)
Real GDP p.c.	-0.12	-0.15	-0.16	-0.17	-1.11	-1.11	-0.29	-0.17
	(0.02)	(0.02)	(0.12)	(0.11)	(0.29)	(0.29)	(0.17)	(0.14)
R^2	0.29	0.29	0.31	0.31	0.40	0.40	0.27	0.30
$N \times T$	380	380	300	300	540	540	180	180

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are autocorrelation and heteroskedasticity robust, with a Bartlett Kernel to account for the 10 years rolling window used to estimate the volatility of GDP. All regressions include time-dummies and country fixed-effects. DVC countries include: Brazil, China, India, Indonesia, Mexico, Russia, South Korea, Turkey, and Taiwan.

Table 3 investigates composition effects by splitting the analysis in samples of OECD countries, and relatively less developed economies including some emerging markets.[17] Specifications (1) to (4) in the Table suggest the mechanism prevails exclusively in rich developed countries, i.e., in a narrow sample of OECD economies or in the core of the European Union. In those samples, we find that the fundamental determinants of volatility are channeled by both the international and domestic components of intermediate trade. In the rest of the world, however, the effect is absent: the coefficients of

[17] OECD-19 includes Australia, Austria, Belgium, Canada, Germany, Denmark, Spain, Finland, France, the UK, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, Portugal, Sweden, and the USA. EU-15 includes Austria, Belgium, Germany, Denmark, Spain, Finland, France, the UK, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Sweden. EU-27 adds Bulgaria, Cyprus, the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia, and Slovenia. DVC includes Brazil, China, Indonesia, India, South Korea, Mexico, Russia, Turkey, and Taiwan.

interest are insignificant in a sample formed by 27 EU members, including most of the recent accession countries, and in a sample of developing countries.[18] Fundamental determinants of aggregate volatility seem to prevail in rich countries: according to Imbs and Wacziarg (2003), those are the ones specializing, whereas less rich countries tend to diversify.

Table 4: Volatility of GDP – pre-2001 and post-2007

	(1)	(2)	(3)	(4)
$\sum_i^n(\alpha_i\nu_{i,t})^2 \times \text{pre-2001}$	-16.60	-15.62		
	(3.46)	(3.10)		
$\sum_i^n(\alpha_i\nu_{i,t})^2$	15.31	10.07		
	(3.17)	(2.74)		
$\sum_i^n(\alpha_i\nu_{i,t})^2 \times \text{post-2007}$	1.14	-1.50		
	(1.58)	(1.86)		
$\sum_i^n(\alpha_i\nu_{i,t}^{\text{DOM}})^2 \times \text{pre-2001}$			-20.65	-18.80
			(4.40)	(3.85)
$\sum_i^n \alpha_i\nu_{i,t}^{\text{TRADE}} \times \text{pre-2001}$			-12.62	-12.63
			(2.62)	(2.44)
$\sum_i^n(\alpha_i\nu_{i,t}^{\text{DOM}})^2$			3.73	0.22
			(4.48)	(3.80)
$\sum_i^n \alpha_i^2\nu_{i,t}^{\text{TRADE}}$			22.43	16.65
			(3.97)	(3.28)
$\sum_i^n(\alpha_i\nu_{i,t}^{\text{DOM}})^2 \times \text{post-2007}$			1.31	-1.40
			(1.99)	(2.30)
$\sum_i^n \alpha_i^2\nu_{i,t}^{\text{TRADE}} \times \text{post-2007}$			-0.51	-2.63
			(1.44)	(1.70)
Crises		0.01		0.01
		(0.03)		(0.03)
Real GDP p.c.		-0.64		-0.60
		(0.17)		(0.15)
R^2	0.29	0.40	0.34	0.42
$N \times T$	800	800	800	800

Notes: Standard errors are in parentheses. The dummy variable pre-2001 takes value 1 for $t < 2001$ and 0 otherwise; post-2007 takes value 1 for $t > 2007$ and 0 otherwise. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are autocorrelation and heteroskedasticity robust, with a Bartlett Kernel to account for the 10 years rolling window used to estimate the volatility of GDP. All regressions include time-dummies and country fixed-effects.

[18]The large point estimates for developing countries come from the time pattern of volatility experienced by Russia over the sample, which correlates highly with $\sum_i^n \alpha_i\nu_i^{\text{TRADE}}$ because of commodity prices. Without Russia, the coefficient on $\sum_i^n \alpha_i\nu_i^{\text{TRADE}}$ becomes insignificant.

Table 4 checks how the results hold through the sample period. We split the sample into three periods: (i) from 1995 to 2000, the early years of the Great Moderation, (ii) from 2001 to 2007, the globalization years, with China becoming a member of the World Trade Organization, and (iii) from 2008 to 2014, the Great Recession years. Specification (1) examines how the estimates of α change over time, introducing two indicator variables: the first taking values one before 2001, and the second taking values one after 2007. Unconditional estimates correspond to the globalization period. The results are interesting: the period before 2001 displays significantly less fundamental volatility than the rest of the sample, suggesting the mechanism at play started in earnest with the globalization period, where the coefficient is in fact positive and significant. But there was no acceleration of the phenomenon after 2007. Specification (3) examines the role of trade in each of the sub-period: whereas the negative coefficient in the pre-2001 period applies to both domestic and international fundamental volatilities, the acceleration during the globalization period is exclusively driven by the traded component of fundamental volatility. These conclusions are unchanged by the inclusion of the controls in specifications (2) and (4). The emergence of fundamental determinants to aggregate volatility seems to be strongly associated with the globalization of the world economy from 2001, but left unchanged by the global financial crisis from 2008 onwards.

Table 5 investigates whether these results are driven by specific sectors. The table focuses on the three samples of countries where we found significant results. We computed $\nu_t'^{-j}$ for all j measured at the one-digit level, and estimated equation (3) for each implied value of $\sum_{i=1,i\neq j}^{n} \left(\alpha_i \nu_{i,t}\right)^2$. The table reports results for all the sectors whose omission affects the significance of α in equation (5), considering all three samples. We find Finance and Real Estate (FIRE) has by far the strongest influence on the results: When fundamental volatility is computed without FIRE, it becomes insignificant for GDP volatility in all considered samples. There are other sectors that have some effects on the estimates, but they are more limited. For example, wholesale trade, agriculture, and equipment all result in insignificant estimates of α in the world sample, but not elsewhere. Finally, for illustrative purposes we include Telecommunications, which does not affect any of the estimates: This is the case for all other sectors, not listed in the Table for the sake of brevity. We conclude that in developed countries, fundamental volatility is driven by the FIRE sector. In the world at large, it is globally influent sectors that matter for aggregate volatility: wholesale trade, agriculture, and equipment. We note the list includes sectors whose influence has been increasing since the 1990's, and both traded and non-traded activities.

