Essays on Global Value Chains

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by

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed:

Date: February 1st, 2017

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Thesis Abstract

The past four decades have seen a large increase in trade via Global Value Chains (GVCs) as well as the relative demand for skilled labour. This thesis centres around the question how the former influences the latter. It firstly describes the large theoretical and empirical ambiguity that exists in the literature before proposing a novel graphical exposition of the channels by which GVCs affect the relative demand for skilled labour. This graph can synthesize the literature and show how small changes in microeconomic foundations can crucially alter predicted outcomes, greatly reducing theoretical ambiguity. It can also serve as a conceptual framework for empirical analysis which should remain the key method to analyse the research question. Therefore, Chapters 2 and 3 employ micro and macro level data, respectively, and condition their results on the conclusions drawn from this conceptual framework. In line with that framework, this thesis finds that the *relative* skill abundance of the countries engaged in the GVC, which is used as a proxy for the factor bias of the GVC activity, crucially determines the results. On the other hand, the skill intensity of the sector that engages in GVCs does not seem to affect the results. This can best be interpreted in that GVCs allow (firms within) countries to specialise in their comparative advantage at an even more granular level than before, i.e. in the production of intermediate goods or tasks, rather than final goods. Finally, Chapter 4, rather than looking at the effects of GVCs, looks at some of the causes. While formal tariffs have been going down, allowing the expansion of GVCs, non-tariff measures (NTMs) have increased. Chapter 4, however, finds that these NTMs do not significantly affect the export values of goods within that same value chain.

Table of Contents

Table of Figures

List of Tables

List of Abbreviations

DVA = Domestic Value Added

FVA = Foreign Value Added

FTE = Full Time Employees

GVC = Global Value Chains

ICIO = Inter Country Input Output

ITC = International Trade Centre

IV = Instrumental Variable

HO = Heckscher - Ohlin

KWW = Koopman Wang Wei

NTM = Non-Tariff Measures

SBTC = Skilled Biased Technological Change

SK = Share of Skilled workers (skilled production and non-production workers) in total FTE

SNPW = Share of Non-Production Workers in total amount of FTE

SSP = Share Skilled Production workers in total production workers

SSPfte = Share Skilled Production workers in total FTE

TiVA = Trade in Value Added

VAX = Domestic Value Added Exported

VS = Vertical Specialisation (= Foreign Value Added Exported)

VS1 = Vertical Specialisation 1 (=Domestic value added in foreign indirect exports)

VS1* = Vertical Specialisation 1* (=Domestic value added exported that returns home)

WBES = World Bank Enterprise Surveys

WIOD = World Input Output Data

WWZ = Wang Wei Zhu

Introduction

One man draws out the wire, another straights it, a third cuts it, a fourth points it, a fifth grinds it at the top for receiving the head; to make the head requires two or three distinct operations; to put it on, is a peculiar business, to whiten the pins is another; it is even a trade by itself to put them into the paper; and the important business of making a pin is, in this manner, divided into about eighteen distinct operations, which in some manufactories, are all performed by distinct hands, though in some others the same man will sometimes perform two or three of them. (Smith, 1776, p. 4)[1]

Nearly two and a half centuries after Adam Smith wrote his magnum opus, some of its lessons, such as the importance of specialisation, still feature strongly in todays' trade literature. Based on this principle, productivity could be increased if workers would focus on the production of intermediate tasks which would then be combined into a final good. An underlying assumption to this lesson was that the individual tasks had to be produced in proximity to each other, as it was too expensive to separate the production process geographically. This principle serves prominently in the economic contributions by David Ricardo's (1817) as well as Eli Heckscher and Bertil Ohlin (1933) models of international trade, where countries specialise in producing that product they have the comparative advantage in and export it in turn for the good in which it has the comparative disadvantage. These models served well to explain the pattern of international trade observed from the Industrial Revolution in the early 19th century up until the new millennium, a period described by Baldwin and Martin (1999) as the first unbundling of globalisation. Due to falling costs in transportation, it became economically profitable to separate production from consumption locations internationally, by benefiting from productivity adjusted wage gaps. Financial and timeliness constraints, however, ensured that production would remain clustered under one roof.

However, further advancements in technology (See Figure 0.1) have led to radical drops in communication and coordination costs. This, combined with falling trade costs (See Figure 0.2), has made it more viable to not only separate production from consumption, but to

[1] Naturally, a doctoral thesis on international trade written from Glasgow, U.K. can only start with a quote to Adam Smith's (1776) Wealth of Nations.

separate production processes themselves as well, leading to the second wave of unbundling (Baldwin, 2006).

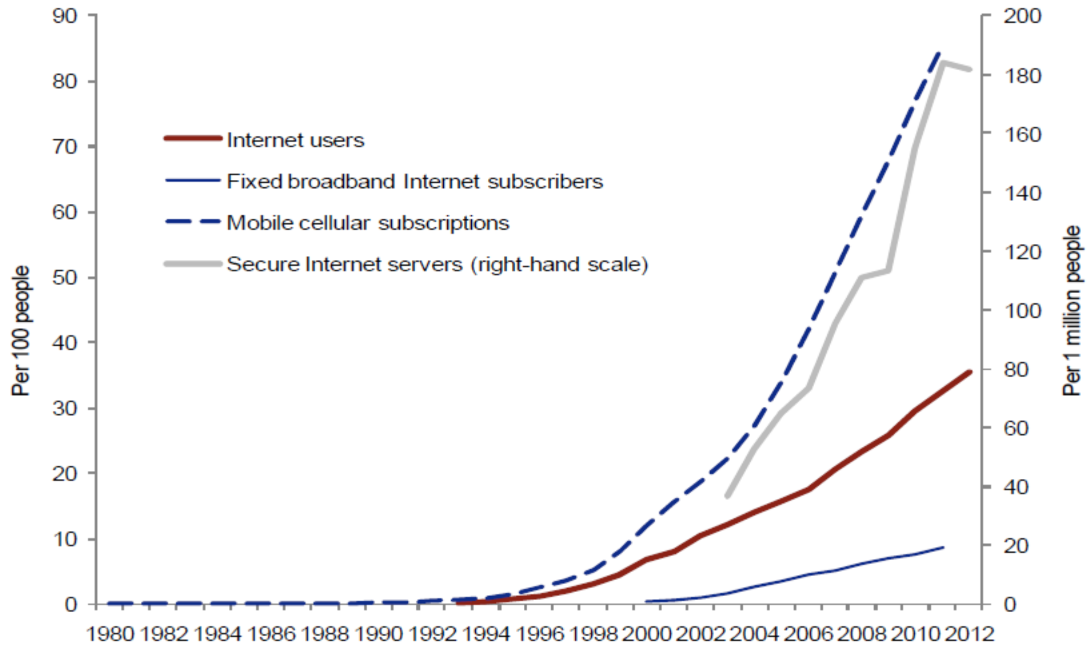

Figure 0.1 World indicators of information and communication technologies.
Source: Amador and Cabral (2015) who used the World Bank's World Development Indicators

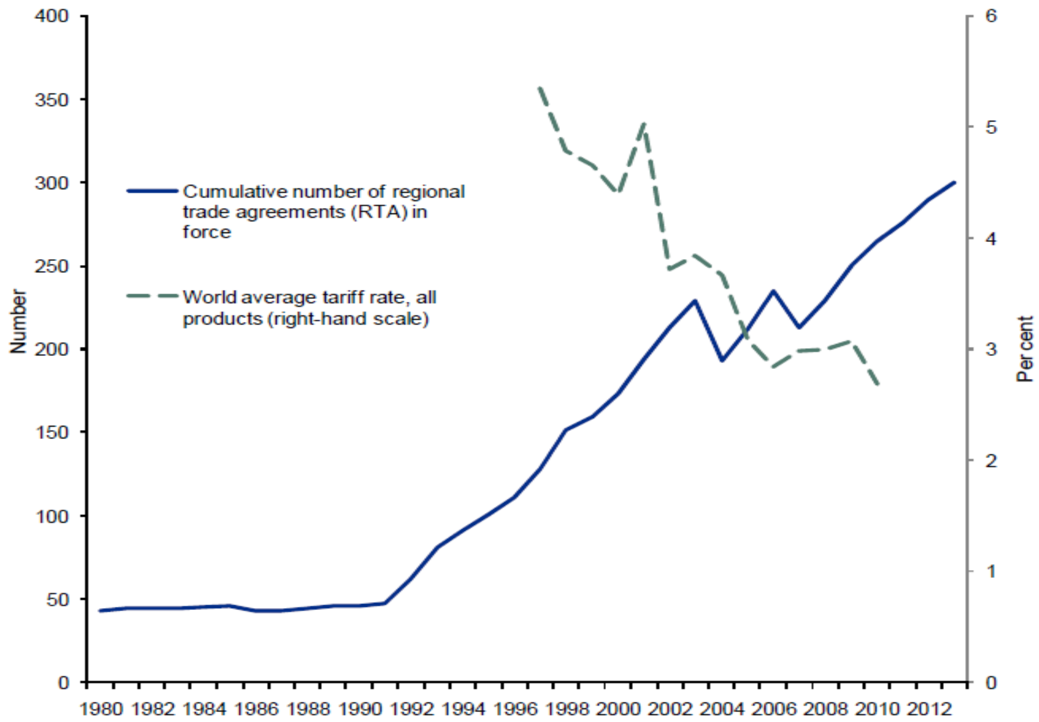

Figure 0.2 Trade costs have fallen Source: Amador and Cabral (2015)

This second wave of unbundling can be represented by the sharp increase in the trade in intermediate as opposed to final goods (Johnson and Noguera, 2012) or the use of foreign inputs in exports (Figure 0.3).

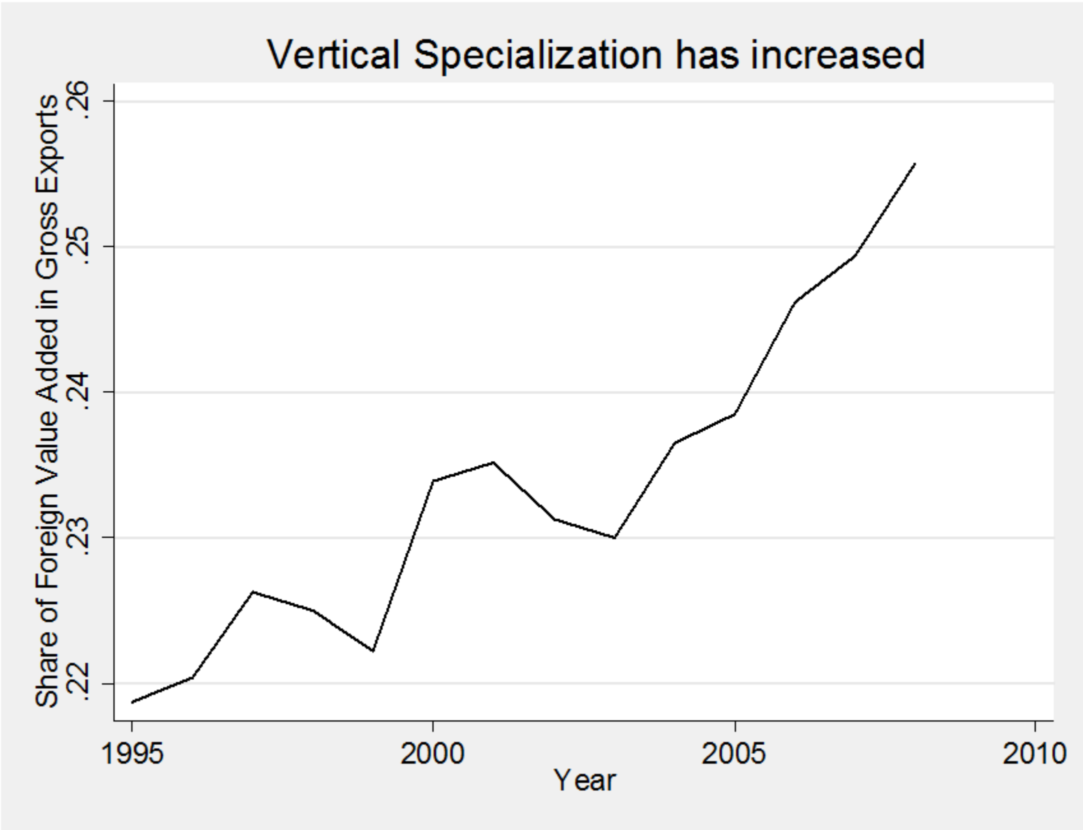

Figure 0.3: Growth in Vertical Specialisation. Source (WIOD)

During this second unbundling, which started roughly 40 years ago, the world has seen large increases in within country inequality, both in the developed as in the developing world (Chusseau and Hellier, 2012; Goldberg and Pavcnik, 2007). One can look, for example, at the wage premium, which represents the ratio of the wages earned by high skilled labour to low skilled labour. Framing inequality in terms of this premium directs the question towards demand shifters in the relative demand for skilled labour. To that extent, Figure 0.4 shows that the cost share of high skilled labour has increased significantly between 1995 and 2008, while the share of low skilled labour has decreased.

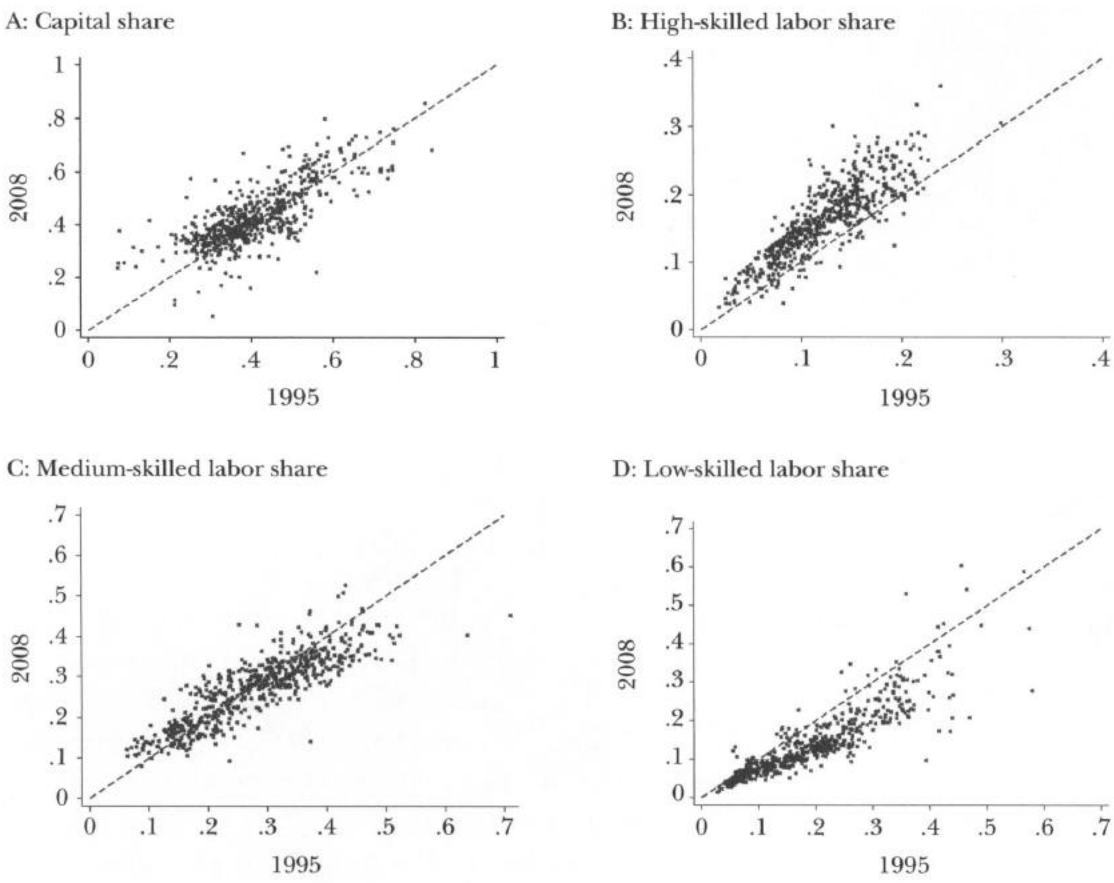

Figure 0.4: Factor shares in value added in 1995 and 2008.
Source: Timmer, Erumban, Los, Stehrer and de Vries, (2014)

Investigating this issue further, Amador and Cabral (2015) state that most developed countries witnessed a shift in labour demand towards more skilled workers, combined with an increase in wage and employment inequality, over the past decade (p. 6). This process, which is known as skill upgrading, "presents a severe problem for societies in developing countries as they precipitate the negative social consequences associated with higher initial poverty levels and income disparities" (Pavcnik, 2003, p. 2). It is in this light that the connection can be drawn between increased within-country inequality and the second unbundling, or wave of globalisation.

However, the models that served so well to explain the distributional effects from international trade during the first unbundling can no longer do so, as their predictions seem at odds with the current *"Inequality-Globalization nexus"* (Hellier, 2013). For example, the Heckscher-Ohlin theorem predicts that developed countries would specialise in the production of skilled intensive goods and therefore increase the relative demand for skilled labour and consequently the wage premium. While this seems to be in line with empirical evidence, the story is different for developing countries. According to Heckscher-Ohlin, they would specialise in the production of low skilled activities, increasing the relative demand for low skilled labour and consequently experience a *decrease* in the wage premium. However, as shown by Chusseau and Hellier (2012), inequality, and the demand for skilled labour, has not just increased in the developed world, but also in emerging economies. It is against this backdrop that Grossman and Rossi-Hansberg (2008) advocate a new paradigm where the effects of *trade in tasks*, as opposed to trade in final goods, should be leading. While this shift has been acknowledged by more authors (Blinder, 2006; Baldwin, 2006, 2016), the literature still suffers from theoretical and empirical ambiguity, as will be made clear in the first Chapter of this thesis. These conditions not only call for further examination of this topic, but also provide fertile ground for fresh thinking and new insights. Accordingly, this thesis will provide both theoretical and empirical contributions to the following research question:

"What are the effects of global value chains on the relative demand for skilled labour?"

This thesis will draw on a wide variety of both theoretical and empirical sources to provide further insights into this research question. Chapter 1 will provide a theoretical answer to this question, by firstly reviewing the extensive literature that has been written on this subject. In doing so, it will agree with the conclusion by Kohler (2003, p.4) that the literature is fragmented into casuistic sources that explain what might happen in a specific instance but that an all-encompassing framework is still missing. This Chapter will therefore contribute to the literature by providing a novel graphical exposition of the main channels by which GVCs can affect the relative demand for skilled labour. In doing so, it manages to synthesize the ambiguous literature and can so be used as a pedagogical tool to understand the complex interplay between GVCs and the relative demand for skilled labour, without the need to understand various complex models that seem to contradict each other.

Chapter 2 and 3 will use micro and macro level data, respectively, to provide an empirical answer to the research question. Building on a conceptual framework outlined in Chapter 1, they will provide empirical contributions to the literature. After that, Chapter 4 will deviate somewhat from the research question as it, rather than examining the consequences of global value chains, looks at their respective drivers. Specifically, it will examine the effect of non-tariff measures levied at the import component of global value chains on the export of final goods within the same value chain. In the end, Chapter 5 will provide a summary of the main contributions this thesis adds to the literature, as well as some promising avenues for future research.

Chapter 1

Clearing up ambiguity on the distributional consequences of GVCs:

A Graphical Synthesis of neoclassical theories

Abstract

Recent technological advancements and reductions in trade tariffs have made it increasingly profitable for firms to separate their production chain into individual tasks. These tasks can then be sourced internationally to firms in countries which have a comparative advantage in executing this specific task, giving rise to global value chains (GVCs). The theoretical literature on the distributional effects in terms of changes in the relative demand for skilled labour is large, but ambiguous, as shown e.g. by Görg (2011), Egger and Egger (2001), Kohler (2009) and Feenstra (2010). Navigating through the literature can be frustrating as micro economic foundations of various models have crucial implications on key predictions. This Chapter will firstly review those key neoclassical models and consequently contribute to the literature by proposing an all-encompassing graphical exposition of the main channels by which GVCs affect the relative demand for skilled labour. The explanatory power of this figure is vast. Firstly, it can synthesize the ambiguous literature in a coherent and intuitive framework and show how subtle differences in the microeconomic foundations of various models can have widespread effects on key predictions. Secondly, the figure can serve as a conceptual framework and as a guide to empirical analysis, which should remain the dominant method for answering the question as to how GVCs affect relative employment and wages. Ultimately, the proposed figure can be used as a pedagogical tool for policy makers and (under)graduate students alike, without the need to understand complex algebra.

1.0. Introduction

Theories of international trade have long built on the foundations provided by Eli Heckscher (1919) and Bertil Ohlin (1933). In their original model, they assume the world consists of 2 countries (North and South), 2 factors of production (capital and labour) and 2 sectors that would differ in their capital intensity. Differences in capital endowments between countries would provide a motive for countries to specialise, with the North specialising in capital intensive production and the South in labour intensive production. As a result, capital (labour) owners would benefit in the North (South) while suffer in the South (North). In short, this very simple model was able to explain how international trade would affect the relative demand for skilled labour to a great extent.

Empirical evidence started to disagree with this highly simplified framework in the 1980s. One can look at Latin America, for example, that opened their economy to international trade in this period. From the perspective of a low skilled abundant region, Latin American countries should have received low skilled intensive tasks that would increase the demand for low skilled labour and therefore decrease their pay gap with higher skilled workers. However, inequality increased vastly in this region. More recently, Lorentowicz, Marin and Raubold (2005) found that Poland, Czech Republic and Hungary experienced an increased skill gap after opening up to trade from West Europe (specifically Germany) while Shepherd and Stone (2013) found that internationalisation increased the relative demand for skilled labour among firms in the developing countries of Brazil, India, Indonesia, China and South Africa.

Looking for an explanation of this conflicting evidence, it is not surprising that the Heckscher-Ohlin model (HO for short) can no longer explain effects of trade on relative demand for skilled labour. Triggered by a decrease in transportation costs and increases in technology, it has become increasingly profitable to unbundle (Baldwin, 2006) the production process into various individual parts, that can be executed in the country that has the comparative advantage in that specific task. This has far reaching consequences for the implications on the relative demand for skilled labour, so much that Grossman and Rossi-Hansberg (2008) refer to a new paradigm within international trade.

As is the case in a paradigm shift, many new models have been introduced to either complement or substitute the HO framework in order to be better able to explain empirical findings. Unfortunately, however, this has only increased the ambiguity. When considering, for example, the offshoring of the relatively low skilled intensive activities of the low skilled sector in a standard 2*2*2 HO framework, the implications for the relative demand for low skilled labour is highly ambiguous, as illustrated in Table 1.1.

Table 1.1 In the case of offshoring low skilled tasks from the low skilled industry form North to South, the demand for low skilled labour would go:

Authors	**North**		**South**	
	Within the industry	Across the Country	Within the industry	Across the Country
Leamer (1994) Arndt (1998a, 1998b, 1997) Jones and Kierzkowski (2001)	Down	Up	Depends on elasticity of factor substitution	Up
Krugman (2000)	Down	Down	Up	Up
Feenstra and Hanson (1996)	Down	Down	Down	Down
Davis (1996) Khalifa and Mengova (2010)	Depends on *relative* skill abundance of the country			
Deardoff (2001)	Depends whether GVCs affect the prices of goods			
Xu (2001)	Depends on: - Rate and extent of global value chain activity - Preferences (Cobb-douglas vs. elastic/inelastic) - Type of economy			
Grossman and Rossi-Hansberg (2008)	Depends on the type of economy			

This ambiguity is well known in the literature. While Table 1.2 shows a compilation of papers that refer to this ambiguous state of the literature, it is probably best put in words by Kohler (2003, p.4) who stated that the literature is fragmented into casuistic sources that explain what might happen in a specific instance but that an all-encompassing framework is still missing. These "casuistic sources" often seem to contradict each other creating theoretical ambiguity.

Table 1.2 A literature review showing that the theoretical implications of a productivity increase, either caused by technological change of GVCs, on the relative demand for skilled labour are ambiguous

Authors (year)	Quoted saying:
Feenstra (2010)	*"The literature is characterized by a high ambiguity, where the effects are highly dependent on the microeconomic foundations of the model chosen" (p. 3)*
Stehrer (2005)	*The theoretical results on the effects of technical change in integrated economy and in (large) trading economies are not conclusive and depend heavily on specific parameter assumptions. (p.1)*
Haskel and Slaughter (2002)	*"Different studies have examined very different cases and general conclusions should not be made from any single study" (p. 1765)*
Egger & Egger (2001)	*"The theoretical conclusions are ambiguous, so that it remains an empirical question" (p.5)*
Helg and Tajoli (2005)	*"Theoretical models of IFP indicate that the sign of the effects of fragmentation on labour demand is a priori ambiguous" (p.1)*
Kohler, (2003)	*"The literature is fragmented into casuistic sources that explain what might happen in a specific instance but an all-encompassing framework is still missing" (p. 4)*
Kohler (2009)	*Titled: "Why do Offshoring stories differ?"*
Feenstra and Hanson (1999)	*"An apparent conflict in the literature" (p. 908)*
Venables (1999)	*"Even in a two sector model … the distributional consequences of international outsourcing are ambiguous, creating some curious cases" (p. 943)*

Where does this leave us, other than being confused and frustrated? Fortunately, some contributions have managed to simultaneously model various contributions. Notably the contributions by Xu (2001) and Grossman and Rossi-Hansberg (2008) will be discussed as examples of this. However, while these models do a good job of streamlining various literature, various contributions are still omitted, as will be outlined later. Secondly, while Grossman and Rossi-Hansberg (2008) refer to their model as "a simple model of offshoring", it might still be complicated to grasp for the uninformed reader. This relates to the third point that an intuitive explanation of the key channels between GVCs and the relative demand for skilled labour is still missing. Therefore, this Chapter argues that, rather than using yet another model that attempts to mathematically incorporate various effects, perhaps a different tool is more appropriate to understand how GVCs affect the relative demand for skilled labour.

That is where this Chapter comes in, as it will propose a single figure in which a wide range of theoretical contributions can be summarized, visualized and synthesized. It can also show how small changes in micro economic foundations can crucially alter the implications for the relative demand of skilled labour. This significantly reduces theoretical ambiguity allowing the figure to serve as a pedagogical tool for policy makers and (under)graduate students alike, without the need to understand the mathematical details of various models. It can also be used to illustrate the model by Grossman and Rossi-Hansberg (2008) and, finally, serve as a guide to empirical analysis which should remain the dominant method for answering the question as to how GVCs affect relative employment and wages. In summary, this figure fills the research gap identified by Kohler (2003) and others (Table 1.2) regarding a missing all-encompassing framework. Rather than doing this by providing another mathematical model as in Grossman and Rossi-Hansberg, for example, this Chapter opts to use a visual and intuitive approach. To the best of our knowledge, no such initiative exists yet, despite the huge explanatory power of one simple figure.

In constructing this framework, we have chosen a simple 2*2*2 HO type framework. The choice for this traditional, neoclassical theory might be surprising as Grossman and Rossi-Hansberg (2008) concluded that international trade theory has reached a new paradigm, where we should move away from such neoclassical models. In addition, some of the models that the figure will synthesize deviate from this standard framework[2]. However, with regards to the first point, Feenstra (2010, p. 4) concluded that the HO model is still relevant for understanding trade in the global economy today, even in the presence of offshoring. With regards to the second point, even when incorporated models differ from the standard set up, the focus will be on their main message and dynamics in our

[2] For example, Feenstra and Hanson (1996) use a continuum of goods, rather than 2 sectors while Davis (1996) uses a many countries, 3 sectors model.

construction of the figure, rather than their microeconomic structure. In doing so, one might lose some precision in the underlying framework of the figure, but this is compensated by an increased understanding of the overall message between papers. This is indeed the key purpose of the figure; to provide a helicopter view of the literature that can streamline various models by focusing on their key message and, where possible, bypass particular modelling differences.

This Chapter is structured as follows. Before getting into the theoretical models, it will discuss some conceptual issues, notably the terminology used in this field. Just like the models, the terminology is ambiguous as well. After that, it will first outline the basic setup under which we will graphically explore the effect of GVCs on relative employment and wages. Once this framework is set, the Chapter will introduce the main channels by which GVCs can affect the relative demand for skilled labour and provide empirical evidence for each channel. Doing so will first introduce the productivity effect of GVCs, by referring to the canonical, classroom example of a small open economy with exogenous prices, following the models used by Leamer (1994), Arndt (1997, 1998a, 1998b) and Jones and Kierzkowski (2001). Then it will endogenize prices and assume Cobb Douglas preferences showing how the productivity effect of offshoring can be exactly offset by a price effect, as demonstrated first by Krugman (2000). Under these assumptions, a third channel can be introduced that affects relative factor returns and usage which is the labour supply effect which features elsewhere in the literature ((Baldwin and Robert-Nicoud, 2007; Grossman and Rossi-Hansberg, 2008)). After demonstrating the effect of these channels graphically, the contribution by Xu (2001) will be demonstrated, who shows that elasticities, both of the substitution of demand in the relative goods market as well as the relative labour market, crucially determine the end result. In the end, we extent offshoring to also include inshoring activities, bringing us closer to the concept of global production sharing which will introduce the important theories by Davis (1996), Khalifa and Mengova (2010) and Feenstra and Hanson (1996). After this literature review, the figure will be used to synthesize all this literature into one all-encompassing framework, before concluding.

1.1. Terminology

Although the term global value chains is relatively new, the phenomenon to which it refers has been researched for several decades. However, it has been rebranded several times, causing some confusion about the terminology used. Therefore, this section sets out the various terms seen in the literature and contrasts them with each other.

Various terms are used both within academic literature and popular press to describe the increasing international interconnectedness of production processes. In chronological order: fragmentation (Jones and Kierzkowski, 1990), slicing up the value chain (Krugman, 1995), delocalization (Leamer, 1998), outsourcing (Feenstra and Hanson, 1999, 1996; Kohler, 2001), global production sharing (Feenstra and Hanson, 2001a), vertical specialisation (Hummels et al., 2001), offshoring ((Baldwin and Robert-Nicoud, 2007, Kohler, 2008, Feenstra, 2010), offshore outsourcing (Mankiw and Swagel, 2006), trade in tasks (Grossman and Rossi-Hansberg, 2008), and most recently, Global Value Chains (Koopman et al., 2014).

Out of these, we can set out three sub-groups and focus on their subtle, yet important, differences. Firstly, and most importantly, there is offshoring, secondly there are more collective terms such as international production sharing, global value chains or vertical specialisation, and finally there is trade in intermediate goods and / or tasks. This section outlines their differences.

Firstly, offshoring refers to a relocation of economic activities abroad (GAO, 2004; Michel, 2008). A slightly more comprehensive definition, based on GAO (2004) and OECD (2007) is that offshoring is the transfer or shift of an activity – an entire production chain or just part of it – from a home country to a host country entailing job losses in the home country. Offshoring is sometimes confused with outsourcing, which refers to a shift in ownership, rather than location. Figure 1.1 provides an overview.

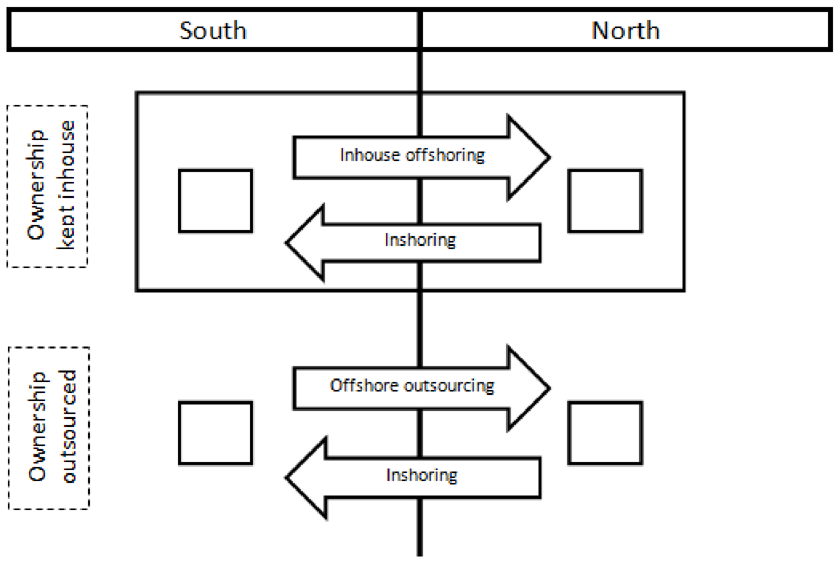

Figure 1.1 Global Value Chain Terminology

Although this relocation of economic activities leads to an interconnectedness of economies, it is not the same thing. Terms such as global value chains, international production sharing, or vertical specialisation, refer to a state, rather than a process. Although this difference seems subtle, it becomes more important when trying to measure offshoring in practice. As an example, authors such as Amiti and Wei (2005) and Hijzen (2005) simply define what they call (international) outsourcing as the import of intermediates by domestic firms but this measurement has serious caveats. Firstly, while trade in intermediates, and specifically the import of intermediates can be a potential consequence of offshoring, it is not necessarily the case[3]. Think for example when a final stage of the production phase is offshored, e.g. the assembly, the goods will then be imported as final goods to the home country, before they are sold. Further, it can also be the case that offshoring rather than leading to an increase in imports can lead to a decrease in exports, if the goods were already meant for a foreign market. In line with that point, even horizontal FDI could be viewed as offshoring if the good was initially produced at home, and then exported and sold abroad. If now, a company decides to offshore its entire production abroad and serve the foreign market from there, that would be a cross border transfer of activities, leading to job losses at home. This would adhere to the definition of offshoring, but not to any change in intermediate good trades, nor an increase in imports.

Finally, the term global value chain refers to the fact that the value chain, which naturally describes the full range of activities that firms and workers perform to bring a product from its conception to end use and beyond, is executed in several countries. Throughout this thesis, various terms will be used interchangeably, except when the subtle differences described here are of especial importance, in which case that will be made clear.

1.2. Laying the groundwork for the graphical exposition

As stated before, the aim of this Chapter is to provide an intuitive and graphical explanation of the effects of GVCs on relative factor returns and employment. In doing so, it focuses on the main messages of various models, rather than the differences in their microeconomic assumptions. Therefore, where possible, the analysis will refrain from stating any functional forms of various equations. However, in order to present the framework for the graphical exposition, we start off with some very basic foundations.

[3] The use of imported intermediate inputs in production is what Michel (2008) refers to as a short cut definition of offshoring.

We start from a standard Heckscher-Ohlin (HO) type framework with 2 countries (North and South), 2 industries (*i = X, Y*) and 2 factors of production, high (H) and low (L) skilled labour (*j = H, L).* We further follow HO assumptions so that both countries operate in a diversified economy where there are no artificial barriers to trade, no transportation costs, perfect competition, constant return to scale, full employment and factor mobility between domestic sectors but not between countries. Output in industry *i* is determined as:

$$Q_i = f(H_i, L_i) \tag{1.1}$$

Assuming constant returns to scale, i.e. a production function that is homogenous of degree one, so that output increases in the same proportion to an increase in endowments. From here, we can state a unit production function as:

$$1_i = f(a_{iH}, a_{iL}) \tag{1.2}$$

Where a_{ij} represent the amount of factor *j* needed to produce 1 unit of sector *i.* From here, it can be shown that the low to high skilled labour ratio in industry *i* = $\frac{L_i}{H_i}$ = $\frac{a_{iL}}{a_{iH}}$ from which it can be shown that:

$$\frac{L_X}{H_X} > \frac{L_Y}{H_Y} = \frac{a_{XL}}{a_{XH}} > \frac{a_{YL}}{a_{YH}} \tag{1.3}$$

So that the production of 1 unit of X requires relatively more low skilled labour than the production of 1 unit of Y does. In other words; sector X is the low skilled intensive sector and sector Y is the relatively high skilled intensive sector.

From the production function, we can state GDP as:

$$GDP = \sum_{i=X,Y} Q_i \cdot p_i \tag{1.4}$$

Which can be written in full as:

$$GDP(p_x, p_y, L, H) = \max_{Q_x Q_y} Q_x p_x + Q_y p_y \quad s.t.\ Q_y = f(Q_x, L, H) \tag{1.5}$$

As explained by Feenstra and Taylor (2008, p. 6), we can solve this problem by substituting the constraint into the objective function and choosing Q_y that maximizes GDP by:

$$p_x + p_y\left(\frac{\partial f}{\partial Q_x}\right) = 0 \tag{1.6}$$

$$p = \frac{p_x}{p_y} = -\frac{\partial f}{\partial Q_x} = -\frac{\partial Q_y}{\partial Q_x} \tag{1.7}$$

Meaning that the economy will produce where the relative price of good X is equal to the slope of the PPF. Relative supply of good X is determined where the economy's isovalue is tangent to its production possibilities frontier. At this point, the slope of the PPF (determined by relative opportunity costs) is equal to the slope of the isovalue line (determined by relative price ratio $\frac{P_x}{P_y}$). Therefore, an increase in $\frac{P_x}{P_y}$ will lead to an increase of $\frac{Q_x}{Q_y}$. Therefore, the relative supply of goods, noted RS_g, is positively related to $\frac{P_x}{P_y}$.

$$RS_g = f\left(\frac{P_x}{P_y}\right) \ where \ \frac{\partial RS_g}{\partial \frac{P_x}{P_y}} > 0 \tag{1.8}$$

This information can be used to introduce the first quadrant in the figure, which is the market for relative goods that shows how relative demand and supply of goods is related to the relative price of goods. While the above explanation has illustrated that the relative supply of $\frac{Q_x}{Q_y}$ is an increasing function of $\frac{P_x}{P_y}$, the relative demand for $\frac{Q_x}{Q_y}$ will be negatively related to $\frac{P_x}{P_y}$ due to substitution effects. The magnitude of this substitution effect will depend on the elasticity of demand, or preferences, noted η. Therefore:

$$RD_g = f\left(\frac{P_x}{P_y}, \eta\right) where \ \eta = \begin{cases} \infty \\ > 1 \\ = 1 \\ < 1 \end{cases} \tag{1.9}$$

That is, the elasticity of demand can be infinite, relatively inelastic (*η<1*), Cobb-Douglas (*η=1)* or relative elastic (*η>1).* We will see that the choice of elasticity will have crucial implications on the eventual effect of GVCs on relative employment and wages. The magnitude of the responsiveness of the relative demand $\frac{Q_x}{Q_y}$ on relative prices $\frac{P_x}{P_y}$ depends on the elasticity of substitution η as follows:

$$\frac{\partial RD_g}{\partial \left(\frac{P_x}{P_y} \mid \eta = \infty\right)} < \frac{\partial RD_g}{\partial \left(\frac{P_x}{P_y} \mid \eta > 1\right)} < \frac{\partial RD_g}{\partial \left(\frac{P_x}{P_y} \mid \eta = 1\right)} < \frac{\partial RD_g}{\partial \left(\frac{P_x}{P_y} \mid \eta < 1\right)} < 0 \tag{1.10}$$

In order to show how changes in the relative goods market affect the relative labour market, we naturally have to lay out some fundamentals for the latter market as well. We can refer again to the GDP function to determine relative factor returns. Since factor returns (w_j) are equal to their respective marginal revenue:

$$w_{ij} = \frac{\partial GDP}{\partial ij} = p_i * MP_{ij} = p_i * \frac{1}{a_{ij}} \tag{1.11}$$

Further note that $w_l = w_{xl} = w_{yl}$ and $w_h = w_{xh} = w_{yh}$ but $w_h > w_l$ because $a_{iL} > a_{iH}$. In words, while wages earned by factor *j* are equal between industries, high skilled labour earns a higher wage than low skilled labour because they are more productive. *Relative* wages, however, are determined in the relative labour market by the relative supply and demand for labour $\frac{L}{H}$. That is, relative factor prices are a function of relative demand and supply for labour.

$$\frac{w_L}{w_H} = f\left(\frac{L}{H}\right) \tag{1.12}$$

Note that we can take the inverse of this relative factor price function to get the relative demand and supply functions as $\frac{L}{H}$= $f(\frac{w_L}{w_H})$. Then, following standard economic theory, the relative supply curve will be upward sloping as a higher relative wage for skilled labour causes more skilled individuals to enter the industry. For example, if $\frac{w_L}{w_H}$ increases, the individuals will invest more in schooling to equip themselves with the skills necessary to earn the higher relative wage (Feenstra and Taylor, 2008 p.204). Secondly, the upward sloping relative supply of production factors, RS_f, can be explained by referring to a leisure-labour trade-off.

$$RS_f = f\left(\frac{w_L}{w_H}\right) > 0 \tag{1.13}$$

The relative demand function, on the other hand, will be downward sloping due to substitution effects. That is, if relative wages would increase, firms will want to substitute low skilled labour for high skilled labour, decreasing $\frac{L}{H}$. Substitution will happen at a rate of σ, the elasticity of substitution in factor demand, such that the relative demand for production factors, RD_f is:

$$RD_f = f\left(\frac{w_L}{w_H}, \sigma\right) \; where \;\; \sigma = \begin{cases} > 1 \\ < 1 \end{cases} \text{and } \frac{\partial RD_f}{\partial \left(\frac{w_L}{w_H} | \sigma > 1\right)} < \frac{\partial RD_f}{\partial \left(\frac{w_L}{w_H} | \sigma < 1\right)} < 0 \tag{1.14}$$

That is, with relative elastic factor substitution ($\sigma > 1$), the relative demand for low skilled labour will decrease even more as a result of increased relative low skilled wages than under relatively inelastic substitution in factor demand.

Both the relative labour and relative goods market will clear, and keep each other in equilibrium via a Stolper-Samuelson and a Rybczynski effect. The former connects both markets by relating the change in relative good prices $\frac{P_x}{P_y}$ to relative factor prices $\frac{w_L}{w_H}$ where the relation is such that an increase in the relative price of a good, $\frac{P_x}{P_y}$, will increase the real return to the factor used intensively in that good, $\frac{w_L}{w_H}$, and reduce the real return to the other factor (Stolper and Samuelson, 1941). This can be written as:

$$\frac{w_L}{w_H} = f\left(\frac{P_x}{P_y}\right) \text{ where } \frac{\partial \frac{w_L}{w_H}}{\partial \frac{P_x}{P_y}} > 0 \quad (1.15)$$

The Rybczynski effect, on the other hand, connects both markets via relative outputs $\frac{Q_x}{Q_y}$ and relative factor endowments/usage $\frac{L}{H}$, keeping relative prices $\frac{P_x}{P_y}$ constant. Since sector X is the relatively low skilled intensive sector, any increase in this sector at the expense of the high skilled sector, will increase the country-wide relative demand for low skilled labour. This can be noted as:

$$\frac{L}{H} = f\left(\frac{Q_x}{Q_y}\right) \text{ where } \frac{\partial \frac{L}{H}}{\partial \frac{Q_x}{Q_y}} > 0 \quad (1.16)$$

[4]

The interrelationships between these four quadrants can therefore be shown graphically as done in Figure 1.2:

[4] See Appendix 1.3 for a proof.

