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High Order Openness

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Keywords

Openness Measure, Openness Instrument, Global Supply Chains, Growth, Productivity, Synchronization

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Abstract

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1 Introduction

Conventional measures of openness build from direct trade. The total values of exports or imports are often compared with value added, see Alcalá and Ciccone (2004). Implicit trade costs are inferred from the values of direct trade normalized according to the gravity model, see Baldwin et al. (2003) or Head and Mayer (2004). This measure is often labelled the "phiness" of trade. Trade in Value Added (TiVA) computes the value added content of direct exports, and so continues to be predicated on a measure of direct trade, see Johnson and Noguera (2012). We introduce a measure of high order trade, "HOT" for short, that altogether abstracts from direct trade. This presents two advantages. First, we can compute precisely exposure to foreign shocks ("openness") for activities that trade none of their output directly, most prominently services. Second, we can introduce instruments for openness at a level of aggregation and coverage that is unprecedented.

We compare the properties of our novel measure, HOT, with its predecessors. We characterize the distributions of openness across sectors and countries as implied by four measures: HOT, TiVA, direct exports as a share of value added, and the phiness of trade. We show service trade is measured with most precision using HOT. We then document the correlates of each of these four measures across 50 sectors in 43 countries, focusing in particular on productivity, growth, and synchronization. Such coverage is of course unattainable in firm-level data. HOT is the only available measure of openness that displays a robust and significantly positive correlation with all three variables at sector level. Thus, HOT is the only available measure that confirms at sector level what is well known today at firm or country level. Finally, we implement our instrumentation strategy for HOT, concluding that (high order) openness *causes* productivity and synchronization, but not growth. This is consistent with a Ricardian view of trade, where openness triggers reallocation with potential level effects, but no permanent growth consequences.

For each sector, HOT computes the fraction of gross output sold to downstream customers located across a border. In general, downstream customers may purchase a sector's output directly, or indirectly from its (direct or indirect) customers. Our innovation is to consider the domestic/foreign status not only of the direct purchasers of a sector's output, but also of its indirect purchasers, at second and higher orders. We think of this as an intuitive generalization of the standard approach to measuring openness, and a timely one as high order linkages increasingly cross borders with the advent of global supply chains.

In practice, HOT is computed from the identity at the heart of input-output tables, equating gross output in a given sector to its downstream final or intermediate uses. We decompose the identity into the uses that are purely domestic and those that are not. In doing so, we allow for offshore outsourcing, in which segments of the supply chain are localized in different countries. This can happen more than once, so that several segments of the supply chain can be outsourced abroad. The identity then traces the back and forth of the supply chain across the border, and HOT takes high value if most of the sector's gross output is in fact used abroad. Since long supply chains are intrinsically likely to be open simply because they have many steps, we normalize by the average number of steps in the sector using the measure of upstreamness introduced in Antràs et al. (2012) and Antràs and Chor (2013). Thus, HOT computes the percentage of a sector's output that is used abroad, holding constant the number of steps that separate that output from its final uses.[1]

Methodologically the identity equating sector output to its downstream uses implies that the vector of sector output in each country is a function of the Leontief inverse of the world input-output matrix. Now downstream uses can be split into two infinite sums: One that isolates the purely domestic uses of the sector's output, and one that contains all the others. The former summarizes all the ways in which the sector's output reaches final demand staying strictly within the same country. The latter includes all the ways borders are crossed down the supply chain: from domestic to foreign countries, potentially onto other foreign countries, and potentially back home. This infinite sum reflects the "open" part of the supply chain, and is the main constituting element of HOT. By definition, it is equal to the difference between the Leontief inverse of the world input-output matrix and the Leontief inverse computed on the purely domestic component of the world input-output matrix. That is, it is given by the difference between all the uses for a given sector's output, and all of its purely domestic uses. HOT is then obtained normalizing this difference by the average length of the supply chain, i.e., by upstreamness.

HOT is computed using the 2016 release of the World Input-Output Tables (WIOT) for 50 sectors in 43 countries between 2000 and 2014, which represents about 85 percent of world GDP.[2] We compute average values for HOT by country and by sector. Across countries HOT correlates highly with existing measures, with small countries like Luxembourg or Ireland at the top of the distribution and large ones like Japan or the US at the bottom. The correlation between HOT and the ratio of direct trade to value added is 0.73 across countries. But across sectors the correlation falls to 0.45. This is because HOT implies more sectors are open. On average, the median value of HOT for services is above 0.40, much more open than for example Construction (0.18) or Real Estate (0.22). Services are consistently more open according to HOT than according to measures based on direct trade. In fact, some services are among the most open sectors

[1] Input-output tables are silent about firm boundaries, so that HOT can in fact correlate with the existence of multinational companies. See Alfaro et al. (2019) or Atalay et al. (2019).

[2] The six public sectors are omitted. For details about WIOT, see Dietzenbacher et al. (2013). The 2016 release of WIOT is described in Timmer et al. (2016).

in some countries - e.g., IT in India.

The main existing measure of high order trade is TiVA, the value added content of observed direct trade. TiVA is typically normalized by total direct exports, with values above one for activities that mostly trade indirectly via the supply chain. With this normalization, the correlation between HOT and TiVA is -0.07 across countries, and -0.06 across sectors. Here TiVA is unbounded and takes very large values for sectors that barely trade directly, like services. It does not correlate with any measure of openness. This is not surprising as TiVA was introduced to measure the extent of integration with supply chains, rather than exposure to foreign shocks. See Johnson and Noguera (2012). Normalizing TiVA by value added instead, the correlation between HOT and TiVA rises to 0.70 across countries, and 0.32 across sectors. TiVA becomes in fact similar to the ratio of direct exports to value added with correlations above 0.70, probably because direct exports are embedded in TiVA by construction.

According to conventional measures, the distribution of openness across sectors is highly skewed: open sectors are typically the exception, even in open countries. For example, the median ratio of export to value added across sectors is 0.15 in the Netherlands, suggesting that most sectors are in fact closed even in a very open country. The same is true of TiVA when it is normalized by value added. When normalized by total exports, TiVA takes low values in very open countries like Luxembourg or the Netherlands, because with a lot of direct trade, the numerator is not much larger than the denominator. See Johnson and Noguera (2012). The distribution of HOT across sectors is much more symmetric than the alternatives. Some sectors are open even in countries that are relatively closed on average, and most countries have a distribution of HOT that spans most of its support, between 0 and 1. This is intuitive: while some sectors do not trade directly across the border, supply chains that never cross a border are rare.

Clearly, there are large differences between HOT and its predecessors, especially across sectors. The question is whether HOT does a better job than other measures at capturing the propagation of shocks across borders, which we know happens via the supply chain.[3] To answer the question we implement three estimations that are common in firm-level data and in country panels. We first ask whether a sector openness correlates systematically with its productivity, a question many times asked in firm-level data. See among many others the seminal studies of Bernard and Jensen (1995, 1999, 2004) at firm level, or productivity enhancing reallocation effects in Amiti and Konings (2007), Topalova and Khandelwal (2011), Bernard et al. (2018), or De Loecker and Van Biesebroeck (2018). Second we ask whether openness correlates with growth, a question that was first asked across countries and more recently at firm level.[4] Third and

[3]See Acemoglu et al. (2015).

[4]See for instance the survey by Baldwin et al. (2003) across countries, or Amiti and Konings (2007), Halpern et al. (2015) or Bøler et al. (2015) at firm level.

finally, we introduce a bilateral version of high order trade and ask whether it correlates with the synchronization of business cycles at sector level. Once again, that question is rampant in the aggregate (see Frankel and Rose, 1998 or Kalemli-Özcan et al., 2013) and at firm level although in a firm-to-country rather than firm-to-firm setup (see for instance di Giovanni et al., 2017, 2018).

We document a systematic positive and significant correlation between HOT, labor productivity and growth at sector level. We also show that bilateral HOT correlates positively and significantly with the synchronization of business cycles between sectors located in different countries (that is, between sectors r and s, located in countries i and j). This is a new result. The estimates have the wrong sign and are unstable using conventional measures. Thus, correlates of openness at sector level are consistent with firm-level (and some aggregate) evidence when openness is measured by HOT, but not when it is measured by any of its predecessors. This illustrates the empirical relevance of the value chain as a channel of shock propagation, and the superiority of HOT to measure the exposure of value chains to foreign shocks.

OLS estimations are plagued by a fundamental issue of endogeneity: Trade does not happen in a vacuum. It tends to happen in high productivity, high growth environments. This selection is at the center of the literature using firm-level data where exporting firms are compared with non-exporting ones, which established forcefully that exporters are special, highly performing firms. But endogeneity does not preclude the fact that HOT correlates significantly with sector-level economic performance but other measures of openness do not. That is sufficient to illustrate the superiority of HOT as a measure of the exposure to foreign shocks at sector level.

Of course, establishing the putative *consequences* of openness to trade continues to be an important area of research. We introduce an instrument for HOT at sector level, over time, and for any country with input-output data. This represents an important improvement over existing measures of openness, which are virtually impossible to instrument at such level of generality. The instrument uses the network structure of HOT: For each sector we separate out the first-order links, which clearly depend endogenously on the circumstances of the considered sector, from the higher-order links. There is little question that a sector's first-order, direct openness can be caused by its productivity: A sector trades more across the border if it is populated by high performing firms. But the fact that downstream sectors themselves are more open is less likely to be caused by upstream productivity: Downstream openness is mostly caused by downstream productivity, and there is no conclusive evidence of positive degree assortative matching between firms along the supply chain.[5] We generalize the intuition to a version of the

[5]In many-to-many matching environments, firms with many buyers tend to sell on average to buyers with few connections, i.e. to relatively low productivity firms. See Bernard et al. (2019) for evidence on Japan and Bernard et al. (2018) on Norway. In a one-to-one matching environment, Dragusanu et al. (2014) shows that positive assortative matching is non-existent for intermediate trade.

instrument that focuses on high-order links, holding low-order links constant. Changes in this version of the instrument come only from the changes in high-order linkages. These are likely exogenous to the performance of a sector.[6]

Two-stage least squares estimates confirm a significant effect of HOT on productivity and synchronization. The coefficient estimate on productivity roughly halves relative to OLS, as expected given that productive sectors tend to be open. But there is no significant effect of HOT on growth, consistent with a Ricardian view of trade where openness triggers reallocation, with level effects but no permanent growth consequences.

We are not the first paper proposing to incorporate input-output linkages in measures of openness. Tintelnot et al. (2018) introduce a measure similar to ours in Belgian firm-to-firm data to study how international trade affects wages and unit costs at firm level. A growing literature uses Leontief inverses to isolate the value-added component of trade, TiVA. The main idea is to obtain a measure of trade that is commensurate with national accounts, i.e., expressed in terms of value created rather than gross output. The two become increasingly disconnected as supply chains integrate globally (see for instance Johnson and Noguera, 2012, Koopman et al., 2014, Bems and Kikkawa, 2019, or Bems and Johnson, 2017). Our purpose is different: While this literature introduces a measure of trade that is consistent with national accounts, we introduce a measure of trade that is consistent with theoretical propagation channels.

Trade in services is hard to measure. Data on service trade are available from balance of payments statistics, but a breakdown into constituent service sectors is very hard to come by. The Bureau of Economic Analysis proposes a decomposition into nine categories for US service trade, but the breakdown is not particularly useful.[7] What we know is that service trade as a whole has risen since the 1980s, without much of a commensurate fall in formal protection. Unsurprisingly, a large literature has deployed treasures of ingenuity to decompose this increase into its sector components. One approach is to compute the phiness of service trade using intermediate trade as reported in input-output tables. See for instance Eaton and Kortum (2018). Another approach is to compute TiVA for services. For example, Johnson (2014) shows service trade is larger in value-added terms than in gross terms, a result reminiscent of one in this paper's, and reflective of the fact that services trade mostly indirectly across borders. Yet another approach is to infer international trade in services from local trade in services. Services with high geographic concentration are tradable locally, and so are presumed to be tradable internationally as well. See for instance Jensen and Kletzer (2005), Eckert et al. (2019), and Gervais and Jensen (2019). A final approach is to build from the fact that

[6] The approach is inspired from Bramoullé et al. (2009).

[7] The categories are: Maintenance and repair services, Transport, Travel, Insurance Services, Financial Services, Charges for the use of intellectual property, Telecommunications, computers, and information services, Other business services, and Government goods and services.

goods and services trade have similar determinants (distance, borders, gravity), so that service trade is related with goods trade. The focus is on services that support goods production. See for instance Eaton and Kortum (2018), Christen and François (2017), or Egger et al. (2017). Our contribution to this literature is to introduce a precise measure of service trade that is readily available from input-output data, that does not depend on a normalization choice, and that correlates significantly with sector-level measures of productivity, growth, and synchronization.

The rest of the paper is structured as follows. Section 2 presents the methodology implemented to compute high order trade and its instrument. Section 3 introduces the empirics and presents some stylized facts. Section 4 presents the paper's main estimation results. Section 5 concludes.

2 Measuring High Order Trade

2.1 High Order Trade

By definition, gross output in each sector must equal all of its downstream final or intermediate uses. Formally, this can be written as:

$$\mathrm{Y}_i^r = \sum_s \sum_j \mathrm{Z}_{ij}^{rs} + \sum_j \mathrm{F}_{ij}^r \tag{1}$$

where Y_i^r is the value of gross output in sector $r = 1, ..., R$ of country $i = 1, ..., N$, Z_{ij}^{rs} is the value of intermediate uses of this good in country j and sector s, and F_{ij}^r is the value of its final uses in country j. Throughout the paper, subscripts denote countries and superscripts denote sectors. Both indexes are ordered so that the first identifies the location of production, and the second identifies the location of use.

