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ASSESSING THE RELIABILITY OF STUDIES ON THE VALUE ADDED DISTRIBUTION IN GLOBALLY FRAGMENTED PRODUCTION PROCESSES BASED ON INPUT-OUTPUT MODELS

MASTER THESIS PRESENTED AS PART OF THE REQUIREMENTS TO ATTAIN THE ACADEMIC DEGREE MASTER OF SCIENCE

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ABSTRACT

Input-output analyses have gained relevance in studies examining the value added distribution along globally fragmented value chains. However, their reliability to reflect true value added contributions has been challenged by biases identified by Nomaler & Verspagen (2014). In order to extend their analysis with an empirical component, we construct hypothetical input-output tables representing global scenarios based on national data. By simulating value added measurements by Los et al. (2015), we identify the distortions empirically but argue that their small magnitude does not justify questioning recent studies of value added distribution within global value chains.

Keywords: Input-Output Analysis, Production Fragmentation, Value Added, Value Chains, Aggregation Bias, Hypothetical Input-Output Analysis

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LIST OF ABBREVIATIONS

EU	EUROPEAN UNION
FD	FINAL DEMAND
GVC	GLOBAL VALUE CHAIN
IO	INPUT-OUTPUT
IS	IMPORT SHARE
NAFTA	NORTH AMERICAN FREE TRADE ORGANISATION
NAICS	NORTH AMERICAN INDUSTRY CLASSIFICATION SYSTEM
NIOT	NATIONAL INPUT-OUTPUT TABLE
N&V	NOMALER & VERSPAGEN
OECD	ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT
PP	PERCENTAGE POINT
US	UNITED STATES (OF AMERICA)
VA	VALUE ADDED
VC	VALUE CHAIN
VAX	VALUE ADDED-TO-GROSS OUTPUT
WIOD	WORLD INPUT-OUTPUT DATABASE
WTO	WORLD TRADE ORGANIZATION

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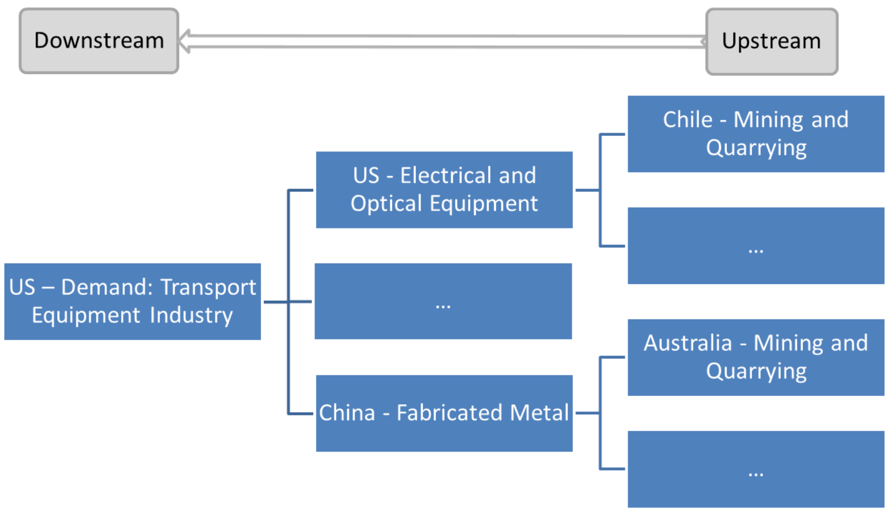
1. Introduction

Production processes have become more and more global in recent years. Therefore, labelling certain products as ‘German’, ‘Dutch’ or the like largely masks the underlying complexity of interrelated industries and countries involved in the production. The extent to which productions are split up within a specific region or across these could embody significant implications for policy-making. For instance, creating incentives to attract (labour-intensive) industries to the domestic economy or promoting trade-agreements with important partner countries are just two of many inferences that may be drawn from findings about segregated productions. Moreover, this emphasises the relevance of our study which will focus on the adequateness of recent methods to examine the global segmentation of production processes.

Assume the purchase of an US-American car as illustrated in Figure 1 in which lines represent intermediate product deliveries (within or across countries) and boxes display industries that contribute to the final product. The demanded car from the US might not only result in manufacturing taking place within the US ‘Transport equipment’ industry but could also spur the economic activity in its domestic ‘Electrical and Optical equipment’ industry. Moreover, China’s steel production, Australia’s iron –and or Chile’s copper quarrying may experience increased demand. This scenario could easily be expanded largely and displays a representative case of the complexity embodied in the emergence of global productions.

Figure 1: Exemplary Production of a Car



It also introduces the term *fragmentation* as the production is split up into different parts realized by various industries and countries. Therefore, fragmentation is defined as the disintegration of production structures across and within national boundaries (López-Gonzalez, 2012). To entitle the emergence of scenarios similar to Figure 1, Gereffi (1989) stated that: 'The Global Factory is on the rise'[1] describing the variety of countries involved in the production of single products and therefore combined under one figurative (factory) roof. Few scholars would disagree with this metaphorical assertion since shrinking transaction costs of trade have certainly contributed to more interdependent global markets with extensive cross-country trade.

In this paper, we will therefore assess the reliability of recent studies which examine the extent to which the involved countries in globally fragmented production processes contribute to the final product value (e.g. Los et al, 2015). This will be relevant as we already established that policy-makers are well-advised to consider trends in global production fragmentations in their decisions.

The extensive international fragmentation of production has been observed in several case studies decomposing production processes into multiple global production stages such as Dedrick et al. (2009) and Dudenhöffer (2005). Moreover, this calls for measures which could expand the phenomenon to a macroeconomic perspective. However, traditional concepts of national competitiveness based on comparisons of gross export statistics are not suitable to account for emerging global intermediate good trade anymore (Koopman, 2014). These always capture the full border-crossing product value instead of the actual contribution of the exporting country and inflate trade statistics relative to the final good value[2]. Thus, Timmer et al. (2013) propose a different definition of competitiveness as the 'ability to perform activities meeting the test of international competition and generate increased income and employment'.

Furthermore, the *value added* (VA) – defined as the contribution of an industry to the overall value of a product – and its fragmentation is misrepresented for the most part when consulting gross export figures (and ratios).

[1] Grunwald & Flamm (1985) and Buckley & Ghauri (2004) offered related but different term interpretations

[2] In Figure 1, this would imply that the entire product value of China's 'Fabricated Metals' delivery to the US-American car production is measured. This not only includes actual Chinese contributions but also Australia's 'Mining and Quarrying' deliveries at an earlier production stage.

Therefore, many studies that examine global production fragmentation are increasingly based on the concept of *input-output (IO) analysis*. By explicitly distinguishing between inter-industry deliveries of intermediate goods (in the so-called *intermediate matrix*) and the supply of finished goods to a final demand (FD) category (in the *FD matrix*), IO analysis is able to identify each industry's contributed VA for the related production stage. Consequently, it traces the factor inputs needed in order to produce a final good and comprehensively computes the overall VA by involved industries embodied in an industry's output (Timmer et al., 2014). In addition, matrix algebra allows the analyses to capture direct but also indirect VA requirements arising for the respective industries[3]. Due to improved data availability, IO analysis nowadays allows for conclusions about complex international production networks. All the more important, this paper will attempt to judge the reliability of global fragmentation studies employing these IO concepts (e.g. Los et al., 2015) by analysing potential biases embodied in these papers.

This necessary research area remained rather unexplored until now[4] and is where this paper fills in by testing for the magnitude of potential biases found by Nomaler & Verspagen (2014) (N&V). These may distort IO analyses about global production fragmentation which are based on the aggregation of multiple different individual production processes within industries at different stages of the overall production. In turn, the aggregation comes up since – other than in the aforementioned case studies by Dedrick et al. (2009) or Dudenhöffer (2005) – broader macroeconomic studies tend to pool multiple different final products together.

Our analytical approach employs simulation results that are – different from N&V's (2014) analysis – based on empirical data for various industrial aggregation levels. We thereby examine the empirical scope of the biases with the research question:

Do the biases identified by Nomaler & Verspagen (2014) significantly distort the empirical findings of studies examining the value added distribution in globally fragmented production processes if input-output analysis is employed?

[3] This would for instance imply that Figure 1's 'Mining industry' of Chile also requires 'Electrical and optical equipment' from the US for the quarrying. The production of a car in the US would not only rely on 'Electrical and optical equipment's direct VA but also on the value that it supplies to 'Mining' in Chile at an earlier stage
[4] A mentionable contribution in this field is Baldwin & López-Gonzales (2015) focusing on data constrains and insufficient consideration of firm heterogeneity.

The remainder of this paper is organised as follows: Chapter 2 provides the reader with a brief overview of the emergence of IO analysis in general, the basic concept underlying it, most important literature contributions studying global fragmentation of production and its recent criticism. Chapter 3 presents the investigated biases in more detail before Chapter 4 focuses on the employed data and its processing. Subsequently, Chapter 5 analyses the data and presents the simulation approach. Chapter 6 documents and illustrates the empirical results. Moreover, it indicates the implications of the findings for recent indicators measuring the value added distribution in globally fragmented production processes. Then, Chapter 7 concludes the paper by summarizing the results and identifying limitations of the paper as well as suggestions for future research.

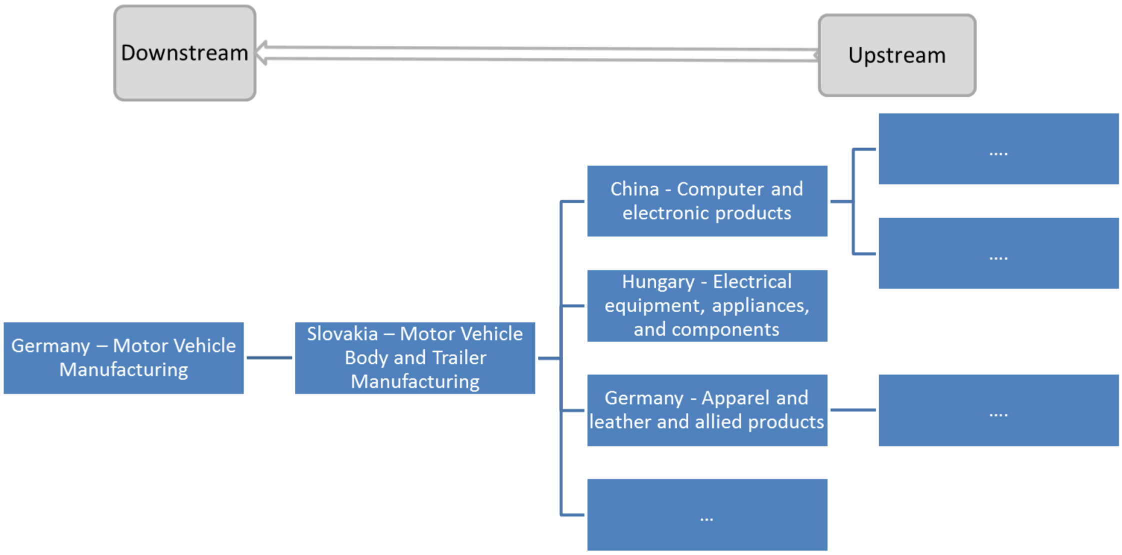
2. Literature Review

Decreasing costs for communication as well as the coordination of trade have led to enormous international fragmentation of economic activity. Consequently, production largely shifted from the national towards the international scope. Thus, *value chains* – the whole range of economic activities required to complete a final good – have become increasingly global (Gereffi, 1999).

2.1. Global Production Fragmentation

By illustrating this claim based on an exemplary product, Dudenhöffer (2005)'s much-cited study of the global value chain (VC) of the luxurious German car 'Porsche Cayenne' has received much attention. Within the study, the author identified the VA which was actually generated within Porsche's domestic market (i.e. Germany) in 2005. The *Porsche Cayenne* completed (and sold) in Germany was examined with regards to the suppliers of the finalising firm (i.e. Porsche). These, however, in turn relied on other – more upstream – component delivering companies themselves. Part of the related VC is depicted in Figure 2.