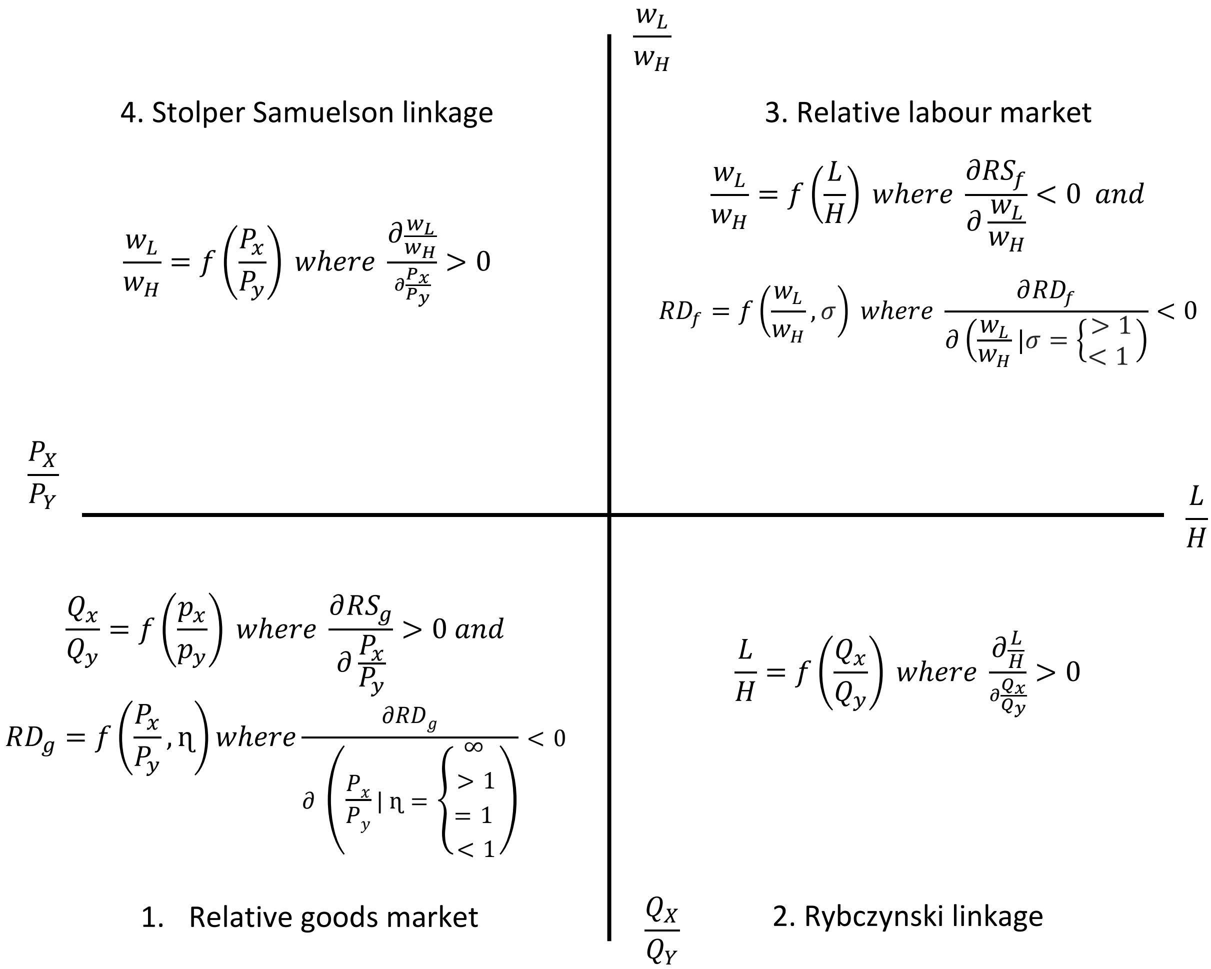

Figure 1.2 The basic foundations

Figure 1.2 can be used to demonstrate various implications of GVCs, which originate in the relative good market (quadrant 1), on the relative labour market (quadrant 3) via either a Rybczynski effect (quadrant 2), a Stolper-Samuelson effect (quadrant 4) or both. In showing the effects of GVCs on the relative factor market, we will allow for fragmentation of final good X into two intermediate tasks, a relatively skilled intensive task, X_1, and a relatively low skilled intensive task, X_2. The analysis will initially follow the perspective from the Northern country, where firms will be inclined to offshore X_2 to low wage countries (the South) in order to achieve cost savings[5]. Doing so will affect the relative labour market in various ways. The next section will first provide a literature review of various effects and show how they, under various microeconomic assumptions, would affect the relative

[5] This means that the sector bias of the productivity increase caused by GVCs is low skilled intensive (sector X) while the factor bias (of the intermediate good that the North specialises in) is high skilled intensive.

demand for skilled labour. After that, this Chapter will show how these effects can be incorporated in the framework as outlined in Figure 1.2.

1.3. Reviewing the literature

Now that we have formalized the graphical framework, we can review the literature. Note that the analysis will work from the assumption that low skilled intensive tasks in the low skilled intensive sector X will be offshored and that the country will thus specialise in the high skilled activities of sector X. As discussed, how this affects the relative demand for skilled labour depends crucially on the microeconomic foundations of the model chosen (Feenstra, 2010). Therefore, this Chapter will analyse the skill demand effects of GVCs under a range of models. Following the literature, it will start with the canonical classroom example of a small open economy where world prices are determined exogenously in a 2 country, 2 sectors and 2 factors of production HO framework. After that, it will show what happens to the predictions if we change various crucial foundations of the model with regards to the size and price determination of good prices, number of countries and number of sectors. In doing so, various streams of the literature can be explained. Whenever we identify a stream or model, appropriate references will be made while each subsection will conclude with empirical evidence of this model discussed. In the end, two key models that have managed to bring some of these conflicting micro economic foundations into one model will be discussed

1.3.1. The canonical neoclassical model

In order to lay bare some of the key channels by which GVCs can affect relative wages and employment, it is useful to follow the classroom example of a small open economy that cannot affect world prices. Doing so will illustrate what has been termed in the literature as the sector bias (Haskel and Slaughter, 2002; Leamer, 1994), productivity (Grossman and Rossi-Hansberg, 2008), direct (Xu, 2001) and the outsourcing (Arndt, 1998) effect of a productivity increase sparked either by technological change or global value chains.

Figure 1.3 shows a Lerner – Pearce diagram representing the economy of the skill abundant country. As you can see, this small open economy is diversified, i.e. it produces both final goods X and Y and factor prices have equalized within the country as can be seen from the line $\frac{w_L}{w_H}$, which is tangent to the *unit-value* isoquants of sector X and Y, denoted X_o and Y_o respectively.

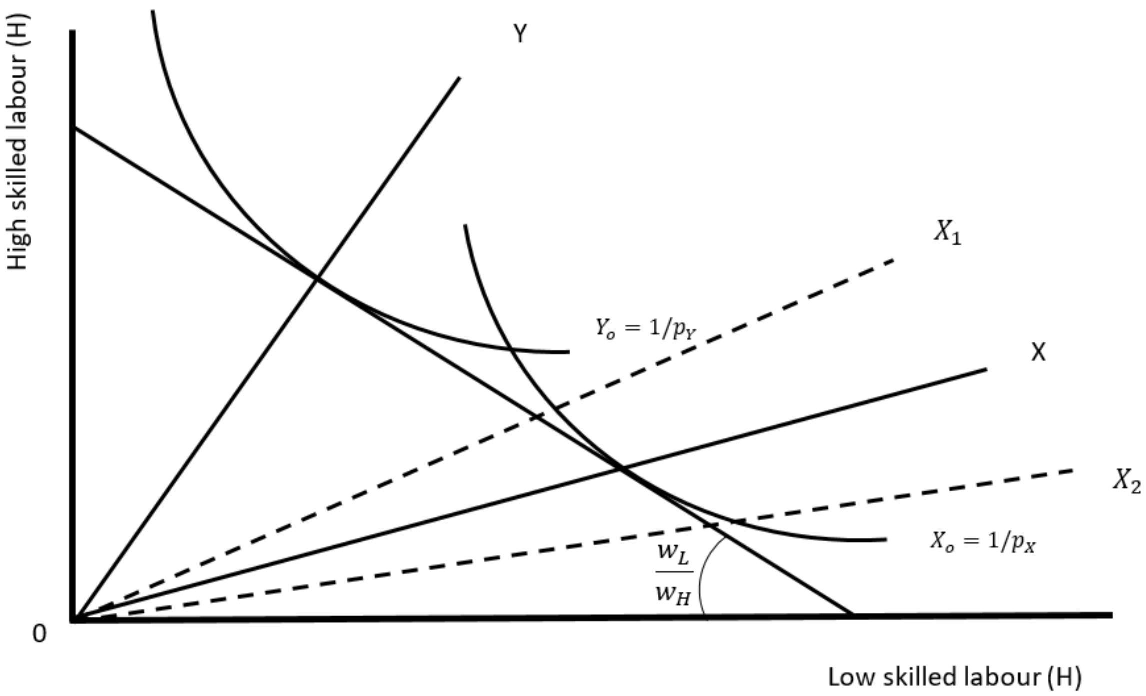

*Figure 1.3: Standard 2*2*2 H-O type model where factor prices have equalized*

From this starting position, we will analyse how the fragmentation of producing good X into a skill intensive intermediate task X_1 (such as the design, the engineering or the research and development) and a low skilled intensive task X_2 (such as assembly, simple processing and/or packaging) affects the relative demand for skilled labour. It would make sense to offshore the low skilled intensive tasks to countries with lower wages, i.e. those that are relatively abundant in low skilled labour, if the resultant costs savings of doing so exceed the costs (Jones and Kierzkowski, 2001). Offshoring X_2 would lead to cost savings in the X industry, causing the unit-value isoquant to shift in to X_o' as it will now take less L and H labour to produce 1 unit value of good X[6]:

[6] In that sense, the marginal productivity of both low and high skilled labour within the X industry have increased. Assuming Px remains constant, there are profit opportunities in the X industry, attracting both factors of production away from industry Y, causing to an increase in the relative output, or supply, of good X. Note that this effect is analogous to the effects of technological improvements in the X sector (Arndt, 1997). It is further important to note that we assume the costs of importing X_2 are assumed to be lower than the cost of producing X_2 by the country themselves.

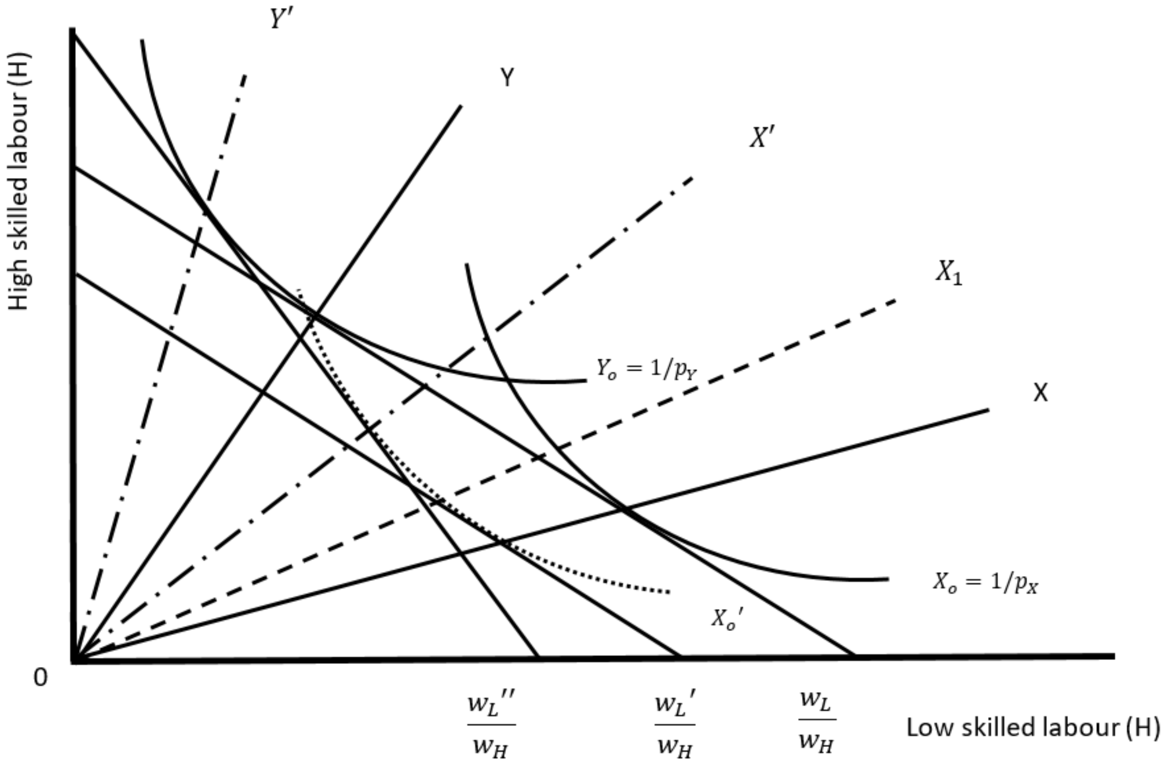

Figure 1.4 Offshoring X_2 shifts unit-isoquant X inwards and increases $\frac{w_L}{w_H}$

Note that the unit isoquant of X has shifted in along the new expansion path of $0X_1$, rather than *0X*, representing the increased skill intensity of the remaining production. This new isoquant, denoted X_o', is tangent to a line $\frac{w_L'}{w_H}$ which is parallel to the original factor price ratio. However, in this scenario, there is no more factor price equalization between the two sectors. Indeed, due to the cost savings and exogenous prices, there are profit opportunities in sector X, which will expand[7], raising the demand for production factors. Since sector X is relatively low skilled intensive, the relative factor price for low skilled workers will increase, indicated by the steeper $\frac{w_L''}{w_H}$ ratio in Figure 1.4. This steeper ratio further leads both industries to substitute high skilled labour for low skilled labour, indicated by the counter-clockwise move of X_1 and *Y* to *X'* and *Y'*.

What happens to relative employment in the offshoring country? While it is clear that due to the scale or productivity effect of offshoring, there is an economy wide skill downgrading effect (as the relative demand for low skilled labour increases due to the expansion of the X

[7] This way, offshoring X_2 has an effect on sector outputs similar to an increase in the endowment of low skilled labour. Through the usual Rybczynski effect, this will increase the home output of the low-skilled intensive sector X.

industry), there is actually a within industry upgrading effect. For the X industry, this is due to two reasons. Firstly, by offshoring X_2, the skill intensity of the remaining production in the X industry increases, rotating the expansion path from 0*X* to $0X_1$. Secondly, due to the increased $\frac{w_L}{w_H}$ ratio, substitution of L for H labour further rotates the expansion path from $0X_1$ to $0X'$. This latter effect is also present in the Y industry (from *OY* to $0Y'$) explaining why we have a skill upgrading effect within industries, but a skill downgrading effect across industries[8]. Appendix 1.2 further gives a numerical example of how this is possible while Figure 1.11 uses the proposed figure to illustrate this point further.

Thus, we see that in this example, offshoring the least skill intensive tasks in the least skill intensive industry would benefit unskilled labour, contrary to general belief and offshoring tasks can actually create more jobs (Kohler and Wrona, 2010). The main reason for this is that we assumed the economy is small and unable to affect world prices. Therefore, the relative commodity-price ratio does not change, even though it has become cheaper to produce good X. We can expand on this by referring to the zero-profit condition of firms in these competitive industries:

$$C_i = P_i = \sum_{j=H,L} a_{ij} \cdot w_j \tag{1.17}$$

Where C_i is the cost to produce one unit of *i, P_i* is the price of good *i*; a_{ij} represents the amount of production factor j requirements to produce one unit of *i* and w_j is the factor cost of j. Using Jones algebra, this equation can be rearranged and differentiated (as outlined extensively in Appendix 1.1) to:

$$\hat{p}_i + TFP_i = \sum_j \theta_{ij} \cdot \hat{w}_j \tag{1.18}$$

Here you can immediately see, that if prices are assumed to remain constant, it is purely the change in TFP that will affect the relative cost share θ_{ij} of factor *j* in industry *i*. Following Feenstra (2010), we can use Figure 1.5 to illustrate this by plotting the zero profit conditions for both the X and Y industry, generating an initial equilibrium at w_L and w_H. Increasing TFP in industry X as a result of offshoring X_2 will shift the zero-profit condition for industry X outward, increasing relative factor return of both factors in that industry.

[8] This effect is not robust. When the most skilled intensive part of good X (x_1) is more skill intensive than the least skill intensive task of y (y_2), fragmentation of x_2 would lead to the declining price of low skilled workers.

Since industry X is relatively low skilled intensive, that factor of production will benefit most which can be seen by the new equilibrium wages $w_L{}'$ and $w_H{}'$ [9].

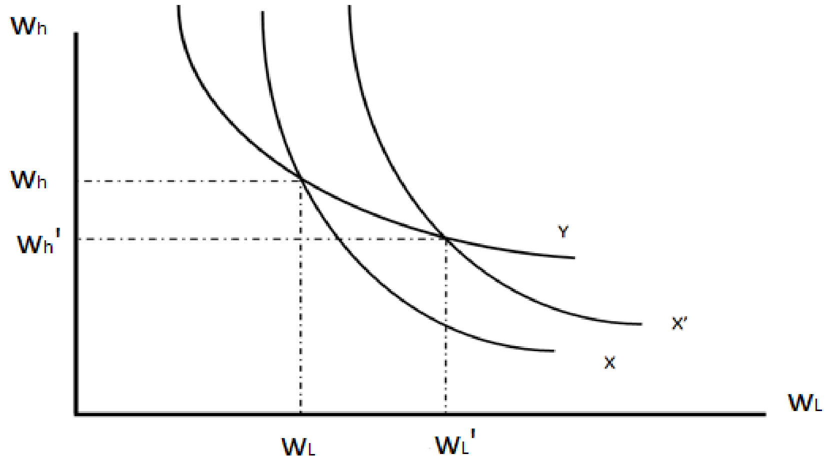

Figure 1.5 The zero-profit condition in sector X shifts out, increasing relative factor returns within that industry

While this model is theoretically appealing, empirical evidence supporting the model is scarce[10] as inequality has generally risen both in the developed and the developing world. Geishecker and Görg (2005) is one example of a paper that acknowledges the importance of controlling for the skill intensity of the industry that experiences fragmentation. In line with the model explained in this section, they find that high skilled labour might be able to receive higher wages when fragmentation occurs in high skilled German industries. On the contrary however, they find that low skilled labour would still experience lower wages when fragmentation occurs in the low skilled industries.

1.3.2. Changing crucial assumptions

After having outlined the effects of fragmentation on relative employment and wages using the standard 2*2*2 HO type trade model, we will now see what happens when we alter crucial foundations of the model, using a wide variety of existing theoretical models. Firstly, we will focus on the effect of endogenizing prices, i.e. examining the effects in a large economy, illustrating the debate between Leamer (1994), Krugman and Xu (2001) has transpired from technological change into international fragmentation of production (See

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[9] Further note that the slopes of the isocosts are given by relative productivity: $\frac{a_{ih}}{ail}$, or the capital labour ratio where $\frac{a_{xh}}{axl} < \frac{a_{yh}}{ayl}$ making X the low skilled labour intensive sector.

[10] Assuming that global production sharing happens in the low skilled intensive sector. If we would assume the sector bias of GVC would be the high skilled intensive sector, then we would be able to link more empirical findings to this model.

Feenstra (2010) Arndt (1998) and Kohler (2003) for example). After that, we will built on the work by Davis (1996) and Khalifa and Mengova (2010) who point to the importance of allowing for more than 2 countries. Indeed, they explain how differences within the global North and South can explain divergent empirical results. This section will then conclude that a proper empirical framework for measuring the effects of fragmentation must condition its results on the skill intensity of the industry in which offshoring occurs (to control for the sector bias), the skill intensity of the specific intermediate good or task the home country specialises in via GVCs (to control for the factor bias of the GVC), as well as the skill abundance of the countries involved in the global value chain.

1.3.2.1. Type of economy

Now that we understand the basic model, we can change some of its key assumptions which will allow us to explain some of the ambiguity in the literature. The strongest criticism against the model explained above came from Krugman (2000). His argument is twofold. Firstly, he criticizes the small open economy model by pointing to the demand for labour, stating that this is in effect infinitely elastic in a small open economy. This is because small open economies are able to accommodate changes in factor supplies via a reshuffling of production, leaving the demand for production factors unchanged (Krugman, 2000 p.58). He then says that a model that assumes infinitely elastic relative demand for factors of production cannot be used to show how relative wages change as a result of productivity changes.

Krugman’s second point can be seen as a reality check. He explains that while the small open economy is a useful classroom example to expose various trade theories, it is far from reality. Specifically, Krugman says that technological change, as can be assumed for global production sharing, is a global phenomenon, rather than a local, happening across countries at the same time. Because of this, commodity prices would not be determined exogenously, but rather endogenously. If that would be the case, an increase in the supply of a good which sector experiences productivity increases would ultimately decrease the price of that good. This, in turn, will affect factor returns via a Stolper-Samuelson effect i.e. decrease the return to that factor of production used intensively in the sector that experiences the productivity increase. Under Krugman’s (2000) assumptions that the productivity increase occurs in an integrated world economy with Cobb-Douglas preferences and Leontief technologies[11], this Stolper-Samuelson effect would exactly offset the sector bias effect. Then, all that would be left to affect relative factor prices is the factor bias effect i.e. whether technological change is skilled, or unskilled biased. Note that skilled (low skilled) biased technological change is defined as technological change that would increase (decrease) the ratio of skilled to unskilled employment at any wage ratio, which could be shown graphically in a relative supply and demand for skilled labour diagram, by shifting the relative demand for skilled labour outwards.

While Krugman's (2000) paper applies the above analysis to technological change, it can be applied to global production sharing. Consider the example followed previously, where the North offshores the low skilled intensive part of the low skilled sector, X_2, to the South. Note that the sector bias is the low skilled sector while the factor bias of the activity the North will now specialise in is high skilled. The factor bias effect on the X industry is an increase in the high to low skilled ratio (akin to high skilled technological change (Arndt, 1998). This, according to Krugman's (2000) analysis where the factor bias effect is the only channel by which a productivity increase affects relative wages, would increase the relative wage of high skilled labour. Note that is *exactly opposite* to the predictions outlined by advocates, such as Leamer (1994, 1998) and Arndt (1998), of the sector bias.

The empirical evidence is in favour of this model by Krugman as skill premia have generally increased in more developed countries over the past 3 or 4 decades (See Amador and Cabral (2014) for an overview). Feenstra and Hanson (2010), for example, show that during the 1980s, both the relative wage and the relative employment of non-production workers (used as a proxy for skilled labour) increased (Figure 1.6)

[11] Krugman (2000) himself pointed out that the assumption of Leontief technologies is not essential for his results. Xu (2001) further specified the assumption by showing that the productivity increase should not just be global, but also identical across countries. When the productivity increase occurs at different rates in various countries, the sector bias will also affect relative factor prices even under Cobb-Douglas preferences (Xu, 2001, p.7).

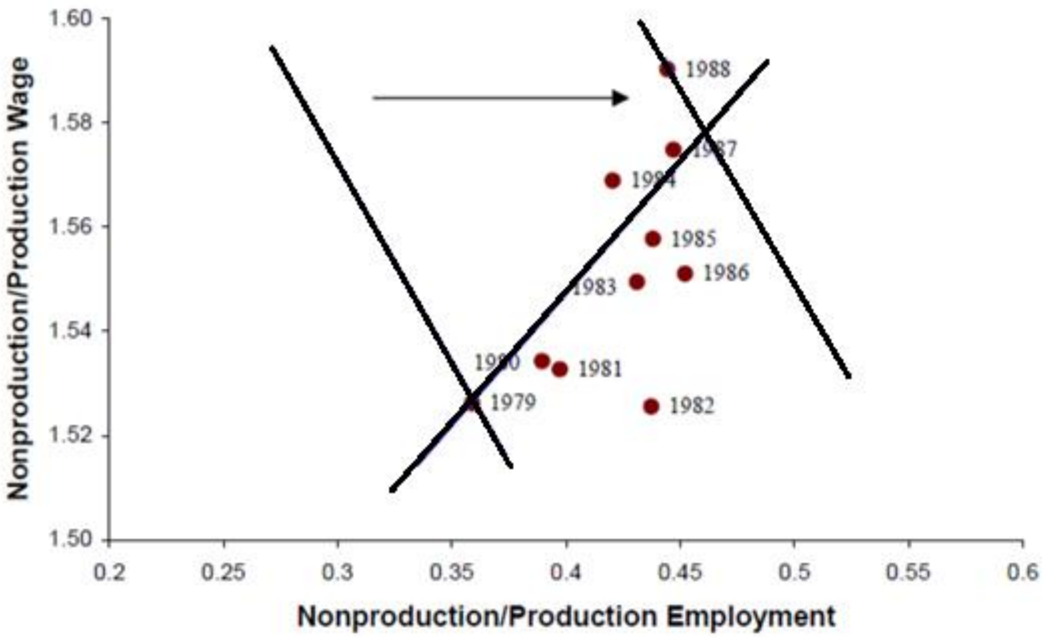

Figure 1.6 Outward shift for demand of skilled labour Source: Feenstra and Hanson (2010, p.8)

Amador and Cabral (2014) provide a good overview of various papers that find that offshoring is positively correlated with wage inequality in developed countries. Some notable contributions are by Becker, Ekholm and Muendler (2013), Geishecker (2006) and Geishecker and Görg (2008) in the case of Germany, Strauss-Kahn (2003) for France, Hijzen, Görg and Hine (2005) for the UK and Hummels, Jørgensen, Munch and Xiang (2014) for Denmark. Outside of Europe, Hsieh and Woo (2005), using a combination of worker and industry level data, found that offshoring from Hong Kong to China contributed to the strong and persistent relative demand shifts for skilled workers. The implications of this model, favouring the factor bias, for the South are such that they would specialise in low skilled intensive activities and should therefore experience an increased relative demand for low skilled labour. Evidence of this has been found in the Czech Republic, Hungary and Poland during the 1990s (Egger and Stehrer, 2003) China in 2003 (Fajnzylber and Fernandes, 2009), as well as Wood (1997) and Japan[12] (Yamashita, 2010).

1.3.2.2. The number of sectors

There is a wide literature that shows how various key theorems derived from the standard 2*2*2 Heckscher-Ohlin theorem, such as factor price equalization, Rybczynski or Stolper

[12] Only in the case where Japan engaged in production sharing with the US, where Japan could be seen as the Southern country. As will be discussed later, when Japan engaged in production sharing with developing East Asian countries, it experienced skill upgrading.

Samuelson, do not hold if one uses higher dimensions than 2*2*2 (Kohler, 2001, p.9). This literature review will not go in to all of those potential outcomes[13], but will show how certain alterations to the microeconomic foundations of the model have led to important theoretical contributions that contradict the outcomes from the standard neoclassical model. We start with the contribution made by Feenstra and Hanson (1996). They showed that while the HO model would predict that relative wages would increase in the North, they should actually decrease in the South, if each country would specialise in that part of the production that they have the comparative advantage in. However, as explained by Harrison, McLaren and McMillan (2011), the 1990s undermined this traditional Heckscher-Ohlin mechanism as inequality grew not only in the North, but also in the South. While this empirical finding lead to various authors refuting trade as an explanation for growing inequality and instead point to skilled biased technological change (See Chusseau, Dumont and Hellier (2008) for a discussion of skilled biased technological change (SBTC) versus North South trade explanations of increased inequality), Feenstra and Hanson (1996, 1997, 2010) were amongst those economists that still favoured a trade explanation by providing an intuitive explanation as to why relative wages have increased both in the North and in the South. Namely, they state that what might be viewed as low skilled intensive by the North, might be viewed as high skilled intensive in the South. Then, as a consequence of the North offshoring their low skilled intensive activities to the South, the skill intensity of the production will increase in both countries.

In order to model this, one needs to bring variation in the number of sectors that are used in the analytical framework. Feenstra and Hanson did that by assuming a one sector model, but one that consists of a continuum of intermediate tasks. The model further assumes that the relative wage of skilled labour is higher in the North, and that the intermediate tasks are arranged in increasing order of their skill intensity, the ratio of North to South unit-costs is downward sloping (See c/c* below). Foreign production or offshoring occurs where the relative costs in the North are greater than unity, in the range [0, z’] while domestic production is done where the relative costs at home are less than unity [z’, 1]. The borderline activity z’ is determined by equal costs in the two countries:

[13] For example, while this section will look at how differences in the number of sectors and number of countries can lead to different effect, it does not analyse the implications of models that include only 1 factor of production. While such Ricardian trade models (Costinot et al., 2013; Rodríguez-Clare, 2010) are interesting from the perspective that they focus on differences in technology between Northern and Southern countries, analysing any change in relative factor returns is, by definition, impossible.

$$\frac{c(w_L, w_H, r, z')}{c(w_L{}^*, w_H{}^*, r^*, z')} = 1 \tag{1.19}$$

Now suppose that an improvement in the offshoring technology, technological progress abroad or a capital flow from North to South reducing foreign rental ratio would increase relative costs of producing at home and therefore increase the number of tasks offshored. As a result, the borderline activity z shifts outward to z* (Figure 1.7).

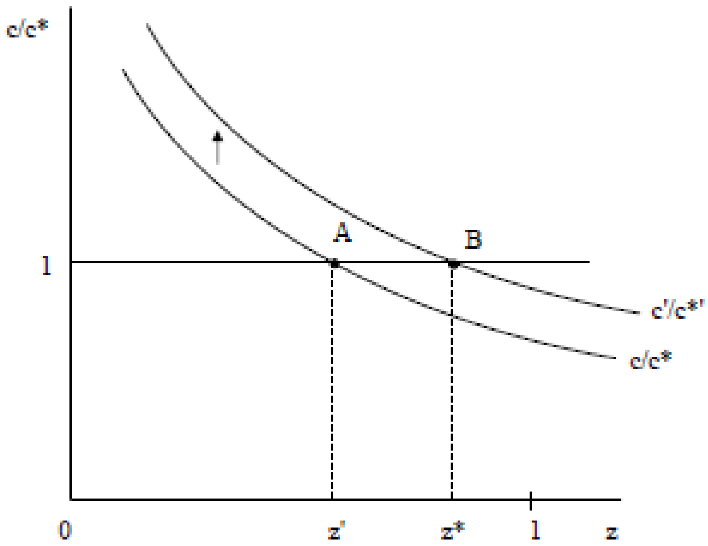

Figure 1.7 An increase in offshoring increases the skill intensity of domestic production.
Source: Feenstra, 2010, p. 18

The effect on relative demand for labour is that there is an upgrading effect both in the North and in the South. This is because the North offshores its lowest skilled intensive tasks thus upgrades the skill intensity of the remaining production. On the other hand, from the Southern perspective, these inshored activities are relatively high skilled and will therefore also induce a skill upgrading effect i.e. increased relative demand for high skilled labour.

Thus, Feenstra and Hanson's (1996, 1997) model would predict skill upgrading both in the North and in the South, as a result of global production sharing. Indeed, this is most in line with empirical evidence. Whereas the previous section cited various empirical evidence that inequality has grown in developed countries, Harrison, McLaren and McMillan (2011) as well as Chusseau and Hellier (2012) are some recent papers that provide clear evidence of this. Latin American countries can be used as a good case study of developing countries that experienced growing inequality as a result of increased openness. Firstly, Feenstra and Hanson's apply their own model in the case of offshoring from the United States to Mexico where they found that offshoring could account for a large portion of the increase in the skilled labour share of total wages during the 1980s. In addition, Fajnzylber and Fernandes (2005, in the case of Brazil) and Ernst and Sánchez – Ancochea (2008, for the case of Costa Rica) provided additional evidence of increasing skill premia as a result of global production sharing. Outside of Latin America, Lorentowicz, Marin and Raubold (2005) applied the model by Feenstra and Hanson on the Eastern European countries of Poland, Czech Republic and Hungary from 1995 – 2005 and found that the observed increased skill premia can also be explained by the fact they receive, via global value chains, relatively skilled intensive tasks. Finally, Shepherd and Stone (2013) found that internationalisation increased the relative demand for skilled labour among firms in the developing countries of Brazil, India, Indonesia, China and South Africa.

1.3.2.3. Number of countries

While Krugman (2000) and Jones (2000), amongst others, criticized the standard neoclassical model on the basis of its applicability to the real world, Feenstra and Hanson criticized it based on its empirical track record. Khalifa and Mengova (2010) as well as Davis (1996) provide an alternative explanation to this ambiguous empirical track record. Their criticism can once again be explained intuitively by saying that they allow for differences between countries *within* the North and the South. Specifically, both their models are based on the principle that *relatively* low (high) skilled abundant Northern (Southern) countries would actually engage in relatively low (high) skilled tasks, via global value chains, which would decrease the skill intensity of their production and therefore lead to effects seen in the standard HO model only for Southern (Northern) countries. The way they modelled this differs slightly however. Khalifa and Mengova built a model that is quite similar to Feenstra and Hanson, using a 2 country, 2 factors and 1 sector model, where the sector consists of a continuum of tasks that are increasing in skill intensity. Davis' model uses a many country, 3 good and 2 factors of production model that reaches the same conclusion.

The rationale can be explained best by using Davis' illustration of the North and South cone of diversification Figure 1.8.

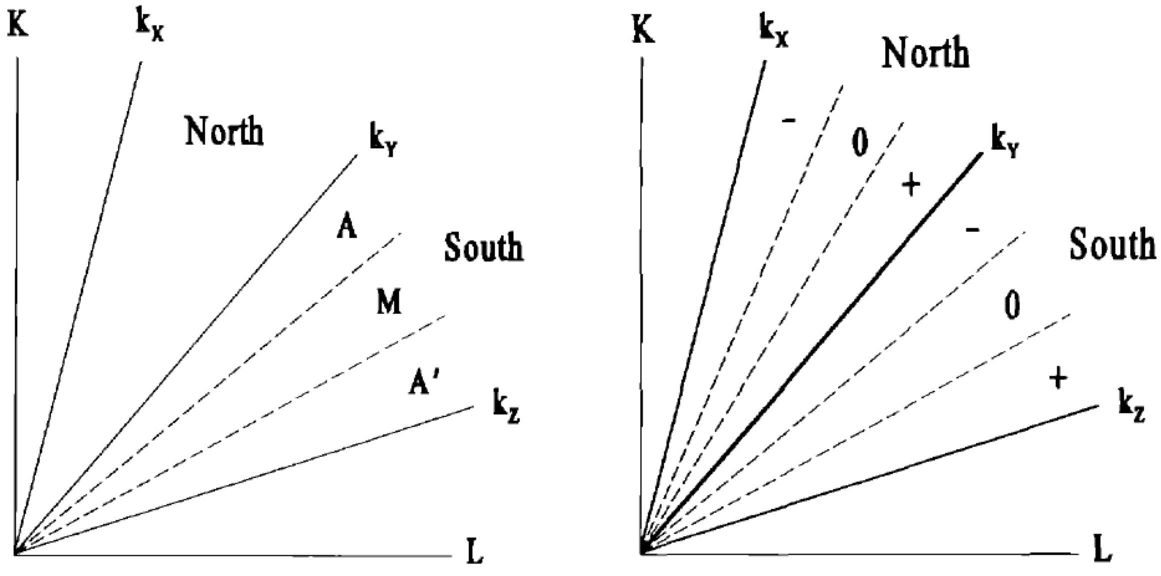

Figure 1.8 After a separation of Northern and Southern countries, we can expect divergent effects of trade liberalization on the wage rental ratio within global divisions of North and South. (Source: Davis 1996, p. 7 & 10)

Figure 1.8 depicts 3 goods, or sectors, that differ in their skill intensity, with K_X being the most skilled intensive and K_Z the least. Davis further assumed that the North specialises in the production of the two most skilled intensive goods K_X and K_Y while the South only produces K_Y and K_Z. The left-hand side of Figure 1.8 shows how the South can be split in those countries that are relatively capital abundant (A) and those that are relatively labour abundant (A'). In that case, a further specialisation takes place with the Southern countries in (A) now only producing K_Y and the Southern countries in (A') only producing K_Z. Since K_Y is the relatively skilled intensive good for the South and K_Z is the relatively low skilled intensive good, we can expect the wage rental ratio to go down in (A) and up in (A'). Khalifa and Mengova's model, although following a different setup, reaches the same conclusion. They further provide empirical evidence of this model, by applying a threshold estimation technique as introduced by (Hansen, 1999) in a sample of 29 developing countries over a period 1982-2000 and indeed find evidence of such a threshold skill abundance level. That is, they find that those Northern (Southern) countries with skill endowment below (above) a certain threshold experience a decrease (an increase) in wage equality as a result from offshoring

At this point we can summarize the contributions by Feenstra and Hanson (1996), Davis (1996) and Khalifa and Mengova (2010) by saying that the relative skill abundance of countries ultimately determines the factor bias of the offshored tasks. What might be low skilled intensive for one country can be high skilled intensive for another, depending on their relative skill abundance. While this might seem like a detail, it can explain some of the ambiguous empirical findings that have been discussed so far. Besides Khalifa and Mengova's own evidence of this existence of such a threshold level, the work cited earlier by Fajnzylber and Fernandes (2005) that found conflicting evidence between Chinese and Brazilian firms engaging in international economic activities can also be explained by this theory. That is, while Brazil can be seen as low skilled labour abundant on a global scale they are skilled labour abundant when compared to China. Similarly, the conflicting evidence between Latin America during the mid-80s and East Asia during the 60s and 70s as discussed by Wood (1997) could be explained for the same reason. In addition, Lorentowicz, Marin and Raubold (2005) explain the observed decrease in the skill premium of Austria from offshoring because while Austria might be human capital abundant on a global level, "Austria is poor in human capital relative to its trading partners" (p. 22). Finally, the work by Yamashita (2010) serves as a final suggestion that this theory tracks reality quite well. He shows that the effect of fragmentation on the Japanese relative demand for labour depends critically on the geographic location of the partner. While components trade with developing East Asian countries lead to skill upgrading, components trade with the US lead to skill downgrading, both in terms of wages and employment, a finding that has been confirmed more recently by Tomiura, Li and Wakasugi (2013). This could, once again, be explained that Japan could be seen as high skilled abundant when compared to developing East Asian countries, but relatively low skilled labour abundant compared to the US. As shown later in this thesis, Chapters 2 and 3 will add to this evidence. Especially Chapter 3, where the employed World Input Output Data (WIOD) allows to separate trading partners on the basis of their relative skill abundance, shows strong evidence of the importance of separating partners as such.

1.3.3. Streamlining various models

So far, we have shown that the distributional effects of GVCs can be ambiguous, and depend on the microeconomic foundations, such as the number of countries and sectors or the assumption regarding the country's ability to influence world prices, of the model chosen. While Kohler (2003, p. 4) concluded that "while the casuistic discussion of the existing literature does shed light on the issue, we are missing a concise formulation of a general principle which is at force in each special case" two notable contributions have been made that are able to include various effects into one model. Specifically, this section will discuss the contribution by Xu (2001) who shows that both the sector and factor bias of technological change can affect relative wages and employment simultaneously, while Grossman and Rossi-Hansberg (2008) constructed a “simple model of offshoring” that also incorporates various channels demonstrated earlier in this review. While these models do a good job of streamlining various literature, various contributions are still omitted. Secondly, while Grossman and Rossi-Hansberg (2008) refer to their model as “a simple model of offshoring”, it might still be complicated to grasp for the uninformed reader, and an intuitive explanation of key channels is still missing.

Starting with Xu (2001), she managed to show how both Leamer (1994) and Krugman (2000) could be right. In an intricate model, she identifies and separates a direct and an indirect effect of technological change where the direct effect is exactly the effect explained in the small open economy model by Leamer. The indirect effect occurs as a result of commodity prices changing as a result of technological change which occurs if the economy is large enough to affect world prices or if technological change happens worldwide across various countries. Then, as explained earlier, the drop in price will spark a Stolper-Samuelson effect on factor prices, offsetting any positive effects generated from the direct effect. She then shows that the models by Leamer and Krugman form two extremes on a range of possibilities how technological change can affect relative wages. One on end of the spectrum, if technological progress is local and the substitution of demand in the goods market is infinitely elastic, relative commodity prices will remain unchanged and only the direct effect of technological change will take place, which is Leamer’s model. On the other hand of the spectrum, in an integrated world economy, where technological change happens identically across many countries and preferences are assumed to be Cobb-Douglas, the sector bias as explained by Leamer will be perfectly offset by a negative price effect, so that only the factor bias matters for relative factor returns which is Krugman’s (2000) model. When preferences are non-Cobb-Douglas, and when technological progress is not identical among countries, the indirect effect can be greater, or smaller than the direct effect, leading to intermediate results. Further details of this model will be demonstrated in the next Chapter.

In the offshoring literature, Grossman and Rossi-Hansberg (2008) provided a model that also incorporates some of the mechanisms explained so far. Specifically, their model identifies a productivity effect, a price effect and a labour supply effect. The novelty of their model is that it allows for analysing small open economies, in which case only the productivity effect plays a role, as well as larger economies, in which case the price and labour supply effect come into play also. Here, the productivity effect is largely the same as Xu's direct or Leamer's sector bias effect while the price effect is largely the same as Jones or Krugman's price effect. The labour supply effect has not yet been discussed and is also less familiar from the literature. However, this effect has many similarities to Baldwin and Robert-Nicoud's (2007) concept of shadow migration[14]. While Grossman and Rossi-Hansberg define the labour supply effect as the fact that a country frees up domestic labour if it chooses to offshore part of its production, Baldwin and Robert-Nicoud define it as the offshoring country's ability to access foreign labour while still using domestic technology and machinery, much like shadow migration. They further explain that in a small open economy the terms of trade are exogenous so that relative price effects are absent. Therefore, in a small open economy, only the productivity effect plays a role. Once this assumption is relaxed, the price effect, much along the same lines as the model by Xu (2001) as well as the labour supply effect come into play as well.

1.3.4. The literature remains ambiguous

This literature review has shown that the theoretical implications of offshoring on relative wages and employment are ambiguous, and depend highly on the microeconomic foundations of the chosen model. The models by Xu (2001) and Grossman and Rossi-Hansberg provide somewhat of a consolation. However, while Xu's model is not specific for GVCs, Grossman and Rossi-Hansberg's model excludes important theoretical contributions such as the Feenstra-Hanson theorem or the importance of distinguishing within Northern and Southern countries. Besides these omissions, both models might still be considered convoluted. Even though Grossman and Rossi-Hansberg's paper is titled "A simple model of offshoring", the uninformed reader might still struggle to understand the basic message the model sends, while Xu's model is even more convoluted. Such an uninformed reader might benefit strongly from an intuitive explanation of the main channels by which GVCs can affect relative wages and employment. Therefore, the next Chapter will summarize and streamline all the aforementioned models into one all-encompassing figure. It is hoped that such a graphical exposition can be used as a classroom example or inform policy makers on the main channels by which GVCs can affect relative employment and wages.

[14] Baldwin and Robert-Nicoud (2014) were the first to point to the analogy of what they call the shadow migration effect of offshoring and the Rybczynski theorem.

Due to the theoretical ambiguity, the literature has often resolved to use empirical methods to answer the research question (see Egger and Egger (2001) for example). However, we have seen that the empirical results are not unambiguous either and fail to reach a consensus (Hoekman and Winters, 2005). In addition, evidence for developing countries is limited (Hansen et al., 2008), which is mainly due to data issues (Amador and Cabral (2014)). Some of this empirical ambiguity can be explained by differences in country and partners' skill endowments (Hansen et al., 2008). In line with the theoretical models by Davis (1996) and Khalifa and Mengova (2010), it is paramount to condition empirical research on the relative skill endowments of participating countries. This thesis will take such lessons and apply it to the empirical exercises executed in Chapters 2 and 3, which use micro and macro data respectively, to answer the research question. These sections will present strong evidence of the importance of conditioning empirical research on the skill endowment of the participating countries.

As such, this thesis will contribute to the literature by providing both theoretical as empirical analyses of the effects of global production sharing on relative wages and employment. It will start, in the next section, with the provision of a figure that can synthesize this ambiguous literature.

1.4. Synthesizing the literature into the graphical framework

By reviewing the literature on the distributional consequences of GVCs, the previous section has highlighted the ambiguity that exists in this field. As this ambiguity complicates our understanding of GVCs, there is the need for an all-encompassing framework that can somehow synthesize the literature in an intuitive manner. Therefore, this section will implement the key channels that we have identified in the previous section 1.3 into the graphical framework that was outlined in section 1.2.

1.4.1. The canonical neoclassical model

As before, we follow Leamer (1994), Arndt (1998), Xu (2001) and Jones and Kierzkowski (2001) in using the classroom example of a small open economy that operates in a standard 2*2*2 HO type framework and is unable to affect world prices. We further assume that the productivity increase that arises from fragmentation is local i.e. happens in isolation in the respective country-industry. In that case, the substitution of demand in the relative goods market is infinite, or $\eta = \infty$, and the relative demand curve for goods $\frac{Q_x}{Q_y}$ is a perfectly vertical line as illustrated in quadrant 1 of Figure 1.9:

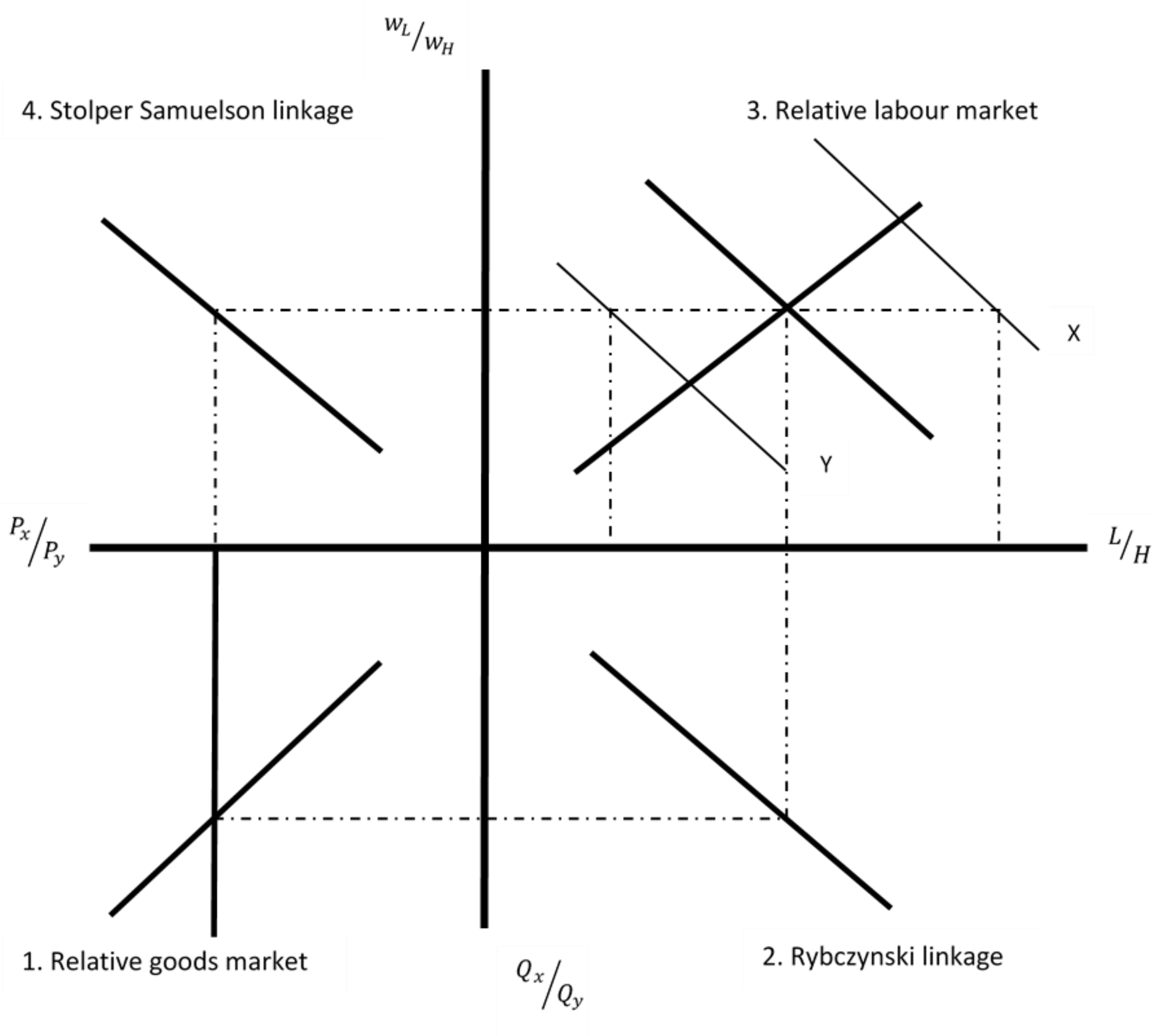

Figure 1.9 The starting point for a small open economy where goods prices are determined exogenously

Note that the relative factor market shows both the relative demand for labour for the industry as a whole (the thicker downward sloping line in the middle) as well as the relative demand within each industry X and Y (the thinner lines noted X and Y respectively). Further remember that the Rybczynski linkage in quadrant 2 only links relative outputs of industries X and Y to the national relative demand for labour, $\frac{L}{H}$, and not the industry specific relative demands, $\frac{L_i}{H_i}$. Finally, remember that we work from the assumption that it is the low skilled intensive tasks in the low skilled intensive sector X that are offshored via GVCs, meaning that the factor bias of the activities that the country specialises in is high skilled, while the sector bias is low skilled. Figure 1.10 will separate the sector from the factor bias effect by using red colours to indicate changes induced by the former and with red and the latter with blue.