Finally, we experimented with estimating equation (6), performed in samples omitting the largest economies in the world, one at a time. We experimented with omitting

Table 5: Volatility of GDP without Industries

Without	FIRE (1)	Wholesale (2)	Agric. (3)	Equip. (4)	Telecom. (5)
			Panel A: World		
$\sum_i^n(\alpha_i\nu_{i,t})^2$	0.02	4.52	-0.01	-0.22	5.65
	(0.03)	(2.89)	(0.003)	(0.29)	(2.77)
Crises	0.03	0.02	0.03	0.03	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Real GDP p.c.	-0.76	-0.74	-0.76	-0.76	-0.73
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
R^2	0.29	0.30	0.29	0.29	0.30
$N \times T$	800	800	800	800	800
			Panel B: OECD-19		
$\sum_i^n(\alpha_i\nu_{i,t})^2$	2.65	5.65	7.03	7.76	6.95
	(1.68)	(2.92)	(2.47)	(2.44)	(2.30)
Crises	0.05	0.05	0.04	0.04	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Real GDP p.c.	-0.13	-0.11	-0.11	-0.13	-0.13
	(0.12)	(0.11)	(0.10)	(0.10)	(0.10)
R^2	0.20	0.24	0.29	0.30	0.29
$N \times T$	380	380	380	380	380
			Panel C: EU-15		
$\sum_i^n(\alpha_i\nu_{i,t})^2$	0.77	5.29	6.57	7.99	6.94
	(1.61)	(3.12)	(2.60)	(2.73)	(2.61)
Crises	0.08	0.07	0.06	0.05	0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Real GDP p.c.	-0.21	-0.17	-0.16	-0.17	-0.17
	(0.15)	(0.13)	(0.12)	(0.11)	(0.12)
R^2	0.20	0.27	0.30	0.32	0.31
$N \times T$	300	300	300	300	300

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are autocorrelation and heteroskedasticity robust, with a Bartlett Kernel to account for the 10 years rolling windows used to estimate the volatility of GDP. All regressions include time-dummies and country fixed-effects. The industries are (1) Finance Intermediation and Real Estate Activities; (2) Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles; (3) Agriculture, Hunting, Forestry and Fishing; (4) Machinery, Electrical, Optical, Transport Equipment, Manufacturing, Recycling; and (5) Post and Telecommunications.

the US, Japan, Germany, or China. We found no instances of significance loss, and no instances of significant changes in point estimates. This suggests that no single country can account for the significance of fundamental volatility, despite its relative prevalence amongst developed economies.

3.3 Fundamental Co-Movements

Define the fundamental correlation coefficient between aggregate fluctuations in two countries c and s:

$$\operatorname{Corr}\left(\sum_{i=1}^{n} \alpha_i^c \nu_{it}^c \varepsilon_{it}, \sum_{i=1}^{n} \alpha_i^s \nu_{it}^s \varepsilon_{it}\right)$$

where we have assumed the sector-level shock ε_{it} affects all countries identically. The coefficient constitutes a fundamental explanation for aggregate cycle synchronization: fluctuations between countries c and s resemble each other whenever influent sectors are similar. This is entirely determined by the fundamental structure of each economy, i.e., input-output linkages.

We estimate the following panel regression

$$\rho_{cs,t} = \alpha_{cs} + \gamma_t + \beta \operatorname{fcorr}_{cs,t} + \theta \mathbf{X}_{cs.t} + \xi_{cs,t}, \tag{7}$$

where $\rho_{cs,t}$ measures the correlation of aggregate fluctuations between countries c and s, and $\operatorname{fcorr}_{cs,t} = \operatorname{Corr}\left(\sum_{i=1}^{n} \alpha_i^c \nu_{it}^c, \sum_{i=1}^{n} \alpha_i^s \nu_{it}^s\right)$. Of course, $\operatorname{fcorr}_{cs,t}$ should involves all of the cross-products between sector-level shocks, $\operatorname{E} \varepsilon_{it}\varepsilon_{jt}$, for all i, j. We omit these cross-products from the regression. This builds from the hypothesis that $\operatorname{E} \varepsilon_{it}^2 = \sigma_i^2$ (for all t), and requires as well that $\operatorname{E} \varepsilon_{it}\varepsilon_{jt} = \sigma_{ij}$ (for all t and $i \neq j$) for all countries. In the robustness section, we relax both assumptions, and investigate how our results are affected with empirically motivated covariances $\operatorname{E} \varepsilon_{it}\varepsilon_{jt}$. α_{cs} denotes a country–pair specific intercept, γ_t accounts for yearly systematic variation in international co-movements, and $\mathbf{X}_{cs.t}$ denotes controls for cycle synchronization that vary across country pairs and over time. The prediction is that estimates of β are positive, i.e., that rising fundamental correlation implies increasingly correlated cycles.

The decomposition of aggregate fluctuations in equation (2) extends readily to measures of co-movements. By definition, we have

$$\begin{aligned} \operatorname{fcorr}_{cs,t} &= \operatorname{Corr}\left(\sum_{i=1}^{n} \alpha_i^c\, \nu_{i,t}^{\mathrm{DOM}\, c} + \sum_{i=1}^{n} \alpha_i^c\, \nu_{i,t}^{\mathrm{INT}\, c}, \sum_{i=1}^{n} \alpha_i^s\, \nu_{i,t}^{\mathrm{DOM}\, s} + \sum_{i=1}^{n} \alpha_i^s\, \nu_{i,t}^{\mathrm{INT}\, s}\right) \\ &= \operatorname{fcorr}_{cs,t}^{\mathrm{DOM}} + \operatorname{fcorr}_{cs,t}^{\mathrm{TRADE}} \end{aligned}$$

where

$$\text{fcorr}_{cs,t}^{\text{DOM}} = \text{Corr}\left(\sum_{i=1}^{n} \alpha_i^c \, \nu_{i,t}^{\text{DOM}\, c}, \sum_{i=1}^{n} \alpha_i^s \, \nu_{i,t}^{\text{DOM}\, s}\right),$$

and $\text{fcorr}_{cs,t}^{\text{TRADE}} = \text{fcorr}_{cs,t} - \text{fcorr}_{cs,t}^{\text{DOM}}$. Equation (7) can then be amended to explore empirically how trade affects fundamental co-movements, as in

$$\rho_{cs,t} = \alpha_{cs} + \gamma_t + \beta_1 \, \text{fcorr}_{cs,t}^{\text{DOM}} + \beta_2 \, \text{fcorr}_{cs,t}^{\text{TRADE}} + \theta \mathbf{X}_{cs.t} + \xi_{cs,t}. \tag{8}$$

The estimates of β_1 and β_2 identify separately the impact of domestic vs. international input-output linkages on the emergence of granular co-movements.