Figure 2: Global Value Chain of a Porsche Cayenne (in 2005)[5]



As becomes clear from the illustration of the VC, large parts of the production process did not take place in Germany anymore. The actual completion of the product (in the 'Motor vehicles' industry) might still have been realized there, however, most parts and components were already supplied from Slovakia. In turn, Slovakia's assembling activities also largely relied on parts delivered by other industries in various countries (e.g. 'Computer and electronic products' from China or 'Electrical equipment, appliances, and components' from Hungary). Since these Chinese / Hungarian suppliers themselves depend on intermediate inputs, this case study could even be extended substantially further (e.g. upstream to the 'Mining' industry in – say – Australia quarrying bauxite needed for the aluminium parts of the car). In doing so, Dudenhöffer (2005) found that the German domestic value creation solely ranged at around 30% of the overall value of the final car in 2005. This example also introduces the expressions *interconnectedness* and *interdependencies* of industries. Single production processes often affect multiple industries and their demands. Transferring this case study back to the macroeconomic perspective, examining production fragmentation is highly relevant as it generates implications for policy-makers. Not only the extent to which it takes place but also the spatial nature of the fragmentation is important. In line with Los et al. (2015), the latter addresses the question whether VCs tend to be split up mostly within supranational regional blocks (regional fragmentation) or across them (global fragmentation). If, for

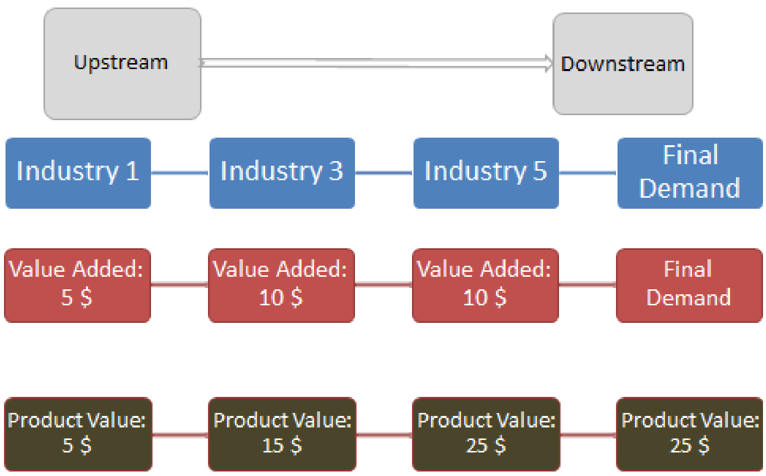
[5] Adapted from Dudenhöffer (2005)

instance, Los et al. (2015) detect the global fragmentation of VCs to grow distinctly more rapid than the regional fragmentation, the consequences for policy-makers might clearly diverge. Sticking with the example, strong regional fragmentation could call for regional trade agreements whereas more intense growth of global fragmentation might require multiregional trade policies. Due to the necessity to study these phenomena, IO analysis has evolved to an important tool for economic analysis. Broadly considered as an adequate approach to reflect complex international interconnectedness which enables the derivation of policy implications, IO analysis' increasing usage obviously depends on its reliability. This fuels the topicality of this paper as we will empirically test the significance of potential distortions in the methodology of IO concepts used to examine the VA distribution within globally fragmented VCs.

2.2. Introduction to Input-Output Analysis

VCs are often illustrated as a linear sequence which starts off with the chronologically first involved industry (the most upstream industry in the production of a final good). From there onwards, the product value is complemented by the second (more downstream) industry and so forth until the final product is ultimately consumed. A simple example of such a VC is shown in Figure 3[6].

Figure 3: General Model of linear Value Chain



[6] Akin to Timmer et al. (2013). Unlike in the figures before boxes represent either industries or FD categories. Industry 2, 4 and 6 will be added at a later stage when introducing multiple VCs.

Figure 3's can be interpreted as follows. Three different industries across different countries represent the VC which generates the final product consumed by FD. Industry 1 forms the most upstream value adding stage in the VC which delivers its intermediate good valued at 5 $ to industry 3. In turn, industry 3 contributes an additional 10 $ worth of product value to the good which sums up to 15 $ of total product value. The same logic applies for the final 10 $ of VA contributed by the most downstream industry 5 amounting to 25 $ of total product value. Here, the product is finalised before being ultimately consumed by the FD category. As observable, the product value within this VC gradually increases as value is added to the product at every VC stage. Consequently, the final product value amounts to the sum of all VA contributions. A VC as in Figure 3 is referred to as *linear* since the output of each VC stage is fully delivered to the ensuing stage and only one sequential path of deliveries is possible (i.e. from Industry 1 to 3 to 5 before the completed product is consumed by the FD).

Several studies examining production fragmentation have been realized in recent years. Apart from the aforementioned study by Dudenhöffer (2005), for instance, Dedrick et al. (2009) employed the iPod as an exemplary product to describe the extensive global production fragmentation of modern VCs. Nevertheless, these microeconomic literature contributions examining production fragmentation were only based on specific product case studies (i.e. the Porsche Cayenne or the iPod). Consequently, broader measures which allowed for generalizations about the fragmentation of VCs on a national, regional and global scale were needed to be able to derive policy implications which would address the related overall economy trends. Moreover, the aforementioned surge of global VCs also challenged the suitability of traditional economic indicators based on gross exports to adequately reflect the contributions of the involved industries and countries to the production processes. Building on earlier pioneer work by Hummels et al. (2001), contributions by Koopman et al. (2014) and Wang et al (2014) documented the so-called 'double-counting' problem causing gross exports to inadequately account for intermediate trade. This issue is relevant for our paper since it forms a major part of the reasons why IO models have increasingly become popular for global production fragmentation studies. This emphasises the importance of our study which examines the suitability of IO models to analyse the distribution of VA in fragmented VCs.

To illustrate the principles of 'double-counting' with the help of Figure 3, suppose that Industry 1 and 3 as well as the consumption by the FD are located in a given country A whereas Industry 5 is situated in country B. Consequently, the VA contributed to the VC by country A amounts to 15$ while country B only adds 10$ to the final product value. However, this set-up yields significant differences between the actual VA generated within the countries and their gross exports as indicated in trade statistics. Although country A contributes more value to the production process, its gross exports (15 $) are lower than country B's (25 $). Therefore, not only does both countries' total sum of gross export value (40 $) exceed the final product value of the consumed good but the difference between gross exports and VA within a country is also mostly not proportionate. In other words, even if a country contributes significantly more to a global VC than another one, its gross export value might be drastically below its trade partner depending on the realized VC stages and their order. Consequently, the meaningfulness of gross trade statistics to adequately represent competitiveness has decreased largely with intensified fragmentation. This links the 'double-counting' to our study. Since IO analysis is able to avoid the illustrated problem while accounting for inter-industry and global interconnectedness, it has recently gained more attention by numerous economic scholars. Moreover, its improved data availability facilitated the use and allows for generalisations about fragmentation instead of limiting insights to case studies like the ones by Dudenhöffer (2005) and Dedrick et al. (2009). Therefore, it will be important to judge the reliability of IO concepts to reflect production fragmentation.

In principle, the concept underlying the usage of IO data for economic analyses is rather straight-forward. The data comprised by national input-output tables (NIOTs) is typically gathered by the country's statistical institutions on a regular (mostly yearly) basis (Timmer et al., 2015). The structure of a NIOT is illustrated in Table 1[7].

Table 1: Structure of a National Input-Output Table

		Country N - Intermediate Uses				Country N - Final Use			Total Output
		Industry 1	Industry 2	...	Industry S	Final Use 1	...	Final Use K	
Country N - Supply	Industry 1								
	Industry 2								
	...								
	Industry S								
Value Added									
Gross Output									

Within this framework, the broad distinction is between an industry's supply (rows) and an industry's use as well as final consumption (as columns) of the delivered goods.

[7] Adapted from Timmer et al. (2015)

Hence, columns depict the required intermediate good deliveries for the production by one respective industry (e.g. coal mining) or the supply of completed products for the consumption by one final use category (e.g. private household consumption). These columns are displayed as vertically (intermediate matrix) and horizontally striped (FD matrix) respectively. Moreover, each industry's particular VA for the regarded timeframe (mostly one year) is added below its intermediate good consumption in the VA row vector which sums up to the overall gross output of the respective industry. On the other hand, the rows of the NIOT generally indicate the value of the deliveries and output generated by the related industries. More specifically, in a NIOT with s = 1,…, S industries the intermediate matrix **Z** contains S x S cells with intermediate deliveries. Each respective cell $z_{i\,j}$ therefore describes how much product value industry i delivers to industry j. On the other hand, the final demand matrix **F** consists of S x K cells where k = 1, …, K denotes the number of FD categories . Furthermore, the VA vector **w'** (where a prime denotes a transposed vector) contains all 1 x S value added elements w_j' where j refers to the value generating industry. The summation of each row therefore yields the related industry's gross output embodied in the S x 1 vector **x** and its counterpart **x'** (Dietzenbacher et al., 2013). Extending this structure to an international dimension, global input-output tables yield a scheme following the logic illustrated in Table 2[8]. This expanded framework lists the deliveries (incl. imports) of intermediate inputs and final goods from all countries in the table's rows. Similarly, industries and FD categories are include all country-industry (e.g. Transport equipment in Germany) or country-FD category (e.g. Dutch Personal consumption expenditure) combinations.

Table 2: Structure of a global Input-Output Table

		Country 1 - Uses			…		Country N - Uses			Country 1 - Final Use (FU)			…		Country N - FU			Total
		Industry 1	…	Industry S	…	…	Industry 1	…	Industry S	FU 1	…	FU K	…	…	FU 1	…	FU K	Output
Country 1 - Supply	Industry 1																	
	…																	
	Industry S																	
⋮	…																	
	…																	
Country N - Supply	Industry 1																	
	…																	
	Industry S																	
Value Added																		
Gross Output																		

[8] Adapted from Timmer et al. (2015)

Consequently, the deliveries to a country's industry or FD category are shown in the vertically (country-industry) and horizontally striped (country-FD category) columns. Since the IO data availability is mostly limited to developed countries, the remainder is summed to a 'Rest-of-World' category (as country *N)*. Assuming $n = 1,\ldots, N$ countries, this results in the extension of the intermediate matrix **Z** to its new dimensions of *SN* x *SN* cells whereas the FD matrix **F** now contains *SN* x *NK* elements. Similarly, **w'** is expanded to 1 x SN cells and **x** now contains *SN* x 1 elements (Los et al., 2015).

2.3. Practical Use of Input-Output Tables in Value Chain Analysis

In order to establish an understanding of the logic underlying the use of IO tables, Table 3 translates the linear VC given in Figure 3 into a NIOT.

Table 3: Translation of linear VC into National Input-Output Table

		Country N - Intermediate Uses						Country N -Final Use	Total
		Industry 1	Industry 2	Industry 3	Industry 4	Industry 5	Industry 6	Final Use	Output
Country N - Supply	Industry 1	0	0	5	0	0	0	0	5
	Industry 2	0	0	0	0	0	0	0	0
	Industry 3	0	0	0	0	15	0	0	15
	Industry 4	0	0	0	0	0	0	0	0
	Industry 5	0	0	0	0	0	0	25	25
	Industry 6	0	0	0	0	0	0	0	0
Value Added		5	0	10	0	10	0		
Gross Output		5	0	15	0	25	0		

In line with the earlier and more general descriptions of IO tables in Table 1 and 2, this table can be interpreted as follows. Since the rows and columns of the square (6-by-6 industries) matrix denoted with 'Intermediate Uses' show the deliveries from the row industry to the column industry which contains the respective cell, it is clearly observable that Industry 1 (first row) delivers 5 $ to industry 3 (third column). Since this forms the first delivery of the VC, the VA by industry 1 equals the value of the delivery (5 $). A similar logic applies to the delivery of 15 $ in product value from industry 3 (third row) to industry 5 (fifth column). However, as industry 1 had already contributed a VA of 5 $ in VC stage 1, the added value by industry 3 only amounts to 10 $ (15 $ product value minus 5 $ intermediate good demand). Finally, industry 5 delivers the finished product to the Final Use category which also marks the stage in which the Intermediate matrix and thereby the VC is left. Since the previous product value already summed up to 15 $ whereas industry 5 delivers 25 $ to the FD, the last VA contribution by industry 5 can be computed as 10 $. In this simple example (which will later be expanded), industry 2, 4 and 6 do not take part in the VC. Following from the double-entry bookkeeping principle is the IO tables' characteristic of each industry's gross output being equal to the sum of all demands (as intermediate or final good) served by the same industry. With this in mind, the introduction of *coefficients* is in order. These do not form part of the general IO table but can be derived from it and are indispensable for the calculations at a later stage. For instance, the elements a_{ij} of the input coefficient matrix **A** with the dimensions *SN* x *SN* describe how much output a given industry *i* (as the row of the intermediate matrix) directly delivers to industry *j* (as the column of the intermediate matrix) in order to produce one additional unit of output in industry *j*. For a_{35}, industry 3's deliveries to industry 5, this would yield 0.6 using

$$a_{ij} = z_{ij} / x_j . \qquad (1)$$

A similar logic applies to the derivation of the VA coefficient vector **p'** with its elements p_j. These coefficients are understood as the shares of a (column) industry's VA in the output value of one unit generated in that industry. In other words, a VA coefficient indicates how much VA a given industry *j* directly generates in order to produce one unit of its output. For instance, p_5 yields 0.4 when employing

$$p_j = w_j / x_j \qquad (2)$$

Moreover, simple matrix algebra enables IO analysis to account for direct and also indirect product requirements (recall Figure 6) drawing on the so-called *Leontief inverse matrix* **M**. Consequently, its elements m_{ij} embody the required production levels of each separate industry *i* necessary to generate one unit of (additional) FD for industry *j*. Therefore, a single element of the inverse matrix is interpreted as the extra output necessary from industry *i* to produce one unit of output in industry *j*. The derivation of the matrix is slightly more complicated although the intuition behind it is rather straight-forward as well. Recall that the input coefficient matrix **A** incorporates elements indicating the output of an industry *i* directly necessary to produce a unit of output in industry *j*. Based thereupon, we multiply **A** with the final demand vector $\mathbf{f}_i$ which includes one unit of demand in industry *i* and zeros for all remaining elements. In mathematical terms this yields $\mathbf{Af}_\mathbf{i}$ which equals the direct production requirements of all industries to generate $\mathbf{f}_i$. However, in order to produce $\mathbf{Af}_i$, additional output is required once more equalling $\mathbf{Af}_i$ * $\mathbf{A}$ = $\mathbf{A}^2$ * $\mathbf{f}_i$ and so forth. Finally, the sum of this geometric series yields the general form of the Leontief inverse given by

$$\mathbf{M} = (\mathbf{I} - \mathbf{A})^{-1} \tag{3}$$

where **I** denotes the *identity matrix* with ones on the diagonal and zeros elsewhere. Consequently, multiplying with **M** accounts for not only the direct output requirements (as in **A**) but also the indirect output necessities. This also enables the calculation of the gross output vector **x** (*SN* x 1) from the FD vector **f** (*SN* x 1) using

$$\mathbf{x} = \mathbf{Mf} \tag{4}$$

which allows for the more thorough examination of scenarios like in Figure 1. Provided this structure and sufficient data availability, IO models can be an important tool used to examine demand-driven interdependencies of industries on a national as well as on a regional or global scale. Moreover, the problem of 'double-counting' as introduced above is avoided since the focal point of the analysis is the VA rather than the gross exports. This has led to increased prominence of the models in economic analyses. Therefore, the aim of our paper to evaluate the reliability of findings about the VA distribution in the course of global production fragmentation based on IO analysis is of high importance.