Recall from Figure 1.4 that offshoring the low skilled intensive tasks X_2 will initially decrease the relative demand for low skilled labour. This is indicated by the blue line in quadrant 3 of Figure 1.10 representing an inward shift of the relative demand in sector X. The sector bias, or productivity effect, is illustrated with the red lines. Remember that the productivity increase achieved by offshoring X_2 will increase the relative output of sector X which can be shown as an outward shift of the relative supply of $\frac{Q_x}{Q_y}$ in quadrant 1:

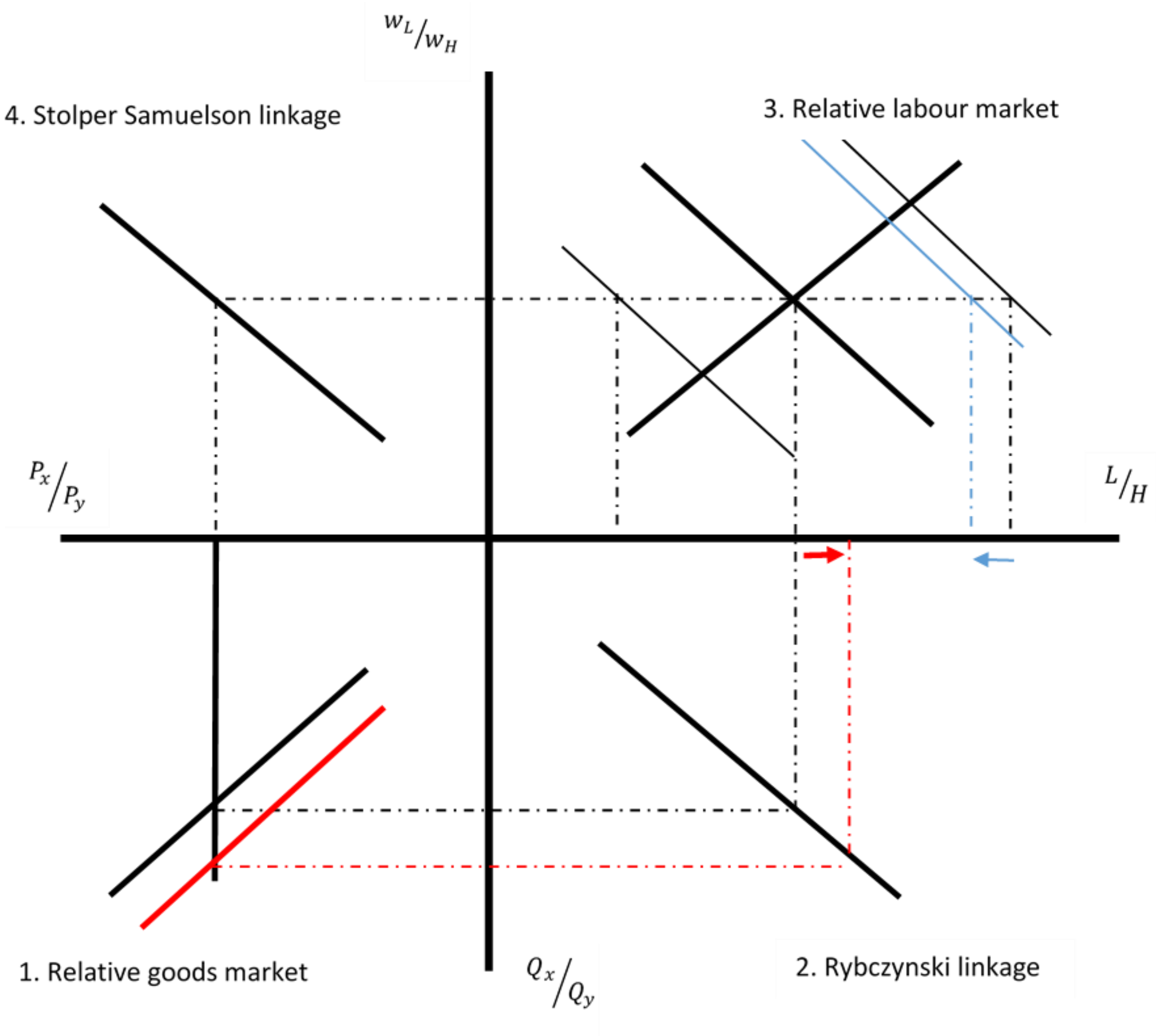

Figure 1.10 In a small open economy with exogenous good prices, offshoring in the X industry will increase its relative output. Red colours show sector bias effect; Blue colours show factor bias effect

Figure 1.10 shows that the relative supply for $\frac{Q_x}{Q_y}$ has shifted outwards. This will have a knock-on effect on the relative demand for labour in the Northern labour market via the Rybczynski linkage. That is, as $\frac{Q_x}{Q_y}$ has increased, the demand for $\frac{L}{H}$ will go up accordingly, as shown in Figure 1.10 as well. This in turn has a knock-on effect on quadrant 3; the relative labour market. Namely, the increased demand for $\frac{L}{H}$ will shift this curve out, as shown in Figure 1.11 below:

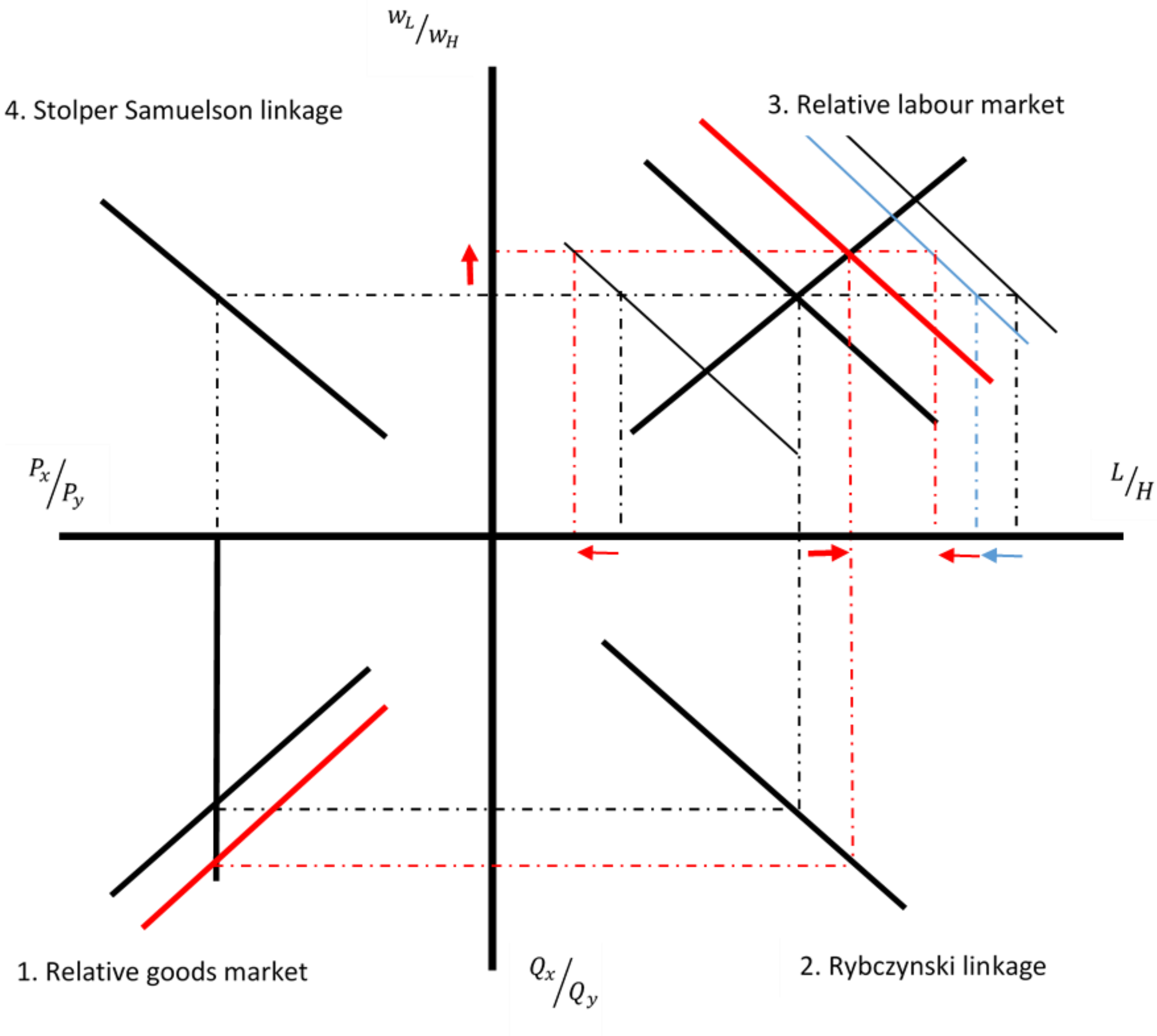

Figure 1.11 The productivity effect. The increased relative output of the X industry increases the national relative demand for low skilled labour, as well as their relative factor return (Arndt, 1998) Red colours show sector bias effect; Blue colours show factor bias effect

As can be seen in Figure 1.11, the outward shift in the relative demand for low skilled labour increases their relative factor return, $\frac{w_l}{w_h}$. While their relative employment on the national level $\frac{L}{H}$ has gone up as well, the relative employment of low skilled labour on the industry level, $\frac{L_i}{H_i}$, has actually gone down. This is due to the substitution of high skilled labour for low skilled labour due to the increased relative price of the latter. While it may seem counterintuitive that the relative employment of L can go up in the economy overall but down in both of its industries, it can be explained by the expansion in the X industry which releases more high skilled labour per low skilled labour from the contracting Y industry which will necessarily have to be absorbed in both industry X and Y. We can state this mathematically as:

$$Relative\ labour\ supply = \frac{\bar{L}}{\bar{H}} \uparrow = Relative\ labour\ demand = \frac{L_x}{H_x} \downarrow * \left(\frac{H_x}{\bar{H}}\right) \uparrow + \frac{L_y}{H_y} \downarrow * \left(\frac{H_y}{\bar{H}}\right) \downarrow \tag{1.20}$$

Where the increase in the X industry $\left(\frac{H_x}{\bar{H}}\right) \uparrow$ increases the country wide relative employment of low skilled labour $\frac{\bar{L}}{\bar{H}} \uparrow$. See Appendix 1.2 for more information as well as a numerical example of how this is possible.

1.4.2. Changing crucial assumptions

Now that we have framed the canonical model into the proposed figure, we can move on to show what happens if we change crucial assumptions that have sparked the wide range of literature outlined in the previous section. We will show what happens when we change the type of economy, the number of sectors and countries and different elasticities, explaining key models such as the ones by Krugman (2000), Grossman and Rossi-Hansberg (2008) and Xu (2001).

1.4.2.1. Type of economy

The assumption on the economy's ability to affect world prices has probably led to the largest ambiguity in the literature, exemplified in the debate between Leamer (1994) and Krugman (2000) about whether it is the sector or the factor bias of GVCs that ultimately affects the relative demand for skilled labour. While the previous section assumed a small open economy that is unable to affect world prices, we will now assume a large open economy that is able to affect world prices. We see that doing so introduces two additional effects: the price effect and the labour supply effect.

1.4.2.1.1. Price effect

While Xu referred to the productivity effect as the direct effect of technological change holding relative prices constant, she referred to an additional indirect effect which is only present when relative prices are not held constant. It therefore makes sense to follow the terminology by Grossman and Rossi-Hansberg and refer to this indirect effect as the price effect of offshoring. While Jones (1965) was the first to describe this channel, it was Krugman (2000) who used it to criticize the conventional model by Leamer (1994). Specifically, Krugman stated that in the "small open economy" scenario by Leamer (1994), factor supplies have no effect on factor prices since small open economies are able to accommodate changes in factor supplies via a reshuffling of production and that the demand for labour is therefore in effect infinitely elastic. A model that assumes infinitely elastic relative demand for factors of production cannot be used to show how relative wages change as a result of productivity changes. This can be shown graphically by not only exogenizing prices in the relative goods market but also exogenizing relative wages in the relative labour market (i.e. apply a horizontal line to relative demand for factors in Q3) in which case every $\frac{w_L}{w_H}$ refers to a unique $\frac{P_x}{P_y}$ (Figure 1.12).

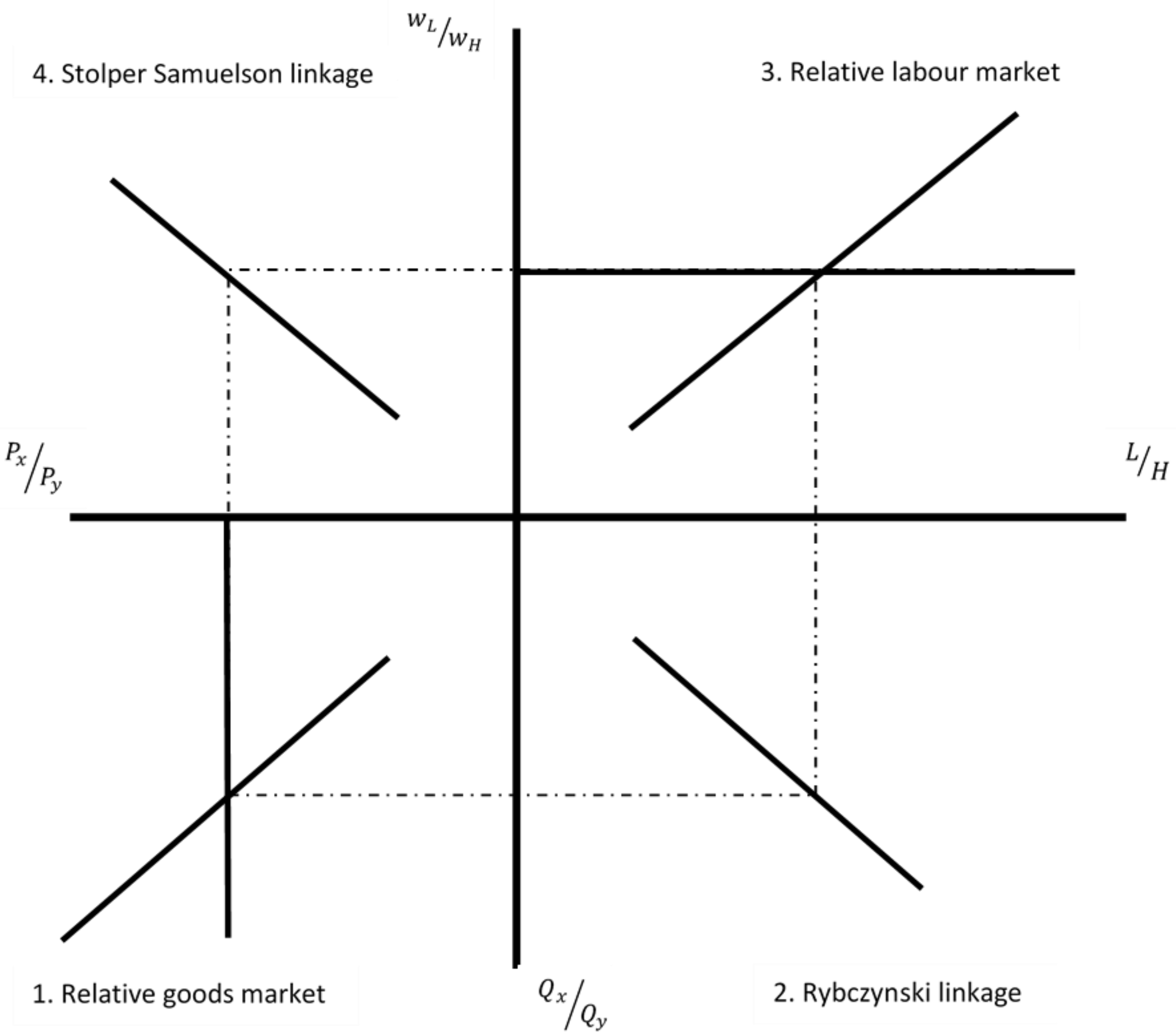

Figure 1.12 summarizes Krugman's (2001) criticism of Leamer's (1998) model, stating that in a small open economy, the relative demand for labour is in effect infinitely elastic due to the economy's ability to accommodate for changes in factor supplies (in Q4) by changes in relative sector outputs (Q1) via Rybczynski like reallocation (Q2)

Krugman (2000) then goes on to criticize Leamer (1994; 1998) on his assumptions of technological change happening in isolation in a country-industry with exogenous price determination by saying:

> *"Examining this scenario is a useful and indeed canonical classroom exercise, but it is not at all what people who attribute recent changes in factor prices to technology have in mind. Rather, what they have in mind is a change in technology that is occurring simultaneously in the United States, Western Europe, and perhaps elsewhere, that is in economies that are individually far from being price-takers on world markets, and that collectively may even be thought of as constituting an ''almost closed'' economy."(Krugman, 2000, p.58)*

Krugman continues by explaining that, in a large open or a closed economy with technological change happening worldwide, prices are determined endogenously. He further assumes a Cobb-Douglas production function so that preferences or $\eta = 1$. The implications of the sector bias effect can be shown again graphically:

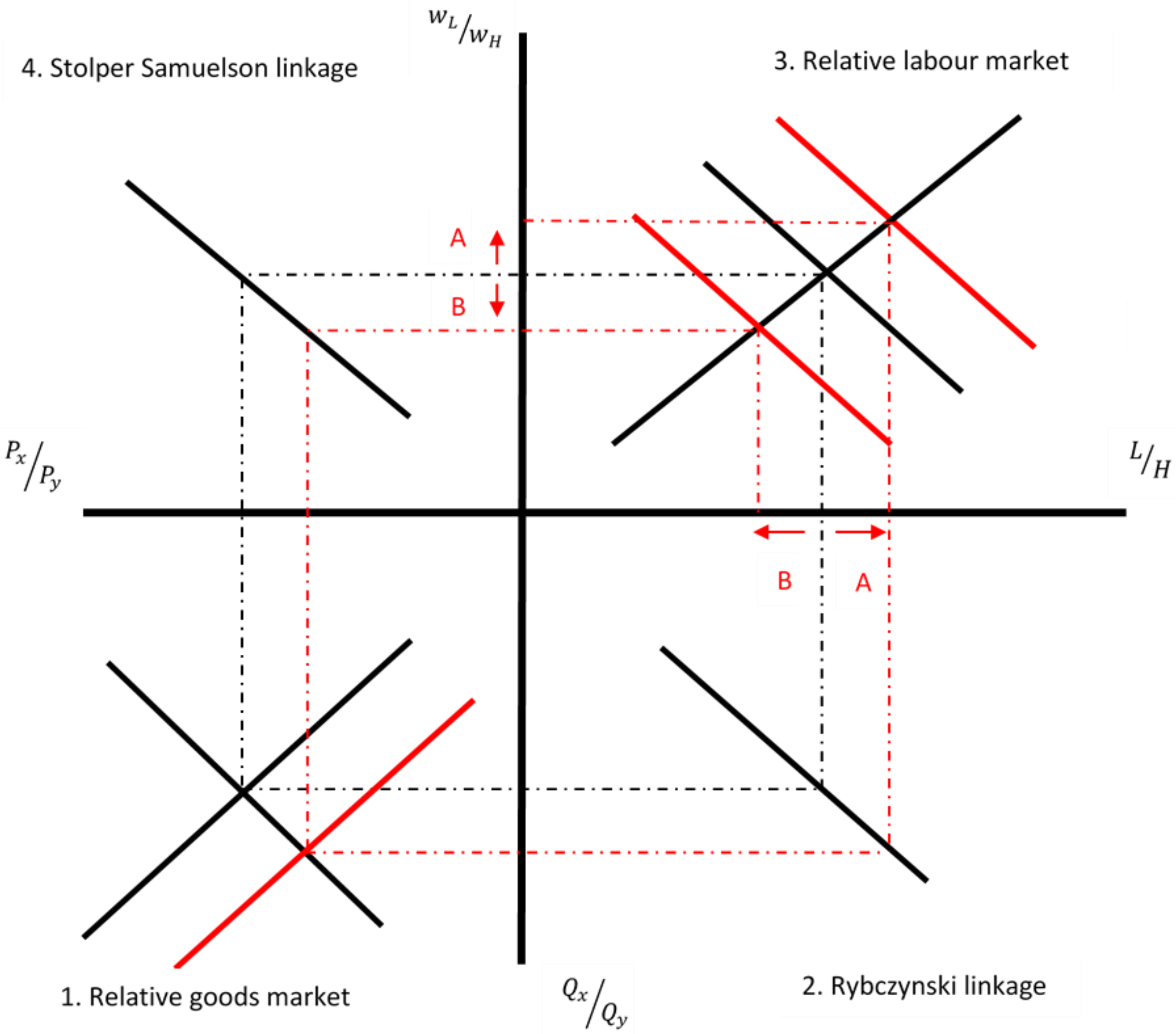

Figure 1.13 Assuming a large open economy with identical productivity changes across countries and Cobb-Douglas preferences, the productivity effect (via Q2, noted A) on the labour market (Q3) will be exactly offset by a price effect (via Q4, noted B) so that the sector bias does not affect the relative demand for skilled labour (Krugman, 2000) Red colours show sector bias effect; Blue colours show factor bias effect

While the dynamics from offshoring in the X industry via the Rybczynski effect on the relative labour market are exactly the same as outlined in Figure 1.11, there is now an additional effect, or “indirect effect” (Xu, 2001) captured by quadrant 4. That is, due to the decrease in $\frac{P_x}{P_y}$, the relative return for the factor of production used intensively in sector X,

$\frac{w_l}{w_h}$, will decrease. This can be shown in the relative factor markets as an *inward* shift of the RD curve. Further note that the productivity effect on the relative demand and factor return is marked with A, while the price effect is marked with the letter B. Under Cobb-Douglas preferences, $\eta = 1$, these two effects exactly cancel each other out (i.e. A=B), and sector bias of GVCs does not affect the relative demand for skilled labour (Krugman, 2000).

However, the factor bias of GVCs does affect the relative demand for skilled labour. Figure 1.10 already showed that offshoring X_2 shifted the relative demand for low skilled labour in the X industry inwards. While that was outdone by the sector bias effect, in this case it will affect the overall relative demand for skilled labour as the sector bias effect has cancelled out. Figure 1.14 shows the exact effects of the factor bias effect.

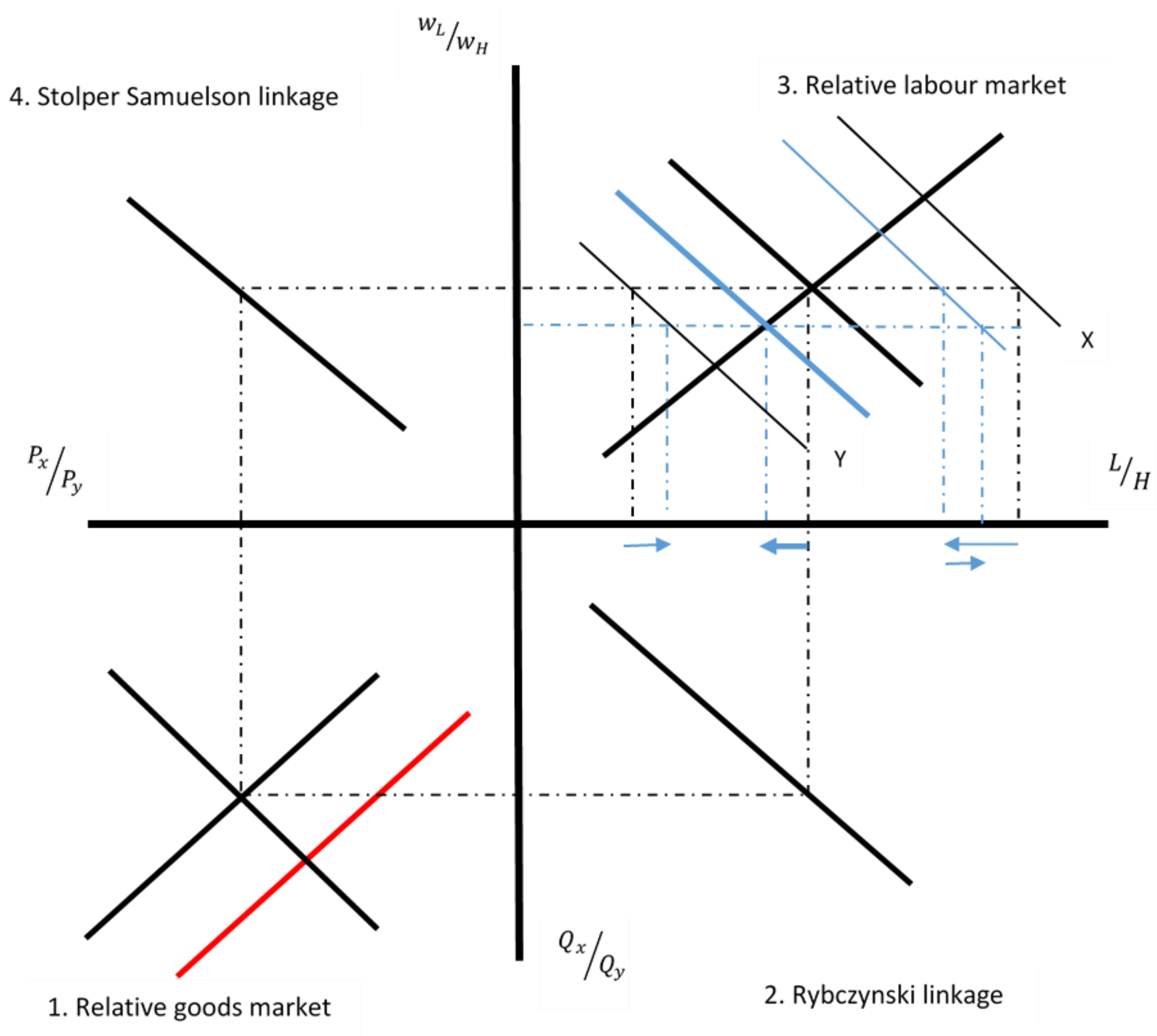

Figure 1.14 In a large open economy, only the factor bias affects the relative demand for skilled labour (Krugman, 2000). Red colours show sector bias effect; Blue colours show factor bias effect

Note that the skill intensity in the X industry has increased as a result of offshoring X_2, shifting $RD\frac{L_x}{H_x}$ inwards. Since there is no productivity effect, the weighted average $RD\ \frac{L}{H}$ will shift in as well decreasing $\frac{w_l}{w_h}$ and $\frac{L}{H}$. This in turn has a knock-on effect on the relative employment within industries. Namely, the decreased $\frac{w_l}{w_h}$ will lead to a substitution effect within sectors X and Y, increasing the relative demand for low skilled labour. Note that while sector Y will unambiguously become less skilled intensive, sector X can become either more skilled or unskilled intensive. In Figure 1.14, the factor bias effect outweighed the substitution effect. As shown by Xu (2001), that depends on the elasticity of factor substitution, σ. When that is relatively elastic (σ>1), the substitution effect will indeed dominate. However, when the elasticity of factor substitution is relatively inelastic (σ<1), the factor bias effect will dominate. This will be shown in section 1.4.2.3., where the importance of elasticities will be discussed.

1.4.2.1.2. Labour supply effect

There is an additional effect if we assume a large open economy that is referred to as the labour supply effect (Grossman and Rossi-Hansberg, 2008) or shadow migration (Baldwin and Robert-Nicoud, 2007). By offshoring the low skilled intensive part of good X to the low wage South, the home country frees up domestic low skilled labour which effectively increases its relative supply[15]. This effect can be shown graphically by shifting out the relative supply curve of low skilled labour to the right, decreasing their relative wage. This will lead to a feedback effect on the goods market via the traditional Rybczynski effect. Namely, by increasing the endowment factor of production L, the relative production of the good that uses this factor intensively should increase. However, as explained by Grossman and Rossi-Hansberg (2008) as well as Feenstra (2010, p. 39): "the effective increase in low-skilled labor due to the productivity effect cannot be absorbed by Rybczynski like reallocation across sectors, and instead will lead to a fall in the relative wage of low-skilled labor". In other words, the mechanism demonstrated in Figure 1.12 will break down and relative demand in both the labour and the goods market will actually be downward sloping. Therefore, the increase in the relative supply of low skilled labour will lower its factor return as indicated by quadrant 3.

[15] Alternatively, as explained before, one can follow the Baldwin-Robert Nicoud (2007) rationale that this effect is just like shadow migration in that, via offshoring, one can access low skilled labour abroad, while still using superior domestic technology, machinery and other skills.

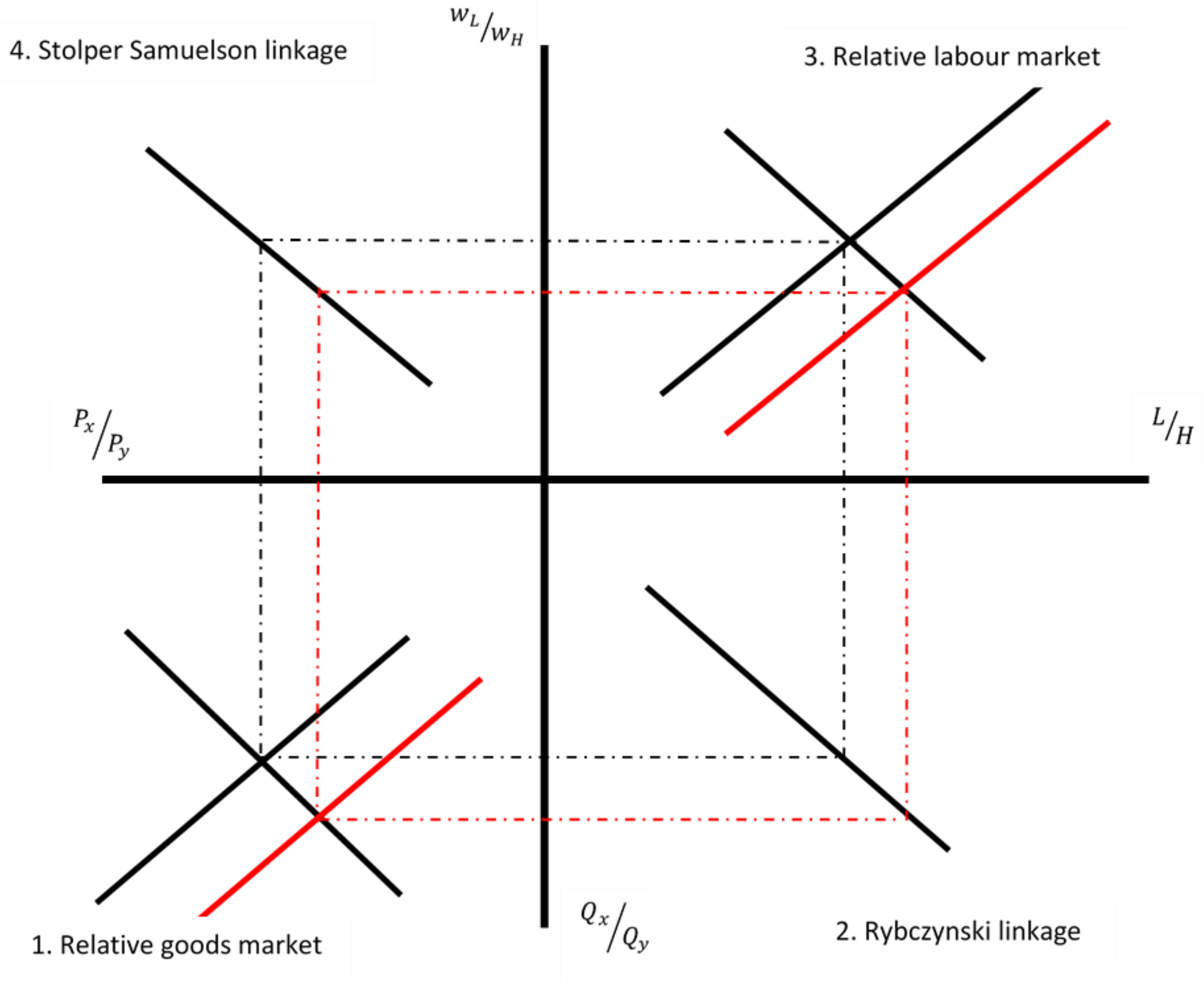

Figure 1.15 The labour supply effect

1.4.2.2. Number of sectors and countries

In the previous section (1.3.2. Changing crucial assumptions), it was shown that changes in the number of sectors, by either going from two to three (Davis 1996) or one sector (Feenstra and Hanson, 1996) as well as the number of countries from two to three (Khalifa and Mengova, 2010) had significant effects on the prediction of the model. With the proposed figure, we can once again overcome this ambiguity by putting aside the microeconomic details and focus instead on the main point of these models which is that perceived changes in the relative demand for skilled labour depend on the country's relative abundance of skilled labour. Therefore, what might be low skilled intensive for one country, could be perceived as high skilled intensive for a country that is less skill-abundant than the first. This can simply be shown in the Figure by changing its starting point. For example, while we have used Figure 1.11 to explain what will happen to the relative demand for skilled labour in the North when it offshores the low skilled intensive tasks of the low skilled intensive sector, it equally applies to relatively skill abundant Southern countries, as per the models of Khalifa and Mengova (2010) as well as Davis (1996).

1.4.2.3. Sector bias effect depends ultimately on price elasticity of demand substitution

The debate between Leamer (1996) and Krugman (2000) has been explained by referring to the type of economy we assume, i.e. a small open economy vs. a large open economy. The critical difference between these two scenarios is the price elasticity of demand substitution in the relative goods market. Xu (2001) described at length how both scenarios represent two extremes on a spectrum of possible outcomes. Remember that the sector bias affects relative wages via the productivity and the price effect. The extent to which those two effects matter depends on the price elasticity. With infinitely elastic price elasticity ($\eta=\infty$), only the productivity effect in quadrant 2 affects relative wages and employment as we saw in Figure 1.11. In contrast, assuming Cobb-Douglas preferences ($\eta=1$) both the productivity and price effect affect relative wages in a way that they exactly offset each other (Figure 1.13). Naturally, we can show that if preferences are relatively elastic ($\eta>1$) the productivity effect will dominate the price effect (Figure 1.16), whereas relatively inelastic preferences ($\eta<1$) would allow the price effect to dominate (Figure 1.17).

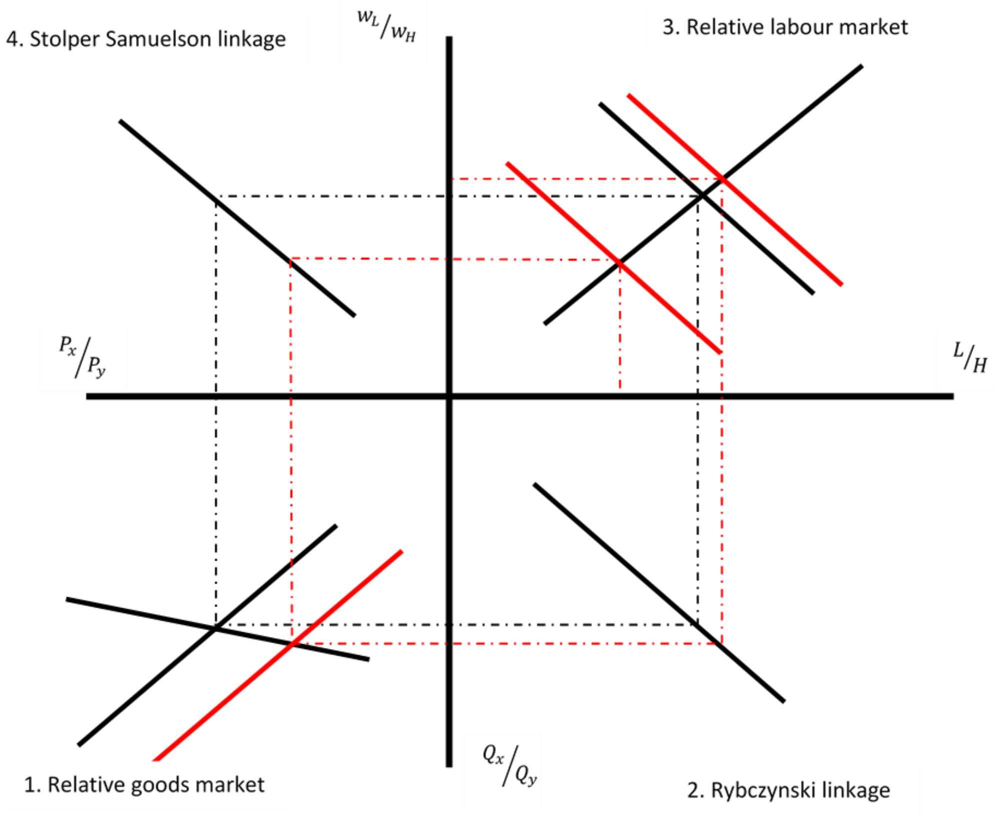

Figure 1.16. With elastic price substitution, the price effect (via quadrant 4) outweighs the productivity effect (via quadrant 2) on the relative demand for skilled labour (in quadrant 3). (Xu, 2001)

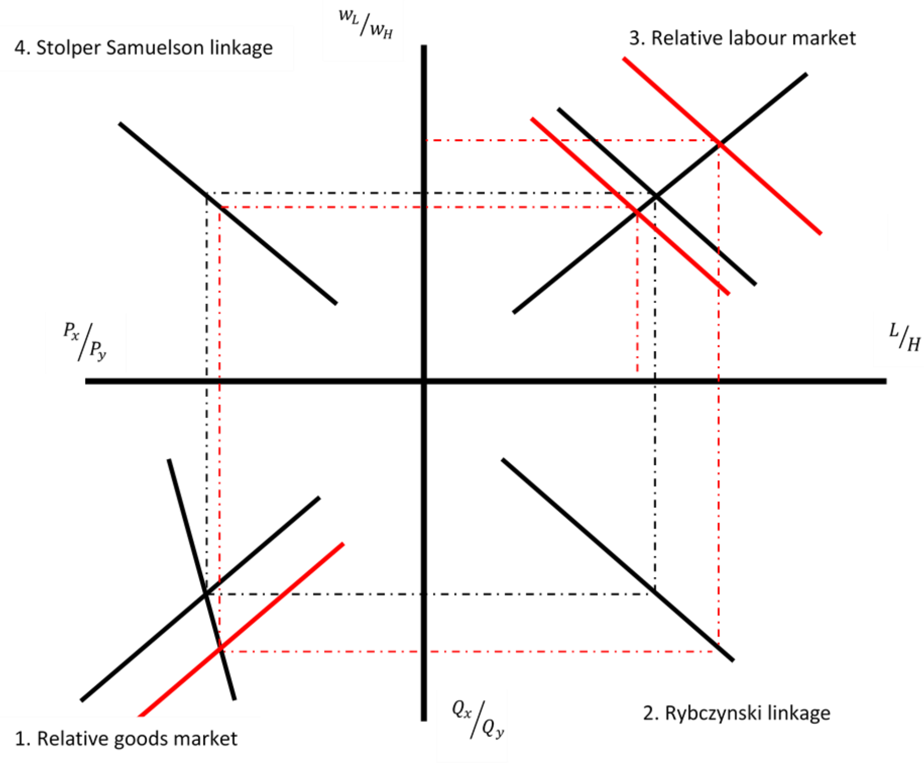

Figure 1.17. With inelastic price substitution, the productivity effect (via quadrant 2) outweighs the price effect (via quadrant 4) on the relative demand for skilled labour (quadrant 3) (Xu, 2001)

Further note that the labour supply and the factor bias effects are omitted in these figures for clarity. We could sketch them however and show that the increased relative supply of $\frac{L}{H}$ as a result of the former as well as the decreased demand for $\frac{L}{H}$ as a result of the latter, would decrease $\frac{w_L}{w_H}$. In terms of employment, the labour supply would increase $\frac{L}{H}$ while the factor bias effect would decrease it. In terms of within industry relative employment $\frac{L_X}{H_X}$ and $\frac{L_Y}{H_Y}$, substitution effects due to lower $\frac{w_L}{w_H}$ would increase those ratios. These results are left out of this diagram to see clearly the relative importance of the productivity and price effect, dependent on elasticities of price substitution.

Finally, we can show the importance of the factor substitution elasticity, which will determine whether the offshoring or the consequent substitution effect will dominate the relative skill intensity in industry X. Firstly, offshoring X_2 will increase the skill intensity in industry X, leading to an inward shift of the relative demand curve for low skilled labour in the X industry, illustrated with the blue relative demand for industry X line. The new equilibrium relative employment ratio in industry X is indicated by $\frac{L_{X'}}{H_{X'}}$. Assuming Krugman (2000) that the productivity effect is completely offset by a price effect, country wide $\frac{L}{H}$ will decrease as a result of the shift in industry X, indicated by the inward shift of the relative demand curve for economy wide $\frac{L}{H}$. This leads to a new and lower relative factor return equilibrium $\frac{w_L}{w_H}*$ which will ignite a substitution effect within industry X, indicated by a movement along the RD $\frac{L_{X'}}{H_{X'}}$ curve to point $\frac{L_{X''}}{H_{X''}}$. Which force dominates, the direct factor bias effect or the indirect substitution effect, depends on the elasticity of factor substitution. Figure 1.18 assumes relatively elastic factor substitution where the substitution effect dominates, while Figure 1.19 assumes relatively inelastic factor substitution where the offshoring effect dominates. More detailed information along with a numerical example is once again provided in Appendix 1.2.