The identity can be decomposed according to border crossings, isolating a component focused on domestic uses only:

$$\mathrm{Y}_i^r = \left[\sum_s \sum_{j \neq i} \mathrm{Z}_{ij}^{rs} + \sum_{j \neq i} \mathrm{F}_{ij}^r \right] + \left[\sum_s \mathrm{Z}_{ii}^{rs} + \mathrm{F}_{ii}^r \right]. \tag{2}$$

The second term focuses on domestic uses. Following Antràs and Chor (2013), define $a_{ij}^{rs} = \frac{\mathrm{Z}_{ij}^{rs}}{\mathrm{Y}_j^s}$. The identity becomes

$$\mathrm{Y}_i^r = \left[\sum_s \sum_{j \neq i} a_{ij}^{rs} \, \mathrm{Y}_j^s + \sum_{j \neq i} \mathrm{F}_{ij}^r \right] + \left[\sum_s a_{ii}^{rs} \, \mathrm{Y}_i^s + \mathrm{F}_{ii}^r \right]. \tag{3}$$

where a_{ij}^{rs} is the dollar amount of output from sector r in country i needed to produce one dollar worth of output in sector s of country j, i.e., the entry in a direct requirement input-output matrix. A simple interpretation is that output of sector r can be used as intermediate and final good domestically or abroad. Iterating:

$$\begin{aligned}
\mathrm{Y}_i^r = & \left[\mathrm{F}_{ii}^r + \sum_s a_{ii}^{rs}\,\mathrm{F}_{ii}^s + \sum_s a_{ii}^{rs} a_{ii}^{st}\,\mathrm{F}_i^t + \dots\right] \\
& + \left[\sum_{j \neq i} \mathrm{F}_{ij}^r + \sum_s \sum_{j \neq i} \left(a_{ij}^{rs}\,\mathrm{F}_j^s + a_{ii}^{rs}\,\mathrm{F}_{ij}^s\right)\right. \\
& \left. + \sum_t \sum_s \sum_{j \neq i} \left(a_{ij}^{rs} a_{jj}^{st}\,\mathrm{F}_j^t + a_{ii}^{rs} a_{ij}^{st}\,\mathrm{F}_j^t + a_{ij}^{rs} \sum_k a_{jk}^{st}\,\mathrm{F}_k^t\right) + \dots\right].
\end{aligned} \tag{4}$$

where $\mathrm{F}_i^r = \sum_j \mathrm{F}_{ij}^r$ is the total final demand for the good r produced in country i. The first infinite sum in equation (4) collects all the manners in which production in sector r reaches final demand while never crossing a border: directly selling to a domestic final consumer at order 1, or as an intermediate input for a producer selling to the final consumer at order 2, and so on. The second infinite sum captures all the ways in which good r in country i can be exported to meet final demand: directly as a final good at order 1, as an intermediate input for a foreign producer or a domestic exporter at order 2, as an intermediate good used for the production of another intermediate input, which in turn meets final demand either at home or abroad at order 3, and so on. This term incorporates sequences of border crossings, for instance intermediate goods serving to produce other intermediates abroad that are eventually used at home to produce a final good. In other words, it captures the offshoring of segments of production, i.e., a global value chain. This infinite sum reflects the "open" part of the supply chain, and is the main constituting element of HOT.

Long supply chains are likely to cross borders at some point, simply because there are many steps to reach final demand. So the fraction of a sector's output that is sold across the border may be systematically higher for long supply chains. HOT should be computed holding the average length of the supply chain constant. We do so using the measure of upstreamness U_i^r introduced by Antràs et al. (2012) and Antràs and Chor (2013). Upstreamness computes the average number of steps from production to final demand, by weighting each use of a sector's output by the order at which it is meeting final demand. It is straightforward to apply the decomposition in equation (4) to upstreamness:

$$\begin{aligned}
\mathrm{U}_i^r = & \left[\mathrm{F}_{ii}^r + 2 \times \sum_s a_{ii}^{rs}\,\mathrm{F}_{ii}^s + 3 \times \sum_s a_{ii}^{rs} a_{ii}^{st}\,\mathrm{F}_i^t + \ldots\right] \\
& + \left[\sum_{j\neq i} \mathrm{F}_{ij}^r + 2 \times \sum_s \sum_{j\neq i} \left(a_{ij}^{rs}\,\mathrm{F}_j^s + a_{ii}^{rs}\,\mathrm{F}_{ij}^s\right)\right. \qquad (5) \\
& \left. + 3 \times \sum_t \sum_s \sum_{j\neq i} \left(a_{ij}^{rs} a_{jj}^{st}\,\mathrm{F}_j^t + a_{ii}^{rs} a_{ij}^{st}\,\mathrm{F}_j^t + a_{ij}^{rs} \sum_k a_{jk}^{st}\,\mathrm{F}_k^t\right) + \ldots\right] \\
& \equiv \mathrm{U}_i^{r\,\mathrm{DOM}} + \mathrm{U}_i^{r\,\mathrm{HOT}} \qquad (6)
\end{aligned}$$

Antràs and Chor (2013, 2018) show that U_i^r is a typical element of $(\mathbf{I}-\mathbf{A})^{-2}\,\mathbf{F}$ where $\mathbf{A}$ is the direct requirement matrix with typical element a_{ij}^{rs}, and $\mathbf{F}$ is the vector of final demand. By analogy, the infinite sum $\mathrm{U}_i^{r\,\mathrm{DOM}}$ focused on domestic transactions in equation (6) is a typical element of the matrix $(\mathbf{I}-\mathbf{A}^{\mathrm{DOM}})^{-2}\,\mathbf{F}^{\mathrm{DOM}}$, where $\mathbf{A}^{\mathrm{DOM}}$ is the direct requirement matrix abstracting from international intermediate trade, with typical element a_{ii}^{rs}. $\mathbf{A}^{\mathrm{DOM}}$ is constituted of the block diagonal of $\mathbf{A}$. $\mathbf{F}^{\mathrm{DOM}}$ is the vector of domestic final demand. It follows that the infinite sum $\mathrm{U}_i^{r\,\mathrm{HOT}}$ is a typical element of the matrix $(\mathbf{I}-\mathbf{A})^{-2}\,\mathbf{F} - (\mathbf{I}-\mathbf{A}^{\mathrm{DOM}})^{-2}\,\mathbf{F}^{\mathrm{DOM}}$.

Definition 1. *We define* HOT_i^r *the normalized measure of high order trade in sector* r *of country* i*, by*

$$\mathrm{HOT}_i^r = \frac{\mathrm{U}_i^{r\,\mathrm{HOT}}}{\mathrm{U}_i^r} \qquad (7)$$

High order trade HOT_i^r measures the extent to which sector r of country i serve downstream sectors that are across a border, holding constant the length of the value chain for that country sector.

Proposition 1. *High order trade* HOT_i^r *is given by the typical element of the following Hadamard division*

$$\left[(\mathbf{I}-\mathbf{A})^{-2}\,\mathbf{F} - (\mathbf{I}-\mathbf{A}^{\mathrm{DOM}})^{-2}\,\mathbf{F}^{\mathrm{DOM}}\right] \oslash \left[(\mathbf{I}-\mathbf{A})^{-2}\,\mathbf{F}\right]$$

High order trade still embeds first order (direct) trade linkages in final or intermediate goods, i.e., F_{ij}^r for all $j \neq i$ and Z_{ij}^{rs} for all s and $j \neq i$. We introduce a version of HOT_i^r that abstracts from all first order trade, in order to focus on the consequences of high order linkages.

Definition 2. *Define*

$$\mathrm{VHOT}_i^r = \frac{\mathrm{U}_i^{r\,\mathrm{HOT}} - \sum_{j\neq i} \mathrm{F}_{ij}^r - \sum_{j\neq i} \sum_s \mathrm{Z}_{ij}^{rs}}{\mathrm{U}_i^r} \qquad (8)$$

VHOT_i^r measures the foreign exposure of sector r in country i abstracting from all direct exports arising from the sector itself.

2.2 Bilateral High Order Trade

HOT_i^r and VHOT_i^r both capture the foreign exposure of sector r in country i *vis à vis* the rest of the world. They are multilateral measures of openness, accounting for the sector's linkages with all other countries j. It is straightforward to specialize the measures to a bilateral context, considering the relevant matrices and vectors focused on a pair of countries ij.

In particular introduce $\mathbf{A}_{ij}$ the $2R \times 2R$ matrix containing all the entries in WIOT that pertain to country i, country j, and the trade linkages between them. The entries in $\mathbf{A}_{ij}$ report how much of the output in country i sector r is required to produce one dollar of output in sector s of country j. $\mathbf{F}_{ij}$ is the vector of final demands in countries i and j including international trade between i and j. By analogy $\mathbf{A}_{ij}^{\mathrm{DOM}}$ denotes the direct requirement matrix for countries i and j focusing exclusively on domestic linkages, i.e., on the block diagonal elements of $\mathbf{A}_{ij}$. $\mathbf{F}_{ij}^{\mathrm{DOM}}$ denotes the vector of domestic final demand in countries i and j. The extension of high order trade to a bilateral version is then computed following the next steps.

Unilateral high order trade follows directly from Definition 1:

$$\mathrm{HOT}_{ij}^r = \frac{\mathrm{U}_{ij}^{r\,\mathrm{HOT}}}{\mathrm{U}_{ij}^r}, \tag{9}$$

where $\mathrm{U}_{ij}^{r\,\mathrm{HOT}}$ is the typical element in $(\mathbf{I} - \mathbf{A}_{ij})^{-2}\,\mathbf{F}_{ij} - (\mathbf{I} - \mathbf{A}_{ij}^{\mathrm{DOM}})^{-2}\,\mathbf{F}_{ij}^{\mathrm{DOM}}$, and U_{ij}^r is the typical element in $(\mathbf{I} - \mathbf{A}_{ij})^{-2}\,\mathbf{F}_{ij}$. Unilateral high order trade HOT_{ij}^r is given by the typical element of the following Hadamard division

$$\left[(\mathbf{I} - \mathbf{A}_{ij})^{-2}\,\mathbf{F}_{ij} - (\mathbf{I} - \mathbf{A}_{ij}^{\mathrm{DOM}})^{-2}\,\mathbf{F}_{ij}^{\mathrm{DOM}}\right] \oslash \left[(\mathbf{I} - \mathbf{A}_{ij})^{-2}\,\mathbf{F}_{ij}\right]. \tag{10}$$

HOT_{ij}^r computes the fraction of the value chain in sector r of country i that crosses the border into country j. It is a unilateral measure, in the sense that it captures the exposure to a given country j of production in sector r of country i. It is not symmetric and $\mathrm{HOT}_{ij}^r \neq \mathrm{HOT}_{ji}^r$.

Definition 3. *We define* BHOT_{ij}^r*, a measure of bilateral high order trade between pairs of countries and pairs of sectors*

$$\mathrm{BHOT}_{ij}^{rs} = \mathrm{HOT}_{ij}^r \times \mathrm{HOT}_{ji}^s. \tag{11}$$

BHOT captures the exposure to country j of sector r in country i, combined with the exposure to country i of sector s in country j. The measure ignores trade linkages between i and j that travel via third countries. It only considers the sectors in country j that Y_i^r is sold to. If Y_i^r travels to country j via a third country k, that will enter BHOT_{ik}^{rs} and BHOT_{kj}^{rs}, but not BHOT_{ij}^{rs}. Thus it represents a narrow concept of bilateral linkages.

Lastly, we introduce a measure of bilateral high order trade that abstracts from any direct trade. Focusing on high order trade only

$$\mathrm{VHOT}_{ij}^{r} = \frac{\mathrm{U}_{ij}^{r^{\mathrm{HOT}}} - \mathrm{F}_{ij}^{r} - \sum_s \mathrm{Z}_{ij}^{rs}}{\mathrm{U}_{ij}^{r}}, \tag{12}$$

where we have subtracted final and intermediate bilateral direct trade. The corresponding measure of bilateral high order trade is

$$\mathrm{BVHOT}_{ij}^{rs} = \mathrm{VHOT}_{ij}^{r} \times \mathrm{VHOT}_{ji}^{s}. \tag{13}$$

None of these measures are symmetric, since $\mathrm{BHOT}_{ij}^{rs} \neq \mathrm{BHOT}_{ij}^{sr}$ and $\mathrm{BHOT}_{ij}^{rs} \neq \mathrm{BHOT}_{ji}^{rs}$. The same is true of BVHOT_{ij}^{rs}.

2.3 Instrumenting High Order Trade

It is notoriously difficult to instrument openness at sector level, especially over time. Exporting firms are high performers, and that is a reason why they are exporting. Parsing out how much of their observed performance actually comes from their exposure to foreign trade is a challenge, since export status and performance are jointly determined. Yet, the existence and magnitude of putative effects of openness are of great interest: Technology is likely to diffuse through trade, new ideas are likely to be stimulated by foreign markets, markups are likely to respond to foreign competition, and unproductive firms are likely to exit.

We introduce an instrument for HOT at sector level that makes use of the network structure of the measure. Changes in HOT_i^r can come from two sources: Either an increase in the intensity of linkages emerging from the sector itself, or increases in the intensity of the linkages emerging downstream from the sector, at orders two and above. We argue only low orders are endogenous to the performance of sector r in country i. What is happening in downstream sectors is determined by these sectors' changing performance, and not by any developments specific to sector r in country i. This second component of HOT constitutes therefore a potentially good instrument: It correlates with HOT_i^r, but not because of what is happening in sector r and country i.

The key identifying assumption for this to constitute an adequate instrument is that downstream linkages do not respond to upstream productivity: We need to rule out positive assortative matching. Using firm-level data Bernard et al. (2019) and Bernard et al. (2018) show that firms with many downstream linkages tend to sell to firms with few connections, i.e., productive firms do not systematically sell to productive firms. This suggests there is no tendency for productive sellers to seek productive buyers. Therefore an increase in downstream linkages does not come from an increase in upstream productivity.