It is straightforward to evaluate the impact of a given country or a given sector on fundamental co-movements. We simply amend equation (7) to make use of the influence vectors defined in Section 2.3, where individual countries or sectors are omitted. In particular we estimate

$$\rho_{cs,t}^{-r} = \alpha_{cs}^{-r} + \gamma_t + \beta \, \text{fcorr}_{cs,t}^{-r} + \theta \mathbf{X}_{cs.t}^{-r} + \xi_{cs,t}^{-r}, \tag{9}$$

where the subscript $-r$ indicates that country r is omitted from the cross section. Similarly, we estimate

$$\rho_{cs,t} = \alpha_{cs} + \gamma_t + \beta \; \text{Corr}\left(\sum_{i=1, i\neq j}^{n} \alpha_i^c \nu_{it}^c, \sum_{i=1, i\neq j}^{n} \alpha_i^s \nu_{it}^s\right) + \theta \mathbf{X}_{cs.t} + \xi_{cs,t}^{-j}, \tag{10}$$

which abstracts from sector j. Equations (9) and (10) explore the empirical importance of country r and sector j in driving co-movements, either globally or within a specific region. Of course, it is possible to combine the decompositions to evaluate whether, for instance, the emergence of a country or a sector that matters for co-movements is related to international trade.

We next present the results associated with the estimations of equations (7) to (10) on the sample formed by the 40 countries with WIOT coverage. The measures of $\rho_{cs,t}$ are computed from the annual growth rates of real GDP in 2005 PPP dollars, as reported by the Penn World Tables (version 9.0). The panel runs from 1995 to 2014. The conventional determinants of co-movements include the magnitude of bilateral goods trade, normalized by total trade (see Frankel and Rose, 1998), and the magnitude of bilateral financial linkages, measured by bank asset holdings across borders normalized by GDP or total population (see Kalemli-Ozcan et al., 2013b). Bilateral trade intensity is measured each year using the IMF's Direction of Trade Statistics, and bilateral financial linkages are measured using the International Locational Banking Statistics released by the Bank of International Settlements.

Columns (1), (2), and (3) of Table 6 present the estimates of β in equation (7). The decomposition into traded and non traded components from equation (8) is presented in specifications (4), (5), and (6). Specifications (1) and (4) use the full sample; specifications (2), (3), (5), and (6) use the reduced sample where the controls are available. The estimates of β are positive and significant across all specifications, irrespective of the sample, and whether the controls $\mathbf{X}_{cs.t}$ are included or not. The results suggest that fundamental explanations for aggregate co-movements are relevant empirically. What is more, both the domestic and the international components of fundamental co-movements appear to affect significantly aggregate co-fluctuations.

Table 6: Correlation of GDP

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{fcorr}_{cs,t}$	16.01	15.57	14.41			
	(2.29)	(2.42)	(2.42)			
$\text{fcorr}^{\text{DOM}}_{cs,t}$				17.45	17.69	16.58
				(2.58)	(2.77)	(2.74)
$\text{fcorr}^{\text{TRADE}}_{cs,t}$				11.43	9.21	7.90
				(3.75)	(4.11)	(4.10)
Banking			0.05			0.04
			(0.04)			(0.04)
Trade			0.32			0.33
			(0.11)			(0.12)
R^2	0.11	0.09	0.09	0.11	0.09	0.09
$N \times T$	15600	11602	11602	15600	11602	11602

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects.

The question whether countries that share identical sectors display positive co-movements is an old one. For instance, Imbs (2004) provides support to the claim, whereas Baxter and Kouparitsas (2005) argue sector similarities are not robustly siginificant. The measure for sector similarities used in this paper has sounder theoretical grounds than earlier papers, as it is implied by theory. It also encapsulates the potential propagation mechanisms created by trade linkages. In fact, columns (4), (5), and (6) in the table confirm that the component of input-output linkages that is associated with international trade does translate in positive co-movements.

Table 7 considers sub-samples first focused on rich developed countries, and introducing progressively less developed economies: OECD-19 and EU-15 are narrow samples of developed economies, EU-27 and DVC include more developing countries. The results suggest that aggregate co-movements do have fundamental origins in rich, developed countries: in the reduced sample of 19 OECD countries, in the core EU-15, and in the enlarged EU-27, but not in a sample focused on developing economies. Both $\text{fcorr}^{\text{DOM}}_{cs,t}$ and $\text{fcorr}^{\text{INT}}_{cs,t}$ affect significantly GDP fluctuations, except in the core EU-15, where it is only the domestic component that matters. The data paint a clear picture: Intermediate trade within and between countries has resulted in international patterns of specialization that tend to increase co-movements: this is true in developed countries, but not in the developing world.

Table 7: Correlation of GDP in regions

Region	OECD-19		EU-15		EU-27		DVC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{fcorr}_{cs,t}$	14.51		10.32		3.42		-8.54	
	(4.06)		(4.95)		(0.83)		(16.7)	
$\text{fcorr}^{\text{DOM}}_{cs,t}$		12.44		10.26		8.54		-2.09
		(4.15)		(5.03)		(2.11)		(18.0)
$\text{fcorr}^{\text{TRADE}}_{cs,t}$		17.27		10.41		2.44		-40.83
		(5.16)		(6.70)		(0.75)		(24.7)
Banking	0.21	0.21	0.32	0.32	0.09	0.08	0.20	0.19
	(0.07)	(0.07)	(0.12)	(0.12)	(0.06)	(0.06)	(0.13)	(0.13)
Trade	0.79	0.65	1.34	1.34	0.59	0.55	1.26	1.03
	(0.18)	(0.19)	(0.23)	(0.23)	(0.16)	(0.16)	(0.84)	(0.90)
R^2	0.10	0.10	0.12	0.12	0.06	0.06	0.24	0.24
$N \times T$	3339	3339	2041	2041	5380	5380	402	402

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects. DVC countries include: Brazil, China, India, Indonesia, Mexico, Russia, South Korea, Turkey, and Taiwan.

Table 8 checks how the results hold through time. We perform the same split as in the previous section, into three periods: (i) from 1995 to 2000, (ii) from 2001 to 2007, and (iii) from 2008 to 2014. Specification (1) performs this split in the sample without controls, while specifications (2) and (3) use the sample with controls. In all three cases, fundamental determinants of aggregate synchronization emerge in 2001, and accelerate with the great recession of 2008. Specifications (4), (5), and (6) examine whether this progression can be ascribed to international trade. The results are ambiguous: while is it trade in the earlier period, prior to 2001, it is not in the middle period, and it is both domestic and international forces from 2008. It seems therefore that the acceleration in fundamental correlation during the great recession came from both domestic and traded intermediates.