2.4. Relevant Prior Studies

Before, however, we will briefly introduce recent studies including measurements of (national) competitiveness, vertical specialisation and regional fragmentation[9]. These will be relevant as they not only help to distinguish which of the IO-based concepts are subject to criticism but also since they build up on each other, subsequently leading towards this paper's subject of investigation: the potential distortion of global production fragmentation studies quantifying the VA distribution. Three similar yet different approaches of studying global VCs can be distinguished.

First, Hummels et al. (2001) developed the concept of *vertical specialisation*. Thus, the degree of vertical specialisation was defined as the share of imported inputs embodied

[9] Vertical specialisation is defined below; exemplary contributions studying its concept include Hummels et al. (2001) and Amador & Cabral (2009). Regional fragmentation receives attention in e.g López-Gonzales (2012), Baldwin & López-Gonzalez (2015), and Los et al. (2015) as well as implicitly in Johnson & Noguera (2012b)

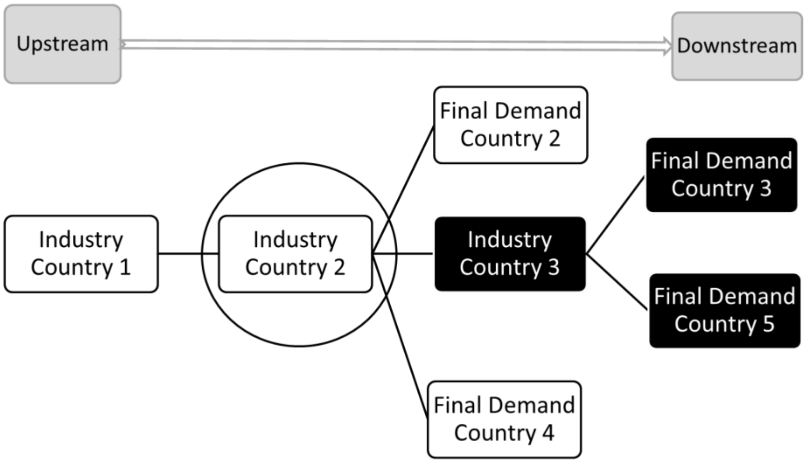
in the total exports to the directly subsequent countries[10]. Consequently, the focus of their study was shifted from traditional trade in final products towards modern trade in intermediate goods to account for the increased fragmentation of production processes. Thereby, Hummels et al. not only considered direct imports embodied in the exports of a given country but also its indirectly imported goods which are contributed to the country's exports. The study finds that vertical specialisation grew by 28 percent up to 21 percent between 1970 and 1990 for ten member countries of the Organisation for Economic Co-Operation and Development (OECD) and four emerging countries. Limited to NIOTs, the model did not account for 'back-and-forth trade' where exports of a country eventually get imported again. Only deliveries directly received from or supplied to foreign countries were regarded. However, the study already emphasised the recently increased extent of production fragmentation while relying on IO models.

A decade later, Johnson & Noguera (2012a) introduced the *value-added-to-gross export ratio* (VAX ratio). The *VAX ratio* is defined as the VA of a country that is eventually consumed as part of FDs in all foreign countries as a ratio of total export value. Thereby, Hummels et al.'s focus on the importing country was shifted towards the country in which the final demand for a product is located. Referring back to Figure 3 and assuming all trade to be international, Hummels et al.'s approach would aim to quantify industry 3's import share embodied in its exports to industry 5. In contrast, the VAX ratio would intent to compute how much VA generated in industry 3 would ultimately be consumed elsewhere. Among their findings, Johnson & Noguera (2012a) concluded that VAX ratios vary largely across countries and industries and that the differences between VA and gross trade are strong (VAX ratio mostly far below 1). Again, these findings shed light on the importance of fragmentation studies that this paper will test for their reliability.

Third and last, Timmer et al. (2013) established the 'Global Value Chain (GVC) approach'. As the term implies, the focal point of this concept is rather one specific global VC and, therefore, the last value adding country before consumption (country-of-completion). The location of the FD is irrelevant. Timmer et al. (2013) therewith also developed to the indicator 'GVC income' which is represented in Figure 4[11].

[10] Thereby, Feenstra & Hanson (1999) is extended where *offshoring* as the share of imported intermediates inputs in total intermediates inputs is measured
[11] Adapted from Los (2016)

Figure 4: Global Value Chain Income of Country 2



The GVC income describes the VA that a country (here Country 2) contributes to the final output of one specific VC (completed in Country 3). Therefore, all output by Country 3 (in black) – to serve FDs in Country 3 and 5 – is considered for this concept. However, only parts of Country 2's output are incorporated in Country 3's output since Country 2 serves other FDs, as well. Consequently, to calculate Country 2's *GVC income* for Country 3's output, only the VA which Country 2 contributes to Country 3 is considered. For instance, Timmer et al. (2013) decompose the output of final goods from the German 'Transport equipment' industry into the GVC income shares of the domestic country and foreign contributions by dividing the respective VA by the overall FD of 'Transport equipment'. Consequently, the GVC income regards one specific VC and examines the involved countries' contribution to it. Based on this approach, Los et al. (2015) distinguish between the domestic, regional and global VA and thereby dived even further into the GVC and its spatial characteristics. They challenged Baldwin & López-Gonzales' (2015) hypothesis that VC trade is still regional and mostly takes place within trade blocks (e.g. the European Union (EU) or the North American Free Trade Organisation (NAFTA)). However, Baldwin & López-Gonzales' (2015) arguments were based on a gross exports perspective. As shown by Los et al. (2015), employing VA instead of gross exports yields different results (recall Chapter 2.2.). Los et al. (2015) forms a major part of this study as it focuses on specific VCs and the examination of their characteristics in terms of the VA distribution. Since this paper seeks to quantify the extent to which such studies may be biased we will refer back to it at a later stage and attempt to quantify its potential distortion. More specifically and in line with Timmer et al.'s (2013) measurement, Los et al. (2015) decompose the value of final products –

defined by the last contributing country in a VC (i.e. the country-of-completion) – into the value contributed by all involved countries, respectively. Consequently, they first sum all FDs for a product i in a country n over its various final use categories (e.g. household expenditure or government consumption). This summation arises from the multiplication of the FD matrix **F** with a summation vector **e** (consisting of ones) and is thereby realized for all industries domestically and abroad. It yields a SN x 1 vector $\bar{\mathbf{f}}$ which displays all total FDs for each product i. These elements shall be decomposed into all industries' respective (direct and indirect) VA distribution. In order to do so, the VA coefficients need to be enriched by their indirect components. Therefore, a matrix $\hat{\mathbf{p}}$ containing the VA coefficients p_j on the diagonal and zeros elsewhere is created. When this matrix $\hat{\mathbf{p}}$ is subsequently multiplied with the Leontief inverse matrix **M** as in equation (1)**,** its VA coefficient elements are increased by their indirect contribution share (through element-wise multiplication with the **M**'s diagonal values). Therefore, by employing the **M**'s capability to account for indirect industry contributions we ensure that all embodied VA requirements are considered in the subsequent computation of VA distributions. As Los et al. (2015) aim to compute how much VA of the FD for one VC is attributable to each industry (domestic or foreign) separately, $\hat{\mathbf{p}}\mathbf{M}$ is multiplied by a SN x 1 vector $\bar{\mathbf{f}}_{\mathbf{i}}$ only containing the FD element for product i and zeros elsewhere. This yields

$$\mathbf{v} = \hat{\mathbf{p}}\mathbf{M}\,\bar{\mathbf{f}}_{\mathbf{i}} \qquad (5)$$

where **v** is a SN x 1 vector in which each cell indicates the VA contribution to the final value of product i directly and indirectly incorporated by the respective industry. A summation of this vector would logically amount to product i's overall value of FDs. Following this, the summation of all VA elements v_i which are generated outside of the country-of-completion of the product i are considered as foreign VA. Dividing this foreign contribution by the overall final product demand for product i therefore yields the *foreign value added share* (FVAS) as the VA contributions generated outside of the country-of-completion as a share of the industry's final output. Thereby, it is distinguished from the *domestic value added share* complementing the FVAS to 1. This indicator's distortion will be examined by realising simulations at a later stage. Subsequently, Los et al. (2015) are able to disaggregate the FVAS further by differentiating between *regional* and *global* FVASs. They argue that although regional fragmentation is still dominant, the global fragmentation share grew substantially faster recently. This development of a new 'Factory World'[12] has only briefly been suspended during the financial crisis of 2008 and regained strength afterwards again. Despite the fact that we will naturally not be able to test the distortion of *regional* compared to *global* foreign value added shares within the scope of this paper since we are limited to national data, the principles underlying the biases also apply for these more specific spatial dimensions of value added shares.

2.5. RESEARCH GAP

The aforementioned studies were largely enabled and facilitated by the improved availability of global IO data (e.g. the OECD – World Trade Organisation (WTO) Trade in Value Added Database[13] or the World Input-Output Database (WIOD))[14]. Therefore and as elaborated upon above, IO analysis has become an important tool to examine global production fragmentation. Consequently, it is important to be able to judge the reliability of the model's findings regarding the VA distribution in global production fragmentation studies which will form the focal point of this paper. Only if it is possible to verify the reliability of the model or at least quantify potential biases in these studies, will results and the subsequent interpretations of them be generalizable.

In order to challenge the meaningfulness of IO analyses investigating the VA distributions within VCs, N&V (2014) use the study by Los et al. (2015) as an initial point to examine potential biases in the employed model. They analyse the IO model theoretically and run simulations identifying biases which are based on the fact that IO analysis assumes that each industry only produces one good whereas in reality this clearly does not hold. If multiple VCs are aggregated and thereby result in the occurrence of one single industry at multiple stages within one VC, the degree to which its contributions are up or downstream might differ largely. This may distort the validity of findings derived from IO analysis attempting to measure the industries' VA contribution to single VCs significantly. According to N&V (2014), the VA generated by the final industry may be overstated which would result in an overestimated VA contribution by the respective country-of-completion. Nevertheless, they also consider scenarios in which the contribution of the final industries will be underestimated if these add a large amount of VA to the VC.

[12] A term akin to the aforementioned 'Global Factory' allegory by Gereffi (1989)
[13] OECD-WTO (2012)
[14] Timmer et al. (2015)

However, so far no empirical quantification of the distortions that the VA distribution is subject to has been done. This is where our paper fills in to close the research gap. In order to do so, this study will simulate concepts introduced by Los et al. (2015) with actual empirical data. As we will obtain and employ the same dataset on various aggregation levels and since N&V's (2014) biases are also based on aggregation, differing results of our simulations will yield inferences on the extent to which global fragmentation studies' findings about VA distributions along the VC are distorted.