We focus on the changes in HOT coming from changes in high-order trade linkages, holding low-order linkages constant. We first hold first-order linkages constant; we will later generalize the approach to orders higher than one. To see how this works, consider the identity decomposition of output in sector r of country i, a slightly rearranged version of equation (4):

$$\mathrm{Y}_i^r = \sum_j \sum_s \left[\mathrm{F}_{ij}^r + a_{ij}^{rs}\, \mathrm{F}_j^s + \sum_k \sum_t a_{ik}^{rt}\, a_{kj}^{ts}\, \mathrm{F}_j^s + \sum_k \sum_t \sum_l \sum_u a_{ik}^{rt}\, a_{kl}^{tu}\, a_{lj}^{us}\, \mathrm{F}_j^s + \dots \right]$$

The instrument holds constant at their initial value all linkages emerging directly from sector r in country i. Define $a_{ij}^{rs}(0)$ the initial value of a_{ij}^{rs}, and $\mathrm{F}_{ij}^r(0)$ the initial value of F_{ij}^r.[8] We introduce a version of upstreamness $\mathrm{U}_{i\ \mathrm{IV}(1)}^r$ that holds constant to their initial values all first order linkages emerging from sector r in country i:

$$\begin{aligned} \mathrm{U}_{i\ \mathrm{IV}(1)}^r = \sum_j \sum_s \Bigg[& \mathrm{F}_{ij}^r(0) \ + \ 2 \times a_{ij}^{rs}(0)\, \mathrm{F}_j^s \ + 3 \times \sum_k \sum_t a_{ik}^{rt}(0)\, a_{kj}^{ts}\, \mathrm{F}_j^s \\ & + 4 \times \sum_k \sum_t \sum_l \sum_u a_{ik}^{rt}(0)\, a_{kl}^{tu}\, a_{lj}^{us}\, \mathrm{F}_j^s + \dots \Bigg] \end{aligned}$$

Proposition 2. *Upstreamness* $\mathrm{U}_{i\ \mathrm{IV}(1)}^r$ *is the typical element of the matrix*

$$\begin{aligned} & \mathbf{F}_0 + 2\ \mathbf{A}_0\ \mathbf{F} + 3\ \mathbf{A}_0\ \mathbf{A}\ \mathbf{F} + 4\ \mathbf{A}_0\ \mathbf{A}^2\ \mathbf{F} + \dots \\ &= \mathbf{F}_0 + \mathbf{A}_0 \left[[\mathbf{I} - \mathbf{A}]^{-2} + [\mathbf{I} - \mathbf{A}]^{-1} \right] \mathbf{F} \\ &\equiv \mathbf{L}_{\mathrm{IV}(1)} \end{aligned}$$

where $\mathbf{A}_0$ *is the initial direct requirement matrix and* $\mathbf{F}_0$ *is the vector of initial final demand.*

Even though first-order linkages are held constant to their initial values, their dispersion in the initial period can still reflect sector performance in the initial period. For example, high values of $\mathrm{F}_{ij}^r(0)$ happen because sector r in country i is highly performing, and this correlation can persist over time. Then the dispersion embedded in $\mathbf{A}_0$ and $\mathbf{F}_0$

[8] To save on notation we do not introduce explicit time subscripts in this section.

can still reflect the distribution of initial sector performance. We address this issue by replacing $\mathbf{A}_0$ with the corresponding adjacency matrix $\tilde{\mathbf{A}}_0$ where all non zero elements are replaced with 1. Analogously, we replace all non zero values in $\mathbf{F}_0$ with 1, defining $\tilde{\mathbf{F}}_0$.

Definition 4. *Introduce*

$$\tilde{\mathbf{L}}_{\mathrm{IV}(1)} = \tilde{\mathbf{F}}_0 + \tilde{\mathbf{A}}_0 \left[[\mathbf{I} - \mathbf{A}]^{-2} + [\mathbf{I} - \mathbf{A}]^{-1} \right] \mathbf{F}$$

and

$$\tilde{\mathbf{L}}^{\mathrm{DOM}}_{\mathrm{IV}(1)} = \tilde{\mathbf{F}}^{\mathrm{DOM}}_0 + \tilde{\mathbf{A}}^{\mathrm{DOM}}_0 \left[[\mathbf{I} - \mathbf{A}^{\mathrm{DOM}}]^{-2} + [\mathbf{I} - \mathbf{A}^{\mathrm{DOM}}]^{-1} \right] \mathbf{F}^{\mathrm{DOM}}$$

where $\tilde{\mathbf{A}}^{\mathrm{DOM}}_0$ contains the initial values of $\mathbf{A}^{\mathrm{DOM}}$ with all non zero entries set to 1, and $\tilde{\mathbf{F}}^{\mathrm{DOM}}_0$ contains the initial values of $\mathbf{F}^{\mathrm{DOM}}$ with all non zero entries set to 1.

Proposition 3. *The instrument $\mathrm{HOT}^r_{i\ \mathrm{IV}(1)}$ holding all first-order trade linkages constant to 1 is given by the typical element of the following Hadamard division*

$$\left(\tilde{\mathbf{L}}_{\mathrm{IV}(1)} - \tilde{\mathbf{L}}^{\mathrm{DOM}}_{\mathrm{IV}(1)} \right) \oslash \tilde{\mathbf{L}}_{\mathrm{IV}(1)}$$

$\mathrm{HOT}^r_{i\ \mathrm{IV}(1)}$ is holding all first-order trade constant to 1. It isolates changes in HOT that come from changes in the foreign exposure of sectors that are at least two steps downstream from sector r in country i. It is correlated with HOT^r_i, but not with the performance of sector r in country i. Since this instrument abstracts from direct trade, it also applies to VHOT. It extends easily to BHOT and BVHOT, whose instruments are given by the pairwise products of the instruments for HOT^r_{ij}.[9]

The instrument generalizes to higher orders. Introduce

$$\tilde{\mathbf{L}}_{\mathrm{IV}(n)} = \left[\mathbf{I} + 2\tilde{\mathbf{A}}_0 + \ldots + n\tilde{\mathbf{A}}^n_0 \right] \tilde{\mathbf{F}}_0 + \tilde{\mathbf{A}}^n_0 \left[[\mathbf{I} - \mathbf{A}]^{-2} + n[\mathbf{I} - \mathbf{A}]^{-1} \right] \mathbf{F}$$

the matrix whose typical element is $\mathrm{U}^r_{i\ \mathrm{IV}(n)}$, i.e., the measure of upstreamness that obtains when holding trade linkages up to the n^{th} order constant to 1. Analogously define:

$$\tilde{\mathbf{L}}^{\mathrm{DOM}}_{\mathrm{IV}(n)} = \left[\mathbf{I} + 2\tilde{\mathbf{A}}^{\mathrm{DOM}}_0 + \ldots + n\left(\tilde{\mathbf{A}}^{\mathrm{DOM}}_0 \right)^n \right] \tilde{\mathbf{F}}^{\mathrm{DOM}}_0 + \left(\tilde{\mathbf{A}}^{\mathrm{DOM}}_0 \right)^n \left[[\mathbf{I} - \mathbf{A}^{\mathrm{DOM}}]^{-2} + n[\mathbf{I} - \mathbf{A}^{\mathrm{DOM}}]^{-1} \right] \mathbf{F}^{\mathrm{DOM}}$$

The instrument for HOT obtained when holding downstream linkages constant to 1 up

[9]The instruments for HOT^r_{ij} are defined using equation 10 in Definition 4 and Proposition 3.

to the n^{th} order is the typical element of the Hadamard division

$$\left(\tilde{\mathbf{L}}_{\mathrm{IV}(n)} - \tilde{\mathbf{L}}^{\mathrm{DOM}}_{\mathrm{IV}(n)}\right) \oslash \tilde{\mathbf{L}}_{\mathrm{IV}(n)}.$$

The thus defined instrument $\mathrm{HOT}^{r}_{i\ \mathrm{IV}(n)}$ holds constant to 1 all linkages of order below n emerging from sector r in country i.

2.4 Conventional measures of trade

Conventional measures of openness are based on direct trade. At country level, the value of exports (or imports) is often normalized by GDP. At sector level, exports can be either in final or in intermediate trade, which in our notation can be rewritten as

$$\mathrm{X}^{r}_{i} = \frac{\sum_j \mathrm{F}^{r}_{ij} + \sum_{j\neq i}\sum_s \mathrm{Z}^{rs}_{ij}}{\mathrm{VA}^{r}_{i}}$$

where the numerator sums the USD value of total exports from sector r in country i in final goods with $\sum_j \mathrm{F}^{r}_{ij}$ and in intermediate goods with $\sum_{j\neq i}\sum_s \mathrm{Z}^{rs}_{ij}$. The denominator is simply value added in the sector converted in USD at PPP exchange rates, following Alcalá and Ciccone (2004).

For bilateral measures only intermediate trade data are available, for example from WIOT. A standard approach is to define :

$$\mathrm{X}^{rs}_{ij} = \left(\frac{\mathrm{Z}^{rs}_{ij} + \mathrm{Z}^{rs}_{ji}}{\mathrm{VA}^{r}_{i} + \mathrm{VA}^{r}_{j}}\right)$$

An alternative is to normalize direct trade in a way that is guided by theory. Baldwin et al. (2003) and Head and Mayer (2004) introduce a measure inspired directly from the gravity model that they label the "phiness" of trade. The idea is to normalize direct bilateral trade at sector level by adequately chosen aggregates so that the ratio maps into trade costs in a way that is grounded in theory. With constant expenditure shares across countries and sectors, the trade costs between sector r in country i and country j map into

$$\phi^{r}_{ij} = \left(\frac{(\mathrm{Z}^{r}_{ij} + \mathrm{F}^{r}_{ij}) \times (\mathrm{Z}^{r}_{ji} + \mathrm{F}^{r}_{ji})}{(\mathrm{Z}^{r}_{ii} + \mathrm{F}^{r}_{ii}) \times (\mathrm{Z}^{r}_{jj} + \mathrm{F}^{r}_{jj})}\right)^{1/2}$$

where $\mathrm{Z}^{r}_{ij} = \sum_s \mathrm{Z}^{rs}_{ij}$ is the total value of the sales of good r produced in country i across all sectors in country j. The denominator contains each country's "imports from itself", calculated as the value of all shipments from sector r to any sector s that remain in the producing country. The phiness of trade for sector r in country i can then be defined as

$$\phi^{r}_{i} = \sum_j \phi^{r}_{ij}$$

A bilateral version of ϕ can only be computed on the basis of intermediate trade, the only bilateral data available. Define:

$$\phi_{ij}^{rs} = \left(\frac{\mathrm{Z}_{ij}^{rs} \times \mathrm{Z}_{ji}^{rs}}{\mathrm{Z}_{ii}^{rs} \times \mathrm{Z}_{jj}^{rs}} \right)^{1/2}$$

Johnson and Noguera (2012) introduce a measure of high order trade based on direct exports, TiVA_i^r. The measure captures the value added content of exports of good r produced in country i. TiVA_i^r is defined as the typical element of the following Hadamard product

$$\left(\frac{\mathbf{VA}}{\mathbf{Y}} \right) \odot (\mathbf{I} - \mathbf{A})^{-1} \left(\mathbf{F} - \mathbf{F}^{\mathrm{DOM}} \right) \mathbf{1} \tag{14}$$

where $\left(\frac{\mathbf{VA}}{\mathbf{Y}} \right)$ is the $NR \times 1$ vector of the ratio of value added to gross output in sector r of country i, $\mathbf{F} - \mathbf{F}^{\mathrm{DOM}}$ is the $NR \times N$ matrix of final good exports, and $\mathbf{1}$ is a $N \times 1$ vector of 1s. TiVA_{ij}^r is defined by equation (14) omitting $\mathbf{1}$.

It may be useful to list the differences between TiVA and HOT. First, TiVA measures the fragmentation of exports, their integration in the global value chain. Instead, HOT measures the fragmentation of output, the fraction of gross output that crosses a border: It reflects the importance of foreign shocks for production by construction.[10] For the same reason HOT can abstract from direct trade altogether. Second, TiVA_{ij}^r is bilateral by construction, since it decomposes bilateral exports between countries i and j. HOT_i^r is not: To obtain a bilateral measure, we have to extract specific pairs of countries from the direct requirement matrix $\mathbf{A}$. As a result in its bilateral version HOT_{ij}^r focuses exclusively on the linkages that run between countries i and j, excluding all links involving third party countries. Third, HOT is naturally scaled and bounded between 0 and 1, whereas TiVA needs to be normalized: It is often scaled by total exports to quantify the importance of indirect trade relative to observed direct exports. Since these ratios are unrelated with the size of a given activity in the economy, Duval et al. (2016) normalize TiVA by value added instead to evaluate the correlation between value added trade and the international synchronization of GDP. Finally HOT holds the length of the value chain constant.

We define the following three variants of TiVA:

$$\tau_i^r(X) = \frac{\mathrm{TiVA}_i^r}{\sum_j \mathrm{F}_{ij}^r + \sum_j \sum_s \mathrm{Z}_{ij}^{rs}}, \;\; \tau_i^r(\mathrm{VA}) = \frac{\mathrm{TiVA}_i^r}{\mathrm{VA}_i^r}$$

[10] This difference is apparent from the fact that HOT applies different Leontief inverses to $\mathbf{F}$ and to $\mathbf{F}^{\mathrm{DOM}}$, whereas TiVA applies the same, i.e., decomposes exports.

and a bilateral version

$$\tau_{ij}^{rs}(\text{VA}) = \frac{\text{TiVA}_{ij}^{r}}{\text{VA}_{i}^{r}} \times \frac{\text{TiVA}_{ji}^{s}}{\text{VA}_{j}^{s}}$$

In what follows, we compare HOT with the three alternatives just listed, X, ϕ, and τ.[11]

3 Empirics

3.1 Implementation

Define the world input-output matrix $\mathbf{W}$ with typical element Z_{ij}^{rs}. $\mathbf{W}$ contains the bulk of the information available from WIOT, and it reports intermediate trade within and between countries, augmented with vectors of final demand F_{ij}^{r}. Final demand breaks down into a domestic and an international component by country j, but not by sector s. These are the key ingredients needed to compute HOT.

In addition, $\mathbf{W}$ also keeps track of the net inventories INV_{ij}^{r} in sector r of country i, broken down by country use j, but not by sector use s. To account for inventories, we follow Antràs and Chor (2013, 2018) and correct the input-output data in WIOT according to a proportion rule. We rescale each entry Z_{ij}^{rs} and F_{ij}^{r} in $\mathbf{W}$ by $\text{Y}_{i}^{r} / (\text{Y}_{i}^{r} - \text{INV}_{i}^{r})$ where $\text{INV}_{i}^{r} = \sum_{j} \text{INV}_{ij}^{r}$. We denote with $\mathbf{W}^{*}$ the resulting rescaled input-output matrix.

The direct requirement matrix $\mathbf{A}$ is then computed on the basis of this rescaled input-output matrix. The typical element of $\mathbf{A}$, a_{ij}^{rs}, is the typical element in $\mathbf{W}^{*}$ normalized by the column-wise sum of its elements, i.e. sector-level gross output (corrected for inventories). To define $\mathbf{A}^{\text{DOM}}$ we extract the block diagonal of $\mathbf{A}$ that contains the within country components of the direct requirement matrix. We also extract the domestic components of $\mathbf{F}$ to define $\mathbf{F}^{\text{DOM}}$.