Table 8: Correlation of GDP – $\mathrm{pre\text{-}2001}$ and $\mathrm{post\text{-}2007}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{fcorr}_{cs,t} \times \mathrm{pre\text{-}2001}$	1.26	0.77	0.63			
	(1.21)	(1.37)	(1.39)			
$\mathrm{fcorr}_{cs,t}$	13.51	13.40	12.2			
	(2.22)	(2.36)	(2.37)			
$\mathrm{fcorr}_{cs,t} \times \mathrm{post\text{-}2007}$	4.33	3.99	4.02			
	(0.80)	(0.86)	(0.84)			
$\mathrm{fcorr}^{\mathrm{DOM}}_{cs,t} \times \mathrm{pre\text{-}2001}$				1.35	0.71	0.59
				(1.14)	(1.23)	(1.25)
$\mathrm{fcorr}^{\mathrm{TRADE}}_{cs,t} \times \mathrm{post\text{-}2007}$				16.75	25.89	25.21
				(3.35)	(3.69)	(3.73)
$\mathrm{fcorr}^{\mathrm{DOM}}_{cs,t}$				13.36	13.84	12.91
				(2.50)	(2.52)	(2.51)
$\mathrm{fcorr}^{\mathrm{TRADE}}_{cs,t}$				4.87	2.00	1.05
				(3.75)	(4.31)	(4.30)
$\mathrm{fcorr}^{\mathrm{DOM}}_{cs,t} \times \mathrm{post\text{-}2007}$				4.27	3.91	3.93
				(0.79)	(0.83)	(0.82)
$\mathrm{fcorr}^{\mathrm{TRADE}}_{cs,t} \times \mathrm{post\text{-}2007}$				9.47	8.60	8.44
				(1.99)	(2.20)	(2.18)
Banking			0.04			0.03
			(0.04)			(0.04)
Trade			0.35			0.29
			(0.12)			(0.11)
R^2	0.11	0.10	0.10	0.11	0.11	0.11
$N \times T$	15600	15600	11602	15600	11602	11602

Notes: Standard errors are in parentheses. The dummy variable $\mathrm{pre\text{-}2001}$ takes value 1 for $t < 2001$ and 0 otherwise; $\mathrm{post\text{-}2007}$ takes value 1 for $t > 2007$ and 0 otherwise. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects.

Can these results be ascribed to one or few sectors? Table 9 presents the results of estimating equation (10), where each sector is omitted from the computation of $\mathrm{fcorr}_{cs,t}$, one at a time. The table reports only the sectors whose omission overturns significance in the samples where GDP correlations are found to have significant fundamental explanations, namely the full world, OECD-19, EU-15, and EU-27. We find that no single sector can explain the significance of $\mathrm{fcorr}_{cs,t}$ in all four samples: In particular, no sin-

Table 9: Correlation of GDP without Industries

Without	Constr. (1)	FIRE (2)	Bus. Serv. (3)	Constr. (1)	FIRE (2)	Bus. Serv. (3)
	Panel A: World			Panel B: OECD-19		
$\text{fcorr}_{cs,t}$	17.9	9.54	11.9	6.76	6.16	1.68
	(1.61)	(0.60)	(1.64)	(3.72)	(1.37)	(3.27)
Banking	0.03	0.07	0.08	0.25	0.27	0.27
	(0.04)	(0.04)	(0.04)	(0.08)	(0.08)	(0.08)
Trade	0.24	0.30	0.34	0.67	0.69	0.65
	(0.11)	(0.11)	(0.11)	(0.23)	(0.23)	(0.23)
R^2	0.09	0.10	0.10	0.10	0.09	0.09
$N \times T$	11602	11602	11602	3339	3339	3339
	Panel C: EU-15			Panel D: EU-27		
$\text{fcorr}_{cs,t}$	-2.01	3.61	-3.42	0.85	10.4	11.7
	(4.54)	(5.63)	(4.05)	(1.08)	(2.50)	(2.66)
Banking	0.40	0.38	0.40	0.25	0.09	0.09
	(0.13)	(0.04)	(0.12)	(0.06)	(0.06)	(0.06)
Trade	1.24	1.30	1.23	0.59	0.50	0.54
	(0.24)	(0.22)	(0.24)	(0.16)	(0.16)	(0.15)
R^2	0.11	0.11	0.11	0.06	0.06	0.07
$N \times T$	2041	2041	2041	5380	5380	5380

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects. The industries are (1) Construction; (2) Finance Intermediation and Real Estate Activities; and (3) Renting of Machinery & Equipment and Other Business Activities.

gle sector can explain the significance in the full world sample, where co-movements have robust fundamental determinants irrespective of what single sector is omitted. We identify three sectors where significance is weakened in two out of four samples. Omitting construction overturns the significance of fundamental correlation in the two EU samples, but not in the OECD where it is still significant at 10 percent confidence level. Omitting FIRE or business services overturns significance in the OECD and EU-15 samples, but not in the EU-27. We conclude construction, FIRE, and business services play a role in explaining fundamental sources of co-movements in developed countries, but not globally, where fundamental co-movements cannot be ascribed to a sector in particular.

Finally, following equation (9) we examined whether the omission of any single (large) economy from the sample alters the results. Just as in the previous section on volatility, there is no single large economy that seems to drive the results, in that omitting the US, China, Japan, or Germany does not affect the significance of any result, nor does it change point estimates significantly.

4 Robustness

4.1 Homogeneous factor and expenditure shares

The paper has so far allowed for sector-specific labor shares α_i, and for empirical final expenditure shares β_i. Given the importance of both parameters in the computation of the influence vectors, and therefore in the definitions of fundamental volatility and co-movements, it is of interest to explore the robustness of our results to homogeneous values for both parameters.

The upper panel of Table 10 presents estimates of fundamental volatility under homogeneous α_i and β_i with similar conclusions as in the main text: fundamental volatility is significant, and mostly driven by international trade. The lower panel of Table 10 presents results for fundamental correlation. Our conclusions are unchanged: fundamental correlation prevails in the data, and finds its sources in both its domestic and traded components.

4.2 Including Sector Shocks

The decomposition of aggregate fluctuations into sector-level components lends great importance to sector-level disturbances, which finds support in a number of papers, e.g., Long and Plosser (1987) or Atalay (2017) for instance. Kose et al. (2008) find that international shocks contribute the majority of country-specific fluctuations. Foerster et al. (2011) and Atalay (2017) show that accounting for endogenous propagation between sectors magnifies the estimated role of sector-specific disturbances.[19] Up to now, we have imposed specific conditions on these shocks: in particular, we have imposed that $\mathrm{E}\,{\varepsilon_{it}}^2 = \sigma_i^2$ and $\mathrm{E}\,\varepsilon_{it}\varepsilon_{jt} = \sigma_{ij}$ (for all t and $i \neq j$), where both σ_i^2 and σ_{ij} are constant across countries.

We now estimate ε_{it} following Gabaix (2011). We compute the growth rate in output per worker $z_{i,c,t}$ for sectors $i = 1, \dots, 31$, countries $c = 1, \dots, 40$, and time $t = 1995, \dots, 2014$. We combine output from WIOT with employment data from the

[19]Here we do not estimate separately "true" sector shocks and their propagation through the economy. Our sector shocks encapsulate both components. Our results that international trade matters for volatility and co-movements suggest input-output linkages propagate shocks across countries, with consequences on aggregate moments. In that, our approach is complementary to Stumpner (2015) or Acemoglu et al. (2016).