3. The Biases Identified by Nomaler & Verspagen (2014)

At this stage and before diving into the explanations of the specific biases by N&V (2014), it is worth to briefly outline the structure of the remainder of this paper. First, the biases which have been identified by N&V (2014) based on the aggregation of multiple individual VCs to a limited number of indicated sets of these in IO databases will be explained and illustrated in more detail. Second, US-American data about inter-industry deliveries as well as FD categories within the country is gathered on which the subsequent simulations will be based. Since the tables rely on the same data but contain information for three different aggregation levels (hence: differing numbers of listed industries) per year, comparisons of the simulation results across this data will shed light on the extent to which aggregation leads to distortion. Consequently, we will convert the data into IO tables like illustrated in Table 3 and compare the results for indicators that measure the VA distribution across the various aggregation levels. Moreover, the emerging NIOTs will be transformed into hypothetical global IO tables since we are interested in the magnitude to which international VCs might be distorted. Multiple scenarios with an adjustable number of countries as well as different degrees of international trade will be developed to enable generalisations about the extent of the biases under various circumstances (i.e. high or low internationalisation; many or few countries). Although these global tables will be hypothetical, they are assumed to describe realistic VCs quite accurately since the data that is being employed is based on empirical data which distinguishes it from the VCs that were used by N&V (2014) to identify the biases. This will enable us to expand the distortions' examination empirically. Third, these different scenarios – with varying number of countries and degrees of international trade – are used to simulate a recent measurement of the VA distribution in the course of global production fragmentation (i.e. the FVAS, recall Chapter 2.4.). The results of these simulations can then be compared across the different obtained aggregation levels. As explained in more detail in this chapter, N&V's (2014) errors are based on the aggregation of single VCs into a limited number of bundled VCs. Therefore, the discrepancy of the results for the VA distribution in globally fragmented productions between the aggregation levels indicates the level of distortion which may be caused by these errors. Thus, it will be possible to quantify the extent to which N&V's (2014) biases distort studies on VA distribution using IO analysis. Forth, the discrepancies across the results derived from the tables which differ in their aggregation extent will be analysed and interpreted. Consequently, the reliability of IO models for global fragmentation studies and their findings with regards to the distribution of VA will be assessed based on the simulation results.

With that in mind, it is crucial to establish a clear and comprehensive understanding of the nature of N&V's (2014) criticism in more depth. Only if the underlying concepts of the errors are grasped, they can be related to the suitability of IO models for studies examining the international segmentation of VCs. When using IO analysis to examine global production fragmentation, the aggregation of all VCs that an industry (e.g. 'Manufacturing') adds value to, might not represent the individual contributions (e.g. to 'Machinery Manufacturing' or to 'Electronic Product Manufacturing') accurately. For instance, the results for the FVAS (Los et al., 2015), might misrepresent the real VA contributed to single VCs. Recall Table 3 as our example of a linear VC translated into an IO table. Moreover, we transfer the example to a more illustrative case assuming that industry 1 constitutes '*Copper mining*', industry 3 represents '*Electronical components*' and industry 5 shows '*Transport equipment*'. '*Personal consumption expenditures*' is the only FD category and the VC's final product may be a car. Intermediate deliveries from the '*Copper mining'* industry (e.g. used to produce wires or cables) are required to produce the car's automobile radio in the '*Electronic components*' industry before the '*Transport equipment*' industry implements this radio to finish off the final car and deliver it to the FD. Therefore, it is the only industry supplying goods to the FD. Figure 6[15] translates the case into an IO following the logic introduced in Chapter 2.3.

[15] Adapted from Timmer et al. (2015)

Table 4: Translation of linear Transport Equipment Value Chain into an Input-Output Table

		Country N - Intermediate Uses						Final Use	
		Copper mining	Industry 2	Electronic components	Industry 4	Transport Equipment	Industry 6	Personal consumption expenditures	Total Output
Country N - Supply	Copper mining	0	0	5	0	0	0	0	5
	Industry 2	0	0	0	0	0	0	0	0
	Electronic components	0	0	0	0	15	0	0	15
	Industry 4	0	0	0	0	0	0	0	0
	Transport Equipment	0	0	0	0	0	0	25	25
	Industry 6	0	0	0	0	0	0	0	0
Value Added		5	0	10	0	10	0		
Gross Output		5	0	15	0	25	0		

Now, suppose that another production process takes place within the same economy. Within this second VC, industry 2 represents '*Lithium mining*', industry 4 constitutes '*Electrical parts*' and industry 6 indicates '*Telecommunication equipment*'. The final product – a mobile phone which needs inputs from the '*Lithium mining*' industry before '*Electrical parts*' manufactures a battery for the phone – is completed in 'Telecommunication equipment'. Then, we translate the VC in which only '*Telecommunication equipment'* supplies the FD, into the previous Table 4 and therewith combine it with the first VC. This yields our new combined Table 5[16].

Table 5: Input-Output Table including two Value Chains

		Country N - Intermediate Uses						Final Use	
		Copper mining	Lithium mining	Electronic components	Electrical parts	Transport Equipment	Tele-communication equipment	Personal consumption expenditures	Total Output
Country N - Supply	Copper mining	0	0	5	0	0	0	0	5
	Lithium mining	0	0	0	10	0	0	0	10
	Electronic components	0	0	0	0	15	0	0	15
	Electrical parts	0	0	0	0	0	20	0	20
	Transport Equipment	0	0	0	0	0	0	25	25
	Tele-communication equipment	0	0	0	0	0	0	25	25
Value Added		5	10	10	10	10	5		
Gross Output		5	10	15	20	25	25		

As observable in the table, all individual VC contributions (e.g. 'Copper mining' supplying 5 $ to 'Electronic components') as well as the respective VA coefficients (e.g. p_4 = 0.5) are clearly observable from the table (recall equation (2)). Now, by using matrix algebra we

[16] Adapted from Timmer et al. (2013)

will be able to compute each industry's VA contribution to a given VC. For exemplary purposes, we will only regard the final demand $\mathbf{f_5}$ of 25 $for the '*Transport Equipment*' industry. The remaining cells of the 6 x 1 vector contain zero-values. Using equation (3) and (4) we can now generate the output level only associated to the FD for cars. To generate the new VA levels necessary to serve the FD, we employ equation (5) yielding a 6 x 1 vector **v** with the VA levels of all respective industries. Since the industries are not interrelated at the disaggregated level, the computations yield the indicated VA (i.e. 5, 10 and 10 $) for industry 1, 3 and 5 from Table 5. Consequently, the IO-based VA calculation reflects the actual contributions of each industry to the VC of '*Transport equipment*'. As mentioned before, however, N&V (2014) base their critic on the aggregation of multiple individual VCs into an aggregated set of VCs industry. Hence, suppose that the 'Electronic components' industry is bundled together with the 'Electrical parts' industry to a new overarching industry called 'Electrical and electronic components'. The emerging IO table now looks slightly different as shown in Table 6.

Table 6: Aggregated IO Table including two Value Chains[17]

		Country N - Intermediate Uses					Final Use	
		Copper mining	Lithium mining	Electrical and electronic components	Transport Equipment	Tele-communication equipment	Personal consumption expenditures	Total Output
Country N - Supply	Copper mining	0	0	5	0	0	0	15
	Lithium mining	0	0	10	0	0	0	10
	Electrical and electronic components	0	0	0	15	20	0	35
	Transport Equipment	0	0	0	0	0	25	25
	Telecommunication equipment	0	0	0	0	0	25	25
Value Added		5	10	20	10	5		
Gross Output		5	10	35	25	25		

This leads to the fact that individual VC contributions of the former industries '*Electronic components*' and '*Electrical parts*' are no longer observable. Consequently, again employing equation (2) now yields a VA coefficient p_3 for both included industries in 'Electrical and electronic components and parts' at 0.57 compared to 0.5 for 'Electrical parts' and 0.67 for 'Electronic components' before.

The difference is due to the fact that less value had already been added to the first VC (5 $) prior to 'Electronic component's contribution to it when compared to the second VC

[17] Adapted from Timmer et al. (2013)

in which the product value prior to the 'Electrical parts' contribution was already higher (10 $). Value that is added when the relative product value is already higher is termed as more downstream whereas the contribution at a stage when the product value is still relatively low is considered more upstream in the VC. Thus, comparing the aggregated VA coefficients with the disaggregated ones, it becomes clear that the VA coefficients of the more downstream contribution (i.e. Electrical parts') is overestimated (0.57 versus 0.5) whereas the more upstream value addition (i.e. Electronic components') is underestimated (0.57 versus 0.667). On first sight, this does seem like a major problem. However, when using the same logic applied earlier to calculate the VA levels of all industries using equation (5), the different VA coefficients matter significantly. Again, using the exemplary '*Transport equipment*´ VC and its final demand $\mathbf{f}_4$ of 25 $, the computed VA contribution of the '*Electronic and electrical components*' industry shrinks to 8.6 $ compared to the actual VA of 10 $[18]. Duplicating the calculations for $\mathbf{f}_5$ of the 'Telecommunication' VC amounts to an actual VA by the aggregated 'Electronic and electrical components' industry of 10 $ while the calculation with IO models yields a VA of 11.4 $. The difference between the two computations is based on the fact that the contribution to the first individual VC takes place further upstream while for the second single VC value is added further downstream. Based on this, N&V (2014) claim that the final industries' VA contribution in aggregated studies based on IO tables might be overestimated whereas more upstream industries would consequently be underestimated. However, N&V (2014) also consider potential scenarios in which the industry of the final production stage (*industry-of-completion*) contributes a relatively high amount of VA to the product. This would consequently result in an understatement of the last VA contribution at the final VC stage due to the fact that the last industry's VA contribution would incorporate a particularly high VA coefficient which would be underestimated by the aggregated average VA coefficient. N&V (2014) refer to this problem as the *fixed VA to output bias* which is caused by the equalisation of VA coefficients. Logically and as shown above, it arises as soon as an industry appears multiple times at different stages of VCs.

This also applies to scenarios with so-called *production cycle* where a given industry *j*'s production makes use of intermediate goods which indirectly embody the products of

[18] Note that due to the realized aggregation process 'Transport equipment' now forms the forth industry in the IO table. The same applies for 'Telecommunication equipment' which becomes the fifth industry through aggregation.

industry *j* itself. When aggregating multiple individual VCs, these production cycles might arise even if the single VCs which the industry contributes to do not exhibit these cycles. Referring back to the two previously examined VCs an example for a production cycle would occur when assuming that the '*Copper mining*' industry also requires '*Electrical parts*' for the quarrying. The disaggregated individual VC of '*Transport* equipment' would still not embody any production cycles whereas combining '*Electronic components*' and '*Electrical parts*' results in the multi-occurrence of the aggregated industry in the VC and, hence, in a production cycle. According to the aforementioned elaboration on the distortion caused by industries that contribute VA at different stages (i.e. more upstream versus further downstream value addition) of VCs, this will significantly distort the VA coefficients representing the second cause of distortion as claimed by N&V (2014). Consequently, product cycles that result from aggregation follow the same distorting logic as the examples before. Since the VA coefficients of individual contributions to VCs differ in reality but are bundled within one aggregating industry including a fixed VA coefficient, a misrepresentation of the individual contribution to VCs arises. This distortion will be positive for early stages in the VC (with high VA coefficients) and negative for later stages (with low VA coefficients).

In order to substantiate the concepts underlying the presented biases, N&V (2014) first theoretically analyse and illustrate the logic by introducing a simple three-industry model with two different short VCs that are aggregated within one IO table similar to the procedure employed for Table 6. Then, N&V (2014) use simulations to construct and account for longer VCs including many more industries. Nevertheless, the industry's order of appearance and their VA contribution as well as the length, structure and shape of the VCs that N&V (2014) construct are largely based on randomisations. Employing these simulations, they find that the aggregation of individual VCs will likely cause an overstatement of the final industries within a VC whereas more upstream industries' contribution will be underestimated. However, N&V (2014) have not identified empirical evidence for the magnitude of the biases by means of VCs that reflect actual production processes. This is where our paper fills in by regarding realistic national data which is extended to a global scenario and compared across aggregation levels. This will shed light on the distortion of VA distribution results caused by the aggregation of single VCs as we will be able to relax N&V's (2014) aforementioned assumptions. The realized comparisons across aggregation levels will consequently enable quantifications of the misrepresentation's extent. Having established a clear understanding of the biases that N&V (2014) claim to be significant, the upcoming chapter illustrates the empirical data and methodology which is used to fill the theoretical concept of N&V (2014) with life.

4. Data and Methodology

After having established a deeper understanding of the regarded aggregation biases, it must now be ensured that the data which is employed to analyse the research question is consistent and suitable for the purpose it serves. Since the reliability of IO models used in global production fragmentation measures is tested, it is necessary to create tables that follow the general principles of such models (as introduced in Chapter 2.3.). Moreover, the tables need to reflect a global scenario with multiple countries and adjustable degree of international trade to allow for generalisations on differences in the biases' magnitude with increasing global production fragmentation. The construction of IO tables will be realized in two ensuing subsections. First, the conversion of the national into a hypothetical global IO table will follow. Second, the creation of different scenarios with multiple countries and varying import shares which are still based on the obtained global IO tables will be made comprehensible. This will ultimately enable us to compare results for fragmentation measurements of the VA contribution across the different aggregation levels and thereby generate an indication of the magnitude of the examined biases based on these aggregations. For the creation of suitable IO tables, US-American IO data for the year 2007 is employed. This can be gathered for three different aggregation levels and contains data based on the producer value which is transformed into consistent NIOTs by using a standard procedure as shown in Horowitz & Planting (2006) as well as Guo el al. (2002) [19]. No more recent years containing data for all three different aggregation levels was made available yet. This yields three different NIOTs for the US with 15-by-15, 71-by-71 and 389-by-389 industries containing the same underlying data.