To compute BHOT we need a direct requirement matrix specialized to a pair of countries ij. We extract each pair of countries from $\mathbf{W}^{*}$, and use the values for sector output implied by each country pair to normalize the corresponding $2R \times 2R$ input-output matrix. The normalization of $\mathbf{A}_{ij}$ is therefore specific to each country pair. We also need to isolate the values of intermediate trade within each of the two countries, which is done by extracting the block diagonal elements of $\mathbf{A}_{ij}$. This defines $\mathbf{A}_{ij}^{\text{DOM}}$. We apply the same selection to final demands, defining $\mathbf{F}_{ij}$ and $\mathbf{F}_{ij}^{\text{DOM}}$.

The 2016 release of the World Input-Output Tables provides data for 43 developed and developing countries from 2000 to 2014. This represents approximately 85 percent

[11] There are other measures of openness, based for example on observed tariff schedules, or model based. For example, Waugh and Ravikumar (2016) propose a measure of potential trade openness, based on the welfare gains that opening up the economy would create.

of world GDP.[12] The input-output data are in millions U.S. dollars at current prices and are available for 56 sectors for each country and each year. We exclude 6 public industries from our analysis.[13]

We use the information on yearly value added to compute the relevant measures of sector and aggregate growth, productivity, and synchronization. These measures are deflated when necessary using the sector price indices from the socio-economic accounts available with the 2016 release of WIOT. Data on PPP exchange rates come from the OECD. The socio-economic indicators from WIOT also report the number of employees at sector level, which we use to compute labor productivity and per capita growth rates. Details on the computation of all variables are reported in Appendix B.[14]

3.2 Descriptive Statistics

Table 1 reports the correlations between the six measures of trade openness we consider: HOT, VHOT, X, ϕ, τ(X), and τ(VA). The first panel reports unconditional correlations, the second one reports correlations between country averages, and the third panel reports correlations between sector averages. Several results are of interest. First, the correlation between HOT and VHOT is always above 0.8. This means that in the data HOT is largely determined by high order trade linkages, of order two and above. Direct trade has little role to play in HOT: In the rest of the paper we will focus the analysis on VHOT.

Second, the correlation between VHOT and X is 0.73 across countries, but 0.45 across sectors. This means that country openness according to VHOT is not going to be much different from what we are used to seeing according to direct trade measures like X. The story is different across sectors: the ranking of sectors according to VHOT appears to be quite different than what conventional measures like X have taught us. This is probably because many sectors are more open according to VHOT, not least services, which are by and large closed according to X. Third τ(X) captures something quite different from all other variables here: Its correlation is essentially zero with all other measures, especially across sectors, a bit less across countries. This reflects the fact that τ(X) does not measure openness: It measures the integration of a sector's exports with the supply chain. In contrast, τ(VA) correlates highly with all other measures, especially with X, probably because they both embed direct exports and they are both normalized by value added. Fourth and finally ϕ is a proxy for openness that is quite different from both VHOT and X, with correlation coefficients that are mostly below 0.2.

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

[13] See Dietzenbacher et al. (2013) for details on the methodology used to construct these data.

[14] An alternative to the number of employees is the "number of persons engaged", reported as part of the socio-economic indicators. We present the corresponding results, largely unchanged, in an online appendix.

Figures 1 and 2 illustrate these findings graphically. Figure 1 reports the median values of VHOT, ϕ, X, τ(X), and τ(VA) in each country, where all five panels are ranked according to VHOT. The ranking of countries according to VHOT is not surprising, in the sense that small countries tend to have large median values, and large countries tend to have low median values. Consistent with Table 1, the country ranking according to X and τ(VA) is by and large similar to VHOT, but it is quite different according to ϕ and τ(X). For example, τ(X) takes highest values for Japan and among the lowest in Luxembourg, perhaps because Japan is highly integrated with the global value chain and Luxembourg is not. Figure 2 reports the median values of VHOT, ϕ, X, τ(X), and τ(VA) in each sector, where once again all five panels are ranked according to VHOT. Consistent with Table 1, the ranking of sectors according to VHOT is quite different from what is implied by X, ϕ, and both normalizations of τ. For example, the highest value of τ(X) occurs in Real Estate followed by Wholesale Retail, for which direct exports are essentially zero in most countries.

To confirm the standard predictions of VHOT at country level, Figure 3 plots country-level averages of VHOT over time for five large economies, along with a world average.[15] The country ranking is not surprising: Germany is the most open country of the five, followed by China, India, Japan, and the US. All countries display a short lived dip in VHOT in 2009, the infamous great trade collapse that followed the great financial crisis. Germany follows an upward trend throughout the period, whereas China peaked in 2007 and has fallen back to early 2000s levels since. In 2014, about a third of the output in the average German sector is used abroad. It is closer to a quarter for China. The world average is 19 percent. India, Japan, and the US are all below world average. The US is by far the most closed economy in this sample, although it is following a mild upward trend.

Figure 4 plots the density estimates of VHOT, X, ϕ, τ(X), and τ(VA). The contrast between VHOT and its predecessors is striking: VHOT displays a symmetric distribution centered around a value of 0.4, whereas the four other measures are highly skewed with most observations very close to zero and a few very large values. In other words, according to conventional measures most sectors are closed and a few are very open. According to VHOT, most sectors are relatively open, very few are closed, and very few are very open. A natural question is whether the difference between the five measures is more salient across countries or across sectors.

Figure 5 plots the distributions of VHOT, X, and both normalizations of τ across sectors for all 40 countries. The distributions are ranked according to the median value of VHOT. The resulting country ranking is not surprising: distributions in small economies

[15]Country values are averages of sector level VHOT weighted by value added shares. World VHOT is an average of country VHOTs weighted by GDP

tends to be centered on high values of VHOT, like in Ireland, the Netherlands, Luxembourg, or Hungary. And distributions in large countries tends to be centered on low values of VHOT, like in Brazil, the US, India, or Japan. The distributions cover a broad range in most countries. There are open sectors in relatively closed countries: VHOT takes maximum values above 0.6 in some sectors in Japan, above 0.5 in some sectors of India, and around 0.4 in some sectors in the US. And there are closed sectors in open economies, even in Ireland, or the Netherlands where minimum values for VHOT are around 0.3. The distributions look radically different for the three other measures, as shown in the lower panels of Figure 5. According to X, τ(X), and τ(VA) country openness is much lower, closed countries have mostly closed sectors, and open countries have a few open sectors but continue to have a majority of closed sectors. In other words, many sectors are closed according to conventional measures of openness, not so according to VHOT. This is not surprising: most sectors do not trade across the border directly, but most do trade across the border indirectly. What is surprising is that τ(X) and τ(VA) share this property with X. This is probably an artefact of normalization, especially by total exports, and of the fact that direct exports are by definition part of τ.

Figure 6 plots the distributions of VHOT, X, τ(X), and τ(VA) across countries for all sectors. The sectors are ranked according to median values of VHOT. Some results are standard: Manufacturing activities tend to display VHOT distributions centered around high values. For example Metals, Mining, and Chemicals are among the most open sectors according to median VHOT. And activities like Construction, Hotels, or Real Estate tend to be centered on relatively low values of VHOT, with median values around 0.2. However, even in these extreme cases the cross-country distributions of VHOT are broad ranged: For instance in Construction VHOT ranges from close to 0 to 0.5, and it ranges from 0.3 to 0.8 in Mining.

The lower panels of Figure 6 reports the same distributions for the other measures, and it is evident that they are not nearly as dispersed as VHOT: According to X, τ(X), and τ(VA) most sectors tend to be closed, and they tend to be closed in all countries. τ(X) is particularly striking, as it takes lowest values for manufacturing sectors, and high values for a few so-called non traded sectors like real estate. Similar results are documented in Johnson and Noguera (2012); they confirm that τ(X) is not constructed to reflect a sector's exposure to foreign shocks. The view that some sectors are closed in all countries prevails for services: Retail, or Wholesale Retail are often viewed as closed everywhere. VHOT paints a very different picture of "closed" sectors in general, and services in particular. According to VHOT services are in fact rather open on average: median VHOT in Wholesale trade, Business services like Legal, Accounting or Marketing services, Architecture, or Administrative Services are all around 0.5, with top values above 0.7. In other words, there are countries where services are very exposed to foreign shocks, just like there are countries where manufacturing is in fact relatively closed.

Within sector, VHOT display much more variation across countries than conventional measures.

4 Estimations

4.1 The Correlates of Openness

This section documents the existence of systematic correlations between openness and productivity, growth, and synchronization at sector level. This is well charted territory, although not in a panel of sectors across countries. As we will show, conventional measures of sector-level openness fare rather poorly at these three tests, even though the correlations are well established in firm-level (and sometimes aggregate) data. This may be a key reason why sector-level data are rarely used to document openness. By contrast, HOT does capture well these well known correlations, with robust and significant coefficient estimates. We conclude HOT provides a better measure of openness at sector level than its predecessors, since it captures best the underlying correlation between openness and economic performance.

4.1.1 Openness and Productivity

We estimate a specification akin to Alcalá and Ciccone (2004), but perform the estimation in a panel of sectors across countries and over time, whereas Alcalá and Ciccone (2004) worked on a cross section of countries. Productivity is value added per employee, measured in real PPP U.S. Dollars. Panel tests reject the null of non-stationarity in the cross section. We estimate:

$$\ln\left(\frac{\mathrm{VA}^r_{i,t}}{\mathrm{N}^r_{i,t}}\right) = \alpha_{ir} + \gamma_t + \beta_1\,\mathrm{VHOT}^r_{i,t} + \beta_2\,\mathrm{X}^r_{i,t} + \beta_3\,\phi^r_{i,t} + \beta_4\,\tau^r_{i,t}(\mathrm{VA}) + \varepsilon^r_{i,t}. \quad (15)$$

The results are reported by increments in the generality of the fixed effects to document the stability of the correlation between different measures of openness and productivity. The most general specifications allow for country-sector and year specific intercepts. These control for any time invariant characteristic in a given sector located in a given country, and for any global cycle in productivity. Table 2 includes each measure of openness separately, while Table 3 includes them simultaneously. The estimations are performed for HOT, X, ϕ, and τ(VA).

Table 2 shows that a significant positive correlation between productivity and HOT survives the inclusion of country, sector, and country-sector effects. The same is true of ϕ, but not of X or τ(VA), which are never significantly correlated with productivity. Table 3 includes combinations of the four measures of openness as regressors, along with year effects. Once again only HOT is systematically correlated with productivity, no matter the other regressors or the inclusion of year effects. X and τ(VA) enter with negative and significant signs, while ϕ is positive but not always significant.

Table 4 decomposes estimation (15) into four coarse sector categories to establish whether the significance of HOT in the previous tables corresponds to specific sectors. Panel A only includes HOT, Panel B combines all measures simultaneously. For agriculture, manufacturing, and services, HOT correlates significantly and positively with productivity. X and τ(VA) never correlate positively with productivity, indeed they correlate negatively with productivity in manufacturing and services. And ϕ is only positive and significant in mining.

The regressions in Tables 2, 3, and 4 have econometric issues, including endogeneity or omitted variables. Our point is that these issues affect all coefficient estimates in these tables, not only HOT. We interpret the systematically positive sign on HOT, but not on any other measure of openness, as the symptom that HOT is the best measure of openness available when it comes to capturing the well known correlation between productivity and openness that is well documented at firm- and country- levels.

4.1.2 Openness and Growth

The existence of a relation between openness and growth is a venerable research question. Most famously Frankel and Romer (1999) established growth can be a consequence of openness at country level, using geographic and gravity variables as instruments for openness. These important results have been subjected to enormous scrutiny since, and it is fair to say the conclusions are not uncontroversial (see for instance Rodríguez and Rodrik, 2000). Asking the question in a panel of sectors across countries is even more difficult, maybe because until Rodrik (2013) the basic growth estimation appeared to be invalid in a cross-sector, cross-country panel.

We follow the approach in Rodrik (2013), extended to include non manufacturing sectors. Sector-level per capita value added growth is regressed on the initial level of value added per capita, a measure of openness, and a battery of fixed effects. Rodrik (2013) includes sector effects only, arguing this constitutes a test of unconditional convergence. We augment the specification with country effects as well, a test for conditional convergence. This is performed in cross-section and in a panel of sub-periods. Specifically, we estimate

$$\Delta \ln \left(\frac{\mathrm{VA}^r_{i,\varsigma}}{\mathrm{N}^r_{i,\varsigma}} \right) = \alpha_r + \alpha_i + \rho \, \frac{\mathrm{VA}^r_{i,\varsigma}}{\mathrm{N}^r_{i,\varsigma}} + \beta_1 \, \mathrm{VHOT}^r_{i,\varsigma} + \beta_2 \, \mathrm{X}^r_{i,\varsigma} + \beta_3 \, \phi^r_{i,\varsigma} + \beta_4 \, \tau^r_{i,\varsigma}(\mathrm{VA}) + \varepsilon^r_{i,\varsigma} \tag{16}$$

where ς denotes a period over which growth rates are computed, $\mathrm{VA}^r_{i,\varsigma}$ is real value added in PPP U.S dollars, and $\frac{\mathrm{VA}^r_{i,\varsigma}}{\mathrm{N}^r_{i,\varsigma}}$ is value added per capita at the beginning of period ς.

The specification can be augmented with period effects when $\varsigma \geq 2$.

Table 5 presents the results in cross-section, with sector effects only. As in Rodrik (2013), there is unconditional convergence as $\rho < 0$ across all specifications. The first four estimations show all four measures of openness enter the regression positively in isolation, but the next four specifications suggest only HOT and ϕ do so robustly. Then Table 6 includes sector and country effects: Only HOT survives with country specific controls.[16] Table 7 decomposes the estimation into four sectors to evaluate whether different measures of openness matter in different activities. HOT correlates positively with growth in manufacturing, as do ϕ and τ(VA).

The growth regressions in this section are performed at sector level, and so enable a rich set of controls in the form of fixed effects. But they are growth regressions, and as such have well known econometric issues, including endogeneity or omitted variables. But once again, all these issues apply equally to all the measures of openness included. They cannot explain the systematic positive correlation between HOT and growth, and at the same time the lack of systematic correlation between growth and X, ϕ, and τ(VA). Our conclusion is that HOT captures best the underlying phenomena that connect growth and openness.