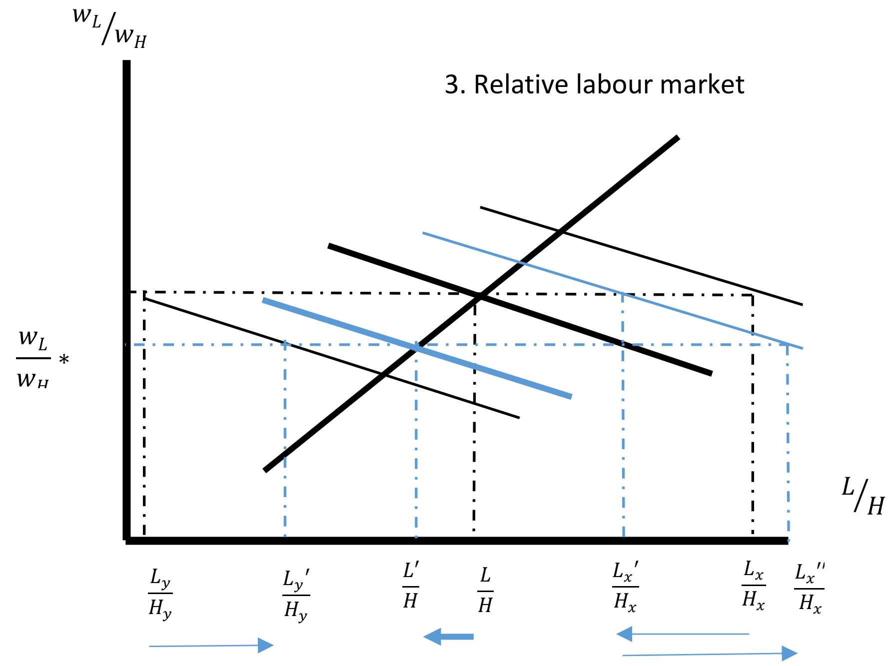

Figure 1.18. With relatively elastic factor substitution, the substitution effect will outweigh the factor bias effect in sector X, making the production ultimately less skilled intensive (Arndt, 1997)

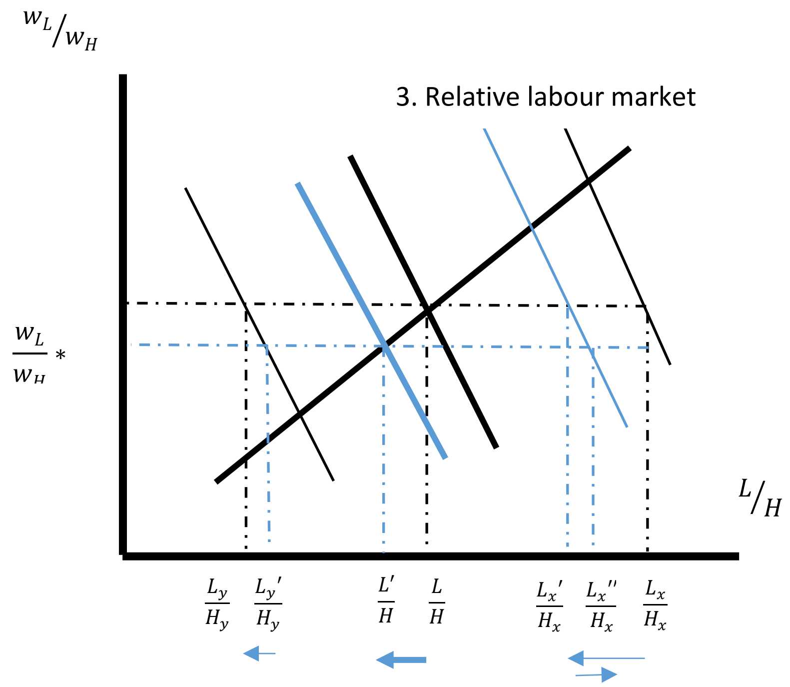

Figure 1.19 With relatively inelastic factor substitution, the factor bias effect will outweigh the substitution effect in sector X, making the production ultimately more skilled intensive

1.4.2.4. Provided insights for an Empirical framework

This section summarizes the effects of international production sharing on the relative wage $\left(\frac{w_L}{w_H}\right)$ and employment $\left(\frac{L}{H}\right)$ of low skilled labour, following various assumptions. As will become apparent, the relative importance of the sector bias (via the price and productivity effect), the factor bias (by specialising in a specific task) and the substitution effect (as a result of a change in relative wages) depends crucially on the elasticities of goods and factor substitution. Throughout this Chapter, we have followed the example that the production of a single final good X could be fragmented into a relatively skill intensive part X_1 and a relatively low skill intensive part X_2. Due to this fragmentation, countries can specialise in those intermediate tasks that they, based on their relative skill endowment, have a comparative advantage in. As a result, the North (South) will specialise in the production of X_1 (X_2) by offshoring the production of X_2 (X_1) to the South (North) and simultaneously inshore, or receive, task X_1 (X_2) from the South (North). Therefore, when the factor bias of the GVC activities in Table 1.3 is high (low) skilled, meaning the country specialises in the high (low) skilled activities of a global value chain, the results can be interpreted as the effect of engaging in GVCs by the North (South).

Besides a breakdown of the sector and factor bias of the activities countries specialise in via GVCs, the table is further broken down by the elasticities of goods substitution and factor substitution. The former one determines the relative strength of the productivity and the price effect, while the latter determines the relative strength of the substitution versus the factor bias effect.

Starting with the extreme case where the demand elasticity in the goods market is infinitely large (η=∞), the sector bias (Leamer, 1994), direct effect (Xu, 2001) or productivity effect (Grossman and Rossi-Hansberg, 2009) will solely determine the effect of GVCs on the relative demand for skilled labour. In line with Figure 1.11, low skilled labour will benefit, increasing their relative return $\frac{W_L}{W_H}$ as well as their country wide employment levels $\frac{L}{H}$. On an industry level, due to the decreased wage premium, substitution will make each industry more skilled intensive, as high skilled labour has become relatively cheaper. Therefore, within industries X and Y, the relative employment of low skilled labour, $\frac{L_i}{H_i}$, will go down. In the Y industry, this is driven solely by the substitution effect. In the X industry, it is driven both by the substitution and the factor bias effect of specialising in X_1. Note that if the country would specialise in X_2 instead, the substitution effect and the factor bias effect would contradict each other. In that case, it depends ultimately on the elasticity of factor substitution which effect will dominate: with relatively inelastic (elastic) factor substitution, the factor bias effect will be greater (less) than the substitution effect so that the X industry will be less (more) skill intensive than before specialising in X_2.

When preferences are Cobb-Douglas, the price effect exactly offsets the productivity effect, and only the factor bias of GVCs affects relative return and endowment changes (Krugman, 2000). Assuming again that the factor bias of the GVC specialisation is high skilled (i.e. the country specialises in the production of in X_1), the relative demand for low skilled labour within the X industry will fall $\frac{L_X}{H_X}\downarrow$, and accordingly will the weighted average $\frac{L}{H}$ fall. Because $\frac{L}{H}$ falls, relative wages $\frac{W_L}{W_H}$ will fall as well. As before, this causes a substitution effect within industries, which will start to hire relatively more high skilled workers, who have gotten relatively less expensive. As before, this will make the Y industry unambiguously less skilled intensive as it only experiences the substitution effect. The X industry, however, also experiences the factor bias effect. As before, with relatively inelastic (elastic) factor substitution, the factor bias effect of specialising in X_1 will be greater (less) than the substitution effect, so that the X industry will be more (less) skill intensive than before specialising in X_1.

In the next scenario, we assume relatively inelastic demand (*η<1*), where the price effects dominates the productivity effect (Figure 1.16). As a result, the positive productivity effect on relative wages, $\frac{W_L}{W_H}$, is more than offset by the price effect, so that the relative demand for low skilled labour $\frac{L}{H}$ will decrease. On the industry level, relative employment of $\frac{L_i}{H_i}$ will go up because of the substitution effect resulting from the lower wage premium: $\frac{W_L}{W_H}\downarrow$. In sector X, however, the increased skill intensity after specialising in X_1 decreases the relative use of low skilled labour so that it depends again on the elasticity of factor substitution. Relatively inelastic (elastic) factor substitution makes the factor bias effect dominate the substitution effect so that relative employment of $\frac{L_X}{H_X}$ will decrease (increase). Finally, when preferences are relatively elastic (η>1), the exact opposite of the aforementioned scenario will occur (Figure 1.17).

Table 1.3: The effects on relative wages $\frac{w_L}{w_H}$ and employment $\frac{L}{H}$ of low skilled labour as a result of specialising in the high (low) skilled intensive activities of the low skilled sector X under different preferences. Note that the effects of labour supply have been omitted in this analysis.

Sector bias	Factor bias	Preferences η	Relative wages $\frac{w_L}{w_H}$	Relative employment $\frac{L}{H}$		
				National level	Industry X	Industry Y
X	High (X_1)	η=∞[16]	+/+	+/+	-/-	-/-
X	Low (X_2)		+/+	+/+	σ>1 -	-/-
					σ<1 +	
X	High (X_1)	η=1	-	-	σ>1 +	+
					σ<1 -	
X	Low (X_2)		+	+	σ>1 -	-
					σ<1 +	
X	High (X_1)	η<1	-	-	σ>1 +	+
					σ<1 -	
X	Low (X_2)		-	-	+	+
X	High (X_1)	η>1	+	+	-	-
X	Low (X_2)		+	+	σ>1 +	-
					σ<1 -	

1.5. Concluding remarks

By reviewing the literature on the effects of GVCs on the relative demand for skilled labour, this Chapter has shown the ambiguity that exists in this field. Table 1.3 tries to summarize the main channels by which GVCs affect the relative demand for skilled labour. It shows how the sector bias effect (via the productivity and price effect), the factor bias effect (by specialising in a particular task) and the substitution effect ultimately determine the effect of GVCs on the relative demand for skilled labour. The relative magnitude of these effects in turn depends on the elasticity of goods and factor substitution. Xu (2001) and Grossman and Rossi-Hansberg (2008) have provided theoretical models that delve deeper into specifying this relative magnitude but unfortunately, this discussion may still be confusing and complex to the uninformed reader.

[16] In the case of infinitely elastic substitution for demand, this economy can be considered a small open economy with no power to influence world prices. This is the standard model as considered by Leamer (1994), Arndt (1998), Jones and Kierzkowski (2001), Yamashita (2010) and others and illustrates the sector bias of offshoring.

Therefore, the novelty of this Chapter is that it provides a graphical exposition of these effects which can be used as an intuitive way to synthesize a wide range of literature. It can be used to show how small changes in the microeconomic foundations of various models has crucial effects on the key prediction. In doing so, it naturally serves as a tool to illustrate various models. Amongst those is the model by Grossman and Rossi-Hansberg (2008), who identify a productivity, a price and a labour supply effect. These effects can be illustrated intuitively into the proposed figures, in quadrants 2, 4 and 3 respectively. In addition, the figure can be used to illustrate the ongoing debate whether it is the sector or the factor bias of a productivity improvement that affects relative factor returns, by referring to the elasticity of goods substitution illustrated by the slope of the relative demand for goods X and Y in quadrant 1.

By providing such an intuitive and visual framework, this framework can be used by (graduate) students and policy makers alike, to understand the key dynamics between GVCs and the relative demand for skilled. Secondly, academics can use this framework to provide insights for empirical analyses, as outlined in the previous section. This thesis will do the same in Chapters 2 and 3, where micro and macro level data, respectively, are employed to empirically examine the relationship between GVCs and the relative demand for skilled labour. There, it will become evident that conditioning any empirical analysis on the sector and factor bias of the GVCs is critical.

Appendix 1.1: The productivity effect

On page 23, the sector bias effect was demonstrated by showing how an increase in the productivity parameter a_{ij} will lead to an increase in the total factor productivity of the sector that experiences the productivity increase. This section elaborates on this demonstration.

Since we assume perfect competition, profits will be zero and thus costs will equal price as in:

$$C_i = P_i = \sum_{j=H,L} a_{ij} \cdot w_j \tag{1.21}$$

Taking the total derivative of the price function we get:

$$dp_i = \sum_j \left(a_{ij} \cdot dw_j + w_j \cdot da_{ij}\right) \tag{1.22}$$

Which can be rewritten as:

$$dp_i = \sum_j \left(a_{ij}w_j \cdot \frac{dw_j}{w_j} + w_j a_{ij} \cdot \frac{da_{ij}}{a_{ij}}\right) \tag{1.23}$$

Dividing this by p_i and using Jones algebra (1965) this can be rewritten as:

$$\widehat{p_i} = \sum_j \left(\frac{a_{ij}w_j}{p_i} \cdot \widehat{w}_j + \frac{w_j a_{ij}}{p_i} \cdot \hat{a}_{ij}\right) \tag{1.24}$$

Substituting p_i for c_i:

$$\widehat{p_i} = \sum_j \left(\frac{a_{ij}w_j}{c_i} \cdot \widehat{w}_j + \frac{w_j a_{ij}}{c_i} \cdot \hat{a}_{ij}\right) \tag{1.25}$$

Since we defined θ_{ij} as the share of labour type j in total costs $\left(\frac{a_{ij} \cdot w_j}{c_i}\right)$, we can further specify:

$$\widehat{p_i} = \sum_j \theta_{ij} \cdot \widehat{w}_j + \sum_j \theta_{ij} \cdot \hat{a}_{ij} \tag{1.26}$$

We can then differentiate the input intensity $\sum_j \theta_{ij} \cdot \hat{a}_{ij}$ to obtain:

$$\hat{a}_{ij} = \hat{x}_{ij} - Q_i \tag{1.27}$$

Using this and the standard measurement for TFP growth implies:

$$TFP_i = \widehat{Q_\iota} - \sum_j \theta_{ij} \cdot \hat{x}_{ij} = -\sum_j \theta_{ij} \cdot \hat{a}_{ij} \tag{1.28}$$

So that:

$$\widehat{p_\iota} + TFP_i = \sum_j \theta_{ij} \cdot \widehat{w}_j \tag{1.29}$$

Appendix 1.2: Across industry downgrading but within industry upgrading

On page 23, it was also stated that offshoring the low skilled intensive part in the low skilled industry: X_2 would naturally increase the skill intensity in that industry, it would decrease the skill intensity in the country as a whole. Recall that one can follow Feenstra and Taylor (2008) who show that the relative supply and demand for labour can be written as:

$$Relative\ labour\ supply = \frac{\bar{L}}{\bar{H}} = Relative\ labour\ demand = \frac{L_x}{H_x} * \left(\frac{H_x}{\bar{H}}\right) + \frac{L_y}{H_y} * \left(\frac{H_y}{\bar{H}}\right) \quad (1.20)$$

One can think of this equation as a weighted average of the skill intensities in industry X, $\frac{L_x}{H_x}$ and industry Y, $\frac{L_y}{H_y}$, weighted by their respective sizes: $\left(\frac{H_x}{\bar{H}}\right)$ and $\left(\frac{H_y}{\bar{H}}\right)$. The various effects are best illustrated by using a numerical example. Assume we start from the following situation where L is low skilled workers, H is high skilled workers, X is the L-intensive industry and Y is the H-intensive industry.

Table 1.4 Starting situation

	L-workers	H-workers	Total workers	Employment share of L labour	L/H
X industry	80	20	100	0.8	4
Y industry	20	80	100	0.2	0.25
Total workers	100	100	200	0.5	1

Then, applying equation (1.20) to Table 1.4, we get:

$$\frac{100}{100} = \frac{80}{20} \cdot \frac{20}{100} + \frac{20}{80} \cdot \frac{80}{100}$$

We now assume, following the example in the text above, that X can be broken up into a low skill-intensive intermediate task and a relatively high skill-intensive intermediate task and that the former is offshored to a less skill abundant country. This has a sector bias effect as well as a factor bias effect. Firstly, the factor bias effect results from offshoring the low skill insensitive tasks within the low skilled industry: X_2, the skill intensity of the overall good would naturally and directly increase. As described by Arndt (1997) using a Lerner-

Pearce diagram, this outsourcing effect would turn the expansion path of the X industry counter clockwise, here indicated as $\frac{L_x}{H_x}$.

At the same time, however, the cost savings that originate from this activity will act as a productivity increase throughout the sector, much like the effect of a technological improvement, causing the sector to expand, indicated by $\left(\frac{H_x}{\bar{H}}\right)$. Applying this rationale to the numbers in Table 1.4 we get:

Table 1.5 Effects on relative employment of a GVC-induced productivity effect

	L-workers	H-workers	Total workers	Employment share of L labour	L/H
X industry	90	30	120	0.75	3
Y industry	20	60	80	0.25	0.33
Total workers	110	90	200	**0.55**	**1.22**

Where:

$$\frac{110}{90}\uparrow = \frac{90}{30}\downarrow \cdot \frac{30}{90}\uparrow + \frac{20}{60}\downarrow \cdot \frac{60}{90}\downarrow$$

This immediately shows that an economy can experience industry specific upgrading $\frac{L_x}{H_x}\downarrow$ and $\frac{L_y}{H_y}\downarrow$, and economy wide downgrading $\frac{\bar{L}}{\bar{H}}\uparrow$ so that the claim on page 23 is validated.

We have not yet reached equilibrium however. Namely, the expansion of industry X and the consequent increase in relative demand for $\frac{\bar{L}}{\bar{H}}$ will increase their respective relative factor return: $\frac{w_L}{w_H}$. This, in turn, will lead to a substitution effect where firms substitute low skilled labour for high skilled labour, within both industries $\frac{L_i}{H_i}\downarrow$, which was illustrated in figures X, and X, for example. The magnitude of this substitution effect depends on the elasticity of factor substitution σ. As shown by Arndt (1997) and Xu (2001), relatively inelastic factor substitution would undermine the productivity effect and $\frac{\bar{L}}{\bar{H}}$ would still exceed the original $\frac{100}{100}$ ratio. Let's assume, for example:

Table 1.6. The substitution effect on relative employment, under relatively inelastic factor substitution

	L-workers	H-workers	Total workers	Employment share of L labour	L/H
X industry	89	31	120	0.74	2.8
Y industry	17	63	80	0.21	0.33
Total workers	106	94	200	**0.53**	**1.13**

$$\frac{106}{94}\downarrow=\frac{89}{31}\downarrow\cdot\frac{31}{94}+\frac{17}{63}\downarrow\cdot\frac{63}{94}$$

Which was illustrated graphically in Figure 1.19. Figure 1.18, on the other hand, shows a situation where the substitution effect is sufficiently large such that $\frac{\bar{L}}{\bar{H}}$ would be less than the original $\frac{100}{100}$ ratio (Table 1.7):

Table 1.7 The substitution effect on relative employment, under relatively elastic factor substitution

	L-workers	H-workers	Total workers	Employment share of L labour	$\boldsymbol{L/H}$
X industry	86	34	120	0.71	2.5
Y industry	16	64	80	0.2	0.25
Total workers	88	112	200	**0.44**	**0.79**

Appendix 1.3: Inverse Rybczynski

While the Rybczynski theorem explains how absolute outputs will change as a result of absolute endowment changes, quadrant 2 of Figure 1.10 shows how relative endowment will change as a result of relative output changes. Specifically, page 18 states that the relative demand for low skilled labour in terms of high skilled labour, $\frac{\bar{L}}{\bar{H}}$, would increase if the relatively low skilled intensive industry, Q_x, would expand at the expense of the high skilled industry, Q_x, or:

$$\frac{\partial \frac{\bar{L}}{\bar{H}}}{\partial \frac{Q_x}{Q_y}} > 0 \tag{1.30}$$

Although this result makes intuitive sense (increasing the weight of a relatively more skilled intensive industry should increase the weighted average), it can be proven mathematically as well by referring to the full employment conditions, which can be described as:

$$\bar{L} = a_{XL}Q_X + a_{YL}Q_Y \tag{1.31}$$

$$\bar{H} = a_{XH}Q_X + a_{YH}Q_Y \tag{1.32}$$

Further, we have assumed that high skilled labour is more productive than low skilled labour, in both industries. Remember that we defined productivity, a_{ij}, as the amount of *j* needed to produce 1 unit of *i*. Therefore, higher productivity would be indicated by lower a_{ij} values and:

$$a_{iL} > a_{iH} \tag{1.33}$$

We can show how the endowment of low skilled labour $\bar{L}$ will change as a result of a change in the relative output of $\frac{Q_x}{Q_y}$, by first reorganizing (1.31), and then taking the derivative w.r.t. $\frac{Q_x}{Q_y}$:

$$\frac{\bar{L}}{Q_y} = \frac{a_{XL}Q_X + a_{YL}Q_Y}{Q_y} \tag{1.34}$$

$$\frac{\bar{L}}{Q_y} = a_{XL}\frac{Q_X}{Q_y} + a_{YL} \tag{1.35}$$

$$\bar{L} = a_{XL}\frac{Q_X}{Q_y} \cdot Q_y + a_{YL} \cdot Q_y \tag{1.36}$$

Which allows us to take the derivative of $\bar{L}$ w.r.t. $\frac{Q_x}{Q_y}$:

$$\frac{\partial \bar{L}}{\partial \frac{Q_X}{Q_y}} = a_{XL} \cdot Q_y \tag{1.37}$$

We can do the same for (1.32), which would yield:

$$\frac{\partial \bar{H}}{\partial \frac{Q_X}{Q_y}} = a_{XH} \cdot Q_y \tag{1.38}$$

From equation (1.33), we know that $a_{iL} > a_{iH}$ implying that $\frac{\partial \bar{L}}{\partial \frac{Q_X}{Q_y}} > \frac{\partial \bar{H}}{\partial \frac{Q_X}{Q_y}}$. In other words, the increased demand for L, as a result of the *relative* expansion of the X industry, would exceed the increased demand for H. Finally, we can rewrite this in relative employment terms as:

$$\frac{\partial \frac{\bar{L}}{\bar{H}}}{\partial \frac{Q_x}{Q_y}} > 0 \tag{1.39}$$

Chapter 2

The effect of Global Value Chains on the skill composition of the workforce of firms in developing countries

Loe Franssen♦

Abstract:

Using data from the World Bank Enterprise Surveys on 115.000 firms in 135 developing countries over the period 2006-2015, this Chapter analyses the relationship between firms' engagement in global value chains and the skill composition of their workforce. Using a translog cost function, we proxy for GVC engagement in 3 ways. Firstly, we follow Shepherd and Stone (2013) by using an interaction term between 2 dummy variables that determine whether a firm imports any of its inputs and exports any of its outputs. The results show that this proxy for GVC engagement is significantly correlated with higher skilled workforces, robust to 4 different proxies for skill. Since the effect of GVCs on relative skill-employment levels crucially depends on its sector and factor bias, we separate the sample on the basis of the skill intensity of the industry as well as the skill abundance of the country the firm is active in. Doing so demonstrates that the skill premium is especially apparent in firms active in low skilled abundant countries, providing proof of a factor bias effect. Since this proxy would include firms that import inputs solely used for the production of goods sold domestically and export goods purely made of domestic inputs, we examine the continuous nature of the import and export variables further. Here we find that at higher levels of GVC engagement, firms tend to hire significantly less skilled workers, which can be explained by the specific type of GVC engagement we are identifying: assembly work. In the end, we use instrumental variables to exclude any form of endogeneity that might arise as a result of omitted variable bias, self-selection bias, or reverse causality. The results confirm the baseline correlations and also conclude on the direction of the correlation i.e. that GVC engagement *causes* changes in skill structures as opposed to the other way around.

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2.0. Introduction

The previous Chapter concluded that there is a large ambiguity, both theoretically and empirically, about the effect of GVCs on the relative demand for skilled labour. As the theoretical implications depend largely on the micro foundations of the model chosen (Feenstra, 2010), the literature has often resorted to searching for empirical evidence instead. However, as Chapter 1 showed as well, this evidence is both mixed and, in the case of developing countries, scarce (Hansen, Schaumburg-Müller and Pottenger, 2008). Chapter 1 then looked at factors that could explain this empirical ambiguity and concluded that empirical analyses should condition their findings on both the sector and factor bias of the GVC activity. This Chapter will take that lesson into account by empirically analysing the relationship between developing country firms' GVC engagements and the skill intensity of their workforce. In doing so, this Chapter intends to contribute to the literature in a number of ways.

Since there is a significant research gap into the effect of GVCs on the relative demand for skilled labour in developing countries (Hansen et al., 2008), the first contribution comes from the dataset that is being used. Namely, the World Bank Enterprise Surveys[17] provide repeated cross sectional data on 115.000 firms in 135 developing countries that allows to construct various proxies for firms being engaged in GVCs. This data is underexploited as only a few papers (Fajnzylber and Fernandes, 2009; Shepherd and Stone, 2013) have used it to estimate the effect of GVCs on skill employment shares. We will initially follow Shepherd and Stone (2013) by identifying firms that are engaged in GVCs as those firms that import at least some (more than zero percent) of their inputs from abroad and export some of their outputs as well. Here, we find that such firms tend to employ relatively more skilled workers. This Chapter, however, extends their analysis in several ways.

Firstly, we condition these results on the sector and factor bias of the GVC activity. Here, we find evidence of a significant factor bias effect, as the skill upgrading effect is largest in relatively skill abundant countries that would naturally specialise in the higher skilled intensive part of a global value chain. Firms in low skilled abundant countries, on the other hand, tend to experience a skill downgrading effect once they engage in GVCs. The sector bias, i.e. the skill intensity of the industry that engages in GVCs does not seem to affect this relationship.

[17] (http://www.enterprisesurveys.org), The World Bank.

The second contribution is related to the identification of firms that are engaged in GVCs, which we shall refer to as GVC firms. The initial proxy for identifying GVC firms, taken by following Shepherd and Stone (2013), is not perfect as it would include firms that import intermediates that are purely used in the production of goods sold domestically as well as firms that export goods made purely out of domestic inputs. Since GVC engagement necessarily includes both an import and an export side (See Hummels, Yi and Ishii (2001) and Baldwin & Lopez-Gonzalez (2015) for example), this proxy could include firms not specifically engaged in GVCs. Therefore, we increase the requirement for firms to be identified as GVCs as those firms that import at least 90% of their inputs and export at least 90% of their outputs. This significantly increases the likelihood that their exported goods are made out of imported inputs and the firm is thus engaged in GVCs. When doing so, we find that the earlier identified skill premium disappears. Indeed, we even find some evidence that engaging in this form of GVCs tends to be associated with significantly *lower* skilled workforces.

This result is confirmed in a third step, where we construct a continuous interaction variable between importing inputs and exporting outputs. While the main effects of each variable are positively related to the skill intensity of the workforce, the interaction term is significantly negative. we then show that at higher levels of imports (exports), the significantly positive effect of export (imports) on the skill composition of the workforce dissipates and even become significantly negative. This finding further confirms that at increased levels of GVC engagement, the skill composition of the workforce decreases, rather than increases.

The final contribution refers to direction of these correlations. To our knowledge, this Chapter is the first work that investigates the causation of GVCs on the relative demand for skilled labour among developing country firms. This is done by using instrumental variables to exclude any potential endogeneity arising from a simultaneity bias between the skill composition of the workforce and GVC engagement and/or omitted variable bias. This robustness check confirms the results from the baseline regression that GVC engagement tends to increase the relative demand for skilled labour at relatively low levels of GVC engagement.

This Chapter is structured as follows. The next section will set out the empirical framework for analysing the effects of GVC engagement by firms in less developed countries on their relative employment of skilled versus less skilled workers. It will do so by discussing the estimation methodology and the various proxies used for skill and GVC engagement. After that, it will present various hypotheses based on the findings in Chapter 1. It will also discuss how endogeneity is dealt with, before presenting the results and concluding.

2.1. Empirical Methodology

This section will start by explaining the empirical function used, which is based on a standard methodology using the translog cost function as a way to examine any correlation between exogenous factors that shift the production function and therefore affect relative wages. After that, the data used will be presented which will serve as an introduction to the proxy used for measuring GVCs. This data will be used in a variety of ways to identify firms engaged in global value chains.

2.1.1. Empirical model

For the first part of the empirical analysis, this Chapter will employ the standard method in estimating the effects of structural variables, such as global value chains, on relative wages and employment. Employed first by Berman, Bound and Griliches (Berman et al., 1994) and later by Feenstra and Hanson (1996), the translog cost function provides a useful way to determine which factors affect relative demand for skilled labour. The empirical model further rests on the assumptions of the neoclassical models outlined under Chapter 1. That is, it assumes constant returns to scale, full employment, sufficiently flexible wages (to allow for market adjustments) factor mobility between different industries (so that all workers within an industry are affected even if GVCs would only be present in just one sector) and no spillovers between firms within an industry. It starts from a short run cost function that is the dual of an industry production function:

$$Cm\ (w, q, K_m\ , Y_m, z) \tag{2.1}$$

Where *w, q,* and K_m denote payments to low skilled labour, high skilled labour and capital, respectively, in industry *m*. Y_m is gross output and *z* stands for any other structural variable that can shift the production function and therefore affect costs, such as technological change (Berman et al. 1994), offshoring (Feenstra and Hanson) or global value chains (this Chapter). From this standard production function, we need a functional form for costs and the translog cost function provides a useful form as it allows to keep certain factors constant. It is denoted as follows:

$$\ln C_m(w,x) = \alpha_m + \sum_{j\epsilon J} \alpha_j \ln w_j + \sum_{k\epsilon K} \beta_k \ln x_k + \frac{1}{2}\sum_{j=1}^{J}\sum_{i=1}^{J} \gamma_{ji}\, lnw_j\, lnw_i + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \delta_{kl}\, lnx_k\, lnx_l + \sum_{j=1}^{J}\sum_{k=1}^{K} \varphi_{jk}\, lnw_j\, lnx_k \tag{2.2}$$

where w_j denotes the prices of the optimally chosen variable inputs j=1,…,J, and x_k denotes the quantity of fixed inputs k or outputs k=1,…,K or any other shift parameters.

From this cost function, we can move swiftly to a cost function for the cost share of labour by computing its first derivatives, $\frac{\partial lnC}{\partial lnw_j} = (\partial C/\partial w_j)(w_j/C)$. Since $(\partial C/\partial w_j)$ equals the demand for the chosen input j, such as skilled labour, for a certain wage rate w_j, it follows that $(\partial C/\partial w_j)(w_j/C)$ equals the payments to factor *j* relative to total costs. In other words, it equals the share of, for example, skilled labour in the total costs of a certain industry.

Thus, taking the first derivative of the log cost with respect to w_j in equation (2.2) gives us the cost share of labour type *j* in industry *m* as :

$$\theta_m^j = \alpha_m + \sum_{i=1}^{J} \gamma_{ji}\, ln\omega_i + \sum_{k=1}^{K} \varphi_k\, lnx_k \qquad j = 1, \dots, J \tag{2.3}$$

It is now in a form where we can add further structural variables on the right-hand side that, besides variable inputs ω_i and fixed inputs x_k, shifts the production function and therefore affects costs. For example, the share equation of labour type *j* in industry *m* will depend on wages for both types of labour as well as capital, output and all other structural variables, as we saw in equation (2.1). However, since this Chapter will estimate equation (2.3) by pooling data from 28 industries across which variation in wages has little information[18], the wage terms are typically dropped from the right-hand side of (2.3). Since the data does not contain information on wages either, we follow this approach.

Feenstra and Hanson (2001a) were the first who added offshoring as an additional structural variable that affects relative costs. It has consequently been used by Lorentowicz,

[18] As explained in Feenstra and Hanson (2001) and Berman, Bound and Griliches (1994), the cross-industry variation in wages can be simply explained by the nature of the industries; high skilled industries need to employ higher skilled workers and pay them a higher wage. Due to their nature, they are unable to hire less high skilled workers, simply because they are more expensive.

Marin and Raubold (2005), Fajnzylber and Fernandes (2009), Hsieh and Woo (2005) and many others and can be measured linearly as:

$$\theta_{fmct}^{j} = \beta_0 + \beta_1 \ln Y_{fmct} + \beta_2 \ln K_{fmct} + \beta_3 GVC_{fmct} + \varepsilon_{fmct} \qquad (2.4)$$

Where the dependent variable is the wage or employment share of a certain labour skill type *j* in firm *f*, in industry *m* of country *c* during year *t, GVC* represents a proxy for firms' engagement in global value chains which will be discussed further in section 2.1.1.2. In order to control for unobserved firm heterogeneity[19], we augment (2.4) in a number of ways.

Firstly, the dependent variable will be a measurement of the employment share of skilled labour. The next section will explain exactly how this is measured, but for now we shall refer to this skill employment share variable as S_{fmct}. On the right-hand side, we add various firm specific control variables. For example, we add a dummy variable, termed *foreign*, which identifies foreign firms as those firms which have at least 10 percent of foreign ownership. Secondly, we add a variable termed *qual.cert* which identifies whether a firm has an internationally recognized quality certificate. Thirdly, following Pavcnik (2003), Fajnzylber and Fernandes (2009), we include managerial experience (termed $man.exp$) in order to control for a firm's ability to adopt foreign technology. We also include access to finance and firm size as control variables as these might significantly constrain firms in hiring skilled personnel. Finally, we include country*industry*year fixed effects marked δ_{mct} as outlined in equation (2.5):

$$\begin{aligned} S_{fmct} = \beta_0 + \beta_1 \ln Y_{fmct} + \beta_2 \ln K_{fmct} + \beta_3 GVC_{fmct} + \beta_4 foreign_{fmct} \\ + \beta_5 qual.cert_{fmct} + \beta_6 \ln(man.exp_{fmct}) + \beta_7 finance_{fmct} \\ + \beta_8 size_{fmct} + \delta_{mct} + \varepsilon_{fmct} \end{aligned} \qquad (2.5)$$

Due to the stratified sampling nature of the World Bank Enterprise Surveys collected after 2006, we further weigh all the regressions by the inverse probability of the observation being selected in the sample to better represent the total population of firms. The next section will outline exactly how we apply equation (2.5) by specifying the dependent variable under section 2.1.1.1 and the different proxies we use for GVC_{fmct} under section 2.1.1.2.

[19] Indeed, as shown by Pavcnik (2003), failing to control for unobserved firm heterogeneity can completely alter the observed correlation between trade and skill.

2.1.1.1. Identifying skill

As explained in the previous section, the dependent variable in equation (2.5) measures the employment share of skilled labour within firm *f*, industry *m*, country *c* in time *t*. This Chapter uses 4 different measures of this employment share, as outlined in Figure 2.1.

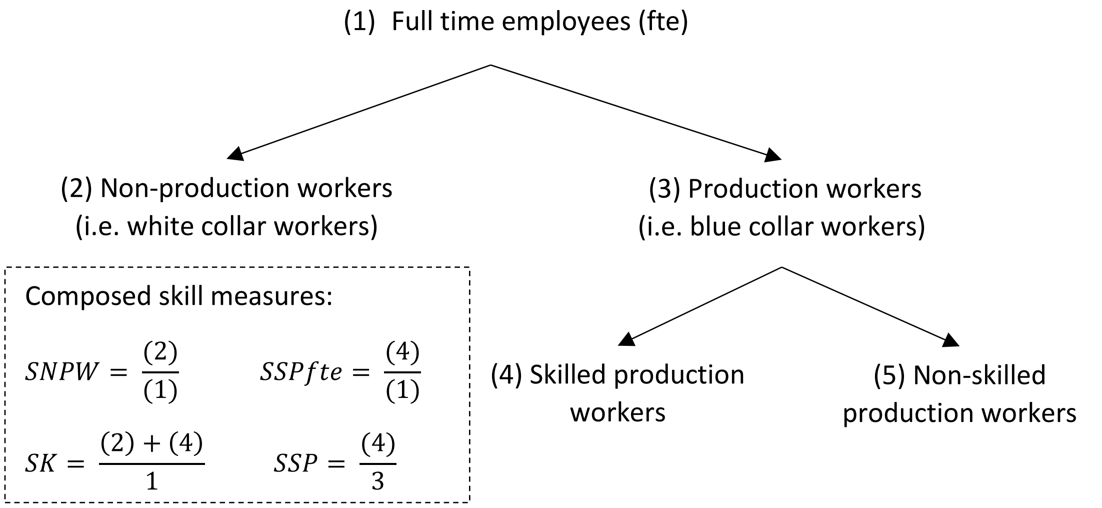

Figure 2.1 Employed skill measures

Figure 2.1 shows that total employment of full time employees (*fte*) is firstly broken down into production (blue collar) and non-production (white collar) workers. From this breakdown, we construct the first proxy, which is the share of non-production workers (*SNPW*) in total employment. In doing so, we follow Feenstra and Hanson's (1997) approach who admit that although there are problems with this classification, there is also evidence (Berman et al (1994) e.g.) that in practice it successfully tracks employment and wages by skill category. The problem with this measure, however, is that production workers can be skilled as well (see number (4) in Figure 2.1). Therefore, we add three more measures to proxy the skill employment share. Firstly, *SSPfte* measures the Share of Skilled Production (*SSP*) workers in the total number of full time employees (*fte*); *SSP* measures the share of skilled production workers in the total production workers while *SK* measures the share of all skilled workers (both white collar and skilled production workers) over the total full time employment. Of these, the latter two (*SSP* and *SK*) both include the portion of skilled workers of their respective denominators in the numerator. They are therefore *cleaner* skill proxies than *SNPW* and *SSPfte,* as these exclude some form of skilled workers (namely white collar workers and skilled production workers respectively) in the numerator while they are included in the denominator. We will however still report these results as *SNPW* is a commonly used measure in the literature while *SK* allows for the probability that white-collar workers are not necessarily skilled.

2.1.1.2. Identifying GVC firms using Enterprise Surveys

This Chapter uses the World Bank Enterprise Surveys (enterprisesurveys.org). Specifically, it uses the standardized dataset from 2006-2014, which includes data on 116.881 firms across 135 developing countries (see Appendix 2.1 for the full list)[20]. While the World Bank and the EBRD do their best to re-interview the same firms over time, and thus to construct a panel dataset on the firm level, the data used here can best be characterized as a repeated cross sectional dataset as most firms are not re-interviewed. The database includes a wide variety of information on individual firms in developing countries and has been used previously to investigate the link between the skill composition and firms' international economic activities (Shepherd and Stone, 2013; Fajnzylber and Fernandes, 2009). The information that we will use specifically is on the firm's workforce and their international activities (see Appendix 2.2 for the details on the variables used). Regarding the firms' workforce, various proxies of their skill composition have already been identified in Figure 2.1. Regarding their GVC involvement, one can use the data on the origin (domestic or foreign) of the intermediates goods they use in their production, as well as the amount of sales that are sold abroad. These variables are particularly interesting because by assuming those foreign inputs are used in the products exported, we can state that the firm is engaged in global value chains (Hummels et al., 2001; Baldwin and Lopez-Gonzalez, 2015). Therefore, we should use interaction variables (as done by Shepherd and Stone, 2013) as opposed to individual variables (as done by Fajnzylber and Fernandes 2009 e.g.). Firstly, we will identify GVC firms as those firms that do both, regardless of how much they import and export. Secondly, we will identify them as such when they import and export at least 90 percent of their inputs and outputs, respectively. Thirdly, we will examine the continuous interaction between these two variables. Finally, to deal with endogeneity, this Chapter will also use various instruments to proxy for GVC engagement. These steps will now be outlined more specifically one by one.

[20] We also experimented with the World Bank Enterprise Surveys from 2002-2006 as well as the Business Enterprise Environment Performance Study (BEEPS) to include more data and identify specific firms that were investigated multiple times (i.e. to construct a clear panel database). However, due to a change in the sampling procedure in 2006, data from before that time is not representable of the respective country's population. Specifically, while data collected before 2006 used quota sampling, post 2006 used stratified sampling.

2.1.1.2.1. Baseline regression

Firstly, we will follow Shepherd and Stone (2013) by identifying a firm's GVC engagement with an interaction term that identifies whether the firm imports intermediates and subsequently exports final goods. Substituting this proxy for GVC_{fmct} into equation (2.5) produces the baseline equation (2.6):

$$\begin{aligned} S_{fmct} = \beta_0 + \ & \beta_1 exporter_{fmct} + \beta_2 importer_{fmct} \\ & + \beta_3 exporter_{fmct} * importer_{fmct} + \beta_4 \ln Y_{fmct} + \beta_5 \ln K_{fmct} \\ & + \beta_6 foreign_{fmct} + \beta_7 qual.cert_{fmct} + \beta_8 \ln(man.exp_{fmct}) \\ & + \beta_9 finance_{fmct} + \beta_{10} size_{fmct} + \delta_{mct} + \varepsilon_{fmct} \end{aligned} \tag{2.6}$$

Where the interaction term, $exporter_{fmct} * importer_{fmct}$, is the main variable of interest as this represents the first GVC proxy as explained in the previous section.

However, in line with the framework outlined in Chapter 1, we directly move on beyond this and separate the effect in high skilled versus low skilled industries to test for the sector bias as well as in high versus low skilled abundant countries to test for the factor bias. This is done by applying (2.6) to firms in 1) low skilled industries and relatively low skilled abundant countries, 2) low skilled industries and relatively high skilled abundant countries, 3) high skilled industries and relatively low skilled abundant countries, and 4) high skilled industries and relatively high skilled abundant countries in line with the discussion in sections 2.1.1.3 and 2.1.1.4[21].

2.1.1.2.2. Increasing cut-off to 90 percent

However, this proxy would include those firms that import intermediates solely for domestic use, and export goods that are made purely of domestic inputs. Such firms are strictly speaking not engaged in GVCs, as GVC engagement requires both an import and an export component (Hummels et al, 2001; Baldwin and Lopez-Gonzalez, 2015). We therefore extend the investigation by exploiting the continuous information of the variables. Firstly, we will increase the cut-off values that determine whether a firm imports or exports, which increases the likelihood that firms use imports that are consequently used for exports. That means that $\beta_1 - \beta_3$ in (2.6) that previously identified an importer and / or exporter as a

[21] Note that we could technically do this as well by interacting the GVC proxy with the skill intensity of the sector or the skill abundance of the country. However, since the GVC proxy is already an interaction term, it was decided to not further complicate the equation and simply apply (2.6) to the identified four groups.

firm that importer and/or exported any inputs and/or outputs, now it will represent firms that import and/or export at least 90 percent of their inputs and/or outputs respectively.

There is one cautionary note when doing so, however. This is that besides increasing the likelihood that the firm is engaged in GVCs, we might also be focusing on a specific type of GVC activity. Namely, those firms that import almost all of their intermediates from abroad, add some value to it and then export almost all of their goods which are then final goods, are most likely to be engaged in assembly activities. Such GVC activities are known to be very low skilled intensive in nature. We have to take this into account when analysing the results.

2.1.1.2.3. Continuous interaction

After identifying GVC firms as those that import and export a particular share of their inputs and outputs, it might be interesting to investigate the continuous nature of these variables further as there might either be a non-linear or conditional effect of each variable on the skill employment share of firms. To that extent, we employ a continuous interaction term as specified in (2.7):

$$\begin{aligned} S_{fmct} = \beta_0 + \; & \beta_1 exporting\ final\ goods_{fmct} + \beta_2 importing\ intermediates_{fmct} \\ & + \beta_3 exporterting\ final\ goods_{fmct} * importing\ intermediates_{fmct} \\ & + \beta_4 \ln Y_{fmct} + \beta_5 \ln K_{fmct} + \beta_6 foreign_{fmct} + \beta_7 qual.cert_{fmct} \\ & + \beta_8 \ln(man.exp_{fmct}) + \beta_9 finance_{fmct} + \beta_{10} size_{fmct} + \delta_{mct} + \varepsilon_{fmct} \end{aligned} \tag{2.7}$$

Note that the difference between (2.6) and (2.7) is that the latter takes the continuous variables of exporting and importing while the former equation uses dummy variable. Equation (2.7) is interesting as it will give the effect of exporting or importing *more,* as opposed to doing so per se. Even more interesting, however, is the interaction variable, which will show the effect of imports (exports) on the skill employment share, conditional upon the level of exports (imports). A positive interaction variable, for example, would imply that more imports (exports) would increase the positive effect of exports (imports) on the skill employment share.

2.1.1.3. Identifying the sector and factor bias

The previous Chapter pointed out the importance of conditioning any effects of GVCs on relative wages and employment on the sector and the factor bias of global value chains. This Chapter will apply that framework by identifying different skill intensive sector and factor biases. The sector bias can be identified by separating industries, on the basis of their technology intensity, into relatively high and low skilled intensive industries. The factor bias, on the other hand, can be identified by separating the countries in the sample into those that are relatively skill abundant and those that are relatively low skill abundant[22]. To separate countries, we use their scores on the human development index, which is a composite measure of 3 dimensions: health, education and standard of living. As this index looks beyond simply economic criteria to assess a country's development, this can be deemed an appropriate proxy for a country's skill endowment. The assumption is then that the countries that score lowest (highest) on this index will engage in the relatively low (high) skilled intensive tasks of a GVC. In other words, the factor bias of GVC activities that firms in these countries engage in will be low (high) skilled intensive.

Using this information generates 4 different groups: 1) firms active in low skilled industries within relatively low skill abundant countries; 2) firms active in low skilled industries within relatively high skill abundant countries; 3) firms active in high skilled industries within relatively low skill abundant countries, and; 4) firms active in high skilled industries within relatively high skill abundant countries. Doing so generates various hypotheses, as will be discussed next.

2.1.1.4. Hypotheses

Chapter 1 outlined a conceptual framework to empirically analyse the effect of GVCs on the relative demand for skilled labour. This Chapter will amend Table 1.3 to fit the data at hand and construct various hypotheses regarding the outcome of equation (2.6). While it is possible to separate firms based on the sector and factor bias of the GVC activity they engage in, it is not possible to identify different goods and factor elasticities. Therefore, we must base our predictions on assumptions regarding the elasticity of factor and goods substitution. Regarding the former, we follow Krugman (2000) who states that economies are large and integrated, and that phenomena such as technological change or GVCs happen worldwide, rather than within an isolated country-industry. Therefore, we assume that the sector bias will be largely offset, and that it is predominantly the factor bias of GVCs that ultimately determines how the relative demand for skilled labour within industries and firms is affected. We should however test this formally, by separating the sector and factor bias of GVCs as outlined in the previous section. Finally, since the data

[22] Remember that the data we are using is already for developing countries only. Therefore, one might think of the separation of countries in this case as a within-Southern countries separation in the style of Davis (1996) and Khalifa and Mengova (2010).

used in this Chapter only has information on employment shares and not on compensation shares, we can only state hypotheses for the former. Doing so, we can collapse the hypotheses of Table 1.3 into the hypotheses stated in Table 2.1:

Table 2.1 Hypotheses on the effect of GVCs on the relative skill employment, conditioned on the sector and factor bias of GVCs

Sector bias	Factor bias	Skill intensity of the workforce
Low skilled	Low skilled	Decrease
Low skilled	High skilled	Increase
High skilled	Low skilled	Decrease
High skilled	High skilled	Increase

Table 2.1 shows that this Chapter follows the assumption by Krugman (2000) that the sector bias will not significantly affect the outcome, while the factor bias will.