Table 10: Homogenous α and β

	(1)	(2)	(3)	(4)
Panel A: Volatility of GDP				
$\sum_i^n \nu_{i,t}^2$	9.27	6.32		
	(2.76)	(2.88)		
$\sum_i^n \nu_{i,t}^{2\ \mathrm{DOM}}$			6.21	-2.47
			(5.39)	(4.31)
$\sum_i^n \nu_{i,t}^{\mathrm{TRADE}}$			11.89	13.58
			(2.39)	(2.55)
Crisis		0.02		0.02
		(0.03)		(0.03)
Real GDP p.c.		-0.74		-0.77
		(0.18)		(0.18)
R^2	0.15	0.30	0.15	0.31
$N \times T$	800	800	800	800
Panel A: Correlation of GDP				
$\mathrm{fcorr}_{cs,t}$	14.3	12.0		
	(2.31)	(2.68)		
$\mathrm{fcorr}_{cs,t}^{\mathrm{DOM}}$			14.5	12.0
			(2.30)	(2.69)
$\mathrm{fcorr}_{cs,t}^{\mathrm{TRADE}}$			21.4	13.3
			(4.15)	(4.58)
Banking		0.06		0.06
		(0.04)		(0.05)
Trade		0.30		0.30
		(0.11)		(0.11)
R^2	0.10	0.09	0.11	0.09
$N \times T$	15600	11602	15600	11602

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. $\alpha_i = \alpha$ for all i and $\beta_i = \frac{1}{n}$, where n is the number of sectors. The computed standard errors in Panel A are autocorrelation and heteroskedasticity robust, with a Bartlett Kernel to account for the 10 years rolling window used to estimate the volatility of GDP. The computed standard errors in Panel B are clustered by country pair. All regressions include time-dummies and either country fixed-effects or country pair fixed-effects.

socio-economic accounts, also published as part of WIOD. We estimate

$$z_{i,c,t} = \gamma + \gamma_i + \gamma_c + \gamma_t + \varepsilon_{i,c,t}.$$

Sector-specific shocks are defined as demeaned labor productivity growth, allowing for sector, country and time specific effects. The shocks are allowed to vary by sector and by country: We want to establish whether these shocks' variances and covariances display a meaningful dispersion across countries.

Armed with estimates of $\varepsilon_{i,c,t}$ we perform a battery of tests to verify our assumptions. We first verify the time invariance of variance estimates $\sigma^2_{i,c}$ for 31 sectors in 40 countries. We compute sector-level variances over two periods, 1996 – 2007 and 2008 – 2014, reasoning the most likely structural break in the data probably happened around the Great Recession. We then perform Levene (1960) tests of variance differences for all 1,240 ($= 31 \times 40$) variance estimates. We find not a single instance of a significant variance change.[20]

Next we test whether sector-level variances are different across countries. For each country c, the null hypothesis is that $\sigma^2_{i,c} = \sigma^2_{i,US}$ where $\sigma^2_{i,US}$ denotes the variance of shocks in sector i measured in the US. The Levene test is performed for each country-sector in comparison with the US, reasoning that sector-level technological developments are best mirrored in US data. We find a total of 197 rejections, out of a total of 1,209 ($= 31 \times 39$), which represents 16.3 percent of instances where sector variances are significantly different from the US.[21] The proportion goes down to 2.5 percent with the False Discovery Rate correction, and to 2.1 percent with the Bonferroni correction. The assumption that sector shocks resembles each other across countries is therefore largely supported by the data.[22]

Finally, we want to investigate the properties of $\mathrm{E}\,\varepsilon_{it}\varepsilon_{jt}$. Our goal is to ascertain the empirical properties of the variance covariance matrices $\mathrm{E}\,\varepsilon_{it}\varepsilon_{jt}$ across sectors for all countries. We first investigate whether the hypothesis that all covariances are time invariant is supported in the data. To do so, we implement the test introduced by Srivastava et al. (2014) that lends itself best to the large number of sectors relative to the small sample size. The test statistic is based on the distance between the two compared variance-covariance matrices, as captured by their traces. We split the sample in 2008, and perform the test (corrected for multiple comparisons) on the two resulting sub-periods. We find that there are only three variance-covariance matrices for which the null of time invariance is rejected: Brazil, Luxembourg, and Slovakia. We conclude

[20] This continues to be true if we split the data in 2006 or in 2008, and if we perform the corrections necessary when performing multiple comparisons, like the Bonferroni or the False Discovery Rate corrections.

[21] Half of these instances prevail in seven small European countries: Estonia, Ireland, Lithuania, Latvia, Malta, Slovakia, and Romania.

[22] On the other hand, sector shocks are clearly heterogeneous within countries: we also test whether $\sigma^2_{i,c} = \sigma^2_{US}$ where σ^2_{US} denotes the average sector variance in the US. That hypothesis is rejected in all cases.

the hypothesis that $\mathrm{E}\,\varepsilon_{it}\varepsilon_{jt}$ is time invariant is supported in the data.[23] We perform our estimation imposing this constraint on the empirical covariances by computing the averages of the shock estimates $\varepsilon_{i,c,t}$ over the full sample 1995 – 2014. As an alternative check, we also compute the averages shock estimates over two sub-periods 1995 – 2007 and 2008 – 2014. That way we actually allow for covariances $\sigma_{ij,c,t}$ that vary by pairs of sectors, by country, and over two periods.

Table 11: Volatility of GDP with sectoral variances

	(1)	(2)	(3)
$\sum_i^n (\alpha_i \nu_{i,t}\, \sigma_i)^2 \times \text{pre-2001}$		-6.00	
		(1.36)	
$\sum_i^n (\alpha_i \nu_{i,t}\, \sigma_i)^2$	4.38	6.23	
	(1.47)	(1.49)	
$\sum_i^n (\alpha_i \nu_{i,t}\, \sigma_i)^2 \times \text{post-2007}$		-0.60	
		(0.89)	
$\sum_i^n (\alpha_i \nu_{i,t}^{\text{DOM}}\, \sigma_i)^2$			1.08
			(2.25)
$\sum_i^n \alpha_i^2 \nu_{i,t}^{\text{TRADE}}\, \sigma_i^2$			6.18
			(1.68)
Crises	0.01	0.002	0.01
	(0.03)	(0.03)	(0.03)
Real GDP p.c.	-0.72	-0.64	-0.70
	(0.17)	(0.17)	(0.18)
R^2	0.31	0.37	0.31
$N \times T$	800	800	800

Notes: Standard errors are in parentheses. The dummy variable pre-2001 takes value 1 for $t < 2001$ and 0 otherwise; post-2007 takes value 1 for $t > 2007$ and 0 otherwise. σ_i^2 are the U.S. sectoral variances. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are autocorrelation and heteroskedasticity robust, with a Bartlett Kernel to account for the 10 years rolling window used to estimate the volatility of GDP. All regressions include time-dummies and country fixed-effects.