The only data issue that was addressed more specifically while constructing IO tables from the US-American data was the allocation of 'Used and Second-hand goods' and 'Non-comparable imports' to the 389-industry IO table which needed to manually be assigned to the intermediate matrix **Z** and the FD matrix **F** to maintain the IO table's balance (recall Chapter 2.2.). We proportionately allocated the values to the

[19] The producer values are the prices that domestic producers receive for their output (Dietzenbacher et al., 2013).

intermediate matrix based on the total intermediate deliveries and subtracted the same values from the identical subindustries' FD supply. This simple method might have led to the allocation of intermediate inputs to subindustries where these do not belong in reality. A more complex method of distributing these specific intermediate inputs in line with the 71-industry table and then allocating them within each of these branches proportionately would have yielded better results but is beyond the scope of our paper. We will once more address this data issue in the limitations.

4.1. CONVERSION TO GLOBAL INPUT-OUTPUT TABLES

As stated in Chapter 2.5., the availability of global IO tables has recently improved drastically. Consequently, using another database (e.g. the WIOD or the OECD – WTO Trade in Value Added Database) for this study instead of creating hypothetical tables based on one country would seem natural. Nevertheless, these would also need to be modified to simulate different extents of fragmentation and adjust the number of involved countries manually. Most importantly, however, the distinctly different extents of VC aggregation provided by the US-American IO data allow for comparisons across the aggregation levels in order to identify the magnitude of the presented biases.

Before doing so, it is necessary to convert the US-American IO tables into hypothetical multi-country tables that encompass all global production to be able to study the global fragmentation of production processes. This calls for one assumption as well as one crucial modification of the data. First, the data which has been used to create the NIOTs (on all three aggregation levels) is naturally limited to the US. If, subsequently, global tables are derived from it, these will also only employ US technology in the production patterns of the respective industries. In other words, we suppose that the US-American production technologies form the global standard for all countries. Consequently, it is assumed that the necessary inputs for all VCs are alike also on a global scale. However, as the US constitute the largest economy of the world and since it is rather the methodology of IO models in global production fragmentation studies that is put to a test, this assumption is not expected to have major consequences on our computations of VA contributions. Moreover, it allows us to benefit from the empirical order of the industries' occurrence in VCs whereas N&V's (2014) VCs depend on randomisations. Second, supposing the national production and demand of the US to be the only global production, imports and exports need to be neglected. A global IO table does by definition not allow for trade with countries which are not incorporated in the table itself as all existing production must be internalised. However, NIOTs typically indicate a FD category denoted as exports. Moreover, imports are also listed in such a national table. Therefore, we need to set both respective columns of the matrix **F** to zero. This is achieved by simply cancelling out these columns from the NIOTs[20]. Nevertheless, when altering the FD for certain industries, it does not suffice to simply change the total output of the producing industry accordingly. Direct as well as indirect contributions by all industries need to be considered to arrive at the new global IO tables. In order to develop a new intermediate matrix **Z** from the multiplication of the input coefficient matrix **A** with the new output vector **x**, we must first calculate the new **x** in line with equation (4). The therefor necessary FD vector $\tilde{\mathbf{f}}$ now includes the sums of all supplied FD categories (without imports and exports) per industry. For instance, all FDs for the 'Construction' industry –irrespective if they are consumed by the government, households or elsewhere – are summed. This enables us to compute the new output level $\tilde{\mathbf{x}}$ by using equation (4). Since the production technologies and thereby the input coefficient matrix **A** remain alike with changing gross output, the allocation of intermediate deliveries follows the exact same proportions which were observed for the (old) output level (including imports and exports). We therefore use the equation

$$\mathbf{Z} = \mathbf{A}\tilde{\mathbf{x}} \tag{6}$$

to generate a new intermediate matrix[21]. Finally, the VA levels need to be adjusted following the change in FD to ultimately convert the NIOT into a global one. The procedure is similar to the calculation of new levels of intermediate deliveries. Instead of the input coefficient matrix, however, the VA coefficient vector is multiplied with the new vector of global output levels as in the equation

$$\mathbf{w} = \mathbf{p}\tilde{\mathbf{x}}\,. \tag{7}$$

Let us summarize the implemented modifications of the NIOT to create a hypothetical global table. First, the imports and exports have been set to zero since no trade imbalances are allowed for in a global table. Second, a new output level has been calculated which disregards imports and exports. Third, the intermediate deliveries as

[20] Since the US has a trade deficit with imports > exports cancelling out both categories will actually increase the overall FD level in the IO tables.
[21] Please note that equations (6) and (7) resemble equation (1) and (2). Only the element's order has changed.

well as the VA levels have been adjusted proportionally in accordance to the previously calculated coefficients. This yields a hypothetical global IO table which embodies all global production but is limited to a single country. Subsequently, it will now be necessary to introduce additional countries as well as international trade to our table which will be elaborated on in the following subsection.

4.2. Creation of Different Global Scenarios

In order to simulate studies of global production fragmentation within multiple set-ups of varying country numbers and differing extents of international trade, this subsection will briefly explain the adjustable construction of these scenarios. Their development will be important as they will allow for general inferences regarding the extent to which the identified biases may differ in their magnitude across these global set-ups. The various scenarios will be based on the hypothetical global IO tables that we have created earlier in this chapter as explained in more detail below. However, at this point it is worth reemphasising that the comparisons of the scenarios only yield meaningful results when assuming that the most disaggregated IO table represents all individual VCs which is why it will be used as a benchmark for the other, more aggregated tables.

Since this paper largely rests upon the simulations by N&V (2014), it is important to underline the differences in our VC constructions from their approach. First, as briefly indicated in Chapter 3, the structure, length and composition of the VCs in this paper do not rely on randomisations. On the contrary, using empirical data from the US – albeit gathered on a national level – will help to effectively stick to the fixed VC structure which is indirectly embodied in the information of the input coefficient matrix **A**. Consequently, product cycles will already be included in the tables which we create from the US-IO tables. Furthermore, the shape of N&V's (2014) constructed VCs also largely differs from reality. While N&V (2014) assume all VCs to be in the form of a 'snake' with final products arising from numerous sequential production stages, Baldwin & Venables (2013) acknowledge that many real global VCs might rather incorporate the form of a 'spider'. This would mean that many intermediate inputs from various industries are eventually merged and assembled. A prominent example for such a VC is Dedrick et al.'s (2009) previously mentioned case study examining the iPod which is assembled in China but relies on intermediate goods such as hard drives from Japan and memories from South Korea. These intermediates, in turn, are subject to multiple preceding production stages themselves, however, making actual VCs a combination of 'snake' and 'spider' shapes with high complexity and variability. This is not accounted for in the simulations implemented by N&V (2014) but underlies our tables' intermediate matrices. Moreover, in contrast to N&V (2014), we do not need to manually define so-called *primary sectors* which do not use intermediate inputs and therefore form the most upstream industries in N&V's (2014) simulations as these also naturally derive from the underlying VC structure embodied in the input coefficient matrix. The same applies for the order appearance of the remaining, non-primary industries which is completely random in N&V's (2014) simulations. In reality, however, it can be expected that numerous industries are most likely to be found either at a rather upstream (e.g. Mining) or downstream (e.g. Education) stage. This is accounted for by relying on an empirically observed input coefficient matrix as realised within our IO table construction. Second, in contrast to N&V (2014) we will not need to specify the various VA levels which are generated at each stage by introducing industry, stage or chain-specific determinants for the contributions. This is due to the fact that we rely on values based on national observations which we assume to reflect individual VCs. The same applies for the respective output levels of the VCs which also follow from the obtained national data. Third, since we will compare the results of our simulations with regards to the VA distribution within global VCs across aggregation levels, the constructed IO tables with multiple countries and certain degrees of internationalisation will, naturally, need to be created on such different levels. No comparison across aggregation extents was realized in N&V (2014). With that in mind, we now explain the scenarios which we will use to represent a global network of VCs. Then, we will show how the global IO table we constructed previously can be expanded to account for these requirements.

The global IO tables which are created in this section will include two major variables. Not only will the number of global countries N be adjustable but we will also be able to alter the import share (IS) as a measure of internationalisation. However, the simulations will be limited to scenarios with equal country size as well as uniform tradability of all goods. Consequently, all countries' respective national and international intermediate deliveries as well as their FD supplies will be alike across all countries. Moreover, no distinction is made across industries that may exhibit higher (e.g. manufacturing) or lower tradability (e.g. most services) in reality.

As all countries need to embody the same number of industries, *SN* industries and an overall intermediate matrix **Z** with *SN* x *SN* elements will emerge in each global scenario assuming n = 1,…, N countries and s = 1,…, S industries. This matrix can be subdivided into the contained matrices defined as $\mathbf{Z}_{nn}$ which represent blocks of deliveries from a given country n to a receiving country and in turn contains S x S elements. Clearly, the diagonal matrices (e.g. $\mathbf{Z}_{11}$, $\mathbf{Z}_{22}$ etc.) reflect domestic deliveries within a country. Similarly, the number of FD categories sums up to *KN* where k = 1,…, K denotes the number of FD categories per country. Over all countries, *SN* x *KN* elements will be displayed. Following the same logic as applied for the subdivided intermediate matrices, the FD matrix **F** may also be split up into submatrices $\mathbf{F}_{nn}$ containing the supply of goods by country n to a recipient country with S x K elements for each block and $\mathbf{F}_{11}$, $\mathbf{F}_{22}$ etc. representing domestic final good deliveries. Moreover, the VA row vector **w’** yields the dimensions 1 x *SN* and the output vector **x** consists of *SN* x 1 elements. Each VA ($\mathbf{w}_n$’) and output block vector ($\mathbf{x}_n$) – with the subscript indicating the generating country – also embodies 1 x S and S x 1 elements (one per industry), respectively. Insofar, the structure clearly follows the model established in Table 2. For instance, consider the scenario of three countries with each 15 industries and four FD categories. Using the structure depicted in Figure 2 and the aforementioned components yields the following Table 7[22].

Table 7: Exemplary Structure of Global IO Table with 3 Countries of each 15 Industries

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Country 1</th><th colspan="2">Country 2</th><th colspan="3">Country 4</th><th colspan="3">Country 1</th><th colspan="2">Country 2</th><th colspan="3">Country 3</th><th rowspan="2">Total Output</th></tr>
<tr><th>Industry 1</th><th>…</th><th>Industry 15</th><th>…</th><th>…</th><th>Ind. 1</th><th>…</th><th>Ind. 15</th><th>Final Use (FU) 1</th><th>…</th><th>FU 4</th><th>…</th><th>…</th><th>FU 1</th><th>…</th><th>FU 4</th></tr>
<tr><td rowspan="3">Country 1</td><td>Industry 1</td><td colspan="3" rowspan="3">Z_{11}</td><td colspan="2" rowspan="3">Z_{12}</td><td colspan="3" rowspan="3">Z_{13}</td><td colspan="3" rowspan="3">F_{11}</td><td colspan="2" rowspan="3">F_{12}</td><td colspan="3" rowspan="3">F_{23}</td><td rowspan="3">x_1</td></tr>
<tr><td>…</td></tr>
<tr><td>Industry 15</td></tr>
<tr><td rowspan="3">Country 2</td><td>…</td><td colspan="3" rowspan="3">Z_{21}</td><td colspan="2" rowspan="3">Z_{22}</td><td colspan="3" rowspan="3">Z_{23}</td><td colspan="3" rowspan="3">F_{21}</td><td colspan="2" rowspan="3">F_{22}</td><td colspan="3" rowspan="3">F_{23}</td><td rowspan="3">x_2</td></tr>
<tr><td></td></tr>
<tr><td>…</td></tr>
<tr><td rowspan="3">Country 3</td><td>Industry 1</td><td colspan="3" rowspan="3">Z_{31}</td><td colspan="2" rowspan="3">Z_{32}</td><td colspan="3" rowspan="3">Z_{33}</td><td colspan="3" rowspan="3">F_{31}</td><td colspan="2" rowspan="3">F_{32}</td><td colspan="3" rowspan="3">F_{33}</td><td rowspan="3">x_3</td></tr>
<tr><td>…</td></tr>
<tr><td>Industry 15</td></tr>
<tr><td colspan="2">Value Added</td><td colspan="3">w_1</td><td colspan="2">w_2</td><td colspan="3">w_3</td></tr>
<tr><td colspan="2">Total Output</td><td colspan="3">x_1</td><td colspan="2">x_2</td><td colspan="3">x_3</td></tr>
</table>

Consequently, in the specific scenario the IO table consists of 45 industries, VA cells and total output elements (vertical and horizontal). Furthermore, 12 final use categories are obtained. The derivation of the total values in each specific block of the global IO table is subject to the IS and yields the following pattern. Assuming the IS at 0.2 (yielding a

[22] Adapted from Dietzenbacher et al. (2013)

domestic share of 0.8 as the complement to one) and that Country 1's overall intermediate demand amounts to 100 \$, 80 \$ (0.8 * 100 \$) will be delivered among the domestic industries within the country whereas the remaining 20 \$ are imported in equal shares from Country 2 and 3 (10\$ each). Referring back to Table 7 this would mean that the total values of the matrix $\mathbf{Z}_{11}$ amount to 80\$ whereas $\mathbf{Z}_{21}$ and $\mathbf{Z}_{21}$ each display total intermediate deliveries of 10 \$. Similarly, country 1's intermediate deliveries to other countries (in $\mathbf{Z}_{12}$ and $\mathbf{Z}_{13}$) each show the total value of 10 \$ as well. In line with this, the supplies of FDs which are represented in the submatrices $\mathbf{F}_{nn}$ can be distinguished between domestic (diagonal) FD blocks and imported FD supplies in the remaining (off-diagonal) blocks. Consequently, supposing the same IS as before and assuming each country's FD to amount up to 100 \$, again, 0.8 * 100 \$ of FD in Country 1 are supplied by domestic industries while the remainder is split up equally among the imports from the other two countries' industries (each 10\$). The overall FD supplies from Country 1, 2 and 3 to serve the FDs of Country 1 therefore amount to $\mathbf{F}_{11}$ = 80 \$ and $\mathbf{F}_{21}$ = $\mathbf{F}_{31}$ = 10. The supplies of FD from Country 1's industries follow the same logic as explained for the intermediate blocks. Moreover, the total value of the output block vectors $\mathbf{x}_n$ but also the total value of the VA block vectors $\mathbf{w}_n$ are equal across countries and can simply be computed by dividing the overall output or VA level in the original IO table by the number of countries N. Assuming the total output in the original (one-country) table to be at 600 \$ and the overall VA in the table to amount up to 300 \$, all $\mathbf{x}_n$ blocks would contain 200 \$ while all $\mathbf{w}_n$ blocks would consist of 100\$ each, based on our assumptions. This explanation of the derivation of the elements in a global IO table with multiple countries and a certain degree of internationalisation allows us to fill the general table presented before with life which yields Table 8.