2.1.1.5. Dealing with endogeneity

So far, this Chapter has specified how to measure the correlation between international trade and the skill composition of the workforce using observational data from the World Bank Enterprise Surveys. While these methods attempt to exclude any endogeneity by including various firm-level control variables as well as country, industry and time fixed effects, the established coefficients may still be biased. Due to the observational nature of the data, as opposed to randomized control experiment, it is difficult to fully exclude endogeneity, which can come in the form of selection bias, omitted variable bias and/or reverse causality.

Selection bias with respect to non-response can occur when a respondent ignores to answer a question. If this question is a variable that is included in the analysis, the respective firm will drop out of the analysis. This creates a bias in the estimation if there is a specific reason why certain firms prefer not to answer particular questions. We therefore follow Geishecker (2008) by supplementing each explanatory variable with a dummy for missing values and subsequently recode the missing values to zero. This includes the full set of firms that have answered the skill employment questions and should therefore minimize estimation bias.

Besides non-response bias, the estimations might also suffer from omitted variable bias or reverse causality. While the fixed effects denoted δ_{mct} in equation (2.7) control for annual country and industry differences, they fail to control for any firm specific differences. We therefore included various firm level control variables measured with $\beta_4 - \beta_{10}$. However, there are likely to be more firm specific indicators that affect their skill employment share that we have not been able to include in the equation because we do not have the data for it. This can leave scope for omitted variable bias (OVB). Besides OVB, endogeneity may further be caused by a potential simultaneity bias between our variable of interest (GVC engagement) and the dependent variable (skill proxies). Indeed, equations (2.6) and (2.7) implicitly assumed that engaging in new production activities via GVCs will change the skill intensity of production and therefore change the relative demand for skilled labour. However, the opposite is also possible, i.e. more skilled abundant firms might be more likely, or able, to engage in global value chains. While previous research has used the World Bank Enterprise Surveys to make inferences about the correlation between international economic activities and the skill composition of the workforce, none of those have said anything about the direction of the correlation[23]. This Chapter attempts to move beyond an investigation of correlations and say something about the direction of those results as well by using instrumental variables.

2.1.1.5.1. Instrumental variable

Instrumental variables can be used to filter the exogenous variation in the endogenous variable (GVC participation in this case) and relate that to the dependent variable (skill composition of the workforce), creating unbiased coefficients. When using an such an instrumental variable (IV) to filter out endogeneity and establish causation, the choice of the instrument is critical (Angrist and Pischke, 2008). Specifically, the instrument has to be both relevant (i.e. sufficiently correlated with the endogenous variable) and valid (i.e. not correlated with the error term of the structural equation). These two requirements can, and will, be tested formally, with the Sanderson-Windmeijer multivariate F test of excluded instruments and the Hansen J test, respectively. However, it is arguably even more important to have a good story why the instruments may be correlated with the endogenous variable but not directly with the dependent variable. Fortunately, the WBES provide a large source of data with many variables with some potential to be used as an

[23] This is probably due to the nature of the data. While the World Bank and the EBRD do their best to interview the same firms over time, and thus to establish a true panel dataset, this often proves to be too difficult a task. Further, while the BEEPS dataset provided by the EBRD does a good job at identifying firms that have been re-interviewed, those interviews examined before 2006 were compiled via quota sampling, lacking any weights associated with the observations. The lack of those weights further obstructs executing analysis on the WBES in a panel setting.

instrument. Out of those variables, information regarding customs and trade regulation provides interesting opportunities to establish the effect of GVC engagement on skill proxies. Specifically, we use information on firms' response to

1) How much of an obstacle customs and trade regulations are to their daily operations, which will be referred to as "*Cust"*;
2) Whether they applied for an import license in the last two years, which will be referred to as "*Imp.license",* and;
3) The maximum amount of days their goods were stalled at the border in customs, which will be referred to as "*Wait".*

The rationale is that while these variables will clearly be correlated with whether a firm will be engaged in GVCs, it is unlikely that it will affect the skill intensity of the workforce in any other way.

For the first instrument, "*Cust"*, we use firm's responses on the question how much of a barrier customs and trade regulations are. The rationale is that only GVC firms can suffer from customs and trade regulations. We then group the answers into those that would likely be answered by firms engaged in GVCs and those that would not be. Specifically, we group "does not apply", no obstacle, and very severe obstacle as non GVC responses, while minor, moderate and minor obstacles are grouped as GVC responses[24].

Secondly, we use information on whether a firm has applied for an import license in the last two years, abbreviated to "*Imp.license"*. While this time period clearly limits the identification of all importers, it will still identify some. In fact, 85 % of the respondents that indicated they did indeed apply for an import license in the last two years do in fact import some of their intermediates, making this a strong instrument.

Thirdly, we use information on the number of days it takes for customs to clear imports and exports, referred to as "*Wait"*. It is a composite measure of 4 variables that indicate the average and maximum number of days firms had to wait for their imports and exports to clear through the borders. From this information, we construct a dummy variable taking the

[24] However, those firms that indicate that this is a "very severe" obstacle are likely to be unable to engage in GVCs, as a result of customs and trade. One might also argue that the answer "no obstacle" might still be given by GVC firms. However, we compared this answer to firm's responses regarding the average and maximum amount of days they have to wait for their goods to clear through customs. Out of those firms that indicated customs were no obstacle, only 15% answered they had to wait for customs, indicating that these firms are predominantly not active in GVCs.

value 1 if firms indicated they had to wait any amount of days for either imports or exports and 0 if they never had to wait for it (including missing variables).

Now that the instruments are clear, we can formalize the use of the instrumental variable more specifically. We will apply the IV methodology to the baseline equation stated in (2.6). Since this equation proxies for GVC engagement with an interaction term between import and export dummies (defined as 1 when a firm imports (exports) more than zero percent of its inputs (outputs), we should instrument for the individual, first order, main effects as well as the interaction term. That is, when estimating (2.6), we take a first stage where we regress the instrumental variable on the endogenous variable of GVCs, as in:

$$\begin{aligned} \widehat{exporter}_{fmct} = {} & \beta_0 + \beta_1 Cust_{fmct} + \beta_2 Wait_{fmct} + \beta_3 Imp.\,license_{fmct} \\ & + \beta_4 Cust * Wait_{fmct} + \beta_5 Cust * Imp.\,license_{fmct} \\ & + \beta_6 Wait * Imp.\,license_{fmct} + \beta_7 \ln Y_{fmct} + \beta_8 \ln K_{fmct} \\ & + \beta_9 foreign_{fmct} + \beta_{10} qual.\,cert_{fmct} + \beta_{11} \ln(man.\,exp_{fmct}) \\ & + \beta_{12} finance_{fmct} + \beta_{13} size_{fmct} + \delta_{mct} + u_{fmct} \end{aligned} \tag{2.8}$$

$$\begin{aligned} \widehat{importer}_{fmct} = {} & \beta_0 + \beta_1 Cust_{fmct} + \beta_2 Wait_{fmct} + \beta_3 Imp.\,license_{fmct} \\ & + \beta_4 Cust * Wait_{fmct} + \beta_5 Cust * Imp.\,license_{fmct} \\ & + \beta_6 Wait * Imp.\,license_{fmct} + \beta_7 \ln Y_{fmct} + \beta_8 \ln K_{fmct} \\ & + \beta_9 foreign_{fmct} + \beta_{10} qual.\,cert_{fmct} + \beta_{11} \ln(man.\,exp_{fmct}) \\ & + \beta_{12} finance_{fmct} + \beta_{13} size_{fmct} + \delta_{mct} + u_{fmct} \end{aligned} \tag{2.9}$$

$$\begin{aligned} & \widehat{exporter * importer}_{fmct} \\ & \quad = \beta_0 + \beta_0 + \beta_1 Cust_{fmct} + \beta_2 Wait_{fmct} + \beta_3 Imp.\,license_{fmct} \\ & \quad + \beta_4 Cust * Wait_{fmct} + \beta_5 Cust * Imp.\,license_{fmct} \\ & \quad + \beta_6 Wait * Imp.\,license_{fmct} + \beta_7 \ln Y_{fmct} + \beta_8 \ln K_{fmct} \\ & \quad + \beta_9 foreign_{fmct} + \beta_{10} qual.\,cert_{fmct} + \beta_{11} \ln(man.\,exp_{fmct}) \\ & \quad + \beta_{12} finance_{fmct} + \beta_{13} size_{fmct} + \delta_{mct} + u_{fmct} \end{aligned} \tag{2.10}$$

As can be seen from equations (2.8)-(2.10), we use both the main effects of the instrumental variables, as well as their first order interaction terms. The instrumented values of the import, export and import*export dummy are then used in the second stage, as outlined in (2.11) which is specified equivalently to the baseline equation (2.6).

$$\begin{aligned} S_{fmct} = \beta_0 + \ & \beta_1 \widehat{exporter}_{fmct} + \beta_2 \widehat{importer}_{fmct} \\ & + \beta_3 \widehat{exporter * importer}_{fmct} + \beta_4 \ln Y_{fmct} + \beta_5 \ln K_{fmct} \\ & + \beta_6 foreign_{fmct} + \beta_7 qual.cert_{fmct} + \beta_8 \ln(man.exp_{fmct}) \\ & + \beta_9 finance_{fmct} + \beta_{10} size_{fmct} + \delta_{mct} + \varepsilon_{fmct} \end{aligned} \tag{2.11}$$

If the instruments are valid, i.e. the IV's used in (2.8)-(2.10) are uncorrelated with the error term ε_{fmct} in (2.11), we are regressing the exogenous variation of GVC on S_{fmct}. This ensures that the GVC proxy is not correlated with any other confounding variables that might affect whether a firm engaged in GVCs, clearing it of such bias. If we find here that the IV-generated fitted values of $\widehat{GVC_{fmct}}$, are significantly correlated with the skill employment share of the workforce, we can infer that this can only be via the engagement in GVCs and that the relationship is thus that GVCs affect the skill composition, and not vice versa.

2.2. Empirical results

2.2.1. Simple interaction term

Starting with the initial estimation as outlined in equation (2.6) where we proxy for GVCs with an interaction term between importing intermediates and exporting final goods, Figure 2.2 (shown here) shows a summary of the main results that can be seen in Table 2.4 (shown in Appendix 2.3). As can be seen, these results show strong evidence that both importing and exporting is significantly and positively related to the share of skilled workers and robust to 4 different proxies for the skill share.

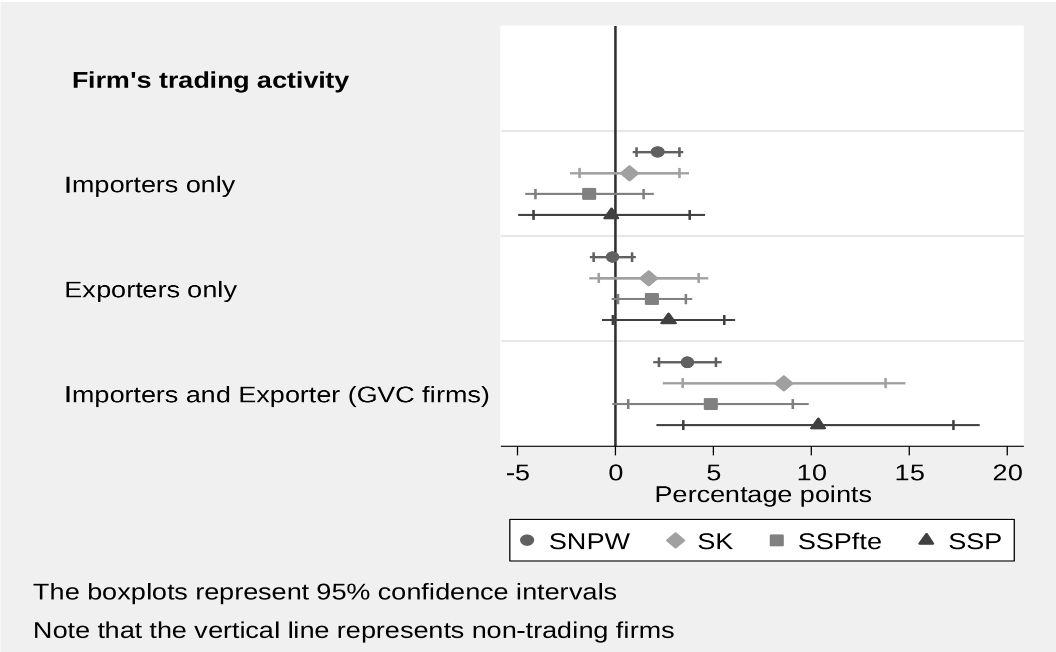

Figure 2.2 Baseline results

As explained extensively in both this Chapter and the previous one, it is critical that we condition these results on the sector and factor bias effect of GVCs. In doing so, we would expect to see the results as outlined in Table 2.1. Figure 2.3 once again summarizes the key results that can be found in full in Table 2.5 and Table 2.6.

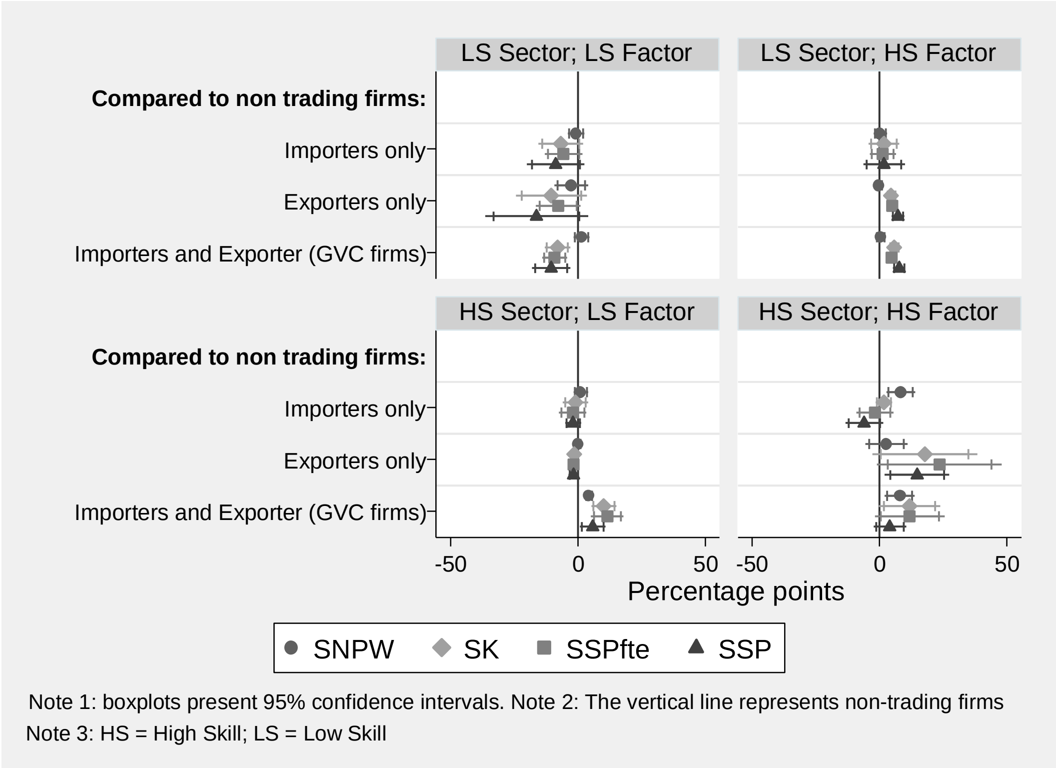

Figure 2.3 Baseline results conditioned on the sector and factor bias.

Figure 2.3 shows evidence that is in line with the predictions based on the factor bias of GVCs. That is, whenever the factor bias of the GVC is high skilled, i.e. when the activity the home country specialises in via GVCs is high skilled as represented by the two right hand quadrants, the demand for high skilled labour increases. On the other hand, when the factor bias is low skilled intensive (shown by the left two quadrants), the relative demand for low skilled labour tends to increase. There is however one notable exception. That is, when the sector bias is high skilled and the factor bias is low skilled (shown by the bottom left quadrant), we find that GVCs tend to *increase* the relative demand for high skilled labour. This can be explained, however, by referring to Feenstra and Hanson (1996) who state that what might be low skilled for skill abundant countries might be experienced as high skilled in less skill abundant countries. This is especially likely in this case as we only find this effect in high skilled industries. In the original model by Feenstra and Hanson (1996), they use a continuum of tasks increasing in skill intensity, as opposed to a two-sector model with high and low skilled goods. Doing so would allow for a higher skill intensity of the low skilled activities in the high skilled sector, explaining the results in the bottom left quadrant of Figure 2.3.

2.2.2. Increased interaction

The previous section showed the baseline results of firms that engage in importing and exporting as a proxy for GVC firms. The downside of this proxy is that it would include firms that import inputs used in outputs sold domestically, and sell outputs abroad made of purely domestic inputs. As GVC activity necessarily includes both an import and an export side, this proxy should be amended. This Chapter does so by increasing the cut-off that determines whether a firm is an importer or exporter, to 90%[25].

[See Table 2.7 on page 98]

Table 2.7 (shown in the Appendix 2.3) shows that, without separating for the skill intensity of the industry and the skill abundance of the country, the positive correlation identified in Table 2.4 has disappeared completely. Indeed, Table 2.7 even shows that firms that import and export at least 90% of their inputs and outputs, respectively, tend to hire significantly *less* white collar workers as opposed to blue collar workers. This results holds when we separate on the sector and factor bias (Table 2.8 and Table 2.9). This can be explained in two ways. On the one hand, one might interpret this result as evidence that GVCs *decrease* the relative demand for skilled labour, as opposed to the baseline finding, since the proxy used here increases the likelihood that GVC firms are identified. However, it is more likely that this finding refers to a specific type of GVC activity that is low skilled in nature, as firms that import nearly all their intermediates and export nearly all of their final goods are most likely involved in assembly work. This can also explain why it is specifically *SNPW* as a skill proxy that decreases, since assembly work will naturally require more production vs. non-production workers. In any case, this finding begs the question for further investigation of the continuous nature of the trade variables. Therefore, the next section explores the correlation between a continuous interaction term and the skill intensity of the workforce.

2.2.3. Continuous interaction

In addition to increasing the cut-off that determines whether a firm is identified as a GVC firm, we can also use the continuous nature of our trade variables to estimate their conditional effect. Table 2.10 shows that while the continuous variable import and export, overall, are positively related to the skill composition of firms' workforces, the interaction term tends to be significantly negative. This implies that the greater export (imports) the more negative the effect of imports (exports) on the skill share in the workforce. We saw

[25] i.e. whereas before we classified an importer as a firm that imports at least 1 percent of its inputs from abroad, now we only classify it as such when it imports at least 90 percent of its intermediates.

this before already that increased levels of imports and exports tends to decrease the share of skilled personnel in the workforce, as opposed to the earlier finding that the baseline estimate was significantly related to *higher* skill shares.

We can dig even further into the continuous nature of the variables. Figure 2.4 shows the conditional effect of importing intermediates at various levels of exports, on the skill share of the workforce. Here, "*SK*" is chosen as a proxy for the skill employment share (See Figure 2.1) but the results hold for the other proxies as well[26].

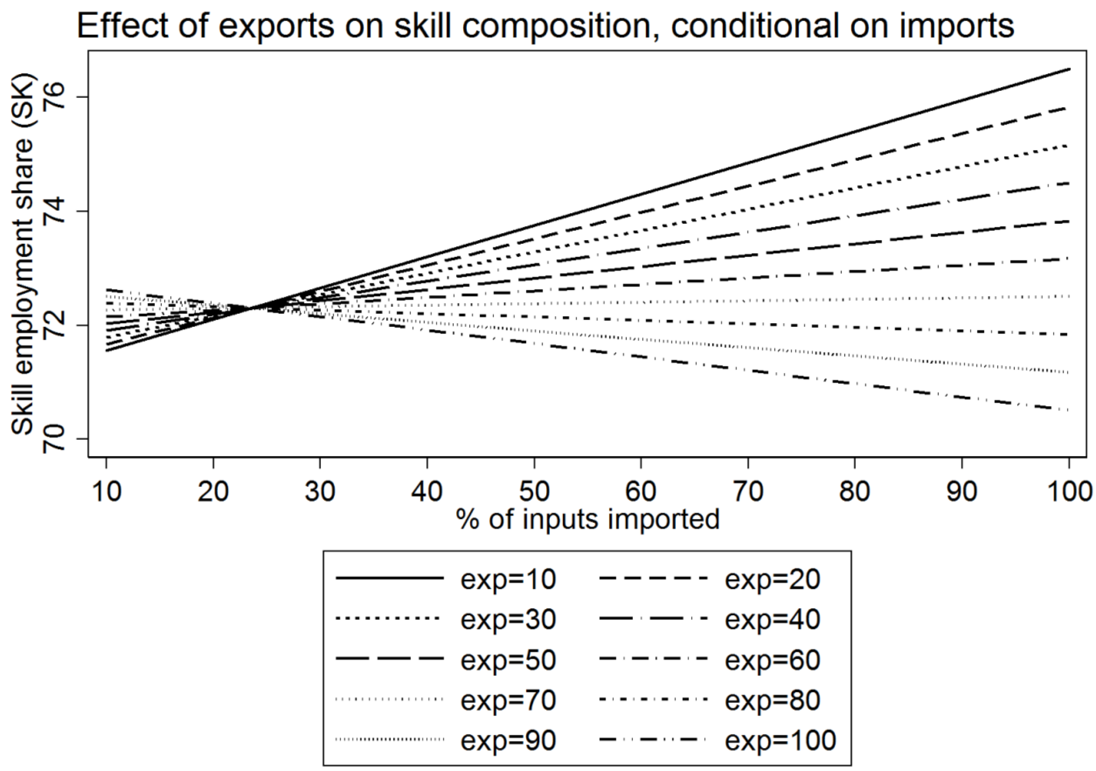

Figure 2.4 The conditional effect of importing on different levels of exporting

Figure 2.4 shows that while importing intermediates tends to have a positive effect on the skill share of the workforce at low levels of exports, the effect is significantly negative for higher values of exports. This provides further evidence of a specialisation effect once firms engage more strongly in GVCs.

[26] Note that we do not provide tabular proof of this result, as this calculation would involve 20 separate tables per proxy.

2.2.4. Robustness Checks for the baseline results

So far, we have seen that at relatively low levels of GVC engagement, i.e. at low levels of both importing inputs and exporting outputs, firms tend to have relatively higher skilled workforces, particularly when the factor bias of the GVC activity is high skilled intensive. When we consequently increased that engagement in these economic activities, we see that the positive correlation becomes insignificant and in some cases even significantly negative. However, as discussed in section 2.1.1.5, endogeneity might still exist in the form of non-response bias, omitted variable bias or reverse causality.

Therefore, we firstly follow Geishecker (2008) in replacing non-response items with a zero and supplement this variable with a dummy indicating that the variable was originally missing. We do this for all the explanatory variables in (2.6) and the results can be seen in Table 2.11, Table 2.12 and Table 2.13

[See Table 2.11-Table 2.13 from page 104 onwards]

Table 2.11 provides the robustness check of the baseline estimations found in Table 2.2. As we can see, the baseline results that GVC engagement is correlated with increased skill-employment shares hold, although the significance has dropped somewhat. In addition, the coefficients on the missing variables are either non-significant (e.g. for exporting, importing and foreign ownership) or in line with the non-missing coefficient (e.g. for sales). The only coefficient that seems at odds with its dummy for missing variables is managerial experience. Here we see that the dummy variable indicates a significantly positive relationship between non-response regarding managerial experience and the skill employment share, which seems counterintuitive.

Table 2.12 and Table 2.13 provide the robustness check for the results found in Tables 2.3 and 2.4, where the results have been conditioned on the sector and factor bias of GVC engagement. Here, the initial results from Table 2.3 are confirmed, i.e. in low skilled sectors, GVC engagement into relatively (low) skilled intensive tasks is correlated with increased (decreased) skill employment shares. In the high skilled industries, the initial result that GVC engagement in relatively low skilled tasks is correlated with higher skill employment shares is also confirmed. Remember that although this is contradictory to the factor bias hypothesis, it makes sense once we realise this is the high skilled sector, and that low skilled intensive tasks in the high skilled sector might still be experienced as high skilled tasks, especially by countries that are relatively low skilled abundant. The only result that seems at odds with the baseline results is GVC engagement in high skilled sectors, by countries that are relatively high skilled abundant. Whereas Table 2.3 showed a consistent skill premium across all the skill proxies, Table 2.13 largely shows insignificant results. This could have something to do with the missing export and import variables, as the dummy variables identifying these missing variables tend to be significantly and positively related with the skill employment share.

Besides non-response bias, this Chapter also looks at omitted variable and reverse causality by applying an IV method as outlined in section 2.1.1.5.1. The first stage, as outlined in equations (2.8)-(2.10), isolates the variation in the GVC proxy that is not correlated with the error term of equation (2.6). The second stage, as outlined in (2.11), then takes that exogenous variation in GVC engagement and regresses it on the dependent skill variable. As can be seen from Table 2.14, the conclusions drawn from the baseline estimation still hold. That is, without conditioning the effects on the sector and factor bias effect of GVCs, there is still a positive correlation between relatively low levels of GVC engagement. This also takes away any question about the direction of the correlation as it is highly unlikely that a more skilled workforce would increase the amount of days goods are stalled at customs, for example. Therefore, the direction of the continuously observed significant correlation between GVC engagement and skill proxies can be assumed to be from GVC engagement to skill demand, as opposed to vice versa. Table 2.14 further shows that the Sanderson-Windmeijer (2016) multivariate F test of excluded instruments tends to be greater than the Stock, Wright and Yogo (2002) suggested rule of thumb of 10, suggesting that the instruments are relevant, i.e. sufficiently correlated with the GVC proxy. Secondly, the Hansen J test shows that the instruments are valid, i.e. not correlated with the error term ε_{fmct} in equation (2.6).

[See Table 2.14 on page 110]

Just as we conditioned the baseline findings of Table 2.4 on the sector and factor bias of the GVC in Table 2.5 and Table 2.6, we also apply the IV method to a baseline-conditioned estimation in Table 2.15 and Table 2.16. Here we find once again that the initial results of Table 2.5 and Table 2.6 still hold. That is, whenever the factor bias of GVCs is high (low), it tends to increase (decrease) the relative demand for skilled labour. The only difference in comparison with the baseline estimation is in the high skilled sector and low skilled abundant countries (columns 1, 3, 5 and 7 of Table 2.16) which do not seem to be significantly correlated with the various skill proxies. Remember that we saw from Table 2.6 that this result was already ambiguous, as a positive correlation was observed, where a negative was expected. While we explained this earlier by referring to Feenstra and Hanson (1996), here we see that this result does not hold once we instrument for the GVC engagement. The other results, however, hold while the both the F statistic and the Hansen J test confirm relevant and valid instruments, respectively.

[See Table 2.15 and Table 2.16 from page 112 onwards]

2.3. Concluding remarks

This thesis centres around the question how global value chains affect the relative demand for skilled labour of the firms that engage in them. Chapter 1 provided an extensive overview of the literature and concluded that there was not one theoretical answer to this question and that it should therefore be answered empirically. However, Chapter 1 did provide various lessons that can be applied to the empirical exercise, which this Chapter has made use of.

Specifically, Chapter 1 showed how the effect depends on a range of factors, most importantly the sector bias (i.e. the skill intensity of the sector the GVC firm operates in) of the GVC as well as its factor bias (i.e. the skill intensity of the activity the GVC firm engages in). The magnitude of these factors, in turn, depends on the elasticity of factor and goods substitution. Unfortunately, the data used in this Chapter did not have any information on these elasticities, so that assumptions had to be made. In line with Krugman (2000), this Chapter assumed that the elasticity of goods substitution is relatively elastic, so that the factor bias should dominate the sector bias effect (See the discussion on page 41 along with Figure 1.13 and Figure 1.16). Based on this assumption, the hypotheses of Table 1.3 could be collapsed into Table 2.1. In short, these hypotheses can be summarized by saying that firms in low (high) skilled abundant countries will use GVCs to specialise in low (high) skilled intensive tasks which will increase the relative demand for low (high) skilled labour at the expense of high (low) skilled labour.

This Chapter tested those hypotheses by following the literature in using a translog cost function and measuring the effect of GVCs as a demand shift parameter on various proxies for the relative demand for skilled labour (Figure 2.1). Here, the baseline estimation identified GVC firms as those firms that simultaneously imported intermediates and exported final goods. While a positive correlation between this proxy and the skill employment share of the workforce was found initially, conditioning those results on the sector and factor bias showed results that were largely in line with the hypotheses outlined in Table 2.1. Figure 2.3 summarized these results, where it is evident that GVC firms in high (low) skilled abundant countries tend to hire relatively more (low) skilled labour than firms that do not engage in GVCs. This can be explained by referring to the factor bias, or the skill intensity, of the activities these firms will specialise in via GVCs. Based on these firms' respective home countries' relative skill abundance and thus their comparative advantage, we can assume these activities will be high (low) skilled intensive. The only deviation from the hypotheses could be found in the bottom left quadrant of Figure 2.3, i.e. in high skilled industries with low skilled activities. Here, contrary to the factor bias hypothesis, we see that firms engaging in relatively low skilled intensive tasks tend to hire relatively more skilled personnel. This can be explained, however, by referring to Feenstra and Hanson (1996) who point out that what might seem low skilled intensive for one country, can be seen as high skilled intensive for another country. This is likely the case here, as we only observe this effect in high skilled industries where the low skilled intensive tasks might actually be relatively high skilled.

Once these baseline results were obtained, they were tested further using two different robustness checks. In order to deal with potential estimation bias as a result of non-responses, we supplemented each explanatory variable with a dummy variable indicating missing values and subsequently recoded the missing values to zeros. Secondly, in order to deal with potential omitted variable bias and reverse causality, we used instrumental variables to test the robustness of the baseline results. In both cases, the baseline results did not change significantly.

Besides these baseline estimations, this Chapter also experimented with two other proxies for GVC engagement, by exploiting the continuous nature of the import and export variables. Firstly, it identified GVC firms as those firms that import and export at least 90% of their inputs and outputs respectively. Doing so prevents the identification of firms that produce exports solely out of domestic inputs or use imported inputs for domestically sold outputs, which is technically not a GVC activity (Hummels et al. 2001; Baldwin and Lopez-Gonzalez, 2015). Using this proxy, the relationship between GVC engagement and the skill employment of the workforce, measured via *SK*, *SSPfte* and *SSP* (Figure 2.1), became insignificant. In the case of measuring skill via *SNPW*, however, a significantly negative relationship became apparent.

This finding was confirmed when using an interaction term between the continuous import and export variables. While the first order, or main, effects were positive, the interaction variable showed a negative correlation with the skill employment share (Table 2.10). Furthermore, while importing (exporting) increased the demand for skilled labour only at low levels of exporting (importing), at higher levels of exporting (importing), a decrease in the relative demand for skilled labour was observed (Figure 2.4). These results can be interpreted in two ways. While it might be the case that at higher levels of GVC engagement, these firms in developing countries might specialise in their comparative advantage of executing low skilled labour, it can also be the case that we are identifying a specific type of GVC activity. Namely, those firms, that import and consequently export a very large share of their intermediates and outputs, are most likely engaged in assembly activities, which is an activity that is low skilled by its very nature. This would explain why it is particularly the SNPW proxy that is so significantly and negatively correlated with this proxy, as assembly activities typically require blue collar workers.

Although this Chapter provides some evidence of the framework outlined in Chapter 1, it has some limitations. Most notably, the proxy for GVC engagement. As stated before, the baseline estimation allows for the identification of firms that are not, strictly speaking, engaged in GVCs. The second GVC proxy, where only firms that import and export a significant share of their goods, is also not perfect, as it targets a specific type of GVC engagement. In order to overcome this problem, future enterprise surveys could potentially include a more direct question whether a firm is engaged in a GVC. This could be done, for example, by asking specifically if they import intermediates that are used in the production of exports, in line with the definition by Hummels, Yi and Ishi (2001) as well as Baldwin and Lopez-Gonzalez (2012). This is something that other institutions such as the International Trade Centre (ITC) have recently started doing.

In addition, although the IV confirmed the baseline results, there might still be omitted variable bias as it is difficult to control for all firm level heterogeneity. For these reasons, it might be interested to use macro level data, rather than micro level data, as Chapter 3 will do next.

Appendix 2.1: Dimensions of the database

Table 2.2 Data coverage

Year: / Country:	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total
Afghanistan	0	0	534	0	0	0	0	0	409	943
Albania	0	304	0	0	0	0	0	360	0	664
Angola	425	0	0	0	360	0	0	0	0	785
Antigua and Barbuda	0	0	0	0	151	0	0	0	0	151
Argentina	1,063	0	0	0	1054	0	0	0	0	2,117
Armenia	0	0	0	374	0	0	0	360	0	734
Azerbaijan	0	0	0	380	0	0	0	390	0	770
Bahamas, The	0	0	0	0	150	0	0	0	0	150
Bangladesh	0	1,504	0	0	0	0	0	1,442	0	2,946
Barbados	0	0	0	0	150	0	0	0	0	150
Belarus	0	0	273	0	0	0	0	360	0	633
Belize	0	0	0	0	150	0	0	0	0	150
Benin	0	0	0	150	0	0	0	0	0	150
Bhutan	0	0	0	250	0	0	0	0	226	476
Bolivia	613	0	0	0	362	0	0	0	0	975
Bosnia and Herzegovina	0	0	0	361	0	0	0	357	0	718
Botswana	342	0	0	0	268	0	0	0	0	610
Brazil	0	0	0	1,802	0	0	0	0	0	1,802
Bulgaria	0	1,015	0	288	0	0	0	291	0	1,594
Burkina Faso	0	0	0	394	0	0	0	0	0	394
Burundi	270	0	0	0	0	0	0	0	154	424
Cambodia	0	0	0	0	0	0	0	423	0	423

Cameroon	0	0	0	363	0	0	0	0	0	363
Cape Verde	0	0	0	156	0	0	0	0	0	156
Central African Rep.	0	0	0	0	0	150	0	0	0	150
Chad	0	0	0	150	0	0	0	0	0	150
Chile	1,017	0	0	0	1,031	0	0	0	0	2,048
China	0	0	0	0	0	0	2,700	0	0	2,700
Colombia	1,000	0	0	0	942	0	0	0	0	1,942
Congo, Dem. Rep.	340	0	0	0	359	0	0	529	0	1,228
Congo, Rep.	0	0	0	151	0	0	0	0	0	151
Costa Rica	0	0	0	0	538	0	0	0	0	538
Cote d'Ivoire	0	0	0	526	0	0	0	0	0	526
Croatia	0	633	0	0	0	0	0	359	0	992
Czech Republic	0	0	0	250	0	0	0	254	0	504
Djibouti	0	0	0	0	0	0	0	266	0	266
Dominica	0	0	0	0	150	0	0	0	0	150
Dominican Republic	0	0	0	0	360	0	0	0	0	360
Ecuador	658	0	0	0	366	0	0	0	0	1,024
Egypt	0	0	0	0	0	0	0	2,897	0	2,897
El Salvador	693	0	0	0	360	0	0	0	0	1,053
Eritrea	0	0	0	179	0	0	0	0	0	179
Estonia	0	0	0	273	0	0	0	273	0	546
Ethiopia	0	0	0	0	0	644	0	0	0	644
Fiji	0	0	0	162	0	0	0	0	0	162
Gabon	0	0	0	179	0	0	0	0	0	179
Gambia	174	0	0	0	0	0	0	0	0	174
Georgia	0	0	373	0	0	0	0	360	0	733

Ghana	0	494	0	0	0	0	0	720	0	1,214
Grenada	0	0	0	0	153	0	0	0	0	153
Guatemala	522	0	0	0	590	0	0	0	0	1,112
Guinea	223	0	0	0	0	0	0	0	0	223
Guinea-Bissau	159	0	0	0	0	0	0	0	0	159
Guyana	0	0	0	0	165	0	0	0	0	165
Honduras	436	0	0	0	360	0	0	0	0	796
Hungary	0	0	0	291	0	0	0	310	0	601
India	0	0	0	0	0	0	0	0	9,210	9,210
Indonesia	0	0	0	1,436	0	0	0	0	0	1,436
Iraq	0	0	0	0	0	756	0	0	0	756
Israel	0	0	0	0	0	0	0	483	0	483
Jamaica	0	0	0	0	376	0	0	0	0	376
Jordan	0	0	0	0	0	0	0	565	0	565
Kazakhstan	0	0	0	544	0	0	0	600	0	1,144
Kenya	0	657	0	0	0	0	0	780	0	1,437
Kosovo	0	0	0	270	0	0	0	198	0	468
Kyrgyzstan	0	0	0	235	0	0	0	270	0	505
Lao PDR	0	0	0	360	0	0	264	0	0	624
Latvia	0	0	0	271	0	0	0	336	0	607
Lebanon	0	0	0	0	0	0	0	530	0	530
Lesotho	0	0	0	151	0	0	0	0	0	151
Liberia	0	0	0	150	0	0	0	0	0	150
Lithuania	0	0	0	276	0	0	0	270	0	546
Macedonia, FYR	0	0	0	366	0	0	0	360	0	726
Madagascar	0	0	0	445	0	0	0	515	0	960

Malawi	0	0	0	150	0	0	0	0	511	661
Mali	0	490	0	0	360	0	0	0	0	850
Mauritania	237	0	0	0	0	0	0	0	121	358
Mauritius	0	0	0	398	0	0	0	0	0	398
Mexico	1,480	0	0	0	1480	0	0	0	0	2,960
Micronesia	0	0	0	67	0	0	0	0	0	67
Moldova	0	0	0	363	0	0	0	360	0	723
Mongolia	0	0	0	362	0	0	0	360	0	722
Montenegro	0	0	0	116	0	0	0	150	0	266
Morocco	0	0	0	0	0	0	0	406	0	406
Mozambique	0	479	0	0	0	0	0	0	0	479
Myanmar	0	0	0	0	0	0	0	0	632	632
Namibia	329	0	0	0	0	0	0	0	562	891
Nepal	0	0	0	368	0	0	0	482	0	850
Nicaragua	478	0	0	0	336	0	0	0	0	814
Niger	0	0	0	150	0	0	0	0	0	150
Nigeria	0	1,891	0	0	0	0	0	0	2,646	4,537
Pakistan	0	935	0	0	0	0	0	1,229	0	2,164
Panama	604	0	0	0	365	0	0	0	0	969
Paraguay	613	0	0	0	361	0	0	0	0	974
Peru	632	0	0	0	1000	0	0	0	0	1,632
Philippines	0	0	0	1,320	0	0	0	0	0	1,320
Poland	0	0	0	455	0	0	0	542	0	997
Romania	0	0	0	541	0	0	0	540	0	1,081
Russia	0	0	0	1,004	0	0	4,220	0	0	5,224
Rwanda	212	0	0	0	0	241	0	0	0	453

Samoa	0	0	0	102	0	0	0	0	0	102
Senegal	0	506	0	0	0	0	0	0	558	1,064
Serbia	0	0	0	388	0	0	0	359	0	747
Sierra Leone	0	0	0	150	0	0	0	0	0	150
Slovakia	0	0	0	275	0	0	0	268	0	543
Slovenia	0	0	0	276	0	0	0	270	0	546
South Africa	0	937	0	0	0	0	0	0	0	937
South Sudan	0	0	0	0	0	0	0	0	733	733
Sri Lanka	0	0	0	0	0	610	0	0	0	610
St. Kitts and Nevis	0	0	0	0	150	0	0	0	0	150
St. Lucia	0	0	0	0	150	0	0	0	0	150
St. Vincent and the Grenadines	0	0	0	0	154	0	0	0	0	154
Sudan	0	0	0	0	0	0	0	0	647	647
Suriname	0	0	0	0	152	0	0	0	0	152
Swaziland	307	0	0	0	0	0	0	0	0	307
Sweden	0	0	0	0	0	0	0	0	600	600
Tajikistan	0	0	360	0	0	0	0	359	0	719
Tanzania	419	0	0	0	0	0	0	813	0	1,232
Timor Leste	0	0	0	150	0	0	0	0	0	150
Togo	0	0	0	155	0	0	0	0	0	155
Tonga	0	0	0	150	0	0	0	0	0	150
Trinidad and Tobago	0	0	0	0	370	0	0	0	0	370
Tunisia	0	0	0	0	0	0	0	592	0	592
Turkey	0	0	1,152	0	0	0	0	1,344	0	2,496
Uganda	563	0	0	0	0	0	0	762	0	1,325
Ukraine	0	0	851	0	0	0	0	1,002	0	1,853

Uruguay	621	0	0	0	607	0	0	0	0	1,228
Uzbekistan	0	0	366	0	0	0	0	390	0	756
Vanuatu	0	0	0	128	0	0	0	0	0	128
Venezuela	500	0	0	0	320	0	0	0	0	820
Vietnam	0	0	0	1,053	0	0	0	0	0	1,053
West Bank and Gaza	0	0	0	0	0	0	0	434	0	434
Yemen, Rep.	0	0	0	0	477	0	0	299	0	776
Zambia	0	484	0	0	0	0	0	720	0	1,204
Zimbabwe	0	0	0	0	0	599	0	0	0	599
Total	14,930	10,329	3,909	19,304	14,677	3,000	7,184	26,539	17,009	116,881

Appendix 2.2: Key variables used in the empirical analysis

Table 2.3 An overview of key variables used in the empirical analysis

Variables	Number of observations	Mean
Regarding international activities		
% of inputs that are foreign	57,265	29%
Share of firms that import intermediates:	57,265	55%
% of sales sold abroad	116,881	11%
Share of firms that export goods	116,881	23%
% of foreign ownership	114,654	8 %
Share of firms that are at least 10% foreign owned:	114,654	10%
Workforce:		
% of workforce that are non-production (white collar workers)	60,287	27%
% of production workers that are skilled	56,000	69%
% of total workforce that are skilled production workers	57,450	51%
% of skilled production workers + white collar workers in total workforce	57,000	51%
% of workers that have a university degree	33,863	10%
Instrumental variable		
How much of an obstacle is: customs and trade regulations?	116,000	
How much of an obstacle is: Access to finance	115,000	

Appendix 2.3: Empirical Results

Table 2.4 Baseline results, where exporters (importers) are defined as firms that export (import) more than 0 % of their outputs (inputs)

VARIABLES	(1) SNPW	(2) SK	(3) SSPfte	(4) SSP
Compared to non-trading firms:				
Exporters only	-0.120	1.707	1.861**	2.741*
	(0.644)	(1.450)	(0.913)	(1.601)
Importers only	2.154***	0.831	-1.200	-0.0507
	(0.655)	(1.522)	(1.633)	(2.356)
Importers and Exporters	3.620***	8.327***	4.668*	9.974**
(as a proxy for GVC)	(0.811)	(3.086)	(2.552)	(4.098)
Foreign ownership	5.092***	6.091***	0.879	6.917**
	(0.919)	(2.153)	(2.021)	(2.942)
Ln (Capital)	-0.629	-0.817**	-0.185	-0.870**
	(0.475)	(0.345)	(0.265)	(0.394)
Ln (Sales)	1.122**	-0.850	-1.984***	-1.532**
	(0.454)	(0.705)	(0.412)	(0.633)
Quality certificate	2.499***	3.098	0.584	2.977
	(0.593)	(2.123)	(1.556)	(2.513)
Managerial experience	-0.0560***	-0.00391	0.0545	0.0204
	(0.0157)	(0.0552)	(0.0641)	(0.0623)
How much of an obstacle is access to finance? (base is no obstacle)				
Minor obstacle	-0.950**	-1.608	-0.653	-1.808
	(0.381)	(1.045)	(1.185)	(1.436)
Moderate obstacle	0.848*	-1.090	-2.073**	-1.425
	(0.510)	(1.152)	(0.890)	(1.224)
Major obstacle	-0.911	-4.668**	-3.761	-5.365**
	(0.706)	(2.216)	(2.270)	(2.567)
Very severe obstacle	-0.939	-1.353	-0.413	-0.929
	(1.074)	(2.954)	(3.173)	(3.546)
Size of the firm compared to small sized firm:				
Medium sized (10-99 employees)	-3.426**	-8.579***	-5.164**	-10.23***
	(1.529)	(2.867)	(2.031)	(3.128)
Large sized (100+ employees)	-8.379***	-8.987***	-0.887	-8.578***
	(1.744)	(2.569)	(2.445)	(2.605)
Constant	17.66***	101.1***	83.58***	104.3***
	(4.698)	(11.35)	(7.811)	(11.59)
Observations	30,903	29,351	29,448	29,206
R-squared	0.238	0.237	0.252	0.253