Table 11 presents the volatility results when fundamental volatility is computed as $\sum_{i=1}^n \left(\alpha_i \nu_{i,t}\right)^2 \sigma_i^2$, using U.S. estimates for σ_i^2. The Table presents the total effect of fundamental volatility, its decomposition between traded and domestic components, and its evolution over time. The results are very similar to the estimates obtained abstract-

[23] On the other hand, the covariances are clearly different across countries: the Srivastava test rejects the null of equality with the US estimate in 80 percent of the cases, down to 60 percent with correction for multiple comparaisons.

ing from σ_i^2: $\sum_{i=1}^{n}\left(\alpha_i \nu_{i,t}\right)^2 \sigma_i^2$ is a significant determinant of GDP volatility, mostly because of trade, and mostly since the globalization period since 2001. There is no observable change with the great recession of 2008. The only difference are slightly smaller point estimates, which happens because the regressors now include a volatility measure.

Table 12 presents the correlation results when sector shocks are allowed back into the measure of fundamental co-movements. Panel A presents results with a measure of fundamental co-movements given by $\mathrm{Corr}\left(\sum_{i=1}^{n} \alpha_i^c \nu_{it}^c \varepsilon_{i,c}, \sum_{i=1}^{n} \alpha_i^s \nu_{it}^s \varepsilon_{i,c}\right)$. Panel B uses instead $\mathrm{Corr}\left(\sum_{i=1}^{n} \alpha_i^c \nu_{it}^c \varepsilon_{i,c,T}, \sum_{i=1}^{n} \alpha_i^s \nu_{it}^s \varepsilon_{i,s,T}\right)$ where $T = 1995 - 2007, 2008 - 2014$. The Table presents the total effect of fundamental correlation, its decomposition into traded and domestic components, and its evolution over time. Our results carry through across the two panels: $\mathrm{fcorr}_{cs,t}$ is significant, its effect prevails from 2001, and accelerates from 2008, and both domestic and traded components matter. The only slight difference relative to Table 6 is the insignificant effect of international trade in Panel B. It was significant at 10 percent confidence level in Table 6.

Table 12: Correlation of GDP with sectoral shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: time invariant			Panel B: pre/post 2008		
$\mathrm{fcorr}_{cs,t,\varepsilon_{i,c}} \times$ pre-2001		0.60			0.91	
		(1.18)			(1.16)	
$\mathrm{fcorr}_{cs,t,\varepsilon_{i,c}}$	14.8	12.2		6.01	3.27	
	(2.46)	(2.42)		(0.84)	(0.95)	
$\mathrm{fcorr}_{cs,t,\varepsilon_{i,c}} \times$ post-2007		3.62			4.06	
		(0.69)			(0.66)	
$\mathrm{fcorr}_{cs,t,\varepsilon_{i,c}}^{\mathrm{DOM}}$			15.6			6.27
			(2.65)			(0.82)
$\mathrm{fcorr}_{cs,t,\varepsilon_{i,c}}^{\mathrm{TRADE}}$			12.4			-0.80
			(4.42)			(2.12)
Banking	0.05	0.04	0.04	0.04	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Trade	0.31	0.33	0.31	0.31	0.34	0.32
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)
R^2	0.10	0.10	0.10	0.09	0.10	0.10
$N \times T$	11602	11602	11602	11602	11602	11602

Notes: Standard errors are in parentheses. The dummy variable pre-2001 takes value 1 for $t < 2001$ and 0 otherwise; post-2007 takes value 1 for $t > 2007$ and 0 otherwise. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects.

4.3 An Alternative Measure of Co-Movements

Giannone et al. (2011), Kalemli-Ozcan et al. (2013a), and Kalemli-Ozcan et al. (2013b) use an alternative measure of co-movements $\mathcal{S}_{cs,t}$, based on the absolute difference in GDP growth rates between countries c and s:

$$\mathcal{S}_{cs,t} = -\left|y_{c,t} - y_{s,t}\right|,$$

where $y_{c,t}$ denotes the growth rate of GDP in country c at time t. The measure presents two key advantages: first it is readily observable at yearly frequency. Second, it is invariant to the volatility of the underlying shock, see Forbes and Rigobon (2002) and Corsetti et al. (2005). With this definition, fundamental co-movements are given by

$$\text{abscorr}_{cs,t} = -\left|\sum_{i=1}^{n}\left(\alpha_{ci}\nu_{ci,t} - \alpha_{si}\nu_{si,t}\right)\varepsilon_{it}\right| = -\sqrt{\left[\sum_{i=1}^{n}\delta_{cs,i,t}\,\varepsilon_{it}\right]^2}$$

where shocks are assumed to be common across borders, and $\delta_{cs,i,t} = \alpha_{ci}\nu_{ci,t} - \alpha_{si}\nu_{si,t}$ denotes the international difference in the contribution of sector i to GDP fluctuations. Since $\mathrm{E}\,\varepsilon_{it}^2 = \sigma_i^2$, and $\mathrm{E}\,\varepsilon_{it}\varepsilon_{jt}$ is constant across countries, the only source of variation in cycle synchronization across country pairs are the values taken by $\sum_{i=1}^{n}\left(\delta_{cs,i,t}\right)^2$.

Table 13: Correlation of GDP – Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{abscorr}_{cs,t}$	27.02	24.17	22.21			
	(4.31)	(4.44)	(4.42)			
$\text{abscorr}_{cs,t}^{\text{DOM}}$				30.60	30.19	28.36
				(6.34)	(6.67)	(6.60)
$\text{abscorr}_{cs,t}^{\text{TRADE}}$				22.50	17.33	15.24
				(6.00)	(6.36)	(6.34)
Banking			0.05			0.05
			(0.04)			(0.04)
Trade			0.36			0.37
			(0.12)			(0.12)
R^2	0.10	0.09	0.09	0.10	0.09	0.09
$N \times T$	15600	11602	11602	15600	11602	11602

Notes: Standard errors are in parentheses. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects.

Table 14: Correlation of GDP – Robustness pre-2001 and post-2007

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{abscorr}_{cs,t} \times \text{pre-2001}$	2.60	2.77	2.46			
	(2.47)	(2.79)	(2.81)			
$\text{abscorr}_{cs,t}$	22.12	19.12	17.00			
	(4.22)	(4.37)	(4.39)			
$\text{abscorr}_{cs,t} \times \text{post-2007}$	7.40	7.07	7.21			
	(1.65)	(1.76)	(1.71)			
$\text{abscorr}^{\text{DOM}}_{cs,t} \times \text{pre-2001}$				-6.29	-8.63	-8.48
				(2.56)	(2.83)	(2.89)
$\text{abscorr}^{\text{TRADE}}_{cs,t} \times \text{pre-2001}$				25.74	30.03	28.77
				(4.34)	(4.68)	(4.67)
$\text{abscorr}^{\text{DOM}}_{cs,t}$				22.55	26.44	25.09
				(6.23)	(6.65)	(6.64)
$\text{abscorr}^{\text{TRADE}}_{cs,t}$				16.07	11.40	9.83
				(5.87)	(6.44)	(6.44)
$\text{abscorr}^{\text{DOM}}_{cs,t} \times \text{post-2007}$				7.57	7.11	7.31
				(1.82)	(1.95)	(1.93)
$\text{abscorr}^{\text{TRADE}}_{cs,t} \times \text{post-2007}$				7.15	6.97	6.89
				(2.63)	(2.72)	(2.68)
Banking			0.05			0.02
			(0.04)			(0.04)
Trade			0.38			0.29
			(0.12)			(0.11)
R^2	0.11	0.09	0.09	0.11	0.10	0.10
$N \times T$	15600	11602	11602	15600	11602	11602

Notes: Standard errors are in parentheses. The dummy variable pre-2001 takes value 1 for $t < 2001$ and 0 otherwise; post-2007 takes value 1 for $t > 2007$ and 0 otherwise. Coefficients and standard errors have been multiplied by 100 to facilitate readability. The computed standard errors are clustered by country pair. All regressions include time-dummies and country pair fixed-effects.