Table 8: Global IO Table with 3 Countries and an Import Share of 0.2

Import Share		Country 1	Country 2	Country 3	Country 1	Country 2	Country 3	Total
0.2		Industry 1 … Industry 15	… …	Ind. 1 … Ind. 15	Final Use (FU) 1 … FU 4	… …	FU 1 … FU 4	Output
Country 1	Industry 1							
	…	80	10	10	80	10	10	
	Industry 15							200
Country 2	…							
		10	80	10	10	80	10	
	…							200
Country 3	Industry 1							
	…	10	10	80	10	10	80	
	Industry 15							200
Value Added		100	100	100				
Total Output		200	200	200				

By implementing these principles in the construction of global IO tables based on our national data, all parts of a consistent global economy scenario can be obtained. This allows us to construct any hypothetical global scenario in terms of country number and IS from our formerly national data by creating IO tables as displayed in Table 8. Consequently, we are enabled to realise simulations examining the VA distribution within globally fragmented production processes while relying on realistic VC structures (assuming that the most disaggregated tables reflect individual VCs) which are maintained in the global tables.

5. Data Analysis and Simulations

The preceding Chapter 4 has extensively elaborated on the construction of IO tables enabling the realisation of international fragmentation studies. However, their suitability to create results that allow for inferences regarding the VA distribution in global VCs is yet to be attested. Consequently, the subsequent chapter will emphasise why the previously created tables are practical in order to run the simulations which are featured afterwards in Chapter 5.2.

5.1 Analysis of the created data

The core of our simulations aiming to quantify N&V's (2014) biases lies in the basic assumption that the results of global fragmentation studies obtained from the most disaggregated 389-industry global IO table which we have created reflect the true VA distribution in individual VCs. Therefore, it is crucial to establish if this assumption is reasonable or to which extent it may be violated.

Since N&V (2014) argue that the aggregation of individual VCs to aggregated sets of these leads to production cycles, this chapter briefly examines the scope with which our three IO tables are subject to these cycles. As the diagonal values of **M** (i.e. m_{11}, m_{22} etc.) indicate how much extra output is directly and indirectly required from a given industry i to produce one unit of output in the same industry, all deviations of these values above 1 clearly emerge from the existence of production cycles. Consequently, to examine the reliance of our IO tables on such cycles, Figure 5 plots the diagonal values of the Leontief inverse **M** minus 1 across our different aggregation levels against their frequency of occurrence (in percent). This is realised for a 10-country scenario with an IS of 0.2. However, it is worth stressing that not all of these production cycles are actually caused by aggregation but could also arise from the multi-occurrence of one industry within one individual VC. Transferring this case to its implications for the VA coefficients, we acknowledge that these would not be biased and instead be well-represented with the mean of the different value contribution's coefficients. Consequently, since not all values above 1 are attributable to production cycles across single VCs, the presented histograms in Figure 5 can only be understood as an indication of the extent to which the biases may distort the respective aggregation table's results.

Figure 5: Diagonal Leontief Inverse Matrix Values (10 Countries, IS 0.2) across Aggregation Levels

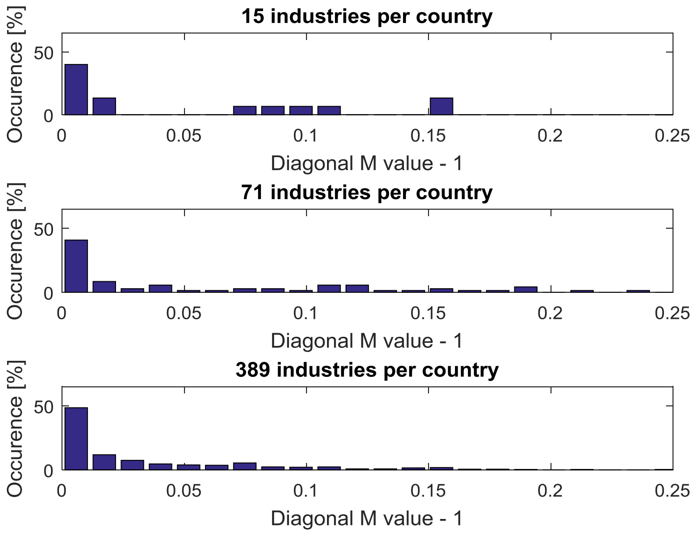


Figure 5 is clearly in line with the expectations by illustrating that the most aggregated industry table seems to display most production cycles when compared to the other two IO tables since it exhibits fewer values close to zero. Moreover, while the more disaggregated 71 x 71 industry table displays more low values but still seems to embody some industries with diagonal **M** values that are significantly different from zero, the most disaggregated 389 x 389 industry table clearly includes mostly low values and only few exceptions of industries that significantly depend on production cycles. This impression is verified by the mean values of the diagonal **M** values indicating 0.10 for the most aggregated, 0.07 for the 71 x 71 industry case and 0.04 for the most disaggregated case since they show that the average dependence of included industries decreases with rising disaggregation. Moreover, Table 9 shows that this gradual incline of diagonal **M** values with increasing disaggregation is also consistent across other hypothetical global set-ups by documenting the respective mean diagonal values of the Leontief inverse in scenarios with either a different country number or IS.

Table 9: Mean Diagonal Values of Leontief Inverse across Aggregation Levels

	Aggregation Level (*S*)		
Scenario	15	71	389
N =3, *IS* =0.2	0.010	0.073	0.037
N =10, *IS* =0.2	0.098	0.072	0.037
N =30, *IS* =0.2	0.098	0.072	0.036
N =10, *IS* =0.3	0.083	0.061	0.032
N =10, *IS* =0.4	0.069	0.051	0.027

The generated scenarios which underlie Figure 5 as well as Table 9 assume that all countries are of equal size and subject to the same input coefficient matrix **A** within the IO tables. Therefore, each of the diagonal blocks in the Leontief inverse matrix (including its diagonal values) is alike across all countries. Therefore, the number of different values on the diagonal of **M** can only equal the number of industries per country at most.

We purposely focus on the analysis and simulation results in a hypothetical global IO set-up with an IS of 0.2 since this value seems most adequate to represent many current production processes in reality. Therefore, this scenario can be considered to be empirically most relevant when considering that large countries like the US (0.17), China (0.19) or India (0.26) exhibit similar overall economy ISs in reality. As mentioned before, no distinction between ISs within our hypothetical global set-up (e.g. smaller ISs for service industries) will be realised in this paper. Moreover, no ISs above 0.5 will be shown since these would represent an *anti-home bias* (with foreign deliveries being more likely used as intermediate and final goods than domestic ones) which is far from reality when limiting the analysis to equal size countries.

Diving into Table 9 in more depth, it appears as if the occurrence of production cycles within the aggregation levels decreases (slightly) with increasing number of countries and shrinks significantly with the extent to which the contained countries engage in foreign trade. The only small differences between the results for varying country numbers is accounted for by the limited VC lengths resulting in an also limited potential global fragmentation of these. Again, these production cycles can only offer an indication of the extent to which the hypothetical country scenarios are exposed to the biases by

N&V (2014). An industry that adds value at multiple stages within one individual VC will not suffer from the aggregation bias and therefore indicate an adequate VA coefficient.

In order to transfer this analysis to our main subject of interest, the VA within individual VCs and their potential distortion, we will now quantify to what extent the industries' respective VA is subject to production cycles. Therefore, Figure 6 plots the diagonal values of the matrix $\hat{\mathbf{p}}$ (ergo the direct VA coefficients p_j) on the x-axis against the same elements which are pre-multiplied with the Leontief inverse $\mathbf{M}$ and therefore include indirect contributions by the respective industry (y-axis). The comparisons of the diagonal values of the $\hat{\mathbf{p}}\mathbf{M}$ matrix with the ones of $\hat{\mathbf{p}}$ therefore shed light on the importance of production cycles in the value adding process. This is again realized for an international case with 10 involved countries and an IS of 0.2. As seen in Table 9, adding additional countries will not change the values significantly due to the limited length of VCs. We replicate the same operation for all aggregation levels. As the values on the vertical axis will account for the indirect VA contributions of an industry to produce one unit of its output, all these values will be at least as large as their direct VA coefficient counterparts on the horizontal axis. No observed values in the generated graphs will therefore be displayed below the 45 degrees line which is added for the sake of clarity.

Figure 6: VA Coefficients including indirect Contributions versus Direct VA Coefficients (IS=0.2)

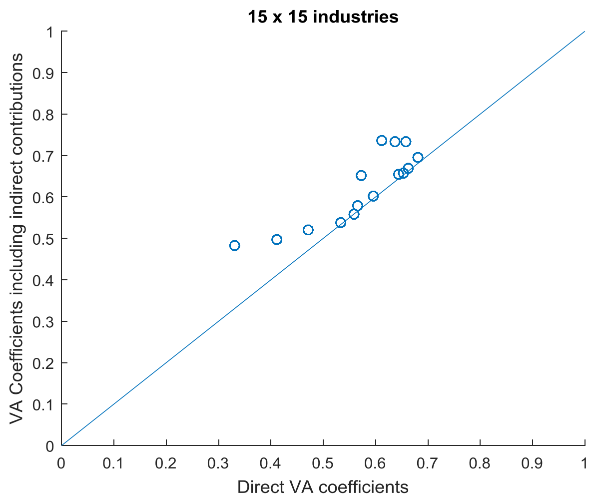


Figure 7: VA Coefficients including indirect Contributions versus Direct VA Coefficients (IS=0.2)

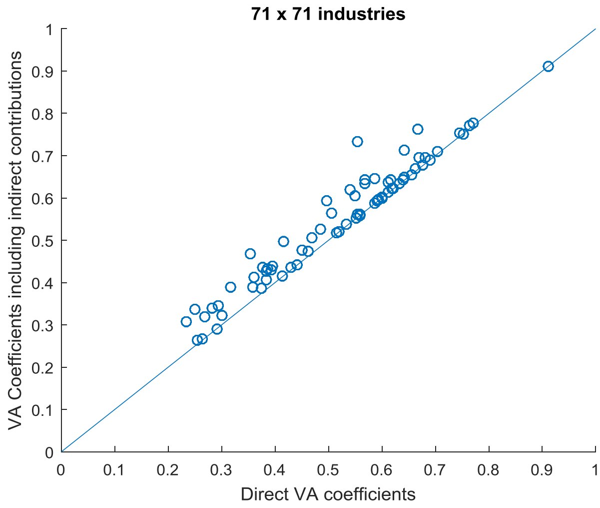
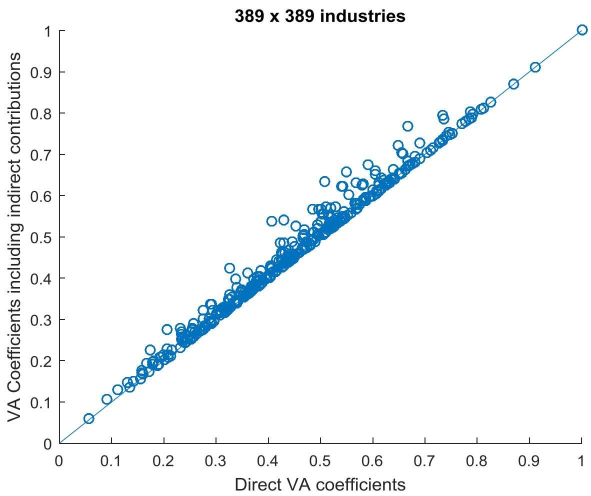


Figure 8: VA Coefficients including indirect Contributions versus Direct VA Coefficients (IS=0.2)



Similar to the analysis of the diagonal values of the Leontief inverse, Figures 6 to 8 are also limited to an amount of observed values that equals the respective number of industries per country S for each aggregation level. This is due to the fact that all countries are equal in size and therefore exhibit the same diagonal values on the Leontief inverse as well as identical VA coefficients. However, the observed values in the three graphs combined with the respective mean differences between the diagonal values of $\hat{\mathbf{p}}\mathbf{M}$ and $\hat{\mathbf{p}}$ (i.e. the quantified deviation from the 45 degrees line in the plots) in

Table 10[23] suffice to derive multiple generalisations. These reconfirm prior findings from Figure 5.