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5 *Effect of GVCs on firms in low skilled sectors where exporters (importers) are defined as firms that export (import) more than 0 % of their outputs (inputs). LSAC = Low Skilled Abundant Countries; HSAC = High Skilled Abundant Countries.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Compared to non-trading firms:								
Exporters only	-1.784	-0.299	-9.386	4.439***	-7.566	4.912***	-14.98	7.035***
	(2.759)	(0.703)	(6.696)	(1.086)	(4.748)	(0.984)	(9.503)	(1.405)
Importers only	-0.0930	0.276	-5.035*	1.618	-4.669*	1.211	-6.968*	1.658
	(1.338)	(1.357)	(2.805)	(3.075)	(2.573)	(2.627)	(3.864)	(4.171)
Importers and Exporters	1.774	0.718	-7.809***	5.534***	-9.339***	4.393***	-10.65***	7.138***
(as a proxy for GVC)	(1.397)	(0.920)	(1.816)	(1.323)	(2.094)	(1.155)	(2.883)	(1.421)
Foreign ownership	2.927**	0.673	-3.399	7.268***	-6.224**	6.348*	-5.404	9.054***
	(1.381)	(2.228)	(2.717)	(2.247)	(2.736)	(3.429)	(3.749)	(2.941)
Ln (Capital)	-0.767*	-0.0256	0.812*	-0.519	1.564***	-0.511	1.300**	-0.755
	(0.430)	(0.449)	(0.475)	(0.792)	(0.421)	(0.359)	(0.499)	(0.756)
Ln (Sales)	1.699***	0.0231	1.090	-2.311	-0.576	-2.338**	0.772	-2.555*
	(0.484)	(0.371)	(1.171)	(1.430)	(0.830)	(1.111)	(1.398)	(1.496)
Quality certificate	0.858	2.536***	0.568	-0.540	-0.210	-3.020***	0.274	-2.400*
	(1.227)	(0.899)	(2.144)	(1.034)	(1.971)	(1.105)	(2.653)	(1.318)
Managerial experience	0.00813	-0.0455**	-0.0203	0.0644	-0.0274	0.112**	-0.0307	0.107*
	(0.0342)	(0.0201)	(0.0957)	(0.0471)	(0.0943)	(0.0512)	(0.129)	(0.0641)
How much of an obstacle is								
Access to finance?								
(base is no obstacle)								
Minor obstacle	2.281*	0.00832	0.755	-3.411	-1.362	-3.504**	-0.662	-3.746
	(1.180)	(0.884)	(1.422)	(2.429)	(1.605)	(1.523)	(1.748)	(2.778)
Moderate obstacle	3.138*	-0.308	3.323	-6.359**	0.204	-6.241***	2.114	-7.294**

	(1.625)	(0.931)	(3.077)	(2.733)	(2.426)	(1.912)	(3.377)	(2.911)
Major obstacle	-0.479	0.0546	-7.713**	-5.733*	-7.047**	-6.111**	-8.495**	-6.341*
	(1.171)	(0.784)	(3.327)	(3.094)	(3.383)	(2.926)	(3.943)	(3.600)
Very severe obstacle	-1.388	-0.0666	-1.392	-9.011*	0.268	-8.879**	-3.767	-8.629
	(1.097)	(1.729)	(2.627)	(5.267)	(2.915)	(3.941)	(2.456)	(5.525)
Size of the firm compared to small sized firm:								
Medium sized (10-99 employees)	-8.694**	-2.529*	-17.13***	-4.819	-8.812***	-2.508	-19.09***	-6.437
	(3.358)	(1.302)	(5.965)	(3.881)	(2.598)	(4.950)	(6.190)	(4.752)
Large sized (100+ employees)	-13.43***	-8.802***	-6.545***	-5.513	6.579*	2.295	-3.686	-4.670
	(3.734)	(1.296)	(2.215)	(5.128)	(3.572)	(5.370)	(2.773)	(5.771)
Constant	16.17***	23.31***	65.23***	121.1***	48.73***	98.41***	59.53***	121.2***
	(3.274)	(7.509)	(8.099)	(19.17)	(9.339)	(14.04)	(11.13)	(20.20)
Observations	8,599	4,897	7,652	4,810	7,680	4,822	7,621	4,772
R-squared	0.321	0.196	0.287	0.242	0.344	0.274	0.290	0.261

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6 Effect of GVCs on firms in high skilled sectors where exporters (importers) are defined as firms that export (import) more than 0 % of their outputs (inputs). LSAC = Low Skilled Abundant Countries; HSAC = High Skilled Abundant Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Compared to non-trading firms								
Exporters only	0.182	3.066	-1.332*	17.97*	-1.478	14.65**	-1.503**	23.93**
	(0.575)	(4.415)	(0.742)	(9.666)	(1.151)	(5.458)	(0.734)	(11.26)
Importers only	1.237	8.338***	-1.096	2.905*	-2.060	-4.904	-2.196	0.0638
	(1.424)	(2.866)	(2.265)	(1.677)	(1.331)	(3.281)	(2.482)	(2.939)
Importers and Exporters	4.486***	7.742***	9.997***	12.15**	5.543**	4.586	10.95***	12.57*
(as a proxy for GVC)	(0.682)	(2.671)	(2.154)	(5.949)	(2.251)	(3.340)	(2.774)	(6.718)
Foreign ownership	3.375	1.836	1.860	9.892**	-1.438	7.872	0.245	14.46*
	(2.272)	(2.103)	(2.860)	(4.834)	(0.889)	(6.589)	(3.113)	(7.700)
Ln (Capital)	-0.251	-0.853***	-0.896***	-1.239	-0.641	-0.370	-0.856***	-1.292
	(0.509)	(0.192)	(0.134)	(0.750)	(0.511)	(0.801)	(0.177)	(1.066)
Ln (Sales)	0.432	1.775***	-1.620***	0.238	-2.060***	-1.515***	-2.554***	-0.493
	(0.524)	(0.311)	(0.456)	(0.334)	(0.620)	(0.257)	(0.575)	(0.326)
Quality certificate	2.132***	3.559**	2.055**	14.75*	-0.113	11.30	1.784*	17.37*
	(0.788)	(1.454)	(0.781)	(8.520)	(1.156)	(7.108)	(0.959)	(9.878)
Managerial experience	-0.0379	-0.0137	0.0934	-0.174*	0.132	-0.148	0.0834	-0.119
	(0.0252)	(0.0507)	(0.0750)	(0.0929)	(0.0896)	(0.139)	(0.101)	(0.119)
How much of an obstacle is								
Access to finance?								
(base is no obstacle)								
Minor obstacle	-1.605***	-0.192	1.659	-4.588*	3.232***	-4.287**	2.271	-5.191**
	(0.562)	(0.943)	(1.127)	(2.424)	(1.189)	(1.967)	(1.557)	(2.333)
Moderate obstacle	-1.787***	3.624*	-1.212	0.215	0.506	-3.780**	-0.130	-2.432

	(0.294)	(1.910)	(0.886)	(1.610)	(0.732)	(1.467)	(1.130)	(1.606)
Major obstacle	-2.866	2.397**	-2.789	-1.007	0.0953	-3.423*	-3.243	-1.894
	(2.327)	(1.092)	(3.817)	(1.833)	(4.910)	(1.947)	(4.752)	(2.922)
Very severe obstacle	-3.519	2.965**	-3.256	2.449	0.305	-0.764	-2.840	3.000
	(2.934)	(1.450)	(3.453)	(2.358)	(3.718)	(2.228)	(4.278)	(3.174)
Size of the firm compared to small sized firm:								
Medium sized (10-99 employees)	-1.722***	-7.449**	-7.649***	-15.54***	-5.866**	-8.043***	-9.120***	-19.10***
	(0.562)	(2.993)	(2.295)	(5.143)	(2.303)	(2.501)	(2.825)	(5.811)
Large sized (100+ employees)	-5.178***	-10.89***	-9.259***	-20.18**	-4.139***	-9.681	-9.189***	-22.51**
	(0.891)	(2.847)	(1.152)	(9.533)	(1.517)	(6.866)	(1.162)	(10.90)
Constant	22.15***	11.39	112.2***	90.01***	90.07***	77.91***	118.2***	92.63***
	(4.068)	(7.214)	(6.317)	(7.987)	(7.073)	(14.58)	(8.291)	(16.94)
Observations	7,844	5,258	7,454	5,166	7,485	5,185	7,411	5,141
R-squared	0.155	0.264	0.199	0.415	0.209	0.399	0.219	0.416

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7 GVC firms identified as firms importing and exporting at least 90% of their inputs and outputs respectively

VARIABLES	(1) SNPW	(2) SK	(3) SSPfte	(4) SSP
Compared to firms that import and export less than 90 % of their inputs and outputs:				
Exporting at least 90% of outputs	-2.514***	-2.053**	0.316	-0.870
	(0.928)	(0.971)	(1.423)	(1.437)
Importers at least 90% of inputs	5.741**	0.374	-5.438*	-0.979
	(2.559)	(1.697)	(2.860)	(3.445)
Importing and exporting at least 90 % of inputs and outputs	-5.422***	-2.212	2.998	-0.496
	(1.339)	(2.621)	(3.542)	(3.513)
Foreign ownership	5.686***	8.117***	2.286	9.344**
	(0.949)	(2.752)	(2.541)	(3.792)
Ln (Capital)	-0.634	-0.873*	-0.233	-0.937*
	(0.492)	(0.443)	(0.244)	(0.508)
Ln (Sales)	1.165***	-0.543	-1.718***	-1.134
	(0.443)	(0.805)	(0.457)	(0.761)
Quality certificate	2.607***	3.385	0.760	3.361
	(0.716)	(2.279)	(1.585)	(2.664)
Managerial experience	-0.0598***	-0.00408	0.0582	0.0234
	(0.0174)	(0.0533)	(0.0617)	(0.0604)
How much of an obstacle is Access to finance? (base is no obstacle)				
Minor obstacle	-0.992**	-1.839*	-0.834	-2.113
	(0.412)	(1.079)	(1.208)	(1.473)
Moderate obstacle	0.769	-0.853	-1.757*	-1.073
	(0.481)	(1.219)	(0.975)	(1.470)
Major obstacle	-0.723	-4.364**	-3.645	-4.996*
	(0.802)	(2.191)	(2.230)	(2.559)
Very severe obstacle	-0.968	-1.500	-0.549	-1.073
	(1.050)	(2.926)	(3.075)	(3.502)
Size of the firm compared to small sized firm:				
Medium sized (10-99 employees)	-3.222**	-8.249***	-5.021**	-9.867***
	(1.447)	(2.898)	(2.036)	(3.233)
Large sized (100+ employees)	-7.423***	-7.674***	-0.485	-7.142***
	(1.526)	(2.433)	(2.243)	(2.455)
Constant	17.58***	98.09***	80.65***	100.1***
	(5.133)	(12.91)	(8.990)	(13.55)
Observations	30,903	29,351	29,448	29,206
R-squared	0.240	0.229	0.250	0.245

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.8 Effect of GVCs on firms in low skilled sectors where GVC firms are identified as firms importing and exporting at least 90% of their inputs and outputs respectively LSAC = Low Skilled Abundant Countries; HSAC = High Skilled Abundant Countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Compared to firms that import and export less than 90 % of their inputs and outputs:								
Exporting at least 90% of outputs	-2.288**	2.559	5.107***	-4.145	7.401***	-6.805*	8.579***	-7.332*
	(0.932)	(2.563)	(1.759)	(2.806)	(1.343)	(3.636)	(1.851)	(3.851)
Importers at least 90% of inputs	2.261	1.963	5.820**	-0.874	3.337	-1.892	5.101	-1.355
	(1.451)	(1.635)	(2.707)	(2.468)	(3.079)	(2.982)	(3.490)	(3.017)
Importing and exporting at least 90 % of inputs and outputs	-1.758	2.287	3.274	-9.294	3.641	-11.39	6.125	-10.91
	(2.562)	(4.287)	(2.789)	(5.547)	(4.356)	(7.225)	(3.788)	(7.048)
Foreign ownership	1.025	3.183**	7.751***	-3.025	6.439*	-6.078**	9.463***	-4.547
	(2.192)	(1.365)	(2.246)	(2.546)	(3.230)	(2.630)	(3.054)	(3.512)
Ln (Capital)	-0.0354	-0.755*	-0.449	0.748	-0.426	1.494***	-0.648	1.197**
	(0.459)	(0.442)	(0.767)	(0.488)	(0.319)	(0.413)	(0.705)	(0.511)
Ln (Sales)	0.0485	1.693***	-2.216	0.698	-2.266**	-0.957	-2.418	0.180
	(0.381)	(0.408)	(1.469)	(0.966)	(1.125)	(0.695)	(1.550)	(1.063)
Quality certificate	2.374***	1.165	0.0250	-0.297	-2.311**	-1.375	-1.507	-0.750
	(0.809)	(1.215)	(1.083)	(2.325)	(1.028)	(2.051)	(1.349)	(2.830)
Managerial experience	-0.0469**	0.00921	0.0670	-0.00749	0.115**	-0.0167	0.113*	-0.0114
	(0.0194)	(0.0356)	(0.0485)	(0.0879)	(0.0535)	(0.0890)	(0.0664)	(0.115)
How much of an obstacle is Access to finance? (base is no obstacle)								
Minor obstacle	-0.134	2.462**	-3.359	0.409	-3.307**	-1.888	-3.605	-1.134
	(0.968)	(1.129)	(2.451)	(1.474)	(1.488)	(1.571)	(2.768)	(1.772)
Moderate obstacle	-0.471	3.270*	-6.501**	3.529	-6.208***	0.294	-7.413**	2.451

	(1.021)	(1.677)	(2.719)	(3.291)	(1.806)	(2.501)	(2.874)	(3.702)
Major obstacle	-0.0295	-0.251	-5.714*	-8.430**	-5.974**	-7.929**	-6.288*	-9.383**
	(0.714)	(1.091)	(3.153)	(3.664)	(2.946)	(3.729)	(3.689)	(4.360)
Very severe obstacle	-0.184	-1.529	-8.701	-2.601	-8.531**	-0.783	-8.188	-5.599***
	(1.672)	(1.076)	(5.216)	(1.766)	(3.935)	(2.068)	(5.463)	(1.940)
Size of the firm compared to small sized firm:								
Medium sized (10-99 employees)	-2.384*	-8.880**	-4.609	-17.89**	-2.441	-9.332***	-6.196	-20.18***
	(1.330)	(3.523)	(4.069)	(6.780)	(5.184)	(3.203)	(5.014)	(7.206)
Large sized (100+ employees)	-8.233***	-13.46***	-5.125	-8.090***	2.181	5.154*	-4.409	-5.757**
	(1.278)	(3.896)	(5.540)	(2.796)	(5.928)	(2.753)	(6.334)	(2.726)
Constant	23.22***	15.98***	118.8***	69.19***	96.14***	52.80***	117.8***	65.81***
	(7.437)	(3.393)	(19.10)	(6.137)	(14.24)	(8.057)	(20.41)	(7.878)
Observations	8,599	4,897	7,652	4,810	7,680	4,822	7,621	4,772
R-squared	0.198	0.320	0.241	0.280	0.273	0.339	0.259	0.280

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.9 Effect of GVCs on firms in high skilled sectors where GVC firms are identified as firms importing and exporting at least 90% of their inputs and outputs respectively LSAC = Low Skilled Abundant Countries; HSAC = High Skilled Abundant Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Compared to firms that import and export less than 90 % of their inputs and outputs:								
Exporting at least 90% of outputs	0.792	-2.353	-6.017***	-4.536*	-6.802**	-2.429	-6.294*	-5.614
	(1.298)	(2.738)	(2.017)	(2.690)	(2.570)	(2.792)	(3.737)	(3.548)
Importers at least 90% of inputs	0.327	7.909**	-2.090	-7.668***	-2.089	-15.72***	-4.087	-14.31***
	(2.547)	(3.160)	(3.289)	(2.185)	(3.949)	(5.092)	(4.423)	(4.669)
Importing and exporting at least	-6.960**	-6.916**	4.364	-5.980	11.35*	-0.454	8.478	-7.863
90 % of inputs and outputs	(2.676)	(3.220)	(4.525)	(7.282)	(6.625)	(8.417)	(5.877)	(9.618)
Foreign ownership	4.623*	3.168**	4.242**	13.91*	-0.330	10.56	2.749	19.38*
	(2.446)	(1.532)	(2.118)	(7.385)	(0.686)	(8.435)	(2.070)	(10.85)
Ln (Capital)	-0.338	-0.900***	-1.036***	-1.049**	-0.691	-0.145	-1.009***	-0.987
	(0.568)	(0.194)	(0.209)	(0.493)	(0.446)	(0.491)	(0.220)	(0.678)
Ln (Sales)	0.506	1.909***	-1.462***	0.773*	-1.975***	-1.117***	-2.365***	0.103
	(0.509)	(0.319)	(0.486)	(0.405)	(0.600)	(0.221)	(0.601)	(0.334)
Quality certificate	2.090**	4.466**	1.694**	14.70*	-0.428	10.29*	1.356*	16.81*
	(0.898)	(2.205)	(0.651)	(7.873)	(0.955)	(5.705)	(0.786)	(8.611)
Managerial experience	-0.0437**	-0.0374	0.0817	-0.163*	0.127	-0.114	0.0724	-0.0901
	(0.0197)	(0.0361)	(0.0746)	(0.0950)	(0.0908)	(0.124)	(0.102)	(0.108)
How much of an obstacle is Access to finance? (base is no obstacle)								
Minor obstacle	-1.550**	0.760	1.438	-5.333*	2.964**	-5.860*	1.947	-6.813**
	(0.663)	(0.897)	(1.144)	(3.057)	(1.164)	(3.058)	(1.559)	(3.339)
Moderate obstacle	-1.330***	3.457**	-0.371	0.559	0.889	-3.169**	0.782	-2.084

	(0.335)	(1.582)	(1.117)	(1.286)	(0.916)	(1.425)	(1.417)	(1.544)
Major obstacle	-2.734	2.260**	-2.430	-1.925	0.315	-4.233**	-2.864	-3.301
	(2.513)	(0.916)	(3.489)	(1.754)	(4.690)	(1.944)	(4.334)	(2.608)
Very severe obstacle	-3.303	2.391	-3.134	1.284	0.286	-1.442	-2.731	1.464
	(3.160)	(1.426)	(3.714)	(1.775)	(3.619)	(1.876)	(4.274)	(2.461)
Size of the firm compared to small sized firm:								
Medium sized (10-99 employees)	-1.592***	-6.468**	-7.751***	-13.88***	-6.094***	-7.285***	-9.295***	-17.10***
	(0.583)	(2.565)	(2.246)	(4.668)	(2.256)	(2.398)	(2.794)	(5.434)
Large sized (100+ employees)	-4.485***	-8.966***	-7.973***	-18.70**	-3.538***	-9.998	-7.826***	-21.25**
	(0.908)	(2.405)	(0.809)	(8.712)	(1.147)	(6.404)	(0.783)	(10.06)
Constant	22.73***	13.57***	112.7***	85.03***	89.96***	71.14***	118.5***	85.58***
	(5.093)	(4.982)	(8.221)	(6.019)	(7.261)	(10.07)	(10.49)	(12.49)
Observations	7,844	5,258	7,454	5,166	7,485	5,185	7,411	5,141
R-squared	0.148	0.244	0.185	0.383	0.207	0.387	0.208	0.388

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.10 Continuous interaction

VARIABLES	(1) SNPW	(2) SK	(3) SSPfte	(4) SSP
Exporting	1.092	6.873**	5.853***	8.145**
	(1.705)	(3.289)	(2.064)	(3.445)
Importing	5.057**	7.158***	2.119	7.679***
	(2.323)	(2.534)	(1.564)	(2.483)
Exporting and importing	-1.104*	-2.356**	-1.283**	-2.632**
	(0.574)	(0.956)	(0.509)	(1.007)
Foreign ownership	3.686	8.101***	4.407	11.62***
	(2.863)	(2.226)	(4.873)	(3.971)
Ln (Capital)	-1.601**	-1.005**	0.690**	-1.002*
	(0.657)	(0.385)	(0.327)	(0.546)
Ln (Sales)	3.045***	0.234	-2.929***	-0.383
	(0.574)	(0.617)	(0.805)	(0.721)
Quality certificate	3.929**	3.487	-0.523	2.938
	(1.755)	(4.435)	(3.916)	(5.290)
Managerial experience	-0.102***	0.0886	0.209**	0.157
	(0.0314)	(0.0831)	(0.101)	(0.123)
How much of an obstacle is Access to finance?				
(base is no obstacle)				
Minor obstacle	0.375	-1.016	-1.389	-1.105
	(0.934)	(1.976)	(2.305)	(3.599)
Moderate obstacle	2.725	2.266	-0.457	4.653
	(2.038)	(3.217)	(1.868)	(4.964)
Major obstacle	3.163	-0.693	-3.842	-0.0955
	(2.501)	(1.408)	(2.359)	(1.985)
Very severe obstacle	5.811***	0.184	-5.600	-1.738
	(1.834)	(3.727)	(3.934)	(4.741)
Size of the firm compared to small sized firm:				
Medium sized (10-99 employees)	-6.017***	-11.08***	-4.715**	-13.12***
	(1.749)	(2.477)	(2.346)	(3.651)
Large sized (100+ employees)	-11.21***	-11.79***	-0.743	-11.77***
	(1.993)	(1.881)	(2.869)	(2.956)
Constant	-3.834	71.64***	75.47***	69.98***
	(9.151)	(16.36)	(14.11)	(18.65)
Observations	8,222	7,705	7,729	7,655
R-squared	0.495	0.434	0.409	0.442

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 2.4: Robustness Checks

Table 2.11 Dealing with non-response bias in the baseline results of Table 2.4

VARIABLES	(1) SNPW	(2) SK	(3) SSPfte	(4) SSP
Non-trading firms	0	0	0	0
	(0)	(0)	(0)	(0)
Exporters	-1.003	-0.0435	1.126	1.092
	(1.299)	(2.291)	(1.033)	(2.043)
Importers	2.336***	0.328	-1.867*	-0.593
	(0.591)	(0.679)	(1.080)	(1.133)
Exporters and importers	3.817***	5.597**	2.119	6.774*
	(0.867)	(2.641)	(2.103)	(3.443)
Missing (non-trading firms)	0	0	0	0
	(0)	(0)	(0)	(0)
Missing (Exporters)	-0.349	10.11*	19.11	13.08
	(8.255)	(5.633)	(11.65)	(10.44)
Missing (Importers)	-0.793	-2.063	-0.709	-2.202
	(0.601)	(1.790)	(1.608)	(2.159)
Missing (Exporters and Importers)	0	0	0	0
	(0)	(0)	(0)	(0)
Foreign ownership	4.359***	2.316***	-2.159***	1.909**
	(1.094)	(0.849)	(0.647)	(0.930)
Missing (Foreign ownership)	-2.239	1.650	-4.480	2.323
	(8.334)	(5.876)	(11.93)	(10.67)
Ln (Capital)	-0.189	-0.562	-0.407	-0.626
	(0.194)	(0.474)	(0.360)	(0.537)
Missing (Ln (Capital))	-2.308	-9.046	-7.405	-10.40
	(2.456)	(8.294)	(6.887)	(9.404)
Ln (Sales)	0.502**	-0.837**	-1.299***	-1.493***
	(0.231)	(0.363)	(0.189)	(0.368)
Missing (Ln (Sales))	7.108*	-10.88**	-17.39***	-20.66***
	(4.148)	(4.335)	(2.975)	(4.551)
Quality Certificate	2.809***	3.664***	0.957	3.019**
	(0.858)	(1.372)	(0.693)	(1.392)
Missing (Quality Certificate)	2.171	2.220	0.0225	1.465
	(1.467)	(1.417)	(2.603)	(2.462)
Managerial Experience	-0.0495***	-0.0195	0.0315	-0.00286
	(0.0187)	(0.0933)	(0.103)	(0.109)
Missing (Managerial Experience)	15.37***	22.33***	6.913**	30.11***
	(2.846)	(3.102)	(2.661)	(3.495)
How much of an obstacle is access to finance?				
Minor obstacle	-1.263	-1.284	-0.00637	-1.083
	(0.895)	(2.541)	(1.802)	(2.997)
Moderate obstacle	-0.553	-0.427	0.0314	-0.271

	(0.441)	(2.224)	(2.106)	(2.646)
Major obstacle	0.133	0.332	0.0897	0.573
	(0.892)	(2.944)	(2.586)	(3.631)
Very severe obstacle	-0.0381	0.0140	0.0866	-0.112
	(0.970)	(2.970)	(2.464)	(3.387)
Missing (how much of an obstacle is access to finance)	-3.757*	-0.676	4.385	-0.428
	(2.027)	(6.718)	(7.303)	(7.987)
Size of the firm compared to a small firm				
Medium sized (10-99 employees)	-3.462***	-6.483**	-3.298**	-7.473***
	(1.298)	(2.753)	(1.552)	(2.827)
Large sized (100+ employees)	-7.473***	-5.923***	0.985	-4.815***
	(1.368)	(1.329)	(1.266)	(1.199)
Missing (Size)	-	-	-	2.947
				(2.752)
Constant	20.94***	97.47***	76.49***	100.8***
	(4.714)	(10.30)	(6.134)	(11.79)
Observations	55,975	53,591	53,876	53,092
R-squared	0.230	0.219	0.242	0.232

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.12 Dealing with non-response bias in the baseline results conditioned on the Factor bias in low skilled industries, i.e. in the results reported in Table 2.5

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Non-trading firms	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Exporters	-1.157	-0.396	-3.083	4.897**	-1.636	5.505***	-6.189	7.422***
	(2.220)	(0.785)	(3.930)	(2.367)	(2.696)	(1.810)	(5.940)	(2.584)
Importers	0.124	0.972	-1.026	2.140	-0.852	1.263	-1.869	2.104
	(1.562)	(1.282)	(1.776)	(2.260)	(1.051)	(2.306)	(2.275)	(3.115)
Exporters and importers	1.311	0.237	-3.526**	4.946***	-4.570***	4.537***	-5.206**	6.607***
	(1.633)	(0.791)	(1.562)	(1.249)	(1.631)	(1.031)	(2.451)	(1.494)
Missing (non-trading firms)	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Missing (Exporters)	0.447	0.721	-12.43**	-1.164	-15.00*	-4.027	-14.91*	-3.025
	(3.321)	(9.478)	(6.124)	(9.192)	(8.124)	(11.52)	(7.902)	(11.71)
Missing (Importers)	4.058**	-1.489**	-4.299	1.888*	-7.396**	3.980***	-5.187	2.498
	(1.921)	(0.571)	(3.404)	(0.976)	(3.155)	(1.122)	(4.240)	(1.553)
Missing (Exporters and Importers)	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Foreign ownership	0.801	2.343	-5.523*	3.747*	-6.149**	1.286	-7.255*	4.358*
	(1.316)	(2.607)	(3.058)	(1.977)	(2.691)	(3.016)	(3.778)	(2.498)
Missing (Foreign ownership)	-3.419	-0.701	10.21*	-0.439	16.04*	-1.513	12.39*	-0.678
	(3.650)	(13.04)	(5.659)	(9.423)	(8.143)	(12.97)	(7.292)	(12.66)
Ln (Capital)	0.112	-0.0902	0.644***	-0.848	0.513**	-0.760	0.775***	-1.014
	(0.142)	(0.291)	(0.174)	(0.850)	(0.205)	(0.630)	(0.215)	(0.947)
Missing (Ln (Capital))	3.911	-2.808	10.32***	-13.14	5.922*	-10.44	11.71***	-15.90
	(3.013)	(4.686)	(2.427)	(14.84)	(3.466)	(10.88)	(2.634)	(16.39)
Ln (Sales)	0.260	-0.303	-0.671***	-1.566***	-0.911***	-1.268***	-1.074***	-1.866***
	(0.159)	(0.490)	(0.202)	(0.529)	(0.242)	(0.282)	(0.201)	(0.500)
Missing (Ln (Sales))	2.666	-6.915	-15.18***	-22.48**	-17.15***	-15.64**	-23.02***	-25.79**
	(3.377)	(9.268)	(2.731)	(10.80)	(4.521)	(5.904)	(2.343)	(10.41)
Quality Certificate	1.709**	2.746***	3.901*	0.370	2.146	-2.291*	4.114	-1.051
	(0.693)	(0.697)	(2.093)	(1.097)	(2.364)	(1.270)	(2.788)	(1.721)
Missing (Quality Certificate)	1.170	7.581***	16.37**	6.024	15.04***	-0.706	20.84**	3.549

	(1.551)	(1.881)	(6.195)	(4.360)	(5.335)	(2.584)	(8.132)	(3.378)
Managerial Experience	-0.0123	0.0375	-0.0720	0.127***	-0.0613	0.0921***	-0.0781	0.155***
	(0.0345)	(0.0359)	(0.0773)	(0.0345)	(0.0989)	(0.0263)	(0.104)	(0.0441)
Missing (Managerial Experience)	-	-4.888	-	-10.52	-	-5.863	-	-6.222
		(4.051)		(15.11)		(10.96)		(15.41)
How much of an obstacle is access to finance?								
Minor obstacle	0.988	-0.104	-2.267	-0.653	-2.846**	-0.640	-2.040	-0.443
	(0.773)	(0.775)	(1.430)	(2.817)	(1.279)	(2.116)	(1.587)	(3.127)
Moderate obstacle	2.097***	-0.926*	0.251	-0.734	-1.748	0.108	-0.289	-0.441
	(0.686)	(0.497)	(0.887)	(3.888)	(1.222)	(3.803)	(1.618)	(4.507)
Major obstacle	-0.313	-1.044	-4.938*	-0.461	-4.533*	0.388	-4.331	-0.0634
	(0.709)	(0.847)	(2.711)	(4.362)	(2.635)	(4.171)	(3.176)	(5.209)
Very severe obstacle	-0.193	-1.734	-4.596***	-3.872	-3.962***	-2.091	-6.617***	-3.416
	(0.574)	(1.649)	(1.031)	(4.087)	(1.433)	(2.849)	(2.072)	(4.441)
Missing (how much of an obstacle is access to finance)	0.397	-5.978***	0.661	6.005*	0.526	11.79***	0.719	7.840*
	(2.231)	(1.261)	(3.140)	(3.479)	(4.417)	(4.051)	(4.756)	(4.175)
Size of the firm compared to a small firm								
Medium sized (10-99 employees)	-5.804***	-2.278***	-12.88***	-3.213*	-7.336***	-1.285	-15.02***	-3.928*
	(1.797)	(0.683)	(4.051)	(1.675)	(2.324)	(2.055)	(4.482)	(2.050)
Large sized (100+ employees)	-9.631***	-7.331***	-2.135	-4.488**	7.145	1.708	0.862	-3.122
	(1.749)	(1.176)	(2.782)	(2.002)	(4.349)	(1.345)	(4.665)	(1.934)
Missing (Size)	-	-	-	-	-	-	-	5.224
								(3.271)
Constant	23.81***	29.16***	91.48***	111.6***	67.53***	82.86***	90.85***	111.3***
	(2.229)	(8.155)	(3.140)	(15.09)	(2.721)	(8.976)	(4.203)	(16.05)
Observations	14,942	8,842	13,378	8,597	13,819	8,646	13,517	8,512
R-squared	0.276	0.252	0.210	0.283	0.248	0.315	0.220	0.302

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.13 Dealing with non-response bias in the baseline results conditioned on the Factor bias in high skilled industries, i.e. in the results reported in Table 2.6

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPl1		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Non-trading firms	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Exporters	-1.137	3.257	-4.103***	10.30	-2.675***	6.943	-3.300***	12.29
	(1.443)	(3.866)	(1.267)	(8.092)	(0.656)	(4.262)	(1.017)	(9.124)
Importers	2.564**	6.732***	-0.337	0.974	-2.533***	-5.656***	-1.636	-1.660
	(1.150)	(2.246)	(1.470)	(1.386)	(0.950)	(1.496)	(1.561)	(1.108)
Exporters and importers	6.497***	6.289**	8.622***	8.757	3.378	2.342	9.163**	9.558
	(0.662)	(2.341)	(2.994)	(6.460)	(2.954)	(4.224)	(3.845)	(7.587)
Missing (non-trading firms)	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Missing (Exporters)	5.610	11.39**	21.25***	-5.201	12.71	-17.41*	35.97***	-5.394
	(6.829)	(4.777)	(4.377)	(4.844)	(10.76)	(9.174)	(13.26)	(5.030)
Missing (Importers)	-1.194**	1.927	-4.151*	5.712**	-2.686	4.507	-5.095	6.560**
	(0.565)	(2.756)	(2.437)	(2.139)	(2.721)	(3.139)	(3.453)	(2.638)
Missing (Exporters and Importers)	0	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Foreign ownership	4.048**	1.482	1.581	0.223	-2.842***	-1.090	-0.489	0.671
	(1.527)	(1.520)	(1.640)	(0.954)	(0.976)	(1.634)	(2.707)	(1.698)
Missing (Foreign ownership)	13.99**	-14.20**	-0.0975	24.49***	-18.17*	39.77***	-21.96	30.58***
	(5.353)	(5.384)	(1.938)	(5.868)	(9.597)	(9.200)	(13.25)	(5.817)
Ln (Capital)	-0.465	-0.422*	-1.753***	-0.333	-1.377***	0.0950	-1.911***	-0.439
	(0.322)	(0.220)	(0.528)	(0.368)	(0.306)	(0.550)	(0.611)	(0.660)
Missing (Ln (Capital))	-8.487	-7.894***	-33.48***	-4.399	-26.70***	3.239	-37.40***	-5.347
	(5.547)	(2.097)	(9.563)	(5.067)	(5.999)	(6.666)	(10.65)	(8.864)
Ln (Sales)	0.559*	1.134***	-0.664	-0.200	-1.087**	-1.318***	-1.379*	-0.897
	(0.291)	(0.127)	(0.653)	(0.395)	(0.531)	(0.299)	(0.784)	(0.599)
Missing (Ln (Sales))	5.785	18.88***	-0.798	-3.239	-4.422	-21.91***	-10.28	-13.96
	(5.593)	(1.320)	(11.31)	(6.383)	(9.562)	(6.023)	(13.88)	(10.23)
Quality Certificate	3.014***	5.359***	4.847***	6.567***	2.118*	1.205	4.611***	5.462***

	(0.301)	(0.646)	(1.133)	(2.265)	(1.256)	(2.033)	(1.239)	(1.869)
Missing (Quality Certificate)	6.023***	-1.999	-1.813	-8.171	-8.014**	-6.172*	-3.400	-10.63**
	(1.766)	(1.839)	(1.450)	(4.887)	(3.179)	(3.272)	(3.192)	(5.238)
Managerial Experience	-0.0895*	-0.00465	0.139*	-0.217*	0.224*	-0.202	0.165	-0.207
	(0.0468)	(0.0285)	(0.0806)	(0.108)	(0.119)	(0.135)	(0.110)	(0.128)
Missing (Managerial Experience)	17.62***	-	28.83***	-	11.18***	-	36.98***	-
	(1.696)		(2.187)		(3.244)		(3.114)	
How much of an obstacle is access to finance?								
Minor obstacle	-1.038	-1.662	0.230	0.538	1.262	2.407	0.873	2.404
	(0.746)	(1.439)	(2.638)	(2.257)	(2.152)	(3.408)	(3.046)	(4.685)
Moderate obstacle	-0.511	-0.975	-0.482	0.132	0.0130	0.974	-0.0328	1.125
	(0.611)	(1.166)	(2.241)	(1.327)	(1.624)	(2.453)	(2.625)	(2.783)
Major obstacle	-0.657	2.995***	-1.106	7.544	-0.282	4.424	-1.170	9.398
	(1.437)	(0.608)	(4.314)	(4.937)	(4.374)	(4.650)	(5.418)	(7.259)
Very severe obstacle	-1.657	2.813***	-1.734	5.498	0.182	2.558	-1.570	6.905
	(2.690)	(0.901)	(4.118)	(4.219)	(3.610)	(4.769)	(4.966)	(6.344)
Missing (how much of an obstacle is access to finance)	0.114	-5.834**	4.503	-16.33***	7.743	-10.55***	3.886	-15.20***
	(5.192)	(2.672)	(5.813)	(3.126)	(7.743)	(2.457)	(9.117)	(2.565)
Size of the firm compared to a small firm								
Medium sized (10-99 employees)	-1.389***	-5.694***	-1.883**	-12.63***	-1.015	-6.851***	-2.404**	-13.94***
	(0.434)	(1.807)	(0.900)	(2.971)	(0.971)	(1.360)	(1.173)	(2.682)
Large sized (100+ employees)	-5.290***	-9.193***	-5.149***	-11.25***	-0.819	-1.931	-4.301*	-10.45***
	(0.495)	(1.753)	(1.889)	(2.977)	(2.355)	(1.642)	(2.255)	(2.446)
Missing (Size)	-	-	-	-	-	-	5.488	-12.27***
							(4.944)	(2.414)
Constant	22.44***	14.61***	107.9***	84.71***	84.69***	69.60***	113.4***	86.96***
	(2.763)	(2.119)	(7.991)	(9.217)	(7.789)	(11.14)	(10.35)	(15.19)
Observations	16,124	9,379	15,555	9,134	15,639	9,187	15,467	9,049
R-squared	0.167	0.270	0.180	0.370	0.209	0.317	0.198	0.343

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.14 Instrumental variable, robustness check for baseline results of Table 2.4

VARIABLES	(1) SNPW	(2) SK	(3) SSPfte	(4) SSP
Exporters only	8.466	-2.049	-9.890*	-12.47**
	(1.275)	(-0.328)	(-1.738)	(-2.233)
Importers only	9.243***	-2.254	-10.97**	-12.74**
	(3.997)	(-0.524)	(-2.499)	(-2.111)
Importers and Exporters	-18.04	14.37**	31.00***	42.30***
	(-0.628)	(2.127)	(2.695)	(2.584)
Foreign ownership	6.663***	5.673**	-1.035	4.598
	(7.003)	(2.087)	(-0.482)	(1.537)
Ln (Capital)	-0.765*	-0.736***	0.0288	-0.579**
	(-1.659)	(-2.885)	(0.0824)	(-2.283)
Ln (Sales)	1.285***	-0.961	-2.245***	-1.887***
	(2.649)	(-1.468)	(-6.395)	(-3.844)
Quality certificate	2.898***	2.937	0.0575	2.300
	(3.724)	(1.325)	(0.0380)	(0.953)
Managerial experience	-0.0598***	-0.00203	0.0590	0.0257
	(-2.798)	(-0.0363)	(0.838)	(0.382)
How much of an obstacle is Access to finance? (base is no obstacle)				
Minor obstacle	-1.188***	-1.540	-0.359	-1.420
	(-3.177)	(-1.483)	(-0.301)	(-0.935)
Moderate obstacle	1.327***	-1.304	-2.748***	-2.266*
	(2.667)	(-1.028)	(-2.653)	(-1.865)
Major obstacle	-0.234	-4.939**	-4.684*	-6.554**
	(-0.278)	(-2.127)	(-1.906)	(-2.317)
Very severe obstacle	-1.153	-1.264	-0.0825	-0.483
	(-0.888)	(-0.439)	(-0.0256)	(-0.134)
Size of the firm compared to a small sized firm:				
Medium sized (10-99 employees)	-4.309**	-8.205***	-3.963**	-8.693***
	(-2.260)	(-2.943)	(-2.378)	(-3.388)
Large sized (100+ employees)	-9.115***	-8.605***	0.198	-7.220***
	(-4.130)	(-4.119)	(0.0978)	(-4.770)
Sanderson Windmeijer multivariate F test of excluded instruments				
Exporters only	36.52	37.55	39.18	38.17
Importers only	8.55	11.10	11.29	11.49
Importers and Exporters	10.92	12.34	12.50	13.03
Hansen J statistic	0.482	2.278	2.148	2.235
P value	0.786	0.320	0.342	0.327

Observations	30,587	29,048	29,144	28,904
R-squared	0.014	0.048	0.016	0.045
Number of fe	1,121	1,106	1,107	1,106

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.15 Instrumental variables conditioned on the Factor and Sector bias. Robustness check for Table 2.5. Effect of GVCs on firms in low skilled sectors. LSAC = Low Skilled Abundant Countries; HSAC = High Skilled Abundant Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Exporters only	6.654	7.774	17.67*	-20.33**	8.496	-26.96***	17.63	-38.26***
	(1.012)	(1.600)	(1.645)	(-2.363)	(0.725)	(-2.917)	(1.507)	(-3.360)
Importers only	9.397	3.629	19.91**	-9.373**	6.305	-12.30***	16.47	-16.15***
	(1.498)	(1.499)	(2.068)	(-2.509)	(0.426)	(-2.701)	(1.277)	(-3.538)
Importers and Exporters	-22.48	-10.62	-47.20***	22.97**	-14.62**	31.86**	-39.12*	46.03***
	(-1.258)	(-1.528)	(-2.856)	(2.082)	(-2.156)	(2.327)	(-1.184)	(3.084)
Foreign ownership	1.015	4.283***	8.371***	-5.222*	6.653**	-9.282***	9.948***	-9.152**
	(0.453)	(2.667)	(3.804)	(-1.821)	(2.186)	(-2.684)	(3.524)	(-2.267)
Ln (Capital)	-0.0693	-0.788*	-0.642	0.836*	-0.550	1.601***	-0.857	1.353***
	(-0.136)	(-1.877)	(-0.712)	(1.868)	(-1.442)	(4.237)	(-1.037)	(2.973)
Ln (Sales)	0.149	1.542***	-2.083	1.252	-2.282**	-0.264	-2.382	1.142
	(0.293)	(4.045)	(-1.357)	(1.056)	(-2.306)	(-0.277)	(-1.562)	(0.756)
Quality certificate	3.178***	1.808	0.762	-0.471	-2.699	-2.048	-1.367	-1.897
	(5.439)	(1.136)	(0.477)	(-0.186)	(-1.508)	(-0.823)	(-0.642)	(-0.599)
Managerial experience	-0.0658**	0.0225	0.0250	-0.0358	0.102***	-0.0556	0.0764	-0.0636
	(-2.542)	(0.622)	(0.533)	(-0.347)	(3.396)	(-0.491)	(1.549)	(-0.429)
How much of an obstacle is Access to finance? (base is no obstacle)								
Minor obstacle	0.100	2.484**	-3.219	0.592	-3.491**	-1.743	-3.622	-1.064
	(0.108)	(2.082)	(-1.283)	(0.435)	(-2.197)	(-1.059)	(-1.281)	(-0.599)
Moderate obstacle	0.0919	3.363*	-5.607*	3.092	-6.033***	-0.231	-6.690**	1.568
	(0.117)	(1.925)	(-1.942)	(1.038)	(-2.762)	(-0.101)	(-2.117)	(0.488)
Major obstacle	-0.0445	-0.381	-6.013*	-7.647**	-6.222**	-7.070**	-6.539*	-8.471**

	(-0.0570)	(-0.322)	(-1.760)	(-2.311)	(-2.117)	(-2.054)	(-1.712)	(-2.121)
Very severe obstacle	-0.392	-2.533	-9.768	-0.00511	-9.066**	2.680	-9.190	-0.855
	(-0.226)	(-1.635)	(-1.630)	(-0.0019)	(-2.076)	(0.762)	(-1.494)	(-0.282)
Size of the firm compared to small sized firm:								
Medium sized (10-99 employees)	-2.782**	-9.719***	-5.325	-15.85***	-2.602	-6.633**	-6.805	-16.45***
	(-2.459)	(-2.634)	(-1.573)	(-2.591)	(-0.590)	(-2.515)	(-1.621)	(-2.651)
Large sized (100+ employees)	-8.383***	-14.43***	-4.744	-5.097*	2.608	8.900**	-3.998	-0.847
	(-6.835)	(-3.388)	(-0.866)	(-1.825)	(0.451)	(2.020)	(-0.648)	(-0.231)
Sanderson Windmeijer multivariate F test of excluded instruments:								
Exporters only	22.29	19.47	19.82	20.74	19.90	20.34	19.11	20.87
Importers only	18.27	40.23	14.80	44.50	15.02	43.65	13.92	46.14
Exporters and Importers	13.66	15.79	13.62	17.10	14.20	16.51	9.48	17.74
Hansen J statistic	1.310	4.778	1.428	1.824	1.437	3.433	1.258	2.212
P value	(0.520)	(0.092)	(0.4896)	(0.402)	(0.488)	(0.178)	(0.533)	(0.331)
Observations	8,545	4,849	7,599	4,763	7,626	4,775	7,566	4,725
R-squared	0.060	0.047	0.048	0.120	0.038	0.052	0.010	0.078
Number of country-industry fixed effects	242	174	237	173	238	173	237	173

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.16 Instrumental Variables Conditioned on the Factor and Sector bias. Robustness check for Table 2.6 Effect of GVCs on firms in high skilled sectors where exporters (importers) are defined as firms that export (import) more than 0 % of their outputs (inputs). LSAC = Low Skilled Abundant Countries; HSAC = High Skilled Abundant Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SNPW		SK		SSPfte		SSP	
VARIABLES	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC	LSAC	HSAC
Exporters only	3.140*	15.58	5.061	-8.960	1.924	-24.29**	2.472	-13.00
	(1.700)	(1.603)	(1.303)	(-1.129)	(0.411)	(-2.552)	(0.434)	(-1.206)
Importers only	5.858	13.75***	9.572*	-8.494*	3.681	-21.42***	4.730	-15.48**
	(1.336)	(3.463)	(1.711)	(-1.700)	(0.496)	(-5.476)	(0.714)	(-2.410)
Importers and Exporters	-6.553	-23.76	-9.378	34.35*	-2.715	57.11***	0.651	47.61**
	(-1.008)	(-1.489)	(-0.866)	(1.834)	(-0.168)	(4.904)	(0.0385)	(2.123)
Foreign ownership	4.284**	3.743	4.002	7.578***	-0.244	3.741	1.774	11.17***
	(2.057)	(1.522)	(1.068)	(3.045)	(-0.130)	(0.940)	(0.409)	(2.584)
Ln (Capital)	-0.356	-0.696***	-1.129***	-1.248	-0.763	-0.507	-0.996***	-1.338
	(-0.639)	(-3.381)	(-5.652)	(-1.448)	(-1.166)	(-0.575)	(-3.533)	(-1.122)
Ln (Sales)	0.404	2.125***	-1.703***	-0.702**	-2.116***	-2.788***	-2.650***	-1.767***
	(0.810)	(6.541)	(-3.782)	(-2.025)	(-3.344)	(-8.088)	(-4.515)	(-3.112)
Quality certificate	2.112***	4.061***	2.066***	14.01*	-0.0693	10.18	1.816**	16.36*
	(2.677)	(3.805)	(3.217)	(1.790)	(-0.0651)	(1.506)	(2.106)	(1.796)
Managerial experience	-0.0445**	-0.00497	0.0788	-0.198*	0.123	-0.179	0.0753	-0.151
	(-2.443)	(-0.0982)	(1.131)	(-1.805)	(1.570)	(-1.162)	(0.832)	(-1.093)
How much of an obstacle is Access to finance? (base is no obstacle)								
Minor obstacle	-1.655***	-0.243	1.543	-4.609**	3.174***	-4.183**	2.189	-5.250**
	(-3.287)	(-0.212)	(1.464)	(-2.061)	(2.909)	(-1.985)	(1.482)	(-1.994)
Moderate obstacle	-1.428***	3.973**	-0.407	-0.286	0.930	-4.596**	0.362	-3.224*
	(-3.178)	(2.211)	(-0.437)	(-0.216)	(1.125)	(-2.204)	(0.342)	(-1.732)
Major obstacle	-2.550	4.680***	-2.111	-5.583	0.453	-10.15**	-2.794	-8.220

	(-1.055)	(3.334)	(-0.563)	(-1.427)	(0.0898)	(-2.476)	(-0.582)	(-1.621)
Very severe obstacle	-3.256	3.395**	-3.153	1.600	0.291	-2.036	-2.831	1.852
	(-1.004)	(2.286)	(-0.794)	(0.793)	(0.0787)	(-0.837)	(-0.646)	(0.661)
Size of the firm compared to small sized firm:								
Medium sized (10-99 employees)	-2.031***	-9.070***	-8.185***	-12.93***	-6.114***	-3.986	-9.417***	-15.45***
	(-2.946)	(-4.381)	(-3.856)	(-3.326)	(-2.842)	(-1.479)	(-3.768)	(-3.262)
Large sized (100+ employees)	-5.287***	-12.06***	-9.247***	-19.08**	-4.019***	-7.660	-9.053***	-20.93**
	(-5.945)	(-6.018)	(-8.467)	(-2.285)	(-2.919)	(-1.207)	(-8.995)	(-2.162)
Sanderson Windmeijer multivariate F test of excluded instruments:								
Exporters only	15.77	9.22	23.99	8.82	25.05	8.96	24.52	9.43
Importers only	8.85	55.96	11.27	63.88	11.49	64.31	11.68	62.32
Exporters and Importers	9.56	9.53	11.19	9.04	11.33	9.20	11.37	8.20
Hansen J statistic	2.152	3.576	0.519	1.912	1.913	2.471	1.429	1.839
P value	0.341	0.167	0.774	0.385	0.384	0.291	0.490	0.399
Observations	7,751	5,177	7,363	5,090	7,394	5,109	7,320	5,068
R-squared	0.017	0.046	0.065	0.057	0.060	-0.147	0.084	0.035
Number of country-industry fixed effects	305	235	300	232	300	232	300	232

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3

The effect of Global Value Chains on the skill composition of the workforce and wage bill

Loe Franssen[♦]

Abstract:

This Chapter uses macro level data from the World Input Output Database (WIOD) and decomposes it along Wang, Wei and Zhu's (2013) decomposition method. Doing so provides various interesting and commonly used proxies for international production sharing, such as VS, VS1, VS1* and an improved VAX ratio, titled VAX_B. Using a translog cost function, we regress these proxies on the relative wage and employment share of different skill types of workers. We show that domestic value added exported (VS1 and VS1*) to a less (more) skilled abundant country increases (decreases) the relative wage and employment share of high skilled labour. While this finding implies a strong factor bias effect, we do not find any significant sector bias effect, i.e. the effect is independent of the skill intensity of the GVC sector. This can be explained on the basis of Krugman (2000) and Xu (2001) that in an integrated world economy, the sector bias of a productivity increase due to GVC does not affect the relative demand for skilled labour. This Chapter further argues, on theoretical and empirical grounds, out of the GVC proxies used, VS1* is the most appropriate to estimate the effect of GVCs on the relative demand for skilled labour.