4.1.3 Openness and Synchronization

Bilateral trade is well known to correlate with cycle synchronization. The evidence is well established between countries (see Frankel and Rose, 1998 or Kalemli-Özcan et al., 2013). In firm-level data we know that firms that are open to a particular country are synchronized with the cycle there (see di Giovanni et al., 2017, 2018). di Giovanni and Levchenko (2010) show that the international synchronization between sectors increases with direct intermediate trade, but they measure intermediate trade in the US only and they are in cross-section.[17]

We extend the conventional panel regression usually performed between countries to a cross-country cross-sector environment. As in Giannone et al. (2010) and Kalemli-Özcan et al. (2013), business cycle synchronization is measured as the (negative) absolute difference between the growth rates of real value added per employee, measured at PPP exchange rates. The differences are measured between sector r in country i and sector s in country j at time t. We consider the $\frac{N(N-1)}{2}$ distinct pairs of countries at each point in time, so that the full cross-section has a maximum of $\frac{N(N-1)}{2} \times R \times R$ observations. With $N = 43$ and $R = 50$, this corresponds to 2,257,500 observations each year, for a

[16] Table A.1 in Appendix A confirms these results for $\tau = 2$.

[17] Huo et al. (2019) and Huo et al. (2020) estimate true TFP shocks at sector level, purged from factor utilization and propagation via input-output linkages. Their purpose is to assess the role of sector-level TFP shocks for aggregate co-movements.

maximum of 33,862,500 observations. We estimate

$$-\left|\Delta \ln\left(\frac{\mathrm{VA}^r_{i,t}}{\mathrm{N}^r_{i,t}}\right) - \Delta \ln\left(\frac{\mathrm{VA}^s_{j,t}}{\mathrm{N}^s_{j,t}}\right)\right| = \mathrm{FE} + \beta_1\,\mathrm{BVHOT}^{rs}_{ij,t} + \beta_2\,\mathrm{X}^{rs}_{ij,t} + \beta_3\phi^{rs}_{ij,t} + \beta_4\tau^{rs}_{ij,t}(\mathrm{VA}) + \varepsilon^{rs}_{ij,t} \tag{17}$$

Table 8 reports the estimates for variants of equation (17) that include the measures of openness individually along with various fixed effects, FE. It first includes country pair-year effects ijt and sector pair-year effects rst. The former control for any change specific to each country pair, for example changes in the extent of financial integration between two countries. The latter control for any change specific to pairs of sectors, for example systematic technological complementarities. The table then includes cross-sectional effects $ijrs$. BVHOT is significantly positive in all cases. The same is not true of either X or ϕ, whose sign and significance are not robust to the inclusion of cross-sectional effects $ijrs$. τ(VA) is positive and significant only with cross-sectional effects $ijrs$.

Table 9 includes all three measures of openness simultaneously, with increments in the generality of the fixed effects. All specifications include country-sector pair effects $ijrs$. We include year effects, country year effects, and country-sector year effects. BVHOT is positive and significant in all cases. The same is not true of any other measure: all three are unstable across specifications.

Table 10 estimates equation (17) separately for all the pairwise combinations between three broad sectors (Agriculture, Manufacturing, and Services) to identify whether the correlation between openness and synchronization prevails between specific activities. The table shows that synchronization and BVHOT are positively correlated for almost all combinations of sectors, especially manufacturing and services. Interestingly τ(VA) performs well for pairs involving agricultural activities, perhaps because these are sectors where indirect linkages via third party countries are important. X or ϕ are only significantly positive for pairs of manufacturing sectors.

The estimations in tables 8, 9, and 10 are once again potentially plagued with some endogeneity concerns. For example, one could argue that trade tends to happen between negatively correlated activities. But once again, these concerns apply equally to all three measures of openness in equation (17). The fact that BVHOT is always significant and positive, while other measures are not, is a sign that it is a better measure of openness.

4.2 Estimating the Effects of Openness

This section discusses the two-stage least squares estimations of equations (15), (16), and (17) using the instrumental variables described in Section 2.3. The adjacency matrix

$\tilde{\mathbf{A}}_0$ and the vector $\tilde{\mathbf{F}}_0$, along with their subsets $\tilde{\mathbf{A}}_0^{\text{DOM}}$ and $\tilde{\mathbf{F}}_0^{\text{DOM}}$ focused on domestic trade, are computed on the basis of WIOT data in 2000.

The distribution of a_{ij}^{rs} is highly skewed: The vast majority are zero, or very close to zero, and there is a few very large entries, typically for $i = j$. The adjacency matrix $\tilde{\mathbf{A}}_0$ gives a value of one to *all* non zero entries in $\mathbf{A}_0$, including very small ones. The same is true of $\tilde{\mathbf{F}}_0$. This creates a distortion, giving the same weight to almost non existent international trade linkages and very large domestic ones. We address this distortion in two steps. First, we introduce a range of threshold values θ below which a non zero entry in $\mathbf{A}_0$ and $\mathbf{F}_0$ is actually set to zero in $\tilde{\mathbf{A}}_0$ and $\tilde{\mathbf{F}}_0$.

Second, we introduce weighted versions of the adjacency matrices. We normalize the entries in $\tilde{\mathbf{A}}_0$ and $\tilde{\mathbf{F}}_0$ according to averages that allow for differences in domestic vs. international linkages, rather than setting them all to 1. We consider two different ways of computing these averages: averages across countries or across sectors. For the domestic entries in $\tilde{\mathbf{A}}_0$, we set them all to the average of a_{ii}^{rs} across all i and s, a sector specific average. Alternatively, we set them to the average of a_{ii}^{rs} across all r and s, a country specific average. We follow the same procedure for the international entries in $\tilde{\mathbf{A}}_0$, setting them either to the average of a_{ij}^{rs} across all $i \neq j$ and s, a sector specific average. Or to the average of a_{ij}^{rs} across all j, r and s, a country specific average. We perform analogous normalizations in the domestic and international components of $\tilde{\mathbf{F}}_0$.

We proceed similarly to compute the instruments for BVHOT_{ij}^{rs} given by the product of the instruments for HOT_{ij}^{r} and HOT_{ji}^{s}. The country and sector averages are computed separately for each country in the pair i, j. For example when we use country averages, we normalize the block diagonal values of $(\tilde{\mathbf{A}}_{ij})_0$ by their average values in country i for the first $R \times R$ block diagonal, and by their average values in country j for the second block diagonal. And we replace all off-diagonal terms in $(\tilde{\mathbf{A}}_{ij})_0$ by the average value of a_{ij}^{rs} between countries i and j. We follow the same procedure for the normalization by sector, taking country specific sector averages for the block diagonal, and considering all bilateral values for the off-diagonal terms.

The weighted adjacency matrices introduce some dispersion in $\tilde{\mathbf{A}}_0$ and $\tilde{\mathbf{F}}_0$ that reflects the vast differences in domestic vs international entries in the typical input-output matrix. It minimizes the distortions created by the use of a simple adjacency matrix, but it can also reflect differences in productivity, as sectors and countries that are systematically more productive have larger entries in $\mathbf{A}_0$ and $\mathbf{F}_0$. The normalization can create endogeneity in the instruments, but it is limited to average country or sector effects. These will be absorbed by the fixed effects included in the two-stage least squares estimations.

The manipulations just described create a potentially long list of instruments, depending on the threshold values θ, the order n at which $\text{HOT}_{i\ \text{IV}(n)}^{r}$ is computed, and the two normalizations of the entries in $\tilde{\mathbf{A}}_0$ and $\tilde{\mathbf{F}}_0$. We consider three threshold values θ = 0.5 million, 1 million, and 2 million USD.[18] We compute the instruments $\mathrm{HOT}^r_{i\ \mathrm{IV}(n)}$ and $\mathrm{HOT}^r_{ij\ \mathrm{IV}(n)}$ up to order three, $n = 1, 2, 3$. This implies a total of three threshold values $\theta \times$ three orders $n \times$ two normalizations, or 18 instruments. These instruments are highly correlated with each other, and so should be included one by one.

Table 11 presents the two-stage least squares estimates for equations (15), (16), and (17) for all combinations of θ and n.[19] Three results are important. First, HOT has a robust effect on productivity, but in most cases it is substantially smaller than the simple correlation implied by ordinary least squares. This confirms that productive firms tend to be large (direct or indirect) exporters, a well known result. The two-stage least squares estimates also establish that exposure to foreign shocks affects productivity, presumably through learning, the diffusion of technology, or the culling of non productive firms active in the sector. The two-stage least squares estimates for $n = 1$ and $\theta = 1$ suggest that a one standard deviation increase in VHOT results in a 3.5 percent increase in sector productivity on average.

Second, HOT has no effect on growth. The significant OLS estimates capture only the fact that growing sectors tend to be open: There is no significant effect going from openness to growth. This is consistent with a Ricardian view of trade, where openness triggers reallocation, with potential level effects, but no permanent growth consequences. Third, HOT increases the synchronization between sectors, consistent with the fact that shocks propagate via the supply chain. The two-stage least squares coefficients are larger than OLS, suggesting an attenuating bias, i.e., trade tends to happen between negatively correlated activities. The two-stage least squares estimates for $n = 1$ and $\theta = 1$ imply that a one standard deviation increase in BVHOT corresponds to a 5.4 percent increase in synchronization for the average sector pair.

Finally, we perform two-stage least squares estimations for three broad sectors, Agriculture, Manufacturing, and Services, setting $n = 1$ and $\theta = 1$. The first panel of Table 12 presents the productivity estimates, where the Akaike Information Criterion is used to select the normalization method. The lower panel of the Table presents the synchronization estimations.[20] The productivity estimates suggest that high order openness has large and significant effects on the productivity of manufacturing sectors: a one standard deviation increase in VHOT results in a 31 percent increase in manufacturing productivity. The effect is smaller in agriculture (9 percent), and insignificant in services. This heterogeneity is intriguing, and calls for further research. An tentative explanation

[18] The average entry in $\mathbf{W}^*$ is 4.96 million USD. The median is zero.

[19] Estimations (15), (16) use Akaike Information Criteria (AIC) to determine which normalization is preferred. Estimation (17) is presented for both normalizations: by country in Table 11, and by sector in Table A.2 in Appendix A. We have to do this because information criteria are dominated by the more than 2 millions fixed effects in equation (17).

[20] We omit growth estimations from Table 12, but confirmed the growth effects are insignificant for all sectors.

is that exit by less productive firms is most prevalent in manufacturing sectors that are exposed to foreign shocks, whereas exit is muted in services, perhaps because of heterogeneity in the constituting service sectors.

The lower panel in Table 12 focuses on synchronization, where the instrument for BVHOT is computed using a normalization by country.[21] The two-stage least squares estimates are all positive and significant, across all pairs of sectors including those involving agricultural activities. This is very different from the estimates in Table 10, consistent with an attenuating bias in synchronization estimations using OLS. The coefficient estimates are largest between services, suggesting that shocks propagate via value chains in services. A one standard deviation increase in BVHOT results in a 6.9 percent increase in synchronization for the average Service-Service pair, and a 5.8 percent increase for the average Manufacturing-Service pair. The effects are smaller when agriculture is involved: 2.4 percent for the average Agriculture-Agriculture pair, 3 percent for the average Agriculture-Manufacturing pair, and 3.5 percent for the average Agriculture-Service pair. This heterogeneity is intriguing, too. A tentative explanation is the typical market structure of agricultural sectors in most countries, with endogenous markups affecting the propagation of shocks. We leave a detailed analysis for further research.

In results available upon request, we estimated equations (15), (16), and (17) using the same instruments, but instrumenting instead the highly ubiquitous export share variable X. The conclusions are similar to Table 11: instrumented export shares affect productivity and synchronization significantly, but not growth. The coefficient magnitudes are comparable, as are their economic significance. This illustrates the versatility of the instruments we introduce: Even though they are constructed on the basis of high order trade, they are in fact valid for completely standard measures of direct trade.

5 Conclusion

We propose a new measure of openness based on high order trade, labeled HOT. The measure captures exposure to foreign shocks. It is computable for all sectors and countries with available international input-output data, including services. According to HOT, sectors are relatively open on average, a few are very closed and a few are very open. This is dramatically different from the distributions of conventional measures of openness, which imply that most of the world is closed except for a few very open sectors in specific countries. HOT implies a ranking of country openness that is not dissimilar to the existing consensus; but it is very different across sectors, with many more open sectors, especially services.

[21] The normalization by sector implies similar conclusions and is reported in Table A.3 in Appendix A.

HOT correlates significantly with sector productivity, growth, and bilateral synchronization. The same is not true of conventional openness measures. We interpret this result as the symptom that HOT captures best the underlying mechanism that codetermines openness and economic performance. For example, fast growing sectors tend to be open according to HOT, but not according to its predecessors. We introduce an instrument for HOT based on network theory, that holds constant low order trade linkages. We explore what are the effects of openness on productivity, growth, and bilateral synchronization. We find openness causes productivity gains, about half of what ordinary least squares estimates imply, and openness causes synchronization. But openness has no measurable effect on growth.

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Table 1: Correlations

	HOT_i^r	VHOT_i^r	ϕ_i^r	X_i^r	$\tau_i^r(\text{X})$	$\tau_i^r(\text{VA})$
			Entire sample			
HOT_i^r	1					
VHOT_i^r	0.874	1				
ϕ_i^r	0.053	0.022	1			
X_i^r	0.460	0.330	0.038	1		
$\tau_i^r(\text{X})$	-0.016	-0.016	-0.0003	-0.004	1	
$\tau_i^r(\text{VA})$	0.480	0.305	0.036	0.465	-0.006	1
			By country			
HOT_i^r	1					
VHOT_i^r	0.987	1				
ϕ_i^r	-0.059	-0.077	1			
X_i^r	0.751	0.734	0.016	1		
$\tau_i^r(\text{X})$	-0.055	-0.068	0.410	-0.034	1	
$\tau_i^r(\text{VA})$	0.709	0.705	-0.015	0.894	-0.036	1
			By sector			
HOT_i^r	1					
VHOT_i^r	0.825	1				
ϕ_i^r	0.194	0.104	1			
X_i^r	0.651	0.447	0.133	1		
$\tau_i^r(\text{X})$	-0.061	-0.060	-0.008	-0.027	1	
$\tau_i^r(\text{VA})$	0.737	0.324	0.212	0.729	-0.039	1

Note: The table reports the Pearson correlation coefficients between different measures of openness. The first panel reports correlations for the whole sample, the second panel reports the correlations of country averages, and the third panel the correlations of sector averages. Germany has been removed from the sample of X_i^r and ϕ_i^r for this table only, as it is an outlier.