Table 10: Mean Difference of VA Coefficients incl. indirect Contributions and direct VA Coefficients

	Aggregation Level (*S*)		
Scenario	15	71	389
N =3, *IS* =0.2	0.049	0.030	0.014
N =10, *IS* =0.2	0.048	0.030	0.014
N =30, *IS* =0.2	0.048	0.030	0.014
N =10, *IS* =0.3	0.041	0.026	0.012
N =10, *IS* =0.4	0.034	0.021	0.010

First, since all deviations from the 45 degrees line in the graphs can be understood as the VA coefficients which are subject to production cycles, it becomes clear that the industries in the more aggregated tables show significantly more reliance on their own VA contribution than observable in the 389 x 389 industry table. Second, it is obvious that an increased production fragmentation represented by a raised IS leads to a decreasing reliance on indirect VA contribution. Furthermore, adding additional countries to the scenarios has a limited but lowering effect on the extent to which VA is subject to production cycles. The limited magnitude with which additional countries decrease the occurrence of production cycles is due to the rather short length of VCs.

At this point we note again that the deviations from the 45 degrees line which are displayed for the most disaggregated table only indicate the extent to which our basic assumption could be violated. Nevertheless and to sum up both previous analyses, the (mean) values of the 389 x 389 IO table that are found both for the diagonal of the Leontief inverse as well as for the deviation between $\hat{\mathbf{p}}\mathbf{M}$ and $\hat{\mathbf{p}}$ are indeed very small when compared to the other two aggregation levels. This finding is complemented by the fact that product cycles are not subject to the examined biases when they arise from the occurrence of an industry multiple times within a single VC. Consequently, this indicates that most production cycles that are caused by the bundling of VCs do not affect the VA coefficients within our most disaggregated table. Therefore, we suppose that our basic assumption is reasonable and that we may, subsequently, use the 389 x

[23] Note that dividing the diagonal values of $\hat{\mathbf{p}}\mathbf{M}$ by the direct VA coefficients as in $\hat{\mathbf{p}}$ and subsequently subtracting 1 to compute the mean proportional differences between the coefficients would yield the same results as in Table 9 since only the diagonal elements of the $\mathbf{M}$ matrix would arise from the calculation.

389-industry table as the benchmark representing the true VA distribution when employed for upcoming simulations and the comparisons with its more aggregated counterparts. This forms the quintessence of this subchapter. We conclude that the IO analysis based on our most disaggregated tables does not incorporate any major production cycles arising from aggregation. Therefore, we may refer to this analysis as a true reflection of the VA distribution which is suitable to identify the influence of N&V's (2014) biases as the deviation from the 389-industry table with individual VCs.

5.2. Simulations of Measurements of the Value Added Distribution

After having established an understanding of our basic assumption that the most disaggregated IO table does not include merged VCs, we may now use the hypothetical global tables to simulate measures of the VA distribution across multi-country and IS scenarios for the three available aggregation levels. Therefore, we apply the method of calculating the foreign VA and its share overall final product output by Los et al. (2015) which was previously introduced to our hypothetical global IO tables in Chapter 2.4.. Recall that the foreign VA is defined as the summation of all industries' VA contributions which are generated outside of the country-of-completion of a given product.

All simulations are realized with gradually increasing ISs from 0.1 to 0.5 in five steps of increases by 0.1 for each (multi-country) scenario and all listed industries in our IO tables separately. The number of simulations per global IO table therefore amounts to 5 * *SN*. Nevertheless, as the foreign and the domestic VA which are contributed to a final product complement each other to the products overall FD value, it suffices to calculate an industry's domestic VA and subtract it from the total FD for the respective product to generate the foreign VA for each industry and IS in the regarded multi-country scenario.

These simulations are realized at the most disaggregated industry level that is available for each table in order to benefit from the 389 x 389-IO table's characteristic to represent the true VA distribution. However, at different aggregation levels, the tables' comparisons will not enable meaningful results. Therefore, we need to apply the same industry classification as in our most aggregated 15 x 15 industry table for the results of the remaining two IO tables to enable comparisons at an aggregation level available for all tables. This is ensured by allocating VA and FDs from branches and subindustries into the overarching industry listed in the most aggregated tables with only 15 industries. No such reallocation is necessary for our most aggregated table as it is already obtained at the aggregation level at which the comparisons across the tables will take place. It is important to emphasise that results regarding the VA distribution within a VC are first gathered at the disaggregated levels before bundling the results according to homogenous industry classifications. Consequently, an ex-post summation of all computed foreign industries' VA levels into the same industry classification indicated by the 15 x 15 industry tables is realized for the more disaggregated results. The same applies to the summation of the disaggregated FD levels of the industries which add up to the same value for all three tables. Since the original IO tables obtained from the US are aggregated according to the North American Industry Classification System (NAICS), the same aggregation structure also needs to apply for our ex-post summations. For instance, while the most aggregated 15 x 15 industry table only indicates VA and FDs for the bundled industry 'Agriculture, forestry, fishing, and hunting', the 71 x 71 table distinguishes between the branches 'Farms' and 'Forestry, fishing, and related activities' whereas e.g. 'Farms' is even further split up into the subindustries 'Oilseed farming', 'Grain farming' etc. in the 389 x 389 industries tables. All foreign VA results for these respective subindustries now need to separately be summed up to three different 15 x 15 industry tables with homogenous industry classifications. The tables therefore distinguish each other in the different degrees of disaggregation in their calculation of (domestic and foreign) VA levels but are identical in terms of the succeeding representation. Table 11 illustrates the summation procedure for the above mentioned case of 'Agriculture' and exemplary foreign VA levels.

Table 11: Ex post Summation of VA according to NAICS[24]

Aggregation Level	Industry	Foreign VA Levels of all indicated industries	Foreign VA Level (15 x 15)
15 x 15	**Agriculture, forestry, fishing, and hunting**	100	100
71 x 71	**Farms**	55	107
	Forestry, fishing, and related activities	52	
389 x 389	**Oilseed farming**	15	110
	Grain farming	12	
	Vegetable and melon farming	16	
	…	67	

[24] Based on U.S. Census Bureau (2012)

Obviously, the same industrial classification applies to the summation of FDs which is not illustrated separately. Only when proceeding accordingly for all industries will it be possible to compare the VA results derived from different extents of aggregation on an equal, more aggregated industry level. From this reallocation of VA levels we subsequently obtain the FVAS for each of the 15 industries in a specifiable scenario with regards to the IS and the country number IS for each level of initial disaggregation computed in line with equation (2). Let us recall that we aim to derive the extent to which N&V's (2014) biases distort the VA distribution. Since these biases are based on the aggregation of VCs into bundled sets of these, the deviation from our disaggregated table (containing the true VA distribution) is attributable to the distortion of the FVASs.

6. RESULTS

In order to visualise the differences in the results for FVASs across our IO tables based on different extents of aggregation, we display tables in which the respective FVASs are subtracted from each other. The first represented scenario in Table 12 shows a set-up with 10 countries and the variations between the FVASs of the most aggregated 15-industry IO table and the respective true shares derived from our 389 x 389 industry IO table. Therefore, it indicates the magnitude of the distortion from the empirical equivalent of Table 5 without any merged VCs[25]. The interpretation of the included values within the table follows the ensuing principles. Since we display the results arising when the simulated FVAS of the aggregated IO table is subtracted from the one in the table containing the true VA distribution, negative values indicate that the FVAS is misrepresented as too high (overstated) in our aggregated tables. In turn, this means that the DVAS will be indicated as too (understated) low compared to its actual share. Similarly, positive values express that DVASs for industries that relate to these values are overestimated by our IO analysis whereas the FVASs would be underestimated.

[25] Please note that the displayed values refer to percentage points (pp) as the absolute difference between the respective FVASs from the IO tables at different aggregation levels.

Table 12: Deviation of true FVASs and FVASs from 15-industry Tables (10 Countries)(in pp)

10 Countries comparing 15x15 and 389x389 industries	Agri-culture, forestry, fishing, and hunting	Mining	Utilities	Construc-tion	Manu-facturing	Whole-sale trade	Retail trade	Transport and ware-housing	Infor-mation	Finance, insurance, real estate, rental, and leasing	Profes-sional & business services	Education, health care, and social assistance	Arts, enter-tainment etc.	Other services, except govern-ment	Govern-ment
IS 0.10	-2.80	-1.66	-0.05	0.24	0.18	0.19	0.38	0.52	-0.12	-1.63	-0.03	0.26	0.50	1.13	0.10
IS 0.20	-5.05	-3.09	-0.08	0.34	0.07	0.29	0.58	1.00	-0.24	-3.16	-0.13	0.39	0.73	1.89	0.14
IS 0.30	-6.86	-4.32	-0.10	0.36	-0.19	0.32	0.66	1.43	-0.35	-4.60	-0.28	0.43	0.78	2.40	0.15
IS 0.40	-8.35	-5.40	-0.11	0.34	-0.51	0.32	0.66	1.79	-0.45	-5.96	-0.44	0.42	0.72	2.74	0.13
IS 0.50	-9.57	-6.36	-0.13	0.30	-0.85	0.28	0.59	2.07	-0.53	-7.24	-0.63	0.37	0.59	2.93	0.10

The results for the 10-country case show mixed evidence of over- and understated foreign industries' VA contributions. More specifically, 6 of the 15 industries' FVASs that are compared across aggregation levels are overestimated in the case of an IS of 0.2. This holds to a special degree for 'Agriculture', 'Mining' and 'Finance' (although, again, the latter will most likely incorporate a lower IS in reality) for which the FVASs are overstated by 3.1 up to 5.1 percentage points. Furthermore, the remaining industries which exhibit an understatement of the FVAS due to bundling of VCs do not deviate significantly across aggregation levels. An exception worth mentioning may be 'Other Services' showing a FVAS which is underestimated by 1.9 percentage points when derived from an aggregated table. Moreover, we find that rising internationalisation – in the form of rising ISs – mostly raises the aggregated results' exposure to the biases.

Despite these heterogeneous results across industries, the findings are in line with the concepts developed by N&V (2014). For instance, agricultural production generally forms a part of VCs which is very upstream and exhibits a high VA coefficient. Therefore, when regarding 'Agriculture' as the industry delivering a final product, its VA that is contributed at a downstream stage is mostly relatively limited. Consequently, the last (domestic) industry would incorporate a particularly high VA coefficient which N&V (2014) expect to be underestimated in such a scenario. The same principle applies for 'Mining' as well as for 'Finance' and subsequently results in an underestimated DVAS for the respective country-of-completion. In contrast, most personal service industries show positive values in Table 12 representing an overstated VA contribution of the domestic country for an empirically relevant range of ISs. Since these industries contribute to production processes relatively further downstream in most cases, a low VA coefficient leads to the overestimation of the DVAS as also proclaimed by N&V (2014).

In order to verify if this explanation is consistent, we employ an indicator by Fally (2012) computing the average number of VC stages between a good's generation and the consumption by the FD in our most disaggregated IO table as a measure of upstreamness. Thereby we aim to confirm that e.g. most agricultural branches show a high degree of upstreamness while personal services are mostly situated further downstream within VCs. In line with Fally (2012), we use the equation

$$\mathbf{d} = (\mathbf{I} - \mathbf{B})^{-1}\mathbf{e} \tag{8}$$

in which the elements b_{ij} denote the ration between an industry i's gross output and the intermediate deliveries from industry i to j. Furthermore, **d** represents a SN x 1 vector indicating the average VC stages until final consumption of the respective product. As assumed, the mean VC length of subindustries differs largely across the aggregated industries and amounts to 2.84 for 'Agriculture', yields 2.19 for 'Manufacturing' and shows 1.05 for 'Education'. This confirms our expectations and is in accordance with the explanation of the heterogeneous directions of the FVASs distortion across industries. Moreover, it emphasises another feature of our analysis compared to N&V's (2014) method since our simulations draw on empirically derived VC lengths whereas N&V (2014) construct VCs with an average length of four which seems longer than in reality according to the computation of Fally's (2012) upstreamness indicator.

Considering the magnitude to which FVASs are also distorted in other empirically relevant global set-ups with different country numbers shows only little difference to the values indicated in the 10-country case[26]. This could be expected since Table 9 and 10 already established that the occurrence of production cycles only differs slightly in multi-country scenarios which is due to the limited length and therefore bounded potential fragmentation of VCs.

Expanding our analysis by considering the distortion of the 71-industry case as displayed in Table 13 yields mostly similar results compared to the biases in the VA distribution based on the 15-industry table. It is worth mentioning, however, that the mean distortion of the FVASs in the less aggregated table (0.57 percentage points for IS of 0.2) is significantly smaller when compared to the 15-industry case (1.14 percentage

[26] The simulation results displaying the magnitude of the discussed biases in a scenario with 5 countries can be found in Appendix' Table 15 which follows the same interpretive logic than Table 12.

points) which is in line with the intuition since the extent to which the bias affects the results is expected to rise with aggregation.