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3.0. Introduction

So far, this thesis has presented a literature review, a graphical exposition of the main channels by which GVCs affect the relative demand for labour along and finally some empirical evidence, using micro level data, on the effects of GVCs on relative skill employment. This Chapter, instead, will use macro data to investigate the effect of GVCs on the employment and wage share of different types of skilled labour building forward on the conceptual framework outlined in Chapter 1.

Namely, the conclusion in Chapter 1 presents various predictions of GVCs on the relative demand for skilled labour. While we will not test these predictions formally, they provide some guidance as to how one should approach the empirical exercise. As was the case in the previous Chapter, the main lesson that will be applied empirically, is the one by Davis (1996) and Khalifa and Mengova (2010). This lesson can be summarized by saying that we should condition the empirical findings on the skill intensity of the industry in which fragmentation takes place as well as the relative skill abundance of the trading partner. While the former will control for the sector bias of the GVC, the latter will control for the factor bias. Namely, once we know which country is the relatively (low) skill abundant country, we can assume this country will experience the effects modelled in the conclusion of Chapter 1 as the North (South).

The contribution of this Chapter comes from the data that it uses. As outlined in Chapter 1, the measurement of global value chains has recently seen some strong improvements with notable contributions by Timmer, Erumban, Los, Stehrer and de Vries (Timmer et al., 2014), Koopman, Wang and Wei (2014) and Wang, Wei and Zhu (2013, henceforth WWZ) whose joint efforts have led to better data on global value chains in the form of the Trade in Value Added (TiVA) and the World Input Output Tables (WIOT). This Chapter will make use of the World Input Output Database (WIOD) and decompose it by the latest decomposition method developed by WWZ. This method improves and extends the information provided by WIOD, for example by correcting for double counting and a separation of value added and consumption per location. Besides that, it provides many interesting proxies for global value chain participation. Since the WIOD further provides us with data on total as well as relative (skill specific) labour compensation, we are able to find the composition of the compensation per skill type. Combining that with the GVC data allows me to empirically examine what the effect is of global value chains on the domestic relative demand for skilled labour. To our knowledge, this data and these specific macro level proxies have not yet been used to estimate the effect of GVCs on the relative demand for skilled labour, allowing me to make a novel contribution to the literature. The second contribution of this Chapter is that it, as in the previous Chapter, conditions the findings on the factor and sector bias of the GVC activity.

The Chapter then uses a translog cost function to estimate the effect of these GVC proxies on the wage bill and employment share of low, medium and high skilled labour. In line with standard production sharing theories that follow the factor bias, we find that domestic value added exported (measured by VS1, VS1*) to less skilled abundant countries is significantly and positively (negatively) related to the wage bill and employment share of high skilled labour. An improved VAX ratio shows statistically significant coefficients that are counter intuitive to this standard trade rationale. This can be explained by the Feenstra Hanson theorem that what is low skilled intensive for the North can be perceived as high skilled intensive for the South and should therefore increase the relative demand and pay for skilled labour, of which we find some evidence. Foreign value added exported can be viewed as a displacement of domestic value added. Therefore, we can assume that if the partner is less skilled intensive, a *displacement* of high skilled work has occurred, which should negatively affect the relative demand for high skilled labour, of which we find evidence as well. While we find strong evidence of such a factor bias effect, this Chapter does not find any significant evidence of a sector bias effect, i.e. global production sharing in lower skilled industries does not seem to affect relative wages significantly different than in higher skilled industries. This can be explained by Krugman (2000) and Xu (2001) who explained that if GVC occurs simultaneously in many industries and countries, the sector bias does not affect relative wages, as outlined extensively in Chapter 1.

This Chapter is structured as follows. As the literature review and conceptual framework have already been explained in Chapter 1, the next section will dive straight into the empirical methodology. It will firstly present the translog cost function employed, along with a description how we will identify the sector and factor bias specifically. Then a discussion on the measurement of global value chains will be presented. Then, for each of those measures presented, we will demonstrate various hypotheses of how they are expected to affect the relative demand for skilled labour specifically. After that, we will discuss the empirical results and conclude.

3.1. Empirical model

For the first part of the empirical analysis, this Chapter will employ a fairly traditional method in estimating the effects of structural variables, such as global value chains, on relative wages and employment. Employed first by Berman et al. (1994) and later by Feenstra and Hanson (1996, 1997), the translog cost function provides a useful way to determine which factors affect relative demand for skilled labour. It starts from a short run cost function that is dual to an industry production function:

$$C_m \,(w, q, K_m\,, Y_m, z) \tag{3.1}$$

Where *w*, *q*, and K_m denote payments to low skilled labour, high skilled labour and capital respectively in industry *m*. Y_m is gross output and z stands for any other structural variable that can shift the production function and therefore affect costs, such as technological change (Berman et al), offshoring (Feenstra and Hanson) or global value chains. From this standard production function, we need a functional form for costs and the translog cost function provides a useful form as it allows to keep certain factors constant. It is denoted as follows:

$$\begin{aligned}\ln C_m\,(w, x) = {} & \alpha_m + \sum_{j\epsilon J} \alpha_j \ln w_j + \sum_{k\epsilon K} \beta_k \ln x_k + \frac{1}{2}\sum_{j=1}^{J}\sum_{i=1}^{J} \gamma_{ji}\, lnw_j\; lnw_i \\ & + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \delta_{kl}\, lnx_k\; lnx_l + \sum_{j=1}^{J}\sum_{k=1}^{K} \varphi_{jk}\, lnw_j\; lnx_k\end{aligned} \tag{3.2}$$

where w_j denotes the prices of the optimally chosen variable inputs j=1,…,J, and x_k denotes the quantity of fixed inputs k or outputs k=1,…,K or any other shift parameters.

From this cost function, we can move swiftly to a cost function for the cost share of labour by computing its first derivatives, $\frac{\partial lnC}{\partial lnw_j} = (\partial C/\partial w_j)(w_j/C)$. Since $(\partial C/\partial w_j)$ equals the demand for the chosen input j, such as skilled labour, for a certain wage rate w_j, it follows that $(\partial C/\partial w_j)(w_j/C)$ equals the payments to factor *j* relative to total costs. In other words, it equals the share of, for example, skilled labour in the total costs of a certain industry.

Thus, taking the first derivative of the log cost with respect to w_j in equation (2.2) gives us the cost share of labour type *j* in industry *m* as :

$$\theta_m^j = \alpha_m + \sum_{i=1}^{J} \gamma_{ji}\, ln\omega_i + \sum_{k=1}^{K} \varphi_k\, lnx_k \qquad j = 1, \dots, J \tag{3.3}$$

It is now in a form where we can add further structural variables on the right-hand side that, besides variable inputs ω_i and fixed inputs x_k, shifts the production function and therefore affects costs. For example, the share equation of labour type *j* in industry *m* will depend on wages for both types of labour as well as capital, output and all other structural variables, as we saw in equation (3.1)[27].

Feenstra and Hanson (2001b) were the first who added offshoring as an additional structural variable that affects relative costs. This Chapter will follow that approach by measuring the effects of various GVC proxies (which will be discussed later) in the following form:

$$\Delta Sh_{cmt}^{j} = \beta_0 + \beta_1 \Delta \ln Y_{cmt} + \beta_2 \Delta \ln K_{cmt} + \beta_3 \Delta \ln \left(\frac{w_h}{w_l}\right)_{cmt} + \beta_4 \Delta \ln \left(\frac{w_h}{w_m}\right)_{cmt} + \beta_5 \Delta \ln GVC_{cmt} + \delta_{cmt} + \Delta\varepsilon_{cmt} \tag{3.4}$$

Where the dependent variable is the share of a certain skill type *j* in total compensation or working hours in industry *m* of country *c* during year *t* while δ_{cmt} represents country-industry-time fixed effects. We further first-difference the variables and weigh all regressions by the average sector share in total labour compensation across countries to give a more representative impact of GVCs on the labour markets of various countries (See Davies and Desbordes (2015) for example). β_5 will be estimated by using the various GVC proxies that will be discussed in section 3.2. Finally, since our dependent variable for j Є LS, MS, HS adds to unity and we run these on the exact same set of regressors, we can use the seemingly unrelated regressions method (SUR) to account for cross equation correlation in the error terms. Consequently, we have to drop one equation from the system of three and therefore estimate the following two:

[27] As explained in Feenstra and Hanson (2001) and Berman, Bound and Griliches (1994), the cross-industry variation in wages can be simply explained by the nature of the industries; high skilled industries need to employ higher skilled workers and pay them a higher wage. Due to their nature, they are unable to hire less high skilled workers, simply because they are more expensive. Therefore, relative wage terms, estimated by β_3 and β_4 in the estimation are often dropped from the specification. The results are robust to the omission of the wage terms (Table 3.11).

$$\Delta Sh_{cmt}^{HS} = \beta_0 + \beta_1 \Delta \ln Y_{cmt} + \beta_2 \Delta \ln K_{cmt} + \beta_3 \Delta \ln \left(\frac{w_h}{w_l}\right)_{cmt} + \beta_4 \Delta \ln \left(\frac{w_h}{w_m}\right)_{cmt} + \beta_5 \Delta \ln GVC_{cmt} + \delta_{cmt} + \Delta \varepsilon_{cmt} \tag{3.5}$$

$$\Delta Sh_{cmt}^{MS} = \beta_0 + \beta_1 \Delta \ln Y_{cmt} + \beta_2 \Delta \ln K_{cmt} + \beta_3 \Delta \ln \left(\frac{w_h}{w_l}\right)_{cmt} + \beta_4 \Delta \ln \left(\frac{w_h}{w_m}\right)_{cmt} + \beta_5 \Delta \ln GVC_{cmt} + \delta_{cmt} + \Delta \varepsilon_{cmt} \tag{3.6}$$

3.1.1. Identifying the sector and factor bias

As was done in Chapter 2, this Chapter will once again condition the baseline equation (3.4) on the sector and factor bias of the GVC. Compared to Chapter 2, however, the data used in this Chapter, which has information on the trade partner, allows us to better identify the factor bias. For example, if the exported foreign value was added by countries with a larger relative abundance in low skilled labour, which we could classify as "the South", we can assume that the skill intensity of this value added was relatively low skilled intensive. Contrarily, if the foreign value added was done by more skilled abundant countries, we can assume the skill intensity of these activities was high. Then, by interacting the GVC proxy with the partner dimension, we can separate those activities that were executed upstream into higher and lower skilled intensive activities, i.e.:

$$\Delta Sh_{cmt}^{j} = \beta_0 + \beta_1 \Delta \ln Y_{cmt} + \beta_2 \Delta \ln K_{cmt} + \beta_3 \Delta \ln \left(\frac{w_h}{w_l}\right)_{cmt} + \beta_4 \Delta \ln \left(\frac{w_h}{w_m}\right)_{cmt} + \beta_5 \Delta \ln GVC_{cmt} * partner + \delta_{cmt} + \Delta \varepsilon_{cmt} \tag{3.7}$$

Where the partner is a categorical variable grouping partner countries that have 1) more skill endowment, classified the North; 2) similar skill endowment and; 3) less skill endowment, classified the South. This classification was established on the basis of the share in total hours worked by high skilled labour. See Forbes (2001) for a further discussion on classifying countries on the basis of their relative skill abundance.

We can identify the sector bias effect in a similar manner, by interacting the GVC proxy with the skill intensity of the industry or global value chain affected. As outlined in the conceptual framework, production sharing allows for productivity effects within the industry, which will expand it and increase the demand and pay to the factor of production used most intensively. For example, VS1*, the share of gross exports that will return home, is a close proxy for offshoring as a country produced part of a product, then exports it for further processing and then reimports it for domestic final use. If this happens in isolation, i.e. only within a certain skill-intensive group of industries, e.g. the low skilled industries, we can assume that the factor demand and return for low skilled labour within the country will increase. Contrarily, if production sharing does not happen in isolation or the country is sufficiently large that it affects world prices, the sector bias effect should play no role (Krugman, 2000). It is therefore vital to separate the skill intensity of industries that engage in production sharing, which can again be done by interacting our GVC proxies with the skill intensity of the industry:

$$\begin{aligned}\Delta Sh^{j}_{cmt} = \; & \beta_0 + \beta_1 \Delta \ln Y_{cmt} + \beta_2 \Delta \ln K_{cmt} + \beta_3 \Delta \ln \left(\frac{w_h}{w_l}\right)_{cmt} + \beta_4 \Delta \ln \left(\frac{w_h}{w_m}\right)_{cmt} \\ & + \beta_5 \Delta \ln GVC_{cmt} * skill\ intensity\ of\ the\ industry + \delta_{cmt} \\ & + \Delta\varepsilon_{cmt}\end{aligned} \tag{3.8}$$

Where the skill intensity is a dummy variable grouping industries that are relatively high and relatively low skilled. As was done for partner countries, industries are also separated on the basis of the share in total hours worked by high skilled labour. As a final step, to include both a factor and sector bias effect, we include a three-way interaction term.

$$\begin{aligned}\Delta Sh^{j}_{cmt} = \; & \beta_0 + \beta_1 \Delta \ln Y_{cmt} + \beta_2 \Delta \ln K_{cmt} + \beta_3 \Delta \ln \left(\frac{w_h}{w_l}\right)_{cmt} + \beta_4 \Delta \ln \left(\frac{w_h}{w_m}\right)_{cmt} \\ & + \beta_5 \Delta \ln GVC_{cmt} * skill\ intensity\ of\ the\ industry * partner \\ & + \delta_{cmt} + \Delta\varepsilon_{cmt}\end{aligned} \tag{3.9}$$

3.2. Measuring Global Value Chains

Before we can test the above model to any type of data, we first have to discuss how GVCs are measured, in theory and in practice. Measuring global production sharing is an extremely difficult concept since offshoring refers to management decisions made at the micro level that cannot be easily linked to macro-economic trade statistics (WTO, 2005). Initially (up until 2012), measuring production sharing was mostly done by identifying foreign intermediates in trade. Starting with Feenstra and Hanson (1997), they measured offshoring as the foreign content, as measured by foreign intermediates, in total domestic output. This was extended by Hummels, Ishi and Yi (2001) who, rather than looking at the proportion of foreign intermediates in final output, looked at the share of foreign inputs in exports[28]. Defined as vertical specialisation or VS, they measured the use of imported inputs in producing goods that are exported. Besides looking at foreign value added in exports, which can be classified as backward participation, they also proposed a measure for forward participation, coined VS1, as the amount of inputs a country exports that are consequently used in another country's production for exports. This measure was eventually extended by Daudin, Rifflart and Schweissguth (Daudin et al., 2011) to look at the share of DVA exported that returns home, termed VS1*. This measure is interesting as it can serve as a fairly direct measure of offshoring, where a country/ firm produces part of a good, exports it for further processing and then reimports it to use at home.

While Hummels et al focused on the share of foreign intermediates, more recent research focuses on measuring value added[29]. It started with the work of Johnson and Noguera (2012) who built on the work by Hummels et al. (2001) by developing a quasi-inverse measure of VS that rather looks at the domestic value added in gross exports (titled VAX), rather than trade in intermediates. While this proxy may work well on a national level, it can lead to significant drawbacks on a sectoral or bilateral level, as shown by Wang Wei and Zhu (2013). Namely, they show that it is vital to distinguish between forward and backward VAX ratios on the sectoral level because they measure different things. On a national level, there is no problem as the total domestic value added by all the sectors in gross exports (backward VAX) will be equal to the domestic value exported (forward VAX). However, on a sectoral level, the domestic value contributed by certain sectors to a particular sector will not be equal to that sectors contribution in other sectors' exports[30]. More specifically, while forward VAX would include a sector's value added exported in other industries, it would exclude contributions by other sectors in its own value added exported. Backward measures on the other hand would include the value added by other sectors in the current sectors exports but exclude its contribution in forward value added exported. This can lead to heavily distorted values as a certain sector can export 0 domestic value added itself but

[28] They also included an import as well as an export side to the proxy that tracks indeed a broader concept of international production sharing rather than just offshoring.
[29] One advantage of this is that we can now overcome the assumption that foreign intermediates are indeed 100% foreign sourced. Using value added as a measure allows for the possibility that imports contain some domestic content.
[30] Further note that while the direct value added contributed by a particular sector will be the same in forward and backward VAX ratio. However, the problem lies in the indirect value added contributed. Namely, the indirect value added contributed by other sectors to, say, sector X (= backward contribution), will not equal sector X's forward contribution in value added of other sectors.

can provide inputs to other sectors that export. In that case, VAX could technically go to infinity[31]. The same concept applies on the bilateral level where trade can go via third countries: two countries can have large volumes of value added trade but little gross exports, as they may go via a third country. A second problem with the traditional VAX ratio identified by WWZ is that it does not capture some of the important features of international production sharing, specifically at what stage of the supply chain a country operates at. For example, 2 countries can have the same VAX ratio but for different reasons. Therefore, WWZ propose a fairly simple modification to the VAX ratio. Namely, instead of dividing domestic value added by gross exports, they propose to divide it by DVA that remains abroad, or (B+C) / I. This (backward) measure would be strictly bounded by 1, while the forward measure of VAX is not.

We can best illustrate these measures using a Figure. Figure 3.1 builds on from the original graphical demonstration by Hummels et al to explain VS, the share of foreign value added (A) divided by gross exports I. The original VAX ratio as outlined by Johnson and Noguera (2012) can be illustrated by domestic value added (B+C) divided by gross exports I and is thus the inverse of VS. More complicatedly, VS1 is the domestic value added that is consequently used by the foreign country in its production of exports (G) as a percentage of gross exports I. VS1*, the domestic value added exported and used in foreign exports (G) as a share of total exports I is found by dividing G by E. Finally, the modified VAX ratio, titled VAX_B, can be indicated by domestic value added (B+C) that remains abroad (I).

[31] There would still be indirect value added of the industry under consideration but 0 gross exports.

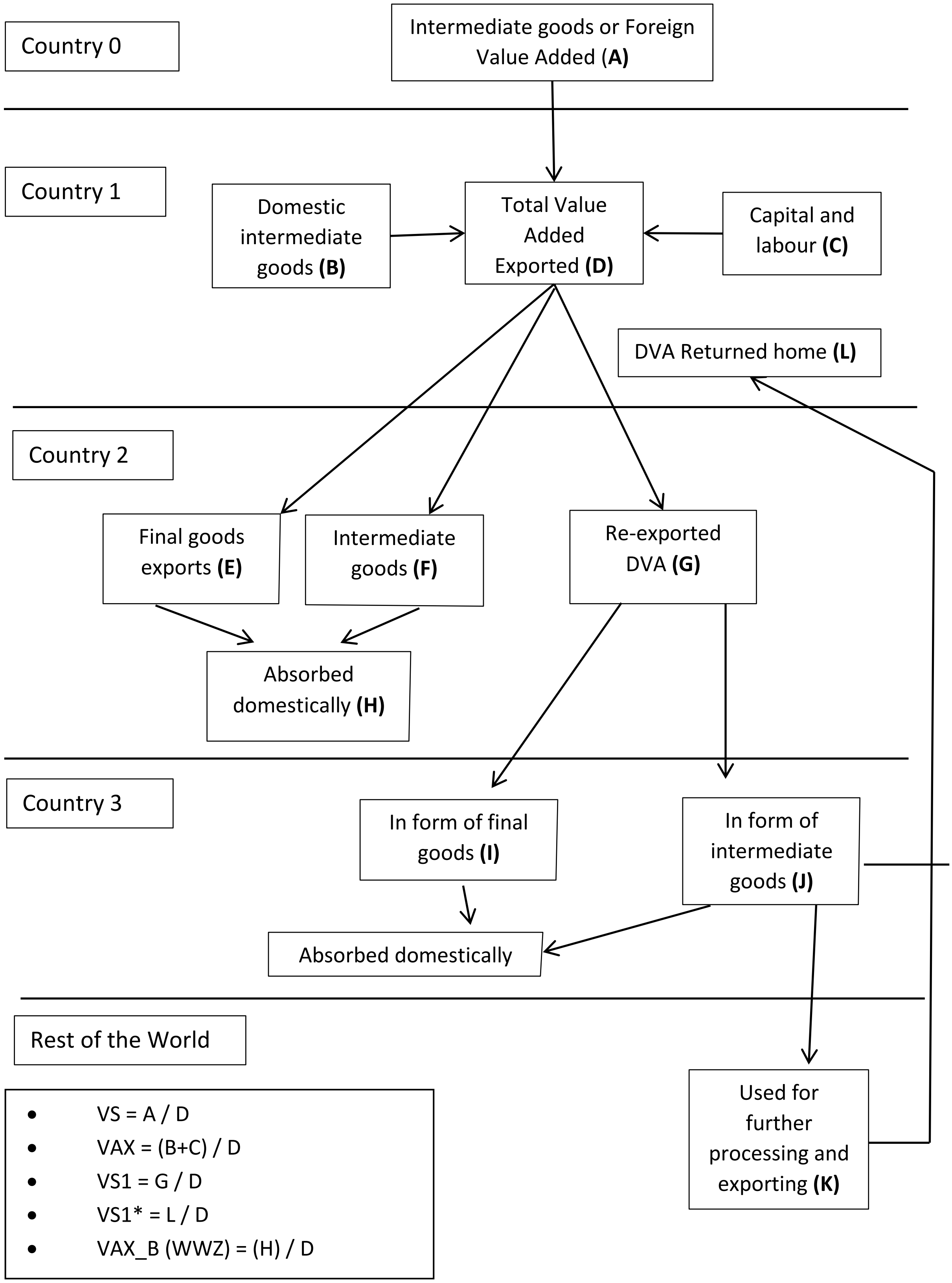

Figure 3.1. An overview of GVC proxies used in this Chapter

In a practical sense, applying the above measures requires detailed trade data on the direction, origin and final destination or use of intermediate and final goods trade, per industry and country. Since such detailed data does not exist, researchers have combined data on intermediate inputs trade from e.g. COMTRADE databases, and matched it to Input Output tables to arrive at the above measures. Input- Output tables are a natural source for data on international production sharing as they break down the inputs received per industry, with international IO tables specifying the international origin of these inputs. They further specify whether certain goods that cannot be naturally classified as a final or intermediate good (e.g. car tires) are indeed used as final demand by households or as intermediate demand by industries and used for further processing. Finally, they show the value added per industry as well as their gross output. Note that I-Os can allow us to apply the proxies proposed by Feenstra and Hanson, and the backward participation or VS1 by Hummels et al. However, it cannot measure VS1, or forward participation, as this would require matching *bilateral* trade flow data to the input output relations (Hummels et al, 2001, p82).

Getting to such a true international Input-Output table that correctly accounts for trade in value added and intermediate goods is one of the main research objectives since the Global Forum on Trade Statistics organized jointly by the WTO and UNCTAD in 2011. From this initiative, various new databases and research papers have emerged that try to compose such an ICIO table that focus on measuring value added, rather than gross trade flows by combining national input-output tables with bilateral trade data from a variety of countries. These initiatives will be discussed next.

The pioneering work of Hummels et al motivated the research by Noguera and Johnson (2012) who, in their construction of a global ICIO, focus on trade in value added, rather than gross terms. This technique combines traditional input-output tables with bilateral trade data from a variety of countries. In doing so, they assume that imports per sector are split in final and intermediate good use in the same proportion as is the case on the national level of imports. Secondly, intermediate imports are split across purchasing sectors in proportion to their overall imported intermediate use[32]. Then, using the resulting global bilateral input-output table, they perform a calculation that allocates the gross output produced in each source country to the destination in which it is ultimately absorbed as

[32] This is the import proportionality assumption, which will be discussed in more detail in the next section

final demand. They then use value added to output ratios from the source country to compute the value added associated with these implicit output transfers. The end result is a data set of "value-added exports" that describes the destination where the value added produced in each source country is absorbed. It is from this database that they were able to construct the VAX ratio.

Timmer et al (2014) and Dietzenbacher et al. (2013) extended the work of Noguera and Johnson (2012) in their construction of World Input Output Tables (WIOD) by combining supply and use tables (as opposed to "constructed" IO tables) with bilateral international trade data, following the conventions of the System of National Accounts. They track the flows of products across countries and industries and trace value added by the labour and capital that is directly and indirectly needed for the production of final manufacturing goods. The breakdown of use tables into domestic and imported origin is a crucial step. It further provides Supply and Use tables (SUTs) against output and final consumption series given in national accounts. Another novel addition in the WIOD as opposed to other ICIOs is how it deals with the import proportionality assumption. Whereas more traditional ICIOs are derived using a simple proportionality assumption that separates individual industry imports into final and intermediate goods by assuming that the use of intermediates is equal to the economy-wide share of imports that are intermediates, the WIOD takes a more elaborate approach. Namely, it first separates national imports into final and intermediate goods using the extended classification scheme of BEC and then uses IPA to allocate products to their respective cells within WIOTs. In other words, the WIOD approach first assigns imports to one of three BECs: 1) intermediate use, 2) final consumption and 3) investment. This can be done by a "concordance" between harmonization codes and BEC categories. After that, they allocate imported intermediate inputs across industries using the IPA. Timmer et al (2014) used these WIOD tables and further decompose them by tracing the value added by all labour and capital that is directly and indirectly needed for the production of final manufacturing goods with the aim to decompose the value of a final product into the value added by all labour and capital employed in its global value chain[33].

[33] From this work, they were able to identify four trends: 1) FVA in production has increased, 2) upgrading in the sense that more value has been added by high skilled labour and capital and less by low skilled labour, 3) within GVCs, especially high income countries increasingly specialise in HS activities, and 4) emerging economies surprisingly specialise in capital-intensive activities.

A third recent ICIO is constructed by the OECD and WTO. This database makes use of standard IO tables and matches them with bilateral trade data to get to an international IO table. As most IO tables are harmonised – true for OECD countries while Koopman et al. (2014) harmonise Chinas processing trade – and they do not extrapolate data to arrive to an annual panel, measurement error will be minimal. It is from this database that the Trade in Value Added (TiVA) has been constructed which provides data for four years.

3.2.1. Beyond the Import Proportionality Assumption

The problem with some of these latest measures is that they rely on the import proportionality assumption when assigning domestic and foreign intermediates on a sectoral level. While this may be necessary as IO data on imported inputs is not available at the sector level, WWZ have shown that doing so can lead to significant biases. The assumption is that an industry's share of import of a particular input is equal to the country's overall import share of this input. For example, assume a country imports 10% of its cotton from abroad, it is then assumed that every industry that uses cotton, such as the textile industry also imports 10% of all its cotton. This assumption is clearly limiting as some industries might rely more on foreign inputs than others, and this is particularly true for developing countries (KWW). Overcoming this assumption requires, once again, detailed information on trade flows. Various attempts have been made to overcome this, for example Feenstra and Jensen (2009), Koopman, Wang and Wei (Koopman et al., 2014) and Zhu, Cimper and Yamano (Zhu et al., 2011). What these techniques come down to is using data with detailed information on product classifications. The goal is to move beyond a broad e.g. 3 end-use categories defined by UN Broad Economic Categories (BEC) to the 6-digit HS level data in e.g. COMTRADE. Zhu et al. (2011), for example, used the Bilateral Trade Database by Industry and end-use (BTDIxE) in which values and quantities of imports and exports are compiled by partner country according to detailed product classifications (HS 2012). The problem with such data, however, is that since it does not measure value added, it suffers from double counting once intermediate goods cross borders more than once, which is a significant limitation. Thus, whereas earlier data sources seem to suffer from a trade-off between coverage – both geographical and over time – and the precision of measurement (Bottini et al, p.10), more recent data seems to suffer from a trade-off between bias caused by various assumptions and double counting. However, Koopman Wang and Wei (2014) overcome the problems created by IPA by using end-use classifications (intermediate or final) of detailed import statistics. Wang Wei and Zhu (2013) then generalize this gross exports accounting framework to one that decomposes trade flows at the sector, bilateral and bilateral sector level. In doing so, they are able to tackle the problems created by IPA while still separating double counted trade flows. Specifically, they decompose gross exports into four separate components, including pure double counted terms (Figure 3.2).

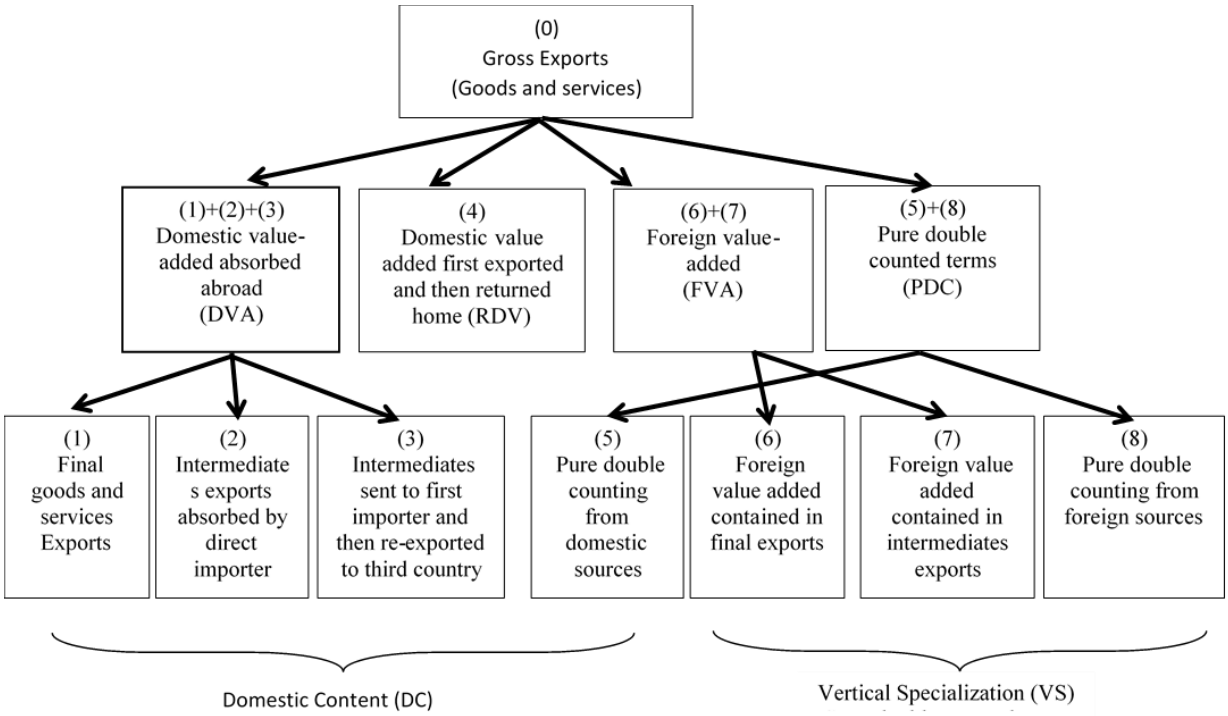

Figure 3.2 An overview of the gross exports decomposition by Wang Wei and Zhu (WWZ, 2013)

Therefore, this research will use that decomposition method and apply it on the WIOD ICIOs. In doing so, it improves and extends the information provided by WIOD, for example by correcting for double counting and a separation of value added and consumed per location (home or foreign). Besides that, it provides many interesting proxies for global value chain participation.

3.2.2. Data used

As outlined, this research will make use of the WIOD tables, and apply the WWZ decomposition method, using the decompr package by Quast and Kummritz (2015) on these export flows. This will provide us with four broad trade flows as outlined in Figure 3.2: domestic value added that is absorbed abroad; domestic value that is initially exported but eventually returned home; foreign value added, and; pure double counting terms. With these flows, we can accurately measure the main proxies of global production sharing as outlined in Figure 3.1, without any bias on the sectoral or bilateral level. As WIOD provides data on wages and hours worked, one only needs to have a breakdown of how those are split between different skill categories and for that, we use EU Klems data. After combining the information of both databases, the database consists of 37 countries and 30 industries across 14 years (1995 – 2011).

3.3. Hypotheses

This section will outline the hypotheses regarding the results of equations (3.7), (3.8) and (3.9). As was done in Chapter 2, we will once again build forward from the conceptual framework outlined in Chapter 1 (Table 1.3) by specifically taking into account the sector and factor bias of the GVC. Table 3.1 shows the hypotheses per GVC proxy.

Table 3.1 Hypothesized effects of various GVC proxies on the relative demand for skilled labour

(1) GVC Proxy	(2) Description	(3) Partner	(4) Expected effect on relative demand for high skilled labour	(5) Skill intensity of the industry	(6) Expected effect on relative demand for high skilled labour
VS	Foreign value added in exports	South	Decrease	Low	Decrease
		North	Increase	High	Increase
VS1	Domestic value added in foreign indirect exports	South	Increase	Low	Not clear
		North	Decrease	High	Not clear
VS1*	Domestic value added exported that returns home	South	Increase	Low	Decrease
		North	Decrease	High	Increase
VAX_B	Domestic value added absorbed abroad	South	Increase according to standard HO theory Decrease according to FH theorem	Low	Decrease
		North	Decrease according to standard HO theory Increase according to FH theorem	High	Increase

Starting with the hypotheses based on the factor bias of the value added that is traded, the general idea is that in any bilateral trade relationship, the more skilled abundant country would engage in the more skilled intensive tasks of the value chain and offshore the less skilled intensive task to its partner. Then, if the proxy includes domestic value added exported (VAX_B, VS1 and VS1*)[34], and the partner is more (less) skilled abundant, we can assume that the home country engages in the lower (higher) skilled intensive tasks of the value chain, increasing the relative demand for low (high) skilled labour at the expense of high (low) skilled labour. Whenever the proxy includes foreign value added (VS) and the partner is more (less) skilled abundant, this can be roughly interpreted as a *displacement* of relatively low (high) skilled intensive tasks and should therefore exert a negative (positive) pressure on the wage share of low skilled labour. The sector bias is more straightforward, as the productivity effect from GVCs expands an industry, increasing the national demand and pay for the factor of production that the sector intensively uses. Therefore, we would expect GVC activity within high (low) skilled sector to benefit high (low) skilled labour. However, as argued strongly by Krugman (2000), it is unlikely for this theoretical concept to hold up empirically as it is built on the assumption that GVC happens locally, i.e. in isolation within a certain country/industry, which is certainly not the case. Therefore, we expect the hypotheses for equation (3.9), where we simultaneously take the factor and sector bias into account to be largely in line with the prediction based on the factor bias outlined in column 3 and 4 of Table 3.1.

We can discuss the various proxies more specifically. For example, VS1* is the measurement that mimics the dynamics of offshoring closest, as the home country produces parts of a good, then exports it for further processing after it eventually returns home for final consumption. When this additional processing happens in the South (North), we can assume the factor bias of these activities will be low (high) skilled in nature, raising (decreasing) the relative demand for high skilled labour at home along the model of Feenstra and Hanson (1996), for example. The sector bias effect would increase (decrease) the demand for high skilled labour if offshoring takes place in high (low) skilled industries.

[34] Further note we leave out the traditional measure of VAX for the reasons mentioned earlier i.e. that is not bounded between 0 and 1. Secondly because it is extremely difficult to make any inferences about its effect on relative wage shares because it is not clear what will happened with the domestic value added exported. It might be re-exported by the partner country or absorbed at home in which case we can better use the proxies VS1 and VAX_B as they measure exactly that. The empirical estimation also showed no significant correlation between this proxy and relative wages.

Much along the same lines, VAX_B could be seen as a measure for inshoring in the sense that it tracks what a home country produces and exports and will ultimately be absorbed abroad. Once again, we can make inferences about the factor bias of this value added. From standard neoclassical trade theory, that is a 2*2*2 HO type model, one would assume that the value added that is destined for more skilled abundant countries would be low skilled intensive, meaning that the South specialises in the low skilled intensive activities. Along these lines, we would expect VAX_B destined for the North to negatively affect the demand for high skilled labour and thus decrease their relative pay. However, as outlined by Feenstra and Hanson (1996), what may be viewed as low skilled from the North may well be high skilled from the South, increasing the demand and pay for high skilled labour, so this effect is ambiguous. The productivity effect is still present and can be explained again by increased specialisation and in the specific case of trade with Northern countries, by technology spillovers.

For the other proxies, the expected coefficients are less predictable as they represent a more infinite stream of production sharing, rather than a more straightforward (bilateral) trade relationship where the home country is producing something that will either be consumed abroad or at home. For example, VS1 measures the domestic value added that is exported and eventually re-exported again. Once a third country comes into play, the distinction between the relative skill abundance of the countries involved becomes blurry[35], making it hard to make inferences about the skill intensity of the domestic value added. However, the general channels described before can still be assumed to hold.

3.4. Discussion of the Empirical Results

Starting with the baseline estimation as described in (3.4), Table 3.3 and Table 3.4 show the effect of 4 different proxies for GVCs: VS, VS1, VS1*, as well as the improved VAX by WWZ on the share of high skilled labour in the total wage bill and employment bill respectively.

[See Table 3.3 and Table 3.4 from page 140 onwards]

From Table 3.3 and Table 3.4 we would conclude that GVCs do not significantly affect high skilled labour share in wages as none of the GVC proxies appear to be significantly correlated with the share of high skilled labour in the total wage bill (Table 3.3) or total

[35] Especially since we have no data on the third country.

employment (Table 3.4). However, as explained thoroughly throughout this thesis, it is crucial to condition the effects on the factor and sector bias.

Therefore, Table 3.5 and Table 3.6 illustrate the effects of GVCs on relative wages and employment conditioned on the trade partner. Here, we can see some – limited – evidence of the factor bias, particularly for VS1* and to a lesser extent for the other proxies. All the signs are in line with our hypotheses described earlier. Namely, domestic value added exported (VS1 and VS1*), to a relatively more (less) skilled abundant partner country increases the demand and pay of low (high) skilled labour at the expense of high (low) skilled labour. We see especially strong evidence of this for VS1* (Table 3.5; columns 7-9), which as we described earlier, is the proxy that closely mimics offshoring and for which the theoretical channels by which GVCs can affect wage shares should be most apparent. Whenever the proxy includes foreign value added (VS) and the partner is more (less) skilled abundant, this can be roughly interpreted as a displacement of relatively low (high) skilled intensive tasks and should exert a positive (negative) pressure on the wage share of high skilled labour. Indeed, we see this in Table 3.5 and Table 3.6 as well.

[See Table 3.5 and Table 3.6 from page 142 onwards]

Table 3.7 and Table 3.8 show that there is not much evidence of a sector bias effect on relative wages as production sharing in different industries does not seem to affect relative wages differently. This could be explained by the fact that production sharing does not happen in isolation i.e. in specific industries. Therefore, any cost savings that can be achieved by GVCs will simply result in lower world prices of the goods experiencing production sharing, as discussed extensively in Chapter 1. As shown by Krugman (2000) and Xu (2001), this price effect can completely offset the productivity effect on wages, and all that is left is a factor bias effect.

[See Table 3.7 and Table 3.8 from page 144 onwards]

In order to estimate the "final" effect of GVCs on relative wages, we should include both the factor and sector bias by using a 3-way interaction term as outlined in equation (3.9). Figure 3.3 provides a visualisation of the empirical results while Table 3.9 and Table 3.10 show more detailed output.