Table 2: Bivariate Productivity Estimations

	(1)	(2)	(3)	(4)	(5)	(6)
VHOT_i^r	0.129***	0.138***	0.137***			
	(0.023)	(0.023)	(0.024)			
X_i^r				-0.018**	-0.012	-0.014
				(0.008)	(0.007)	(0.009)
Fixed Effects:						
Country	Yes	Yes		Yes	Yes	
Sector		Yes			Yes	
Country × Sector			Yes			Yes
N	30,307	30,307	30,307	29,908	29,908	29,908

	(7)	(8)	(9)	(10)	(11)	(12)
ϕ_i^r	0.003**	0.004***	0.004***			
	(0.001)	(0.001)	(0.001)			
τ_i^r(VA)				-0.007	0.001	-0.000
				(0.014)	(0.014)	(0.015)
Fixed Effects:						
Country	Yes	Yes		Yes	Yes	
Sector		Yes			Yes	
Country × Sector			Yes			Yes
N	29,907	29,907	29,907	30,307	30,307	30,307

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is productivity measured as the natural logarithm of real Value Added per worker in sector r of country i. Value Added is in real PPP US dollars.

Table 3: Multivariate Productivity Estimations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VHOT_i^r	0.214***	0.197***	0.135***	0.133***	0.257***	0.287***	0.259***	0.289***
	(0.031)	(0.033)	(0.024)	(0.028)	(0.039)	(0.041)	(0.039)	(0.042)
X_i^r	-0.046***	-0.059***					-0.032***	-0.034***
	(0.012)	(0.015)					(0.011)	(0.012)
ϕ_i^r			0.002*	0.002			0.004***	0.003**
			(0.001)	(0.001)			(0.001)	(0.001)
τ_i^r(VA)					-0.086***	-0.151***	-0.054***	-0.121***
					(0.022)	(0.029)	(0.024)	(0.029)
Fixed Effects:								
Country × Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year		Yes		Yes		Yes		Yes
N	29,908	29,908	29,907	29,907	30,307	30,307	29,907	29,907

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is productivity measured as the natural logarithm of real Value Added per worker in sector r of country i. Value Added is in real PPP US dollars.

Table 4: Productivity Estimations by Sector

	Agr (1)	Min (2)	Mfg (3)	Ser (4)
		Panel A		
VHOT	0.137*	0.515*	0.155***	0.097**
	(0.071)	(0.257)	(0.057)	(0.038)
Country × Sector	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	1,830	625	11,699	13,739
		Panel B		
VHOT_i^r	0.163**	0.530	0.273***	0.346***
	(0.085)	(0.315)	(0.075)	(0.063)
X_i^r	-0.013	-0.013	-0.127**	-0.019
	(0.058)	(0.074)	(0.052)	(0.013)
ϕ_i^r	-0.011	0.114*	0.002	0.003
	(0.055)	(0.061)	(0.002)	(0.003)
τ_i^r(VA)	-0.003	-0.136	0.012	-0.205***
	(0.066)	(0.147)	(0.052)	(0.047)
Fixed Effects:				
Country × Sector	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	1,821	625	11,688	13,470

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is productivity measured as the natural logarithm of real Value Added per worker in sector r of country i. Value Added is in real PPP US dollars.

Table 5: Growth Estimations, cross-section

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial V.A.	-0.025***	-0.024***	-0.025***	-0.024***	-0.025***	-0.025***	-0.025***	-0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
VHOT_i^r	0.014***				0.013***	0.010***	0.013***	0.013***
	(0.002)				(0.003)	(0.003)	(0.003)	(0.003)
X_i^r		0.001***			0.000			-0.002**
		(0.000)			(0.001)			(0.001)
ϕ_i^r			0.003***			0.002***		0.003***
			(0.001)			(0.001)		(0.001)
τ_i^r(VA)				0.005***			0.000	-0.000
				(0.001)			(0.002)	(0.002)
Fixed Effects:								
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,019	2,002	2,002	2,019	2,002	2,002	2,019	2,002

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the natural logarithm of growth in Value Added per employee in country i sector r. Initial V.A. is the initial value added per employee. Value Added is in real PPP US dollars. All variables are averaged over the whole sample period.

Table 6: Growth Estimations, cross-section

	(1)	(2)	(3)	(4)	(5)
Initial V.A.	-0.036***	-0.036***	-0.036***	-0.035***	-0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
VHOT_i^r	0.008***				0.009**
	(0.003)				(0.005)
X_i^r		0.000			-0.000
		(0.000)			(0.001)
ϕ_i^r			0.000		-0.000
			(0.001)		(0.001)
τ_i^r(VA)				0.003*	-0.001
				(0.002)	(0.003)
Fixed Effects:					
Sector	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
N	2,019	2,002	2,002	2,019	2,002

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the natural logarithm of growth in Value Added per employee in country i sector r. Initial V.A. is the initial value added per employee. Value Added is in real PPP US dollars. All variables are averaged over the whole sample period.

Table 7: Growth Estimations by Sector

	Agr (1)	Min (2)	Mfg (3)	Ser (4)
		Panel A		
Initial V.A.	-0.015***	-0.023***	-0.025***	-0.028***
	(0.005)	(0.005)	(0.003)	(0.003)
VHOT_i^r	0.005	0.022	0.031***	0.004
	(0.007)	(0.031)	(0.004)	(0.003)
Fixed Effects:				
Sector	Yes	Yes	Yes	Yes
N	122	41	779	916
		Panel B		
Initial V.A.	-0.014**	-0.026***	-0.027***	-0.029***
	(0.005)	(0.005)	(0.002)	(0.003)
VHOT_i^r	-0.000	0.022	0.036***	0.008
	(0.009)	(0.029)	(0.006)	(0.005)
X_i^r	0.005	-0.006	-0.015***	0.001
	(0.005)	(0.008)	(0.003)	(0.001)
ϕ_i^r	-0.001	0.011*	0.005***	0.002
	(0.004)	(0.006)	(0.001)	(0.001)
τ_i^r(VA)	0.001	-0.006	0.011***	-0.007**
	(0.007)	(0.013)	(0.004)	(0.003)
Fixed Effects:				
Sector	Yes	Yes	Yes	Yes
N	122	41	779	902

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the natural logarithm of growth in Value Added per employee in country i sector r. Initial V.A. is the initial value added per employee. Value Added is in real PPP US dollars. All variables are averaged over the whole sample period.

Table 8: Bivariate Synchronization Estimations

	(1)	(2)	(3)	(4)
BVHOT_{ij}^{rs}	2.571***			
	(0.067)			
X_{ij}^{rs}		1.224***		
		(0.025)		
ϕ_{ij}^{rs}			0.691***	
			(0.032)	
τ_{ij}^{rs}(VA)				-0.466***
				(0.059)
Fixed Effects:				
Country-Year pairs	Yes	Yes	Yes	Yes
Sector-Year pairs	Yes	Yes	Yes	Yes
N	27,876,270	27,595,631	23,998,439	27,860,548

	(5)	(6)	(7)	(8)
BVHOT_{ij}^{rs}	2.441***			
	(0.038)			
X_{ij}^{rs}		-0.590***		
		(0.042)		
ϕ_{ij}^{rs}			-0.258***	
			(0.053)	
τ_{ij}^{rs}(VA)				0.316***
				(0.059)
Fixed Effects:				
Country-Sector pairs	Yes	Yes	Yes	Yes
N	27,876,268	27,593,056	23,993,598	27,860,541

Note: Coefficients and standard errors are multiplied by 1000 for legibility. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $-|\log(\frac{VA_i^r}{N_i^r})-\log(\frac{VA_j^s}{N_j^s})|$. Value Added is in reall PPP US Dollars. The regressions are performed with *reghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

Table 9: Multivariate Synchronization Estimations

	(1)	(2)	(3)	(4)
BVHOT_{ij}^{rs}	4.591***	2.530***	0.938***	3.086***
	(0.056)	(0.064)	(0.049)	(0.057)
X_{ij}^{rs}	-2.612***	-1.487***	0.420***	-1.324***
	(0.080)	(0.080)	(0.065)	(0.081)
ϕ_{ij}^{rs}	0.526***	-0.126*	-1.100***	-0.275***
	(0.075)	(0.074)	(0.062)	(0.075)
τ_{ij}^{rs}(VA)	-2.824***	-4.632***	0.663***	-1.753***
	(0.086)	(0.106)	(0.081)	(0.096)
Fixed Effects:				
Country-Sector pairs	Yes	Yes	Yes	Yes
Country-Year		Yes		
Country-Sector-Year			Yes	
Year				Yes
N 23,970,284	23,970,284	23,970,284	23,970,284	

Note: Coefficients and standard errors are multiplied by 1000 for legibility. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $-|\log(\frac{VA_i^r}{N_i^r})-\log(\frac{VA_j^s}{N_j^s})|$. Value Added is in reall PPP US Dollars. The regressions are performed with *reghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

Table 10: Synchronization Estimations by Sector

Sector r, s	Agr-Agr (1)	Agr-Mfg (2)	Agr-Ser (3)	Mfg-Mfg (4)	Mfg-Ser (5)	Ser-Ser (6)
			Panel A			
BVHOT_{ij}^{rs}	-1.875*	0.288	-0.734***	3.005***	2.160***	1.239***
	(0.987)	(0.235)	(0.222)	(0.102)	(0.069)	(0.093)
Fixed Effects:						
Country-Sector pairs	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	101,668	1,300,124	1,526,429	4,155,582	9,757,759	5,727,330
			Panel B			
BVHOT_{ij}^{rs}	-1.475	1.751***	0.245	2.764***	2.598***	1.736***
	(1.221)	(0.294)	(0.297)	(0.121)	(0.082)	(0.111)
X_{ij}^{rs}	-3.479***	-5.562***	-4.464***	1.336***	-1.018***	-1.443***
	(0.931)	(0.367)	(0.296)	(0.257)	(0.144)	(0.164)
ϕ_{ij}^{rs}	0.805	1.464***	0.134	0.714***	-0.547***	-2.545***
	(0.890)	(0.315)	(0.231)	(0.238)	(0.137)	(0.151)
Fixed Effects:						
Country-Sector pairs	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	74,938	1,043,866	1,104,142	3,843,900	8,536,030	4,927,956
			Panel C			
BVHOT_{ij}^{rs}	-4.374***	1.202***	-1.812***	3.672***	3.588***	1.891***
	(1.275)	(0.320)	(0.322)	(0.139)	(0.096)	(0.124)
X_{ij}^{rs}	-3.682***	-5.633***	-4.872***	1.936***	-0.547***	-1.368***
	(0.935)	(0.366)	(0.299)	(0.255)	(0.144)	(0.167)
ϕ_{ij}^{rs}	0.668	1.447***	0.031	0.788***	-0.473***	-2.525***
	(0.890)	(0.315)	(0.231)	(0.238)	(0.137)	(0.151)
τ_{ij}^{rs}(VA)	8.103***	1.618***	5.595***	-3.744***	-3.374***	-0.486**
	(1.643)	(0.447)	(0.426)	(0.236)	(0.161)	(0.201)
Fixed Effects:						
Country-Sector pairs	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	74,938	1,043,636	1,104,142	3,842,424	8,534,615	4,927,956

Note: Coefficients and standard errors are multiplied by 1000 for legibility. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is $-|\log(\frac{VA_i^r}{N_i^r}) - \log(\frac{VA_j^s}{N_j^s})|$. Value Added is in reall PPP US Dollars. The regressions are performed with *reghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

Table 11: IV Estimations: Productivity, Growth, and Synchronization

	$\theta = 0.5$	$\theta = 1$	$\theta = 2$
		Productivity	
VHOT_i^r, $\text{IV}_{n=1}$	0.060**	0.060**	0.062**
	(0.025)	(0.026)	(0.027)
VHOT_i^r, $\text{IV}_{n=2}$	0.146***	0.148***	0.147***
	(0.018)	(0.019)	(0.020)
VHOT_i^r, $\text{IV}_{n=3}$	0.137***	0.137***	0.119***
	(0.019)	(0.021)	(0.024)
Fixed Effects:			
Country × Sector	Yes	Yes	Yes
N	30,252	30,222	30,208
		Growth (cross-section)	
VHOT_i^r, $\text{IV}_{n=1}$	0.008	0.010	0.020
	(0.018)	(0.020)	(0.021)
VHOT_i^r, $\text{IV}_{n=2}$	0.006	0.009	0.003
	(0.023)	(0.011)	(0.013)
VHOT_i^r, $\text{IV}_{n=3}$	0.011	0.015	0.003
	(0.012)	(0.014)	(0.018)
Fixed Effects:			
Country	Yes	Yes	Yes
Sector	Yes	Yes	Yes
N	2,016	2,014	2,013
		Synchronization (normalized by country)	
BVHOT_i^r, $\text{IV}_{n=1}$	2.908***	3.173***	2.985***
	(0.035)	(0.034)	(0.035)
BVHOT_i^r, $\text{IV}_{n=2}$	2.832***	3.181***	3.122***
	(0.035)	(0.034)	(0.034)
BVHOT_i^r, $\text{IV}_{n=3}$	2.639***	2.916***	2.908***
	(0.035)	(0.034)	(0.034)
Fixed Effects:			
Country-Sector pairs	Yes	Yes	Yes
N	27,687,672	27,625,851	27,553,246

Note: Two-stage least squares estimates of equations (15), (16), and (17). AIC is used to choose the normalization for each threshold and order (θ, n) pair for the productivity and growth estimations. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients and standard errors are multiplied by 1000 for legibility for synchronization. The 2SLS regressions for Synchronization are performed with *ivreghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

Table 12: IV Estimations by Sector: Productivity and Synchronization

	Productivity					
Sector r		Agr (1)		Mfg (2)		Ser (3)
VHOT_i^r, $\text{IV}_{n=1}$		0.133^{**}		0.595^{***}		0.024
		(0.058)		(0.031)		(0.027)
Fixed Effects:						
Country $\times$ Sector		Yes		Yes		Yes
N		1,815		11,654		13,714
	Synchronization (normalized by country)					
Sector r, s	Agr - Agr (1)	Agr - Mfg (2)	Agr - Ser (3)	Mfg - Mfg (4)	Mfg - Ser (5)	Ser - Ser (6)
BVHOT_i^r, $\text{IV}_{n=1}$	1.336^{**}	1.632^{***}	1.835^{***}	2.471^{***}	2.862^{***}	3.291^{***}
	(0.867)	(0.207)	(0.203)	(0.0912)	(0.065)	(0.091)
Fixed Effects:						
Country-Sector pairs	Yes	Yes	Yes	Yes	Yes	Yes
N	98,728	1,274,526	1,498,999	4,112,208	9,672,247	5,686,927