Define $\delta^{\text{DOM}}_{cs,i,t} = \alpha_{ci}\nu^{\text{DOM}}_{ci,t} - \alpha_{si}\nu^{\text{DOM}}_{si,t}$ to reflect the similarities in fundamental fluctuations between countries c and s that arise from purely domestic input-output linkages, and $\delta^{\text{INT}}_{cs,i,t} = \alpha_{ci}\nu^{\text{INT}}_{ci,t} - \alpha_{si}\nu^{\text{INT}}_{si,t}$ to capture those that arise via international trade. We have $\delta_{cs,i,t} = \delta^{\text{DOM}}_{cs,i,t} + \delta^{\text{INT}}_{cs,i,t}$. Then

$$\sum_{i=1}^{n} \left(\delta_{cs,i,t}\right)^2 = \sum_{i=1}^{n} \left(\delta^{\text{DOM}}_{cs,i,t} + \delta^{\text{INT}}_{cs,i,t}\right)^2 \equiv \sum_{i=1}^{n} \left(\delta^{\text{DOM}}_{cs,i,t}\right)^2 + \sum_{i=1}^{n} \delta^{\text{TRADE}}_{cs,i,t}.$$

An approximate decomposition of $\mathrm{abscorr}_{cs,t}$ is given by

$$\begin{aligned}
\mathrm{abscorr}_{cs,t} &= -\sqrt{\sum_{i=1}^{n}\left(\delta_{cs,i,t}^{\mathrm{DOM}}\right)^2 + \sum_{i=1}^{n}\delta_{cs,i,t}^{\mathrm{TRADE}}} \\
&\approx -\sqrt{\sum_{i=1}^{n}\left(\delta_{cs,i,t}^{\mathrm{DOM}}\right)^2} - \sqrt{\sum_{i=1}^{n}\delta_{cs,i,t}^{\mathrm{TRADE}}}
\end{aligned}$$

for negligible values of $\left(\sum_{i=1}^{n}\left(\delta_{cs,i,t}^{\mathrm{DOM}}\right)^2\right)^{\frac{1}{2}}\left(\sum_{i=1}^{n}\delta_{cs,i,t}^{\mathrm{TRADE}}\right)^{\frac{1}{2}}$.

Table 13 present the estimates of β in equations (7) and (8) where the values for $\mathrm{fcorr}_{cs,t}$ are replaced with $\mathrm{abscorr}_{cs,t}$. The first three specifications confirm that aggregate comovements continue to have significant fundamental origins with the alternative measure of correlations. The last three specifications confirm that both domestic and international elements in $\mathrm{abscorr}_{cs,t}$ account for aggregate co-fluctuations.

Table 14 verifies how the significance of $\mathrm{abscorr}_{cs,t}$ evolves over the three subperiods we consider. We confirm that fundamental co-movements appear with the globalization period starting in 2001, and accelerate further after 2007. The decomposition into traded and domestic components confirms both effects continue to be present in the data.

5 Conclusion

We investigate the empirical relevance of granularity in driving aggregate GDP moments in a broad cross-section of countries. The argument builds on a classic model of input-output trade where fluctuations in aggregate GDP are given by a weighted average of sector shocks, with weights reflecting the influence of a sector in the aggregate. We test the model predictions using recently released World Input-Output Tables, with a view to decomposing the changes in granularity in the world economy into a component that originates in purely domestic trade, and another that captures the role of international trade.

We find that granularity increased significantly in developed countries over the past 20 years, in the sense that influent sectors increased further in influence. Worldwide, the trend goes the other way, thanks to the emergence in China of newly influent sectors, which results in a diversifying Chinese economy. In developed countries we find that GDP volatility depends significantly on fundamental volatility, i.e., on the granularity of the economy. This is especially true since the start of the globalization period in 2001, and it is mostly due to international trade in intermediate goods. In developed countries, GDP co-movements also depend significantly on their fundamental determinants, i.e., on similarities in granularity across countries. This has been prevalent since 2001, has accelerated since 2008, and is due to both domestic and international trade in intermediate goods.

Finally, we find that a few sectors can explain some of these results. The FIRE sector is central in accounting for fundamental sources of GDP volatility in developed countries. In contrast, no single sector can explain away the fundamental origins of GDP co-movements. In developed countries, the Construction, FIRE, and Business Services weaken some, but not all, of the significant estimates. Interestingly, this paper's results cannot be ascribed to a single country: Our conclusions are similar in samples where the US economy, China, Japan, Germany, or the UK are omitted from the exercise. In other words, the importance of granularity in developed countries depends much more on specific sectors than it does on specific countries.

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Appendix

Table A1: Pervasiveness of sectors

	1995 – 2014	1995 – 2007	2008 – 2014
World	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments
World w/o USA	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments
World w/o China	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments
Germany	Renting & Other Bus. Trans serv. Equipments	Renting & Other Bus Equipments Trans serv.	Renting & Other Bus. Trans serv. Equipments
USA	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Real Est.
China	Equipments Chemicals Agricult.	Equipments Chemicals Agricult.	Equipments Chemicals Petrol
EU15	Renting & Other Bus. Fin Intermed. Wholesale	Renting & Other Bus. Fin Intermed. Equipments	Renting & Other Bus. Fin Intermed. Elect.

Notes: The dominant sectors are given by the estimators of $\delta_{\max}$ proposed by Pesaran and Yang (2016). The sectors with top three values of δ_i are presented in the Table. The industries featured in this table are: Renting of Machinery & Equipment and Other Business Services; Financial Intermediation; Machinery, Electrical, Optical, Transport Equipment, Manufacturing, Recycling; Other Supporting and Auxiliary Transport Activities, Activities of Travel Agencies; Agriculture, Hunting, Forestry and Fishing; Wholesale Trade and Commission Trade; Real Estate Activities; Coke, Refined Petroleum and Nuclear Fuel; Chemicals and Chemical Products; Electricity, Gas and Water Supply.