Table 13: Deviation of true FVASs and FVASs from 71-industry Tables (10 Countries)(in pp)

10 Countries comparing 71x71 and 389x389 industries	Agri-culture, forestry, fishing, and hunting	Mining	Utilities	Construc-tion	Manu-facturing	Whole-sale trade	Retail trade	Transport and ware-housing	Infor-mation	Finance, insurance, real estate, rental, and leasing	Profes-sional & business services	Education, health care, and social assistance	Arts, enter-tainment etc.	Other services, except govern-ment	Govern-ment
IS 0.10	-3.14	-0.04	-0.04	0.14	-0.11	-0.02	-0.02	0.04	-0.16	0.04	0.15	-0.15	0.03	0.57	0.12
IS 0.20	-5.65	-0.08	-0.09	0.20	-0.29	-0.03	-0.03	0.06	-0.27	0.05	0.28	-0.25	0.02	1.05	0.20
IS 0.30	-7.68	-0.12	-0.14	0.21	-0.48	-0.04	-0.03	0.07	-0.35	0.05	0.40	-0.30	-0.01	1.45	0.25
IS 0.40	-9.34	-0.14	-0.18	0.21	-0.67	-0.04	-0.03	0.08	-0.40	0.03	0.51	-0.31	-0.04	1.79	0.29
IS 0.50	-10.71	-0.16	-0.23	0.19	-0.84	-0.04	-0.03	0.07	-0.43	0.00	0.61	-0.29	-0.08	2.08	0.31

More generally, Table 12 and 13 show evidence of distortions in the VA distribution based on the aggregation of VCs following the identified concepts by N&V (2014). However, the differences between the computed FVASs based on aggregated IO tables and the true shares based on VCs that are not merged are mostly very small. This is particularly the case when focusing on the empirically relevant ISs of 0.1 and 0.2.

Since Los et al.’s (2015) main area of interest in the examination of global VCs is manufacturing products as these are particularly subject to global fragmentation, we zoom in on this aggregated industry more closely. This will help to establish a more profound understanding of the distortion of Manufacturing’s branches as defined at the more detailed 71-industry level. We thereby do not decompose the FD for the respective 19 branches of ‘Manufacturing’ but only regard the distortion of each of these in the generation of all ‘Manufacturing’ final products. Consequently, Table 14 lists the distortion of ‘Manufacturing’ branches on a 71-industry level by comparing the true VA distribution to the results based on the more aggregated 71 x 71 IO table. As before, we display the 10-country case but only focus on the empirically most relevant scenario with an IS of 0.2. All other results with different ISs can be expected to be in line with the pattern observed on the more aggregated levels in Table 12 and 13.

Table 14: Deviation of true FVASs and their Values from 71 x 71 Tables for Manufactures branches (10 Countries) (in pp)

10 countries comparing 71 and 389 industries	Wood products	Non-metallic mineral products	Primary metals	Fabricated metal products	Machinery	Computer and electronics	Electrical equipment etc.	Motor vehicles, bodies and trailers	Other transport equipment	Furniture and related products	Miscellaneous manufacturing	Food and beverage and tobacco products	Textile mills etc.	Apparel and leather	Paper products	Printing and related support activities	Petroleum and coal	Chemical products	Plastic and rubber
IS 0.20	-0.29	-2.19	-18.75	-1.53	-0.52	1.25	0.42	0.99	1.02	0.43	1.94	-0.66	1.21	0.57	-1.21	0.36	0.17	-7.19	2.00

Table 14 generally exhibits rather small deviations between the true VA distribution and the more aggregated classification but also shows two exceptions. With an underestimation of the domestic VA by 18.8 and 7.2 percentage points, respectively, the branches 'Primary metals' and 'Chemical Products' clearly diverge largely from their actual VA contribution when regarding 'Manufacturing' as the industry-of-completion. The reasoning is similar to the previous elaboration on the results for the 15-industry aggregation level (e.g. for Agriculture). Again, the cause for the relatively large distortion is found in the very strong upstreamness[27] of most 'Primary metals' and 'Chemical Products' subindustries which results in a high VA coefficient and the understatement of the respective branch's VA contribution in line with N&V (2014).

Despite the fact that results regarding the generated VA of these branches may potentially be biased and require caution as they distort studies regarding the FVASs of final manufacturing products as examined in Los et al. (2015), we must also note that the contribution of these (especially of the most distorted branch 'Primary metals') as a share of the overall final output of 'Manufacturing' is rather limited[28].

Therefore, although we find selected industrial branches that show a larger distortion based on their high upstreamness, their relative importance for indicators as introduced in Los et al. (2015) seems rather limited. Since the same applied for the distortion of the VA distribution found for the most aggregated 15-industry case, we can summarise the results by stating that the biases identified by N&V (2014) can also be detected in an empirical analysis. Their magnitude and direction vary largely depending on the upstreamness of the respective sector's subindustries but is mostly found to be of minor relative importance. Referring back to the research question that formed the outline for this paper, we do not find that the biases in the IO concepts significantly distort findings of studies which examine the VA distribution in globally fragmented VCs.

[27] The previously introduced upstreamness indicator by Fally (2012) yields average values of 3.76 for 'Primary metals' and 2.98 for 'Chemical Products' within the computed vector **d**.

[28] The final output of 'Primary metals' forms 2.6 percent of final 'Manufacturing' output while the final output of 'Chemical products' amounts to 7.2 percent thereof.

7. Concluding Remarks

This paper addressed the reliability of findings regarding the VA distribution in global production fragmentation studies which employ IO analysis. N&V (2014) identified biases that arise from the aggregation of VCs into sets of these. Following from simulations based on VCs that are largely constructed by randomisations, they argue that the VA contribution of the industry-of-completion will be understated if this industry mostly appears at upstream production stages in VCs. In turn, the VA of industries which generally contribute to VCs at a downstream stage will be overestimated. We extend N&V's (2014) analysis by employing empirical data on different levels of aggregation to examine the biases' magnitude for realistic production processes. Thereby, we are guided by the following research question:

Do the biases identified by Nomaler & Verspagen (2014) significantly distort the empirical findings of studies examining the value added distribution in globally fragmented production processes if input-output analysis is employed?

Other than N&V (2014), we are able to base our simulations of IO measurements for VA distribution on empirically observed VCs as well as their underlying characteristics and succeed in quantifying the empirical extent to which these distributions are biased. We conclude by presenting our main outcome, clarifying the limitations of our analysis and suggesting future research in line with our study.

7.1. Main Findings

The major contribution of this paper is the fact that it extends N&V's (2014) analysis of aggregation biases by an empirical component. Based on national IO data that we transformed into hypothetical global set-ups, we constructed several scenarios with regards to the number of countries and the degree to which these engage in international trade. Moreover, we improved N&V's (2014) analysis by relying on realistic VCs. We find that the length of VCs is generally shorter than assumed by N&V (2014) and that their constructed 'snake'-shaped VCs do not match the empirical pattern. Moreover and other than N&V (2014), the order and upstreamness of industries' appearances as well as their VA contribution within VCs is naturally derived from actual production processes. These improvements allow for a more profound analysis of the distortion's empirical relevance.

Despite these differences in the approaches our results are largely in line with the analysis of N&V (2014) as we find that the empirical direction and extent of the distortions of indicators like the domestic value added share by Los et al. (2015) depend on the general upstreamness of the regarded industry. Thus, examining the VA contribution for VCs whose industry-of-completion generally appears far upstream in VCs (e.g. agriculture, mining or finance) will cause an overstatement of the FVAS. In contrast, analysing VCs whose industry-of-completion mostly contributes to VCs at production stages that are close to the consumption of the good (e.g. personal services like education or entertainment) may result in an overstatement of the domestic contribution share. A similar pattern also holds when regarding the distortion of branches of the 'Manufacturing' industry more specifically which are generally most exposed to global production fragmentation.

The distortions of the FVASs are most pronounced in scenarios of high international trade but hardly differ with the number of countries. The latter is due to the fact that we find the average number of VC stages before the final product's consumption to be rather limited which decreases the potential for its fragmentation. In terms of the magnitude of the biases, our results differ from those obtained by N&V (2014). For empirically relevant degrees of ISs, our comparisons between the true VA distribution and the results for the analysis based on the most aggregated industry classification yield an overstatement of the FVASs by 5 percentage points at most whereas N&V (2014) expect the bias to be far more influential. The distortion of most industries' VA contributions ranges between plus and minus 1 percentage points which is only surpassed by the industries which show the most distinct general pattern of up- (e.g. Agriculture and Mining) or downstreamness (e.g. Other Services). Comparing across different degrees of the bundling of VCs, we find that the mean distortions indeed increase with aggregation (from the 71 to a 15-industry level) in line with the nature of the biases but do not change their magnitude drastically.

7.2. LIMITATIONS AND FUTURE RESEARCH SUGGESTIONS

Although we employed empirical data for our analysis, it stills builds upon several assumptions and limitations which restrict the scope of our paper but could potentially be relaxed in more extensive studies. First, we purely based our evaluations on US-American IO data. Consequently, the underlying VC structures are exclusively subject to the domestic production technology and do not reflect global diversity in international production processes. This does not allow for differences in the extent to which the distortions affect the VA distribution in production processes across countries of equal size. For instance, differences in the industries general up- and downstreamness across countries may increase or decrease the distortion's extent in line with our explanations of the biases' principles. Second, the regarded global scenarios are limited to countries of the same economy size as well as equal ISs. This assumption clearly does not hold in reality where countries' economic dimensions and their exposure to international trade largely vary. Differences in the magnitude of the distortions could for instance arise when comparing small and larger economies. More specifically, smaller countries may be particularly exposed to the biases due to a mostly high degree of internationalisation. Third, we focused on the extent of distortions based on one single year's observations. No dynamic component is incorporated in our analysis although it may be meaningful to examine the empirical magnitude of the identified biases when comparing multiple years and their industries' respective FVASs. N&V (2014) assume changes in the FVASs to be understated whereas our results rather suggest the opposite. We call for an empirical verification of this conjecture. Lastly, this study assumes equal degrees of tradability across industries which is far from reality where personal service industries mostly exhibit significantly smaller import shares than other sectors (e.g. manufacturing). Accounting for this would not only change the results for the VA distribution of industries whose IS would be altered but the interdependences among industries would likely also cause differences for the remaining sectors. For instance, since service industries mostly appear further downstream in VCs, decreases in the tradability of their goods may contribute to an overstatement of the domestic VA shares.

As far as future research and extensions of our approach are concerned, we encountered a data issue when allocating specific intermediate inputs to our most disaggregated IO table. Our rather simple method to solve the problem by assigning the related values to the intermediate and FD matrix in proportion to the total intermediate deliveries could be improved upon in later studies. Moreover, it may be meaningful to alter the applied aggregation levels in line with industrial classifications of major databases (e.g. 35 industries in the WIOD) to enable the examination of the distortions' magnitude at aggregation levels that are more commonly used for economic studies based on IO analysis. In line with the limitations, our assumptions of homogeneous country size as well as ISs across sectors also clearly do not hold in reality and could be relaxed (e.g. by assuming no tradability of service industries) as part of future research. Furthermore, it may be worthwhile to extend the scope of the distortions' analysis to the influence on other IO-based indicators focusing on VA and its global trade (e.g. Johnson & Noguera, 2012a). These may also be affected by the regarded biases although the extent of the distortion is likely to be highest when investigating specific VCs as part of the GVC approach as e.g. in Los et al. (2015). Lastly, examining the magnitude to which the identified distortions affect the results about changes in the VA distribution between two points in time might shed even more light on the distortion's dynamic nature.

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APPENDIX

Table 15: Deviation of true FVASs and their Values from aggregated 15-industry Tables for 5 Country case (in pp)

5 Countries comparing 15x15 and 389x389 industries	Agri-culture, forestry, fishing, and hunting	Mining	Utilities	Construc-tion	Manu-facturing	Whole-sale trade	Retail trade	Transport and ware-housing	Infor-mation	Finance, insurance, real estate, rental, and leasing	Profes-sional & business services	Education, health care, and social assistance	Arts, enter-tainment etc.	Other services, except govern-ment	Govern-ment
IS 0.10	-2.76	-1.65	-0.05	0.23	0.16	0.19	0.37	0.52	-0.12	-1.62	-0.04	0.25	0.48	1.10	0.10
IS 0.20	-4.92	-3.03	-0.08	0.31	0.01	0.27	0.54	0.99	-0.24	-3.14	-0.15	0.36	0.67	1.81	0.13
IS 0.30	-6.63	-4.21	-0.09	0.32	-0.27	0.29	0.60	1.40	-0.34	-4.55	-0.30	0.38	0.68	2.26	0.13
IS 0.40	-7.99	-5.24	-0.11	0.28	-0.60	0.27	0.56	1.73	-0.44	-5.87	-0.47	0.35	0.59	2.53	0.10
IS 0.50	-9.09	-6.14	-0.13	0.24	-0.94	0.22	0.47	1.97	-0.51	-7.11	-0.66	0.29	0.43	2.67	0.06