Note: Two-stage least squares estimates of equations (15) and (17) for threshold $\theta = 1$. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients and standard errors are multiplied by 1000 for legibility for synchronization. AIC is used to choose the normalization of productivity. The 2SLS regressions for Synchronization are performed with *ivreghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

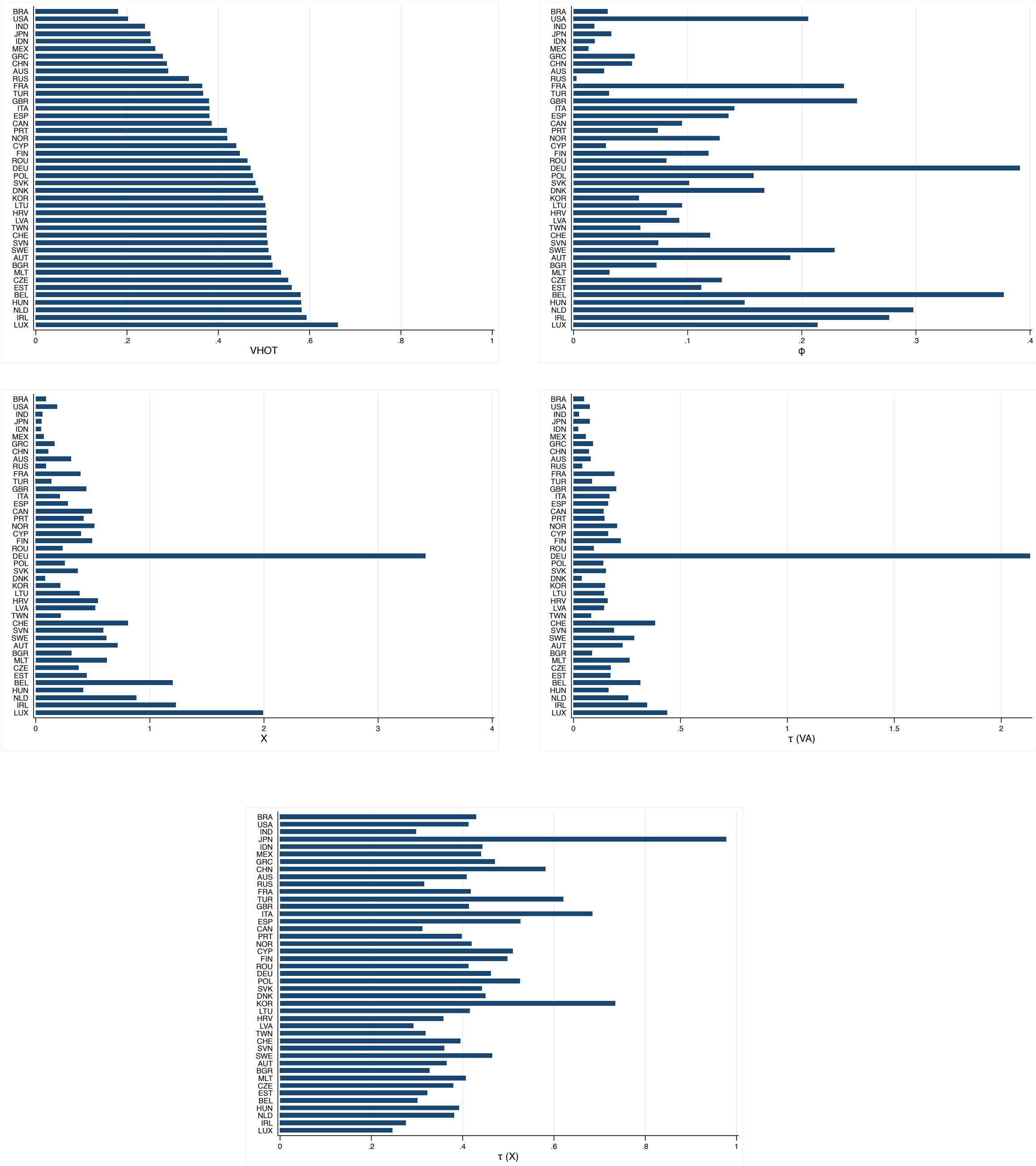

Figure 1: Median sector values of VHOT_i^r, ϕ_i^r, X_i^r, $\tau_i^r(\mathrm{VA})$ and $\tau_i^r(\mathrm{X})$ by country in 2014.

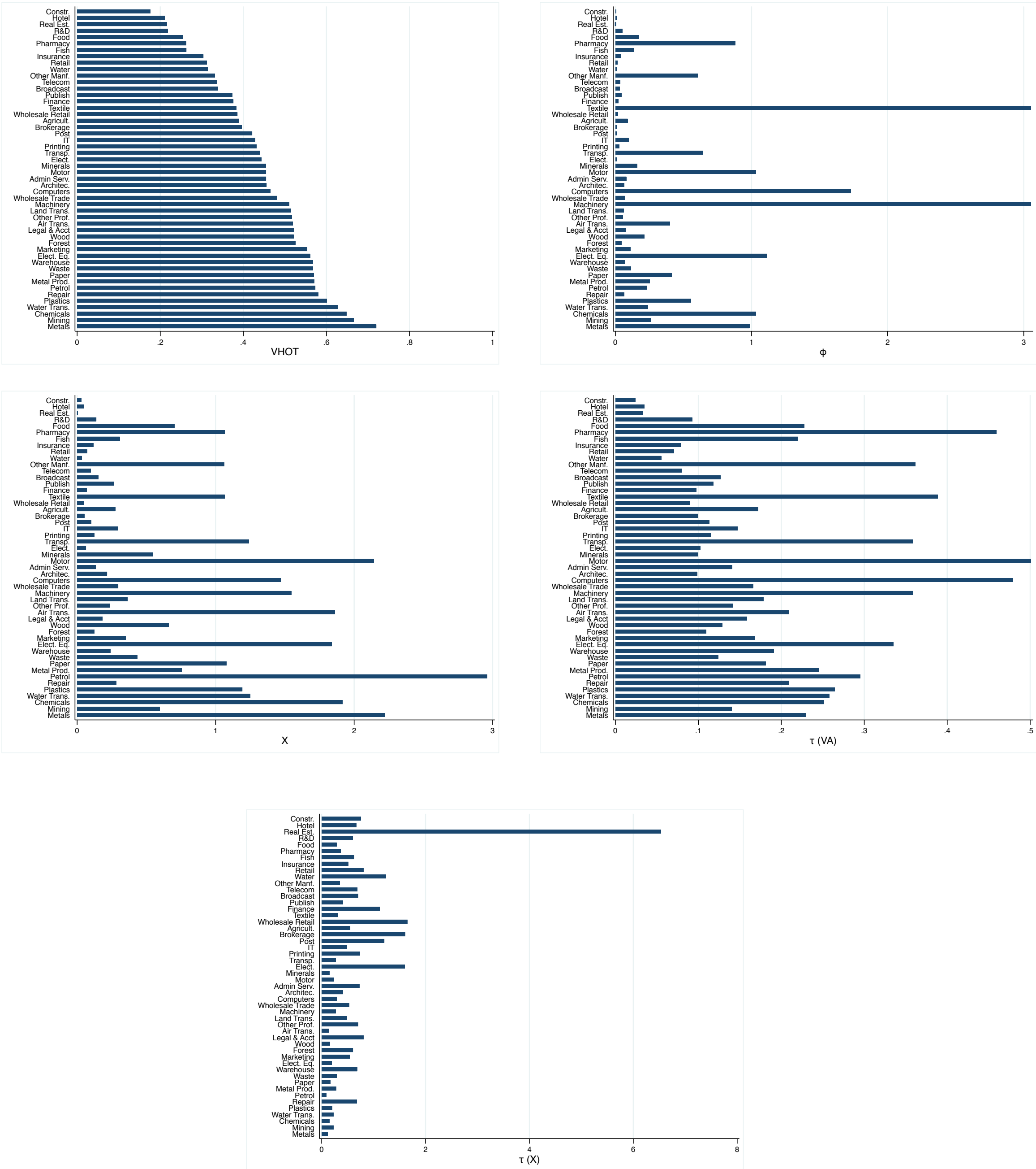

Figure 2: Median country value of VHOT_i^r, ϕ_i^r, X_i^r, $\tau_i^r(\text{VA})$ and $\tau_i^r(\text{X})$ by sector in 2014.

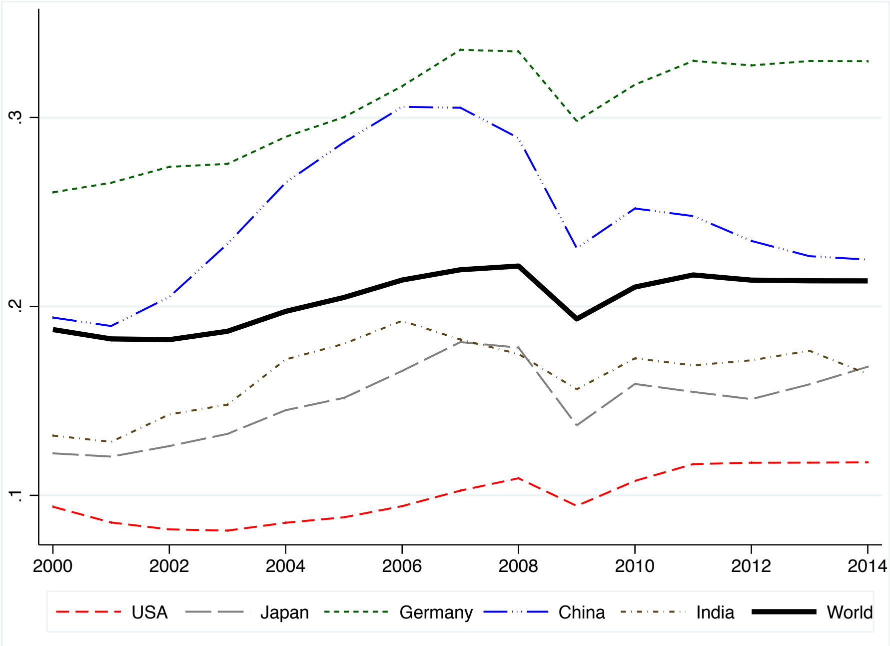

Figure 3: VHOT is depicted over time for five countries and the World. Country values are averages of sector level VHOT_i^r weighted by value added. World VHOT is a GDP weighted average of country VHOT. Value added is converted in USD at PPP exchange rate.

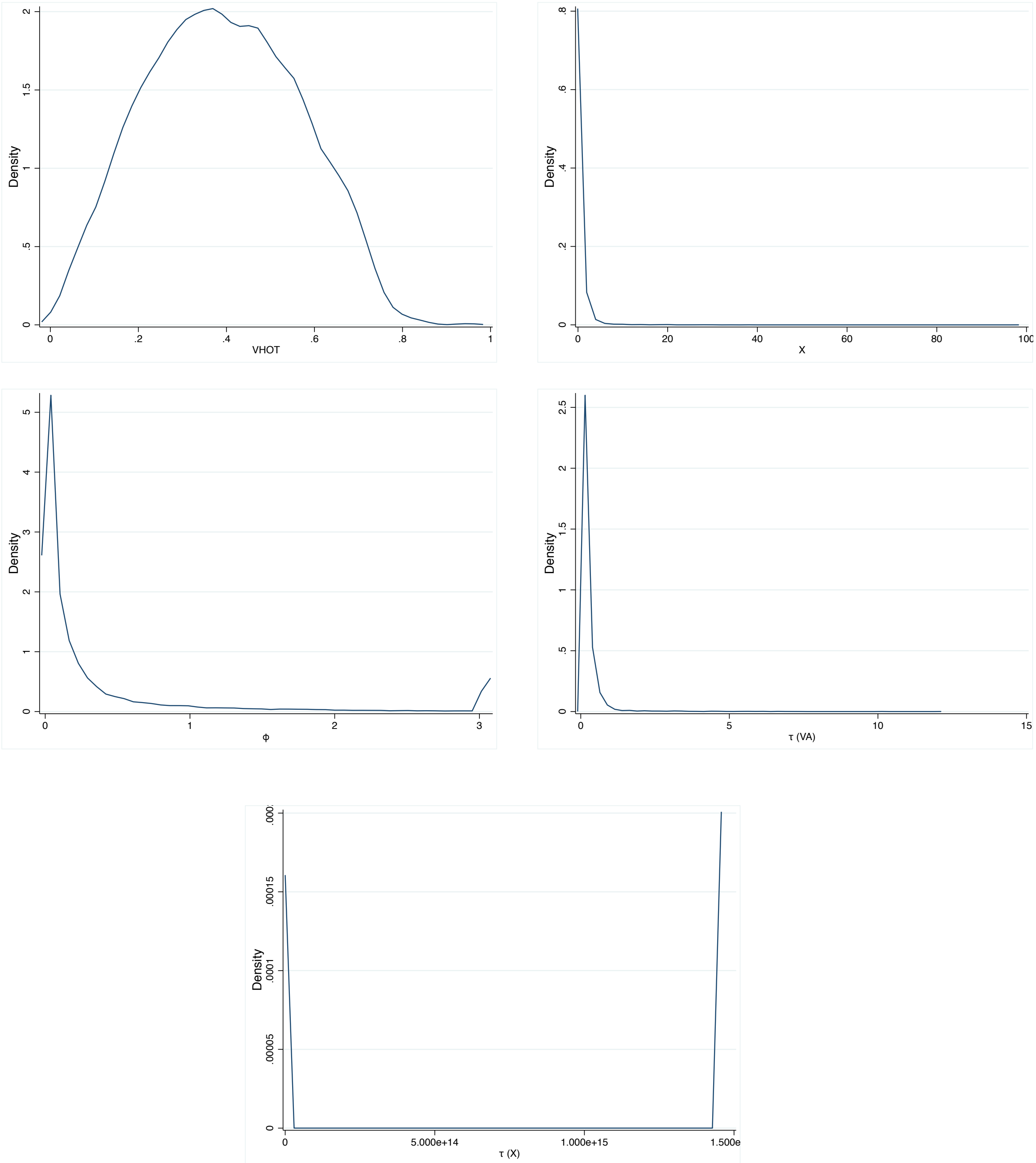

Figure 4: Densities of VHOT_i^r, X_i^r, ϕ_i^r, $\tau_i^r(\mathrm{VA})$ and $\tau_i^r(\mathrm{X})$