Table A2: Tail estimations (η), all countries

	With Trade			Without Trade		
Country	1995 – 2014	1995 – 2007	2008 – 2014	1995 – 2014	1995 – 2007	2008 – 2014
Australia	1.720 (0.12)	1.752 (0.18)	1.665 (0.03)	1.659 (0.05)	1.721 (0.06)	1.559 (0.04)

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Table A2 – *Continued from previous page*

Country	With Trade 1995 – 2014	With Trade 1995 – 2007	With Trade 2008 – 2014	Without Trade 1995 – 2014	Without Trade 1995 – 2007	Without Trade 2008 – 2014
Austria	1.665	1.732	1.553	1.651	1.759	1.482
	(0.05)	(0.07)	(0.02)	(0.06)	(0.09)	(0.03)
Belgium	1.540	1.563	1.499	1.266	1.428	1.199
	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)
Bulgaria	2.306	2.324	2.273	2.110	2.139	2.058
	(0.19)	(0.27)	(0.11)	(0.22)	(0.32)	(0.06)
Brazil	1.578	1.627	1.495	1.895	1.959	1.787
	(0.05)	(0.07)	(0.01)	(0.07)	(0.10)	(0.02)
Canada	1.814	1.929	1.633	1.805	1.864	1.774
	(0.13)	(0.18)	(0.04)	(0.08)	(0.11)	(0.03)
China	1.575	1.510	1.710	2.205	2.067	2.415
	(0.08)	(0.08)	(0.09)	(0.13)	(0.15)	(0.06)
Cyprus	1.886	1.901	1.857	1.706	1.691	1.730
	(0.15)	(0.20)	(0.05)	(0.21)	(0.29)	(0.08)
Czech Rep.	1.938	1.981	1.864	2.124	2.195	2.003
	(0.06)	(0.09)	(0.04)	(0.15)	(0.21)	(0.10)
Germany	1.447	1.436	1.469	1.518	1.511	1.531
	(0.04)	(0.05)	(0.03)	(0.06)	(0.06)	(0.07)
Denmark	1.843	1.911	1.729	1.531	1.587	1.430
	(0.11)	(0.16)	(0.02)	(0.13)	(0.19)	(0.10)
Spain	1.806	1.876	1.690	2.176	2.300	1.978
	(0.06)	(0.06)	(0.06)	(0.08)	(0.09)	(0.10)
Estonia	1.881	1.989	1.708	1.883	2.072	1.610
	(0.05)	(0.08)	(0.02)	(0.10)	(0.13)	(0.10)
Finland	1.874	2.004	1.673	2.309	2.469	2.062
	(0.05)	(0.07)	(0.03)	(0.07)	(0.10)	(0.05)
France	1.475	1.520	1.397	1.241	1.391	1.032
	(0.08)	(0.05)	(0.12)	(0.31)	(0.06)	(0.54)
UK	1.614	1.651	1.549	1.455	1.476	1.418
	(0.05)	(0.04)	(0.06)	(0.06)	(0.06)	(0.08)
Greece	1.565	1.634	1.399	1.545	1.653	1.358
	(0.07)	(0.10)	(0.03)	(0.11)	(0.17)	(0.05)
Hungary	1.487	1.472	1.514	1.588	1.617	1.539
	(0.06)	(0.08)	(0.04)	(0.09)	(0.12)	(0.07)
Indonesia	2.322	2.352	2.105	2.628	2.438	2.684
	(0.22)	(0.31)	(0.10)	(0.48)	(0.63)	(0.12)
India	1.650	1.681	1.594	1.549	1.773	1.226
	(0.14)	(0.20)	(0.03)	(0.54)	(0.68)	(0.56)
Ireland	1.389	1.531	1.185	1.369	1.535	1.291
	(0.05)	(0.07)	(0.04)	(0.09)	(0.13)	(0.11)

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Table A2 – *Continued from previous page*

Country	With Trade 1995 – 2014	With Trade 1995 – 2007	With Trade 2008 – 2014	Without Trade 1995 – 2014	Without Trade 1995 – 2007	Without Trade 2008 – 2014
Italy	1.493	1.533	1.423	1.408	1.449	1.337
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)
Japan	2.072	2.092	2.037	2.079	2.146	1.965
	(0.17)	(0.24)	(0.02)	(0.05)	(0.07)	(0.02)
South Korea	1.718	1.775	1.621	1.806	1.848	1.733
	(0.09)	(0.13)	(0.04)	(0.26)	(0.41)	(0.07)
Lithuania	1.905	1.919	1.881	2.124	2.018	1.881
	(0.06)	(0.09)	(0.03)	(0.15)	(0.19)	(0.08)
Luxembourg	1.370	1.415	1.293	1.287	1.294	1.276
	(0.05)	(0.07)	(0.03)	(0.08)	(0.11)	(0.06)
Latvia	1.854	1.993	1.641	1.528	1.499	1.587
	(0.09)	(0.16)	(0.03)	(0.43)	(0.58)	(0.11)
Mexico	1.126	1.179	1.041	1.266	1.313	1.211
	(0.06)	(0.10)	(0.01)	(0.04)	(0.07)	(0.03)
Malta	1.709	1.628	1.883	1.835	1.777	1.914
	(0.20)	(0.22)	(0.07)	(0.19)	(0.24)	(0.15)
Netherlands	1.433	1.449	1.405	1.374	1.402	1.325
	(0.06)	(0.08)	(0.08)	(0.09)	(0.11)	(0.16)
Poland	1.984	2.072	1.839	2.220	2.328	2.040
	(0.11)	(0.16)	(0.06)	(0.15)	(0.23)	(0.09)
Portugal	1.707	1.737	1.652	1.924	1.980	1.827
	(0.04)	(0.05)	(0.02)	(0.05)	(0.08)	(0.03)
Romania	1.913	1.898	1.621	1.993	2.032	1.675
	(0.15)	(0.20)	(0.06)	(0.10)	(0.12)	(0.09)
Russia	1.665	1.649	1.696	1.893	1.859	1.960
	(0.04)	(0.05)	(0.03)	(0.07)	(0.07)	(0.04)
Slovakia	2.045	2.089	1.882	1.945	1.971	1.836
	(0.08)	(0.10)	(0.09)	(0.13)	(0.16)	(0.14)
Slovenia	1.646	1.672	1.600	1.752	1.803	1.664
	(0.04)	(0.06)	(0.02)	(0.05)	(0.07)	(0.02)
Sweden	1.554	1.596	1.482	1.628	1.691	1.522
	(0.03)	(0.04)	(0.02)	(0.05)	(0.06)	(0.06)
Turkey	2.172	2.078	1.905	2.729	2.721	2.260
	(0.14)	(0.19)	(0.05)	(0.17)	(0.22)	(0.06)
Taiwan	1.914	1.884	1.916	1.734	1.763	1.677
	(0.10)	(0.11)	(0.10)	(0.09)	(0.08)	(0.11)
USA	1.488	1.512	1.443	1.473	1.501	1.424
	(0.03)	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)