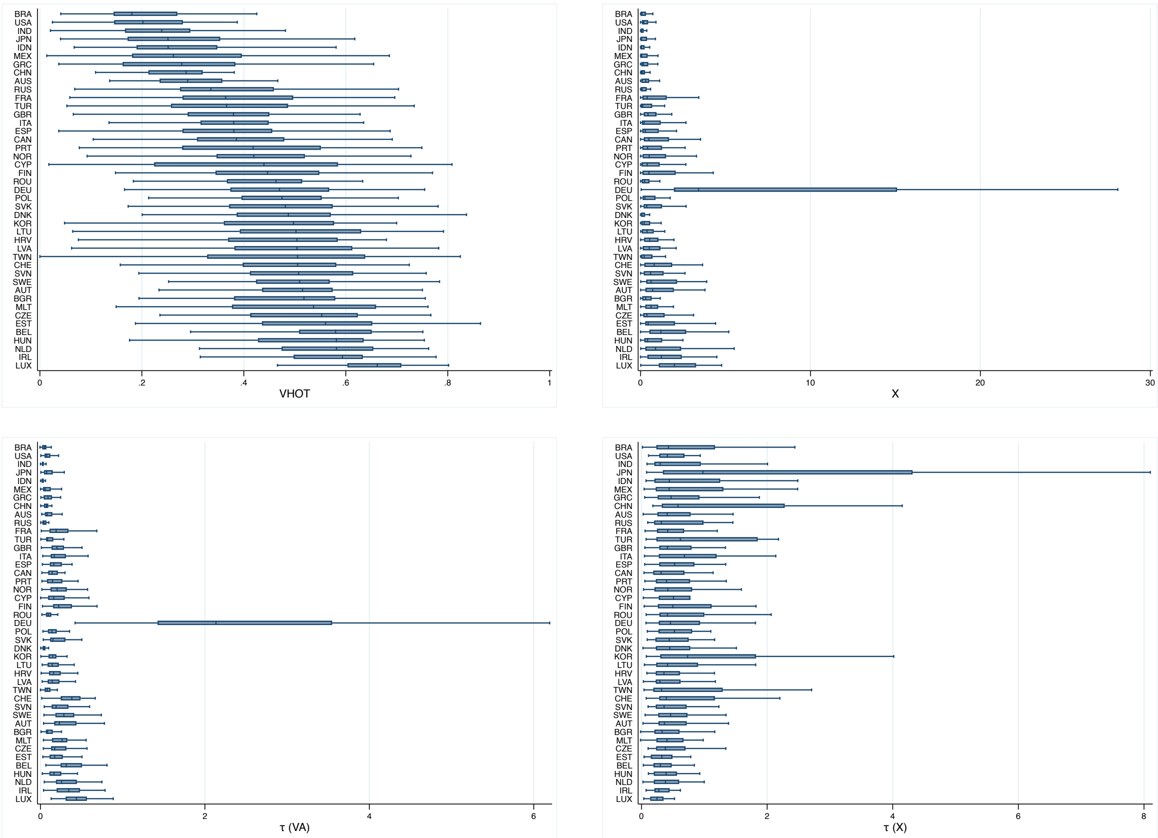

Figure 5: Dispersion of VHOT, X, τ_i^r(VA) and τ_i^r(X)across sectors for each country in 2014. The mid-point is the median, the thick segment is the interquartile range, and the whiskers are extreme values.

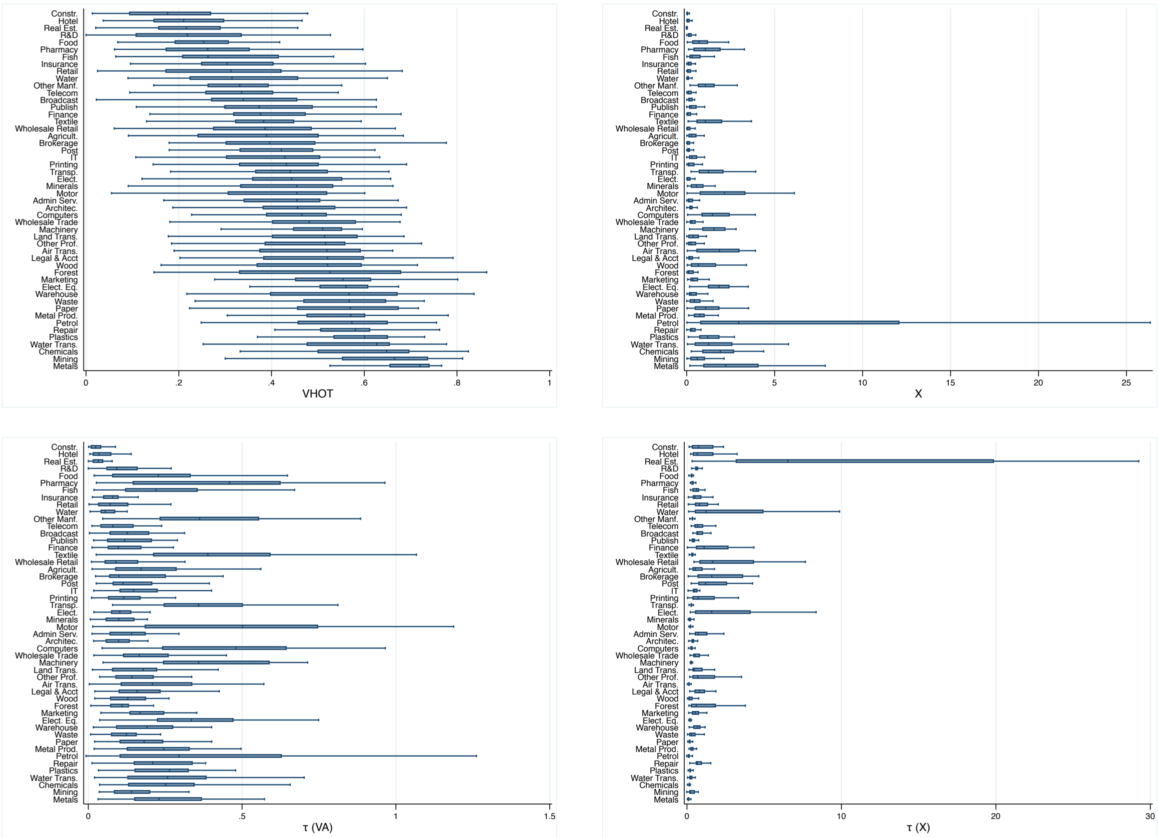

Figure 6: Dispersion of VHOT X, $\tau_i^r(\mathrm{VA})$ and $\tau_i^r(\mathrm{X})$ across countries for each sector in 2014. The mid-point is the median, the thick segment is the interquartile range, and the whiskers are extreme values.

Appendix A: Additional Tables

Table A.1: Growth Estimations, two periods

	(1)	(2)	(3)	(4)
Initial V.A.	-0.023***	-0.023***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)
VHOT_i^r	0.012***			
	(0.002)			
X_i^r		0.001***		
		(0.000)		
ϕ_i^r			0.001***	
			(0.000)	
τ_i^r(VA)				0.004***
				(0.001)
Fixed Effects:				
Sector	Yes	Yes	Yes	Yes
N	4,041	3,996	3,997	4,041

	(5)	(6)	(7)	(8)	(9)
Initial V.A.	-0.023***	-0.024***	-0.023***	-0.042***	-0.042***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
VHOT_i^r	0.011***	0.010***	0.010***	0.009***	0.009
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)
X_i^r	0.000			-0.001	-0.001
	(0.001)			(0.001)	(0.000)
ϕ_i^r		0.001		-0.000	-0.000
		(0.000)		(0.000)	(0.000)
τ_i^r(VA)			0.001		0.000
			(0.002)		(0.004)
Fixed Effects:					
Sector	Yes	Yes	Yes	Yes	Yes
Country				Yes	Yes
Year				Yes	Yes
N	3,996	3,997	4,041	3,996	3,996

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the natural logarithm of growth in Value Added per employee in country i sector r. Initial V.A. is the initial value added per employee. Value Added is in real PPP U.S. Dollars. All variables are averaged over 2 sample periods of 7 years, i.e. 2001 – 2007 and 2008 – 2014.

Table A.2: IV Estimations: Synchronization (normalized by sector)

	$\theta = 0.5$	$\theta = 1$	$\theta = 2$
BVHOT_{ij}^{rs}, $\text{IV}_{n=1}$	3.028***	3.217***	2.992***
	(0.035)	(0.035)	(0.035)
BVHOT_{ij}^{rs}, $\text{IV}_{n=2}$	2.973***	3.145***	3.245***
	(0.035)	(0.035)	(0.035)
BVHOT_{ij}^{rs}, $\text{IV}_{n=3}$	2.926***	3.104***	3.156***
	(0.035)	(0.035)	(0.035)
Fixed Effects:			
Country-Sector pairs	Yes	Yes	Yes
N	27,685,810	27,623,317	27,546,876

Note: Two-stage least squares estimates of equation (17). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients and standard errors are multiplied by 1000 for legibility. The 2SLS regressions are performed with *ivreghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

Table A.3: IV Estimations by Sector: Synchronization (normalized by sector)

	Agr-Agr (1)	Agr-Mfg (2)	Agr-Ser (3)	Mfg-Mfg (4)	Mfg-Ser (5)	Ser-Ser (6)
BVHOT_{i}^{r}, $\text{IV}_{n=1}$	2.612***	2.197***	2.418***	2.415***	2.835***	3.302***
	(0.704)	(0.174)	(0.168)	(0.084)	(0.058)	(0.079)
Fixed Effects:						
Country-Sector pairs	Yes	Yes	Yes	Yes	Yes	Yes
N	98,728	1,274,526	1,498,831	4,112,208	9,671,225	5,685,835

Note: Two-stage least squares estimates of equation (17) for threshold $\theta = 1$. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients and standard errors are multiplied by 1000 for legibility. The 2SLS regressions are performed with *ivreghdfe* in STATA, which allows for multiple level fixed effects (see Correia, 2017 for further details).

Appendix B: Data Appendix

B.1. High Order Trade

All High Order Trade measures used in the paper are constructed using the World Input-Output Tables provided by World Input Output Database (WIOD). The dataset spans over the years 2000 – 2014. The data covers 44 countries (including a "rest of the world") and 56 sectors classified according to the International Standard Industrial Classification (ISIC) revision 4. The data are available at wiod.org. The methods to calculate HOT and VHOT are described in Section 2.1 and BHOT and BVHOT are described in Section 2.2. We take the logarithm of these measures in all regressions.

All High Order Trade instrumental variables are calculated from the same source. Details of the methods to calculate them are given in Section 2.3. We take the logarithm of the instruments in all IV regressions.

B.2. Productivity

Productivity is calculated as the logarithm of real PPP U.S. Dollars sector level value added per employee (or per person engaged in the Supplementary Appendix). Value added is converted in PPP U.S. Dollar and deflated using industry price levels of gross value added. Value added is in millions of national currency, price levels are indexed at 2010 = 100, the number of employees and number of person engaged are in thousands. All data are sourced from WIOD Socio-Economic Accounts (SEA). PPP USD exchange rates are sourced from the OECD.

B.3. Growth

Growth is constructed as the logarithm of sector level value added growth per employee (or per person engaged in the Supplementary Appendix), expressed in real PPP U.S. Dollars. Value added is in national currency and converted in USD at PPP exchange rate; it is deflated using industry price indices of gross value added. The 2-period growth measures are calculated for two 7 years subsamples spanning 2001 - 2007 and 2008 - 2014. The data are sourced from WIOD SEA and the OECD.

B.4. Initial Value Added

Initial value added is computed as the logarithm of sector level value added per employee (or per person engaged in the Supplementary Appendix), in real PPP U.S Dollars. In the cross section it is measured in 2000. In the two-period estimations, initial value added are the values in 2000 and in 2008. The data are sourced from WIOD SEA and the OECD.

B.5. Business Cycles Synchronization

Synchronization is measured as minus the absolute pairwise difference in the logarithm of real value added growth between country-sector pairs, measured each year. Value added is in national currency and converted in USD at PPP exchange rate. It is deflated using industry price indices. The source of the data are the WIOD SEA and the OECD.

B.6. Direct Trade measures: X and ϕ

Direct exports, X, are given by the ratio of total exports of intermediate and final goods to value added for each country-sector. Both numerator and denominator are expressed in current USD at PPP exchange rates. The bilateral version of X is given by the ratio of $\mathrm{Z}_{ij}^{rs} + \mathrm{Z}_{ji}^{rs}$ to $\mathrm{VA}_i^r + \mathrm{VA}_j^r$ for lack of data on bilateral trade in final goods. Both numerator and denominator are expressed in current PPP USD. ϕ is defined in section 2.4, and all its components are measured in PPP USD. We take the logarithm of all direct trade measures in all regressions. Intermediate goods exports and final goods exports are obtained from WIOD's World Input-Output Tables. Value added is in national currency and converted in U.S. Dollars at PPP exchange rate. Value added is sourced from WIOD SEA and PPP exchange rate from the OECD.

B.7. Trade in Value Added (TiVA): τ_i^r and τ_{ij}^{rs}

The variants of TiVA used in the paper, namely $\tau_i^r(\mathrm{X})$, $\tau_i^r(\mathrm{VA})$ and $\tau_{ij}^{rs}(\mathrm{VA})$ are described in section 2.4. TiVA measures are constructed using the Input-Output Tables from WIOD. $\tau_i^r(\mathrm{VA})$ and $\tau_{ij}^{rs}(\mathrm{VA})$ are normalized by Value Added in real PPP U.S Dollars. Value added is sourced from WIOD SEA and PPP exchange rate from the OECD. $\tau_i^r(\mathrm{X})$ is normalized by gross exports which are the sum of intermediate and final exports found in World Input-Output Tables provided by WIOD. All measures are expressed in logarithms.