[See Table 3.9 and Table 3.10 from page 146 onwards]

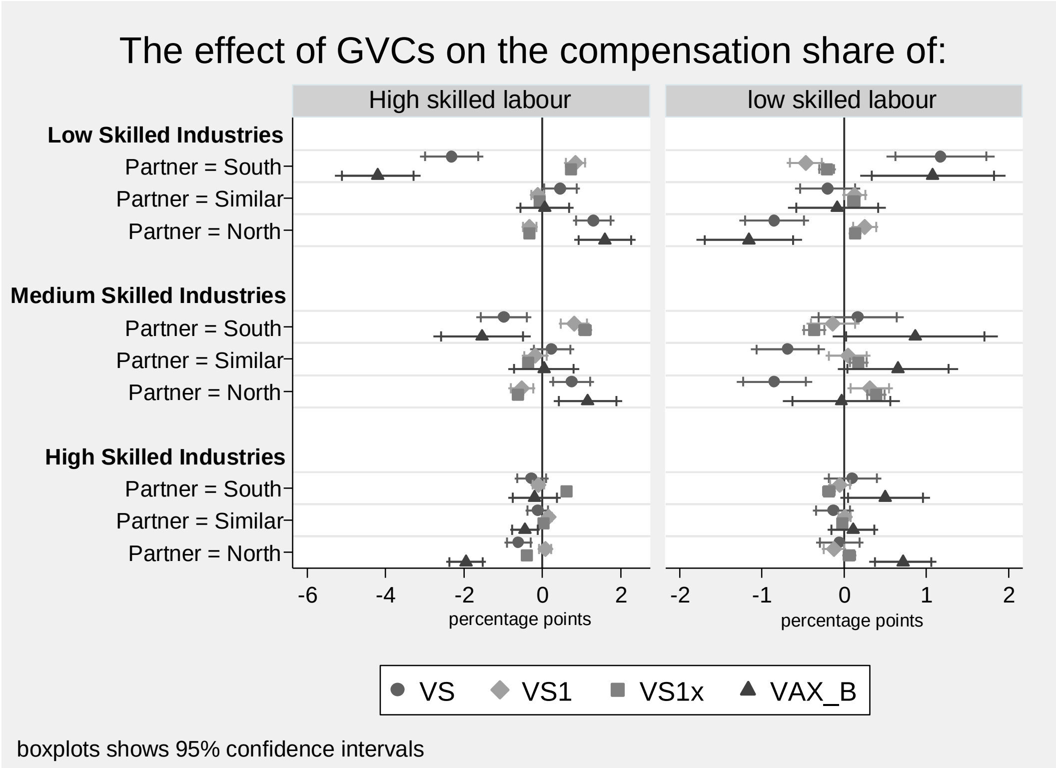

Figure 3.3 Graphical output of equation (3.9). Full tabular output in Table 3.9 and Table 3.10 from page 146 onwards

Remember that we assume that the factor bias of the value added exported will be relatively low (high) skilled if the partner is less (more) skilled abundant than the home country. Then, any domestic value added exported (VS1, VS1* and VAX_B) to a less (more) skilled intensive partner should increase (decrease) the relative demand for skilled labour and thus their relative pay. We see strong evidence of this for VS1 and VS1* in the low and medium skilled industries. We do not observe this effect for VAX_B where we even see the opposite in low skilled industries where the partner is the South as well as the medium skilled industries where the partner is the North. This can be explained, however, by the Feenstra – Hanson theorem that what might be viewed as low (high) skilled by the North (South) can be viewed as high (low) skilled by the South (North). We see evidence of this in column (13 – 15) of Table 3.9 and Table 3.10 in the low and medium skilled sectors where the partner is the South and North respectively. The former can be explained by the fact that the inshored activities from the South are perceived as low skilled – or indeed *medium* skilled – by the North as the relative pay for high skilled labour decreases at the expense of medium skilled labour. The latter case provides further evidence of the point Feenstra and Hanson (2001) tried to make. Here, domestic value produced for a country more skilled abundant than the home country, tends to increase relative demand for high skilled labour at the expense of both medium and low skilled labour, providing evidence that the activities are perceived as high skilled by the inshoring or less skilled abundant country.

Regarding *foreign* value added exported (VS), the signs are also as we expected. Namely, whenever the proxy includes foreign value added (VS) and the export partner is more (less) skilled abundant, this can be roughly interpreted as a *displacement* of relatively low (high) skilled intensive tasks and should therefore exert a negative (positive) pressure on the wage share of low skilled labour of which we see evidence in the low and medium skilled industries as well.

One somewhat surprising result is that there are no significant coefficients in the high skilled industries. This could potentially be explained by the fact that we lumped manufacturing sectors with service sectors. Table 3.12 separates high, medium and low skilled manufacturing sectors from high medium and low skilled services sectors. Here we see that the signs are driven by the manufacturing sectors. Indeed, within high skilled manufacturing sectors, we do see the signs as expected according to the dynamics outlined above. On the other hand, GVC in the services sectors does only seem to affect relative wages in the North (i.e. when the partner is the South). We could explain this by the fact that Northern countries are more likely to offshore services to the South rather than the other way around.

3.5. Concluding remarks

This Chapter has used macro data to empirically determine the effect of GVCs on the relative demand for skilled labour. In doing so, it used a recent decomposition method by WWZ that provides a set of GVC proxies that are well established in the literature. These proxies were then correlated with the relative employment and wage share of different skill types of workers and conditioned on the factor and sector bias of the offshored activities. Based on the lessons from Chapter 1, Table 3.1 stated hypotheses what would happen to the relative demand for skilled labour once a country would engage in a specific type of GVC engagement. The results showed strong evidence of a factor bias effect, i.e. the hypotheses in column (4) of Table 3.1, but not of a sector bias effect as outlined in column (6).

Most importantly, any domestic value added exported to a more (less) skilled abundant partner, measured via VS1 and VS1*, was found to be positively (negatively) correlated with the employment and wage-bill share of low skilled labour. Here, the partner dimension is crucial in making inferences about the factor bias of the activities the home country specialises in via GVCs. It rests on the assumption that exporting to more (less) skilled abundant countries typically involves the relatively low (high) skilled intensive tasks of that value chain. This is because – within this bilateral trade relationship – the home country is the one that has the comparative advantage in producing low (high) skilled activities, meaning that the factor bias of the GVC activity will be low (high) skilled intensive.

This finding, that the factor bias crucially determines the skill bias effect of GVCs rather than the sector bias, is in line with Krugman (2000) and Xu (2001) that in an integrated world economy where productivity increases occur across many countries and industries simultaneously, the sector bias effect would be offset by a price effect, and only the factor bias effect determines the change in the relative demand for skilled labour.

In terms of the different GVC proxies that were used in this Chapter, we would argue that VS1* is the most appropriate proxy to estimate the effect of GVCs on the relative demand for skilled labour. On a theoretical basis, both VS1* and VAX_B have clear hypotheses as they represent a well-defined stream of international production sharing. Namely, while VAX_B measures the domestic value added exported and directly absorbed by the export partner, VS1* measures the domestic value added that is initially exported and then returns home again. Compare this to VS and VS1, which measure a more infinite stream of global production sharing. That is, VS1 measures the domestic value added that is exported and eventually re-exported again. Once a third country comes into play, the distinction between the relative skill abundance of the countries involved becomes blurry, making it hard to make inferences about the skill intensity of the domestic value added. The predicted effects of VS on the relative demand for skilled labour are even more convoluted, as it represents *foreign* value added exported. Since we have no data on where this value was added specifically, this Chapter worked on the assumption that it represents a displacement of work, where the skill bias of that displacement depends on the export partner. Compare this to VS1*, which is a fairly direct measure of offshoring and thus allows for the direct application of various theories on the effect of offshoring on the relative demand for skilled labour.

These theoretical priors were confirmed with the empirical results, as this Chapter found the most significant results for VS1*. Therefore, both on a theoretical and empirical ground, this Chapter argues that VS1* is the most appropriate measure to estimate the effect of GVCs on the relative demand for skilled labour.

While this Chapter put a lot of emphasis on the relative skill endowment of the home and the partner country in hypothesizing the skill bias of GVCs, future research could look more into the importance of the final destination of the GVC. When comparing VS1* and VAX, for example, while they both refer to domestic value added exported, they differ in terms of the location of final consumption. Namely, while VAX measures domestic value added that is directly absorbed by the export partner, VS1* measures the domestic value added exported that then returns home and is ultimately consumed there. The empirical relationship with the skill bias differs, as demonstrated in the previous section. This was explained by referring to the Feenstra-Hanson (1996) theorem which argues that what might be viewed as low skilled intensive for a skill abundant country might be high skilled intensive for a low skill abundant country and therefore increase the relative demand for skilled labour in the latter, rather than decrease it. However, rather than explaining this difference by referring to the Feenstra Hanson theorem, future research could look more into the role played by the final destination market as this might have further implications on the required skill intensity of the GVC activities.

Appendix 3.1: Data dimensions

As outlined on page 129, this research uses the decomposition method by Quast and Kummritz (2015) to decompose the WIOD tables, following the decomposition method by Wang, Wei and Zhu (2013). This creates a database of the following 40 countries plus a block being "the rest of the world (ROW)", 28 industries and a time period of 15 years: 1995-2009.

Table 3.2. Data Dimensions

Countries		Industries	
Australia	Japan	A	Agriculture, Forestry and Fishing
Austria	Korea	B	Mining and Quarrying
Belgium	Latvia	C10	Manufacturing of food products
Brazil	Lithuania	C13	Manufacturing of textile products
Bulgaria	Luxembour g	C15	Manufacturing of leather and related products
Canada	Malta	C16	Manufacturing of wood and of related products
China	Mexico	C17	Manufacture of paper and paper products
Chinese Taipei	Netherlands	C19	Manufacture of coke and refined petroleum products
Cyprus	Poland	C20	Manufacture of chemicals and chemical products
Czech Republic	Portugal	C22	Manufacture of rubber and plastic products
Denmark	ROW	C23	Manufacture of other, non-metallic products
Estonia	Romania	C24, 5	Manufacture of basic metals, fabricated metal products, except machinery and equipment
Finland	Russian Federation	C26	Manufacture of computer, electronic and optical products
France	Slovak Republic	C28	Manufacture of machinery and equipment, n.e.c.
Germany	Slovenia	C30	Manufacture of transport equipment
Greece	Spain	C32	Other manufacturing
Hungary	Sweden	D	Electricity, gas, steam and air conditioning
India	Turkey	F	Construction
Indonesia	United Kingdom	G	Wholesale and retail trade, repair of motor vehicles and motorcycles
Ireland	United States	H	Transportation and storage
Italy		I	Accommodation and food service activities
		J	Information and Communication
		K	Financial and Insurance activities
		L	Real estate activities
		N	Administrative and support service activities

	O	Public administration and defence
	P	Education
	Q	Human health and social work activities

Appendix 3.2: Empirical output

Table 3.3 Baseline estimation: Effect of GVCs on relative wage shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS
GVC effect	-0.0304	0.280	-0.249	0.0409	-0.0927	0.0519	0.0386	-0.0701**	0.0314	-0.502	0.276	0.226
	(-0.109)	(1.448)	(-1.135)	(0.931)	(-1.534)	(1.174)	(1.002)	(-2.191)	(1.458)	(-1.463)	(1.188)	(1.394)
Ln(Capital)	-0.351	0.352	-0.00108	-0.337	0.318	0.0193	-0.334	0.312	0.0222	-0.335	0.317	0.0178
	(-1.297)	(0.844)	(-0.00254)	(-1.259)	(0.762)	(0.0451)	(-1.248)	(0.741)	(0.0514)	(-1.273)	(0.779)	(0.0420)
Ln(Sales)	-0.207	0.0799	0.127	-0.254	-0.0519	0.306	-0.273	-0.0223	0.296	-0.115	-0.151	0.266
	(-0.157)	(0.0633)	(0.105)	(-0.189)	(-0.0413)	(0.256)	(-0.201)	(-0.0177)	(0.247)	(-0.0864)	(-0.124)	(0.223)
Ln(Wage premium High:Low skilled)	6.615***	5.688***	-12.30***	6.639***	5.632***	-12.27***	6.639***	5.633***	-12.27***	6.614***	5.681***	-12.30***
	(4.871)	(4.983)	(-7.882)	(4.837)	(4.866)	(-7.855)	(4.838)	(4.869)	(-7.859)	(4.868)	(4.965)	(-7.891)
Ln(Wage premium High:Medium skilled)	7.101***	-14.15***	7.049***	6.806***	-14.39***	7.580***	6.803***	-14.38***	7.578***	7.099***	-14.15***	7.055***
	(4.526)	(-8.686)	(5.707)	(3.928)	(-9.060)	(5.808)	(3.926)	(-9.050)	(5.807)	(4.517)	(-8.694)	(5.705)
Constant	0.0381	0.787***	-0.825***	0.0360	0.790***	-0.826***	0.0344	0.792***	-0.827***	0.0373	0.791***	-0.828***
	(0.389)	(6.330)	(-6.627)	(0.368)	(6.513)	(-6.772)	(0.350)	(6.508)	(-6.754)	(0.381)	(6.437)	(-6.712)
	1.372***	1.289***	0.967***	1.365***	1.285***	0.950***	1.365***	1.285***	0.950***	1.371***	1.289***	0.968***
	(7.070)	(7.579)	(6.415)	(6.971)	(7.545)	(6.380)	(6.970)	(7.541)	(6.378)	(7.081)	(7.576)	(6.418)
Observations	47,875	47,875	47,875	47,410	47,410	47,410	47,413	47,413	47,413	47,888	47,888	47,888

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4 Baseline estimation: Effect of GVCs on relative employment shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS
GVC:	-0.184	0.197	-0.0137	0.0483	-0.0545	0.00627	0.0341	-0.0473**	0.0132	-0.365	0.285	0.0800
	(-1.031)	(1.067)	(-0.0822)	(1.140)	(-1.029)	(0.158)	(1.071)	(-2.023)	(0.615)	(-1.188)	(1.306)	(0.500)
Ln(Capital)	-0.184	0.212	-0.0280	-0.161	0.163	-0.00251	-0.157	0.160	-0.00211	-0.157	0.185	-0.0276
	(-0.969)	(0.477)	(-0.0774)	(-0.839)	(0.367)	(-0.00689)	(-0.820)	(0.357)	(-0.00577)	(-0.879)	(0.426)	(-0.0760)
Ln(Sales)	-0.596	-0.192	0.787	-0.544	-0.299	0.842	-0.557	-0.276	0.834	-0.399	-0.354	0.752
	(-0.709)	(-0.182)	(0.754)	(-0.639)	(-0.282)	(0.838)	(-0.644)	(-0.262)	(0.831)	(-0.475)	(-0.343)	(0.737)
Ln(Wage premium High:Low skilled)	1.320	-1.633**	0.313	1.375	-1.648**	0.272	1.375	-1.647**	0.272	1.324	-1.638**	0.314
	(1.352)	(-2.268)	(0.672)	(1.397)	(-2.258)	(0.609)	(1.397)	(-2.256)	(0.609)	(1.353)	(-2.264)	(0.674)
Ln(Wage premium High:Medium skilled)	-0.926	2.639**	-1.713**	-0.987	2.654**	-1.666**	-0.989	2.656**	-1.667**	-0.923	2.636**	-1.713**
	(-0.967)	(2.031)	(-2.494)	(-0.993)	(2.014)	(-2.501)	(-0.995)	(2.016)	(-2.502)	(-0.965)	(2.030)	(-2.498)
Constant	-0.0744	0.839***	-0.764***	-0.0757	0.842***	-0.766***	-0.0766	0.843***	-0.767***	-0.0751	0.842***	-0.767***
	(-1.056)	(8.101)	(-6.797)	(-1.085)	(8.335)	(-6.954)	(-1.094)	(8.326)	(-6.956)	(-1.069)	(8.257)	(-6.888)
	0.909***	1.014***	0.735***	0.903***	1.014***	0.721***	0.903***	1.014***	0.721***	0.908***	1.014***	0.737***
	(4.320)	(5.480)	(4.941)	(4.247)	(5.465)	(4.931)	(4.246)	(5.463)	(4.932)	(4.323)	(5.486)	(4.959)
Observations	47,875	47,875	47,875	47,410	47,410	47,410	47,413	47,413	47,413	47,888	47,888	47,888

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.5 The effect of GVC on relative wage shares; controlling for the factor bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS
GVC effect where the partner =												
South	-0.785*	0.484	0.300	0.243	-0.0811	-0.162	0.732***	-0.509***	-0.223***	-1.341*	0.644	0.698*
	(-1.727)	(1.306)	(1.376)	(1.245)	(-0.383)	(-1.560)	(4.043)	(-3.552)	(-3.949)	(-1.762)	(1.146)	(1.783)
Similar	0.0778	0.169	-0.247	0.0638	-0.101	0.0371	-0.0614	0.0109	0.0505	-0.294	0.154	0.141
	(0.256)	(0.825)	(-1.068)	(0.482)	(-0.763)	(0.599)	(-0.527)	(0.123)	(0.985)	(-0.559)	(0.392)	(0.521)
North	0.161	0.262	-0.423*	-0.161	0.0804	0.0801	-0.405***	0.255**	0.150***	-0.528	0.392	0.136
	(0.455)	(0.906)	(-1.688)	(-1.102)	(0.867)	(0.801)	(-3.007)	(2.213)	(3.438)	(-1.025)	(0.805)	(0.506)
Ln(Capital)	-0.412	0.426	-0.0139	-0.399	0.402	-0.00284	-0.404	0.399	0.00464	-0.380	0.385	-0.00495
	(-1.513)	(1.035)	(-0.0335)	(-1.533)	(1.010)	(-0.00682)	(-1.602)	(1.008)	(0.0111)	(-1.436)	(0.964)	(-0.0119)
Ln(Sales)	-0.144	0.198	-0.0545	-0.0698	0.0526	0.0172	0.0381	-0.0128	-0.0253	-0.0460	-0.0162	0.0622
	(-0.106)	(0.157)	(-0.0436)	(-0.0507)	(0.0429)	(0.0139)	(0.0283)	(-0.0107)	(-0.0203)	(-0.0332)	(-0.0132)	(0.0498)
Ln(Wage premium High:Low skilled)	6.653***	5.493***	-12.15***	6.638***	5.453***	-12.09***	6.614***	5.469***	-12.08***	6.657***	5.485***	-12.14***
	(4.803)	(4.808)	(-7.873)	(4.760)	(4.777)	(-7.864)	(4.825)	(4.839)	(-7.872)	(4.798)	(4.785)	(-7.885)
Ln(Wage premium High:Medium skilled)	7.138***	-14.51***	7.368***	7.158***	-14.47***	7.316***	7.187***	-14.49***	7.306***	7.139***	-14.51***	7.372***
	(4.196)	(-8.961)	(5.631)	(4.166)	(-8.956)	(5.546)	(4.246)	(-9.109)	(5.527)	(4.182)	(-8.970)	(5.625)
Constant	0.0271	0.804***	-0.831***	0.0334	0.805***	-0.839***	0.0248	0.812***	-0.837***	0.0266	0.808***	-0.835***
	(0.272)	(6.678)	(-6.731)	(0.337)	(6.779)	(-6.945)	(0.256)	(6.876)	(-6.920)	(0.267)	(6.783)	(-6.839)
	1.374***	1.294***	0.949***	1.374***	1.293***	0.948***	1.359***	1.286***	0.945***	1.373***	1.293***	0.950***
	(7.040)	(7.555)	(6.305)	(7.036)	(7.544)	(6.286)	(7.128)	(7.638)	(6.278)	(7.057)	(7.555)	(6.315)
Observations	35,284	35,284	35,284	35,281	35,281	35,281	35,281	35,281	35,281	35,296	35,296	35,296

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6 The effect of GVC on employment shares; controlling for the factor bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS
GVC effect where the partner is:												
South	-0.625*	0.220	0.404*	0.144	0.0887	-0.233***	0.573***	-0.356***	-0.217***	-0.857	0.192	0.666*
	(-1.777)	(0.699)	(1.927)	(0.848)	(0.600)	(-3.054)	(3.984)	(-2.686)	(-3.556)	(-1.447)	(0.403)	(1.907)
Similar	0.0256	0.0902	-0.116	0.0555	-0.0682	0.0126	-0.0519	-0.0163	0.0682	-0.0343	0.0915	-0.0572
	(0.107)	(0.440)	(-0.639)	(0.403)	(-0.601)	(0.183)	(-0.522)	(-0.194)	(1.438)	(-0.0685)	(0.259)	(-0.242)
North	-0.212	0.329	-0.118	-0.0319	0.00491	0.0270	-0.317***	0.217**	0.0997***	-0.738	0.684	0.0546
	(-0.801)	(1.036)	(-0.563)	(-0.268)	(0.0570)	(0.257)	(-2.809)	(2.234)	(2.640)	(-1.521)	(1.309)	(0.199)
Ln(Capital)	-0.213	0.251	-0.0373	-0.189	0.241	-0.0522	-0.193	0.236	-0.0433	-0.176	0.220	-0.0445
	(-1.093)	(0.571)	(-0.107)	(-1.027)	(0.565)	(-0.150)	(-1.082)	(0.554)	(-0.125)	(-0.965)	(0.516)	(-0.127)
Ln(Sales)	-0.575	-0.0912	0.666	-0.438	-0.222	0.660	-0.332	-0.285	0.617	-0.365	-0.274	0.639
	(-0.664)	(-0.0850)	(0.611)	(-0.507)	(-0.211)	(0.615)	(-0.396)	(-0.274)	(0.574)	(-0.417)	(-0.260)	(0.590)
Ln(Wage premium	1.378	-1.679**	0.300	1.389	-1.690**	0.301	1.369	-1.675**	0.306	1.386	-1.684**	0.298
High:Low skilled)	(1.372)	(-2.254)	(0.657)	(1.372)	(-2.247)	(0.655)	(1.382)	(-2.269)	(0.670)	(1.375)	(-2.245)	(0.652)
Ln(Wage premium High:Medium	-0.905	2.723**	-1.818**	-0.904	2.711**	-1.807**	-0.880	2.691**	-1.811**	-0.901	2.720**	-1.818**
skilled)	(-0.894)	(1.993)	(-2.576)	(-0.890)	(1.974)	(-2.546)	(-0.894)	(1.986)	(-2.542)	(-0.890)	(1.992)	(-2.573)
Constant	-0.0863	0.862***	-0.776***	-0.0835	0.866***	-0.782***	-0.0877	0.867***	-0.780***	-0.0885	0.867***	-0.779***
	(-1.215)	(8.436)	(-6.889)	(-1.186)	(8.596)	(-7.073)	(-1.269)	(8.580)	(-7.081)	(-1.251)	(8.620)	(-7.004)
	0.918***	1.028***	0.729***	0.918***	1.029***	0.731***	0.904***	1.023***	0.729***	0.917***	1.028***	0.731***
	(4.365)	(5.539)	(4.958)	(4.364)	(5.532)	(4.971)	(4.386)	(5.587)	(4.959)	(4.374)	(5.549)	(4.978)
Observations	35,284	35,284	35,284	35,281	35,281	35,281	35,281	35,281	35,281	35,296	35,296	35,296

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.7 The effect of GVC on relative wage shares; controlling for sector bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS
Effect of GVC in a:												
Low skilled industry	0.320	-0.267	-0.0529	0.0444	-0.0831	0.0387	0.00188	-0.0598	0.0579	-0.500	0.391	0.109
	(0.712)	(-0.877)	(-0.116)	(0.728)	(-0.969)	(0.559)	(0.0334)	(-1.395)	(1.456)	(-1.262)	(0.724)	(0.257)
Medium skilled industry	0.285	0.143	-0.428	-0.113	0.0788	0.0338	-0.0563	-0.0334	0.0896**	0.664**	-0.366	-0.298
	(1.059)	(0.509)	(-1.069)	(-1.246)	(0.987)	(0.532)	(-1.153)	(-0.724)	(2.292)	(2.126)	(-1.291)	(-1.142)
High skilled industry	-0.226	0.478*	-0.253	0.0756	-0.139*	0.0634	0.101*	-0.0913*	-0.00929	-0.856	0.438	0.417*
	(-0.688)	(1.819)	(-1.504)	(1.273)	(-1.875)	(1.372)	(1.767)	(-1.732)	(-0.286)	(-1.604)	(1.223)	(1.926)
Ln(Capital)	-0.341	0.339	0.00235	-0.337	0.318	0.0189	-0.335	0.312	0.0227	-0.341	0.319	0.0218
	(-1.267)	(0.811)	(0.00551)	(-1.258)	(0.763)	(0.0440)	(-1.253)	(0.743)	(0.0526)	(-1.290)	(0.781)	(0.0516)
Ln(Sales)	-0.182	0.0403	0.141	-0.240	-0.0686	0.308	-0.230	-0.0379	0.268	-0.0757	-0.173	0.249
	(-0.139)	(0.0322)	(0.117)	(-0.178)	(-0.0545)	(0.258)	(-0.170)	(-0.0302)	(0.224)	(-0.0568)	(-0.142)	(0.208)
Ln(Wage premium High:Low skilled)	6.613***	5.688***	-12.30***	6.639***	5.633***	-12.27***	6.638***	5.633***	-12.27***	6.610***	5.683***	-12.29***
	(4.874)	(4.990)	(-7.882)	(4.837)	(4.869)	(-7.855)	(4.840)	(4.869)	(-7.860)	(4.879)	(4.967)	(-7.894)
Ln(Wage premium High:Medium skilled)	7.109***	-14.16***	7.055***	6.806***	-14.39***	7.580***	6.806***	-14.38***	7.576***	7.101***	-14.16***	7.054***
	(4.554)	(-8.736)	(5.699)	(3.926)	(-9.053)	(5.808)	(3.930)	(-9.051)	(5.809)	(4.516)	(-8.690)	(5.707)
Constant	0.0319	0.797***	-0.828***	0.0357	0.790***	-0.825***	0.0384	0.791***	-0.830***	0.0345	0.793***	-0.828***
	(0.328)	(6.412)	(-6.641)	(0.366)	(6.528)	(-6.768)	(0.395)	(6.542)	(-6.795)	(0.356)	(6.540)	(-6.763)
	1.371***	1.288***	0.967***	1.365***	1.285***	0.950***	1.365***	1.285***	0.950***	1.370***	1.288***	0.967***
	(7.076)	(7.581)	(6.414)	(6.973)	(7.546)	(6.380)	(6.972)	(7.542)	(6.381)	(7.089)	(7.580)	(6.419)
Observations	47,875	47,875	47,875	47,410	47,410	47,410	47,413	47,413	47,413	47,888	47,888	47,888

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.8 The effect of GVC on Employment shares; controlling for sector bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS
Effect of GVC in a:												
Low skilled industry	-0.0373	-0.110	0.147	0.0440	-0.0865	0.0425	0.00843	-0.0569*	0.0485	-0.262	0.362	-0.101
	(-0.170)	(-0.378)	(0.366)	(1.138)	(-1.092)	(0.622)	(0.246)	(-1.722)	(1.066)	(-0.934)	(0.656)	(-0.212)
Medium skilled industry	0.123	-0.0512	-0.0720	-0.105	0.100*	0.00467	-0.0509	-0.000950	0.0518**	0.443**	-0.132	-0.311
	(0.744)	(-0.231)	(-0.250)	(-1.556)	(1.725)	(0.0817)	(-1.423)	(-0.0309)	(2.018)	(2.176)	(-0.515)	(-1.139)
High skilled industry	-0.318	0.360	-0.0424	0.0873	-0.0740	-0.0133	0.0846*	-0.0584	-0.0262	-0.639	0.390	0.249
	(-1.283)	(1.471)	(-0.306)	(1.424)	(-1.139)	(-0.325)	(1.815)	(-1.416)	(-1.125)	(-1.337)	(1.095)	(1.477)
Ln(Capital)	-0.179	0.203	-0.0246	-0.161	0.162	-0.00122	-0.158	0.160	-0.00162	-0.163	0.186	-0.0235
	(-0.945)	(0.456)	(-0.0679)	(-0.838)	(0.364)	(-0.00335)	(-0.825)	(0.358)	(-0.00442)	(-0.896)	(0.428)	(-0.0649)
Ln(Sales)	-0.586	-0.213	0.799	-0.529	-0.313	0.842	-0.521	-0.289	0.809	-0.372	-0.368	0.740
	(-0.695)	(-0.201)	(0.761)	(-0.620)	(-0.297)	(0.838)	(-0.604)	(-0.275)	(0.808)	(-0.441)	(-0.359)	(0.723)
Ln(Wage premium	1.319	-1.632**	0.313	1.375	-1.647**	0.272	1.375	-1.647**	0.272	1.322	-1.637**	0.315
High:Low skilled)	(1.352)	(-2.270)	(0.673)	(1.397)	(-2.257)	(0.610)	(1.397)	(-2.256)	(0.610)	(1.353)	(-2.266)	(0.679)
Ln(Wage premium	-0.923	2.631**	-1.708**	-0.987	2.655**	-1.668**	-0.988	2.658**	-1.670**	-0.922	2.636**	-1.713**
High:Medium skilled)	(-0.965)	(2.022)	(-2.475)	(-0.992)	(2.014)	(-2.503)	(-0.994)	(2.017)	(-2.509)	(-0.964)	(2.029)	(-2.499)
Constant	-0.0772	0.844***	-0.767***	-0.0756	0.843***	-0.768***	-0.0738	0.844***	-0.771***	-0.0761	0.844***	-0.767***
	(-1.099)	(8.128)	(-6.790)	(-1.087)	(8.405)	(-6.989)	(-1.057)	(8.387)	(-7.035)	(-1.098)	(8.420)	(-6.955)
	0.909***	1.014***	0.735***	0.903***	1.014***	0.721***	0.903***	1.014***	0.721***	0.908***	1.014***	0.737***
	(4.322)	(5.482)	(4.941)	(4.247)	(5.466)	(4.931)	(4.246)	(5.463)	(4.931)	(4.328)	(5.489)	(4.959)
Observations	47,875	47,875	47,875	47,410	47,410	47,410	47,413	47,413	47,413	47,888	47,888	47,888

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.9 The effect of GVC on wage shares; simultaneously controlling for sector and factor bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(13)	(14)	(15)
GVC proxy:		VS			VS1			VS1*			VAX_B	
Effect on:	WHS	WMS	WLS	WHS	WML	WLS	WHS	WMS	WLS	WHS	WMS	WLS
Low skilled industry and partner =												
South	-2.182***	1.023*	1.16*	0.747***	-0.288	-0.459**	0.668***	-0.469***	-0.199	-4.03***	2.86**	1.17
	(-2.633)	(1.948)	(1.829)	(3.559)	(-1.546)	(-2.273)	(3.952)	(-4.138)	(-1.428)	(-3.020)	(2.055)	(1.333)
Similar	0. 713	-0.596*	-0.118	-0.263*	0.0627	0.200*	-0.0822	-0.0683	0.151**	0.234	-0.258	0.0236
	(1.505)	(-1.713)	(-0.284)	(-1.957)	(0.469)	(1.743)	(-0.439)	(-0.444)	(2.187)	(0.356)	(-0.370)	(0.0646)
North	1.17*	-0.747*	-0.421	-0.175	0.0365	0.139	-0.367**	0.249**	0.118**	0.870	-0.304	-0.566
	(1.787)	(-1.719)	(-0.768)	(-0.998)	(0.245)	(0.942)	(-2.364)	(2.003)	(2.093)	(1.440)	(-0.740)	(-0.835)
Medium skilled industry and Partner =												
South	-0.989	0.117	0.872***	0.568**	-0.257	-0.311**	0.889***	-0.567***	-0.322***	-1.58	6.99	0.884
	(-1.516)	(0.170)	(2.835)	(2.302)	(-1.091)	(-2.043)	(6.431)	(-3.690)	(-3.269)	(-1.254)	(0.646)	(1.574)
Similar	0.186	0.238	-0. 424	-0.109	0.0859	0.0233	-0.192	0.111	0.0807	0.235	-0.0693	-0.00165
	(0.485)	(0.793)	(-0.903)	(-0.469)	(0.450)	(0.184)	(-1.479)	(1.027)	(1.565)	(0.345)	(-0.144)	(-0.341)
North	1.30**	-0.226	-1.07**	-0.805***	0.430***	0.375*	-0.496***	0.153**	0.343***	2.48***	-1.27*	-1.21**
	(2.334)	(-0.498)	(-2.169)	(-3.010)	(2.852)	(1.845)	(-3.587)	(2.019)	(3.185)	(2.774)	(-1.857)	(-2.527)
High skilled industry and partner =												
South	-0. 445	0. 459	-0.0135	-0.0277	0.0399	-0.0121	0.716***	-0.513***	-0.204**	-0.332	-0.137	0.469
	(-0.893)	(0.980)	(-5.96)	(-0.107)	(0.143)	(-0.0950)	(2.737)	(-2.583)	(-2.459)	(-0.379)	(-0.189)	(1.080)
Similar	-0. 122	0. 352	-0.230	0.191	-0.00184	-7.50e-03	-3.12e-03	0.0152	-0.0121	-0.524	0.289	0.235
	(-0.345)	(1.312)	(-1.143)	(1.191)	(-1.179)	(-0.0864)	(-0.0247)	(0.177)	(-0.152)	(-0.754)	(0.526)	(0.694)
North	-0. 547	0. 747	-0.200	0.123	-0.0305	-0.0921	-0.394*	0.321	0.0733	-2.06*	1.22	0.849**
	(-0.941)	(1.599)	(-0.945)	(0.529)	(-0.194)	(-0.716)	(-1.722)	(1.513)	(1.440)	(-1.853)	(1.427)	(2.167)

Ln(Capital)	-0.394	0.409	-0.0150	-0.389	0.393	-4.49e-03	-0.404	0.400	3.36e-03	-0.387	0.389	-2.35e-03
	(-1.488)	(0.991)	(-0.0361)	(-1.536)	(0.992)	(-0.0108)	(-1.611)	(1.013)	(0.00795)	(-1.514)	(0.977)	(-0.00565)
Ln(Sales)	-0.0743	0.126	-0.0515	-0.0494	0.0512	-1.78e-03	0.0458	6.15e-03	-0.0520	-0.0162	-0.0287	0.0449
	(-0.0554)	(0.101)	(-0.0411)	(-0.0359)	(0.0413)	(-0.00144)	(0.0342)	(0.00513)	(-0.0417)	(-0.0116)	(-0.0233)	(0.0359)
Ln(Wage premium High:Low skilled)	6.66***	5.49***	12.1***	6.65***	5.45***	-12.1***	6.62***	5.47***	-12.1***	6.68***	5.47***	-12.1***
	(4.812)	(4.810)	(-7.877)	(4.763)	(4.772)	(-7.859)	(4.854)	(4.858)	(-7.884)	(4.825)	(4.769)	(-7.890)
Ln(Wage premium High:Medium skilled)	7.15***	-14.5***	7.38***	7.15***	-14.5***	7.32***	0.0718***	-0.145***	0.0731***	7.10***	-14.5***	7.38***
	(4.253)	(-9.050)	(5.627)	(4.182)	(-8.965)	(5.563)	(4.261)	(-9.142)	(5.544)	(4.179)	(-8.977)	(5.642)
Observations	35,284	35,284	35,284	35,281	35,281	35,281	35,281	35,281	35,281	35,296	35,296	35,296

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.10 The effect of GVC on employment shares; simultaneously controlling for sector and factor bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(13)	(14)	(15)
GVC proxy:		VS			VS1			VS1*			VAX_B	
Effect on:	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS	EHS	EMS	ELS
					Low skilled industry and partner =							
South	-1.439***	0.346	1.093**	0.501***	-0.00921	-0.491***	0.460***	-0.278***	-0.182	-2.563***	1.964*	0.599
	(-2.760)	(0.883)	(2.000)	(3.638)	(-0.0818)	(-3.836)	(3.979)	(-3.025)	(-1.384)	(-2.956)	(1.954)	(0.928)
Similar	0.132	-0.245	0.113	-0.114	-0.0531	0.167	-0.0331	-0.127	0.160**	0.0393	-0.0431	0.00373
	(0.671)	(-0.746)	(0.301)	(-1.244)	(-0.495)	(1.505)	(-0.239)	(-1.009)	(2.227)	(0.0870)	(-0.0761)	(0.00978)
North	0.478	-0.335	-0.143	-0.0889	-0.0458	0.135	-0.252**	0.181**	0.0712	0.577	-0.0676	-0.509
	(1.210)	(-1.002)	(-0.300)	(-0.699)	(-0.335)	(1.051)	(-2.182)	(2.178)	(1.229)	(1.368)	(-0.108)	(-0.698)
					Medium skilled industry and Partner =							
South	-0.637	-0.131	0.768**	0.343*	-0.0494	-0.294**	0.646***	-0.430***	-0.215**	-0.902	0.0736	0.829
	(-1.302)	(-0.205)	(2.478)	(1.889)	(-0.235)	(-2.165)	(5.905)	(-2.920)	(-1.978)	(-0.922)	(0.0793)	(1.544)
Similar	0.0128	0.132	-0.145	-0.0911	0.0724	0.0188	-0.151	0.121	0.0297	0.0467	0.278	-0.325
	(0.0448)	(0.595)	(-0.458)	(-0.469)	(0.477)	(0.153)	(-1.574)	(1.164)	(0.722)	(0.0831)	(0.718)	(-0.779)
North	0.856**	-0.448	-0.408	-0.574***	0.421***	0.153	-0.369***	0.145**	0.225***	1.726***	-1.043	-0.683*
	(2.063)	(-1.234)	(-1.115)	(-2.924)	(3.060)	(1.111)	(-3.947)	(2.249)	(3.683)	(2.684)	(-1.589)	(-1.802)
					High skilled industry and partner =							
South	-0.454	0.277	0.177	-0.0396	0.158	-0.119	0.610***	-0.374**	-0.236***	-0.248	-0.382	0.630
	(-1.100)	(0.693)	(0.754)	(-0.164)	(0.772)	(-1.144)	(2.901)	(-2.224)	(-3.327)	(-0.341)	(-0.627)	(1.525)
Similar	0.00295	0.165	-0.168	0.133	-0.0991	-0.0335	-0.0255	-0.00949	0.0350	-0.0595	0.0672	-0.00774
	(0.00879)	(0.623)	(-0.879)	(0.737)	(-0.699)	(-0.355)	(-0.222)	(-0.111)	(0.514)	(-0.0888)	(0.128)	(-0.0258)
North	-0.796	0.804*	-0.00792	0.243	-0.128	-0.114	-0.360*	0.300	0.0594	-2.056**	1.552*	0.504
	(-1.621)	(1.654)	(-0.0402)	(1.142)	(-0.980)	(-0.669)	(-1.784)	(1.604)	(1.034)	(-2.014)	(1.701)	(1.329)
Ln(Capital)	-0.203	0.237	-0.0339	-0.182	0.230	-0.0487	-0.188	0.235	-0.0465	-0.182	0.224	-0.0419
	(-1.051)	(0.538)	(-0.0973)	(-0.996)	(0.540)	(-0.140)	(-1.076)	(0.552)	(-0.133)	(-1.014)	(0.523)	(-0.120)
Ln(Sales)	-0.545	-0.125	0.670	-0.410	-0.223	0.633	-0.333	-0.265	0.598	-0.328	-0.297	0.625
	(-0.634)	(-0.115)	(0.613)	(-0.476)	(-0.209)	(0.595)	(-0.398)	(-0.256)	(0.559)	(-0.369)	(-0.283)	(0.576)

Ln(Wage premium High:Low skilled)	1.383	-1.681**	0.298	1.396	-1.693**	0.297	1.367	-1.671**	0.304	1.404	-1.699**	0.295
	(1.378)	(-2.262)	(0.652)	(1.377)	(-2.249)	(0.645)	(1.389)	(-2.279)	(0.667)	(1.395)	(-2.271)	(0.646)
Ln(Wage premium High:Medium skilled)	-0.902	2.713**	-1.811**	-0.912	2.715**	-1.803**	-0.876	2.689**	-1.813**	-0.930	2.743**	-1.813**
	(-0.893)	(1.984)	(-2.550)	(-0.898)	(1.977)	(-2.549)	(-0.896)	(1.995)	(-2.546)	(-0.924)	(2.013)	(-2.562)
Constant	-0.0872	0.869***	-0.781***	-0.0827	0.868***	-0.785***	-0.0885	0.871***	-0.782***	-0.0860	0.867***	-0.781***
	(-1.231)	(8.469)	(-6.914)	(-1.171)	(8.653)	(-7.127)	(-1.266)	(8.642)	(-7.140)	(-1.232)	(8.675)	(-7.089)
	0.916***	1.027***	0.729***	0.917***	1.028***	0.730***	0.904***	1.023***	0.729***	0.913***	1.026***	0.731***
	(4.377)	(5.549)	(4.959)	(4.360)	(5.532)	(4.972)	(4.391)	(5.597)	(4.960)	(4.392)	(5.562)	(4.980)
Observations	35,284	35,284	35,284	35,281	35,281	35,281	35,281	35,281	35,281	35,296	35,296	35,296

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3.3: Robustness Checks

Table 3.11 exclusion of relative wage terms

	(1)	(3)	(4)	(5)	(7)	(8)	(9)	(11)	(12)	(13)	(15)	(16)
		VS			VS1			VS1*			Vax_b	
VARIABLES	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS	WHS	WMS	WLS
GVC effect												
Low skilled industry and partner =												
South	-2.500***	1.099**	1.438*	0.798***	-0.365**	-0.430**	0.771***	-0.502***	-0.263*	-3.562**	3.234**	0.306
	(-2.639)	(1.977)	(1.795)	(3.738)	(-1.983)	(-2.142)	(3.940)	(-4.505)	(-1.787)	(-2.544)	(2.300)	(0.307)
Similar	-0.161	-0.330	0.506	-0.137	0.0181	0.116	-0.0125	-0.102	0.113	0.0765	-0.293	0.229
	(-0.390)	(-1.118)	(1.135)	(-1.042)	(0.135)	(0.860)	(-0.0637)	(-0.672)	(1.188)	(0.111)	(-0.416)	(0.589)
North	0.391	-0.492	0.100	-0.119	0.0340	0.0879	-0.315*	0.239*	0.0770	1.066	-0.477	-0.611
	(0.611)	(-1.185)	(0.179)	(-0.736)	(0.223)	(0.504)	(-1.835)	(1.819)	(1.146)	(1.557)	(-1.046)	(-0.770)
Medium skilled industry and Partner =												
South	-1.018	0.0300	1.011***	0.606**	-0.264	-0.337**	0.881***	-0.632***	-0.248***	-1.660	0.857	0.769
	(-1.447)	(0.0412)	(2.779)	(2.280)	(-0.988)	(-2.248)	(5.882)	(-4.691)	(-3.658)	(-1.347)	(0.699)	(1.302)
Similar	0.234	0.258	-0.476	-0.169	0.0827	0.0833	-0.222*	0.117	0.104*	0.276	0.0452	-0.328
	(0.548)	(0.670)	(-0.961)	(-0.727)	(0.373)	(0.748)	(-1.704)	(1.102)	(1.741)	(0.406)	(0.0671)	(-0.797)
North	1.291**	-0.347	-0.924	-0.781***	0.448**	0.325	-0.460***	0.181*	0.279***	2.226**	-1.422*	-0.800
	(2.389)	(-0.661)	(-1.622)	(-2.790)	(2.458)	(1.293)	(-3.041)	(1.844)	(2.774)	(2.415)	(-1.834)	(-1.354)
High skilled industry and partner =												
South	-0.746	0.291	0.459	-0.0907	0.118	-0.103	0.733**	-0.464**	-0.301**	-0.00996	-0.575	0.806
	(-1.207)	(0.566)	(1.541)	(-0.291)	(0.451)	(-0.705)	(2.347)	(-2.459)	(-2.249)	(-0.00913)	(-0.762)	(1.328)
Similar	-0.401	0.312	0.0897	0.233	-0.162	-0.103	-0.0148	0.0334	-0.0506	-0.771	0.270	0.583

	(-0.981)	(1.070)	(0.336)	(1.345)	(-1.091)	(-1.063)	(-0.116)	(0.380)	(-0.536)	(-1.000)	(0.511)	(1.241)
North	-0.650	0.735	-0.144	0.0340	-0.0555	0.0394	-0.400	0.249	0.154*	-1.960*	1.321	0.657
	(-1.052)	(1.491)	(-0.530)	(0.127)	(-0.362)	(0.232)	(-1.526)	(1.243)	(1.748)	(-1.764)	(1.589)	(1.615)
Ln(Capital)	-0.268	0.324	-0.0594	-0.236	0.300	-0.0673	-0.252	0.308	-0.0615	-0.235	0.303	-0.0731
	(-0.877)	(0.675)	(-0.109)	(-0.811)	(0.648)	(-0.122)	(-0.871)	(0.666)	(-0.111)	(-0.806)	(0.658)	(-0.134)
Ln(sales)	-0.126	0.649	-0.509	0.161	0.553	-0.690	0.230	0.520	-0.729	0.186	0.479	-0.651
	(-0.0759)	(0.463)	(-0.344)	(0.0955)	(0.399)	(-0.458)	(0.139)	(0.386)	(-0.482)	(0.108)	(0.345)	(-0.428)
Constant	-0.0486	0.860***	-0.865***	-0.0497	0.859***	-0.862***	-0.0614	0.867***	-0.859***	-0.0518	0.859***	-0.860***
	(-0.379)	(6.604)	(-6.159)	(-0.377)	(6.640)	(-6.224)	(-0.471)	(6.754)	(-6.197)	(-0.399)	(6.652)	(-6.220)
	1.665***	1.419***	1.374***	1.664***	1.417***	1.370***	1.654***	1.412***	1.368***	1.663***	1.417***	1.375***
	(8.252)	(9.829)	(7.967)	(8.218)	(9.788)	(7.958)	(8.317)	(9.924)	(7.965)	(8.267)	(9.821)	(7.983)
Observations	35,298	35,298	35,298	35,295	35,295	35,295	35,295	35,295	35,295	35,310	35,310	35,310

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.12 Effect of GVCs on wage shares: Industries divided into 6 groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		VS			VS1			VS1*			VAX_B	
VARIABLES	WHS	WMS	WLS	WHS	WML	WLS	WHS	WMS	WLS	WHS	WMS	WLS
Manufacturing sectors												
Low skilled												
Partner = South	-2.902**	1.638	1.264*	0.684**	-0.120	-0.564**	0.760***	-0.437***	-0.323**	-3.450**	2.026	1.424
	(-2.188)	(1.467)	(1.648)	(2.512)	(-0.342)	(-2.429)	(5.962)	(-3.042)	(-2.114)	(-2.397)	(1.242)	(1.381)
Partner = Similar	0.386	-0.262	-0.124	-0.286	-0.0559	0.342**	-0.0543	-0.0464	0.101	0.115	-0.273	0.158
	(0.532)	(-0.589)	(-0.225)	(-1.616)	(-0.367)	(2.429)	(-0.275)	(-0.274)	(1.424)	(0.155)	(-0.365)	(0.330)
Partner = North	1.624*	-1.176**	-0.448	-0.329	0.132	0.197*	-0.509***	0.298**	0.212***	2.882**	-2.277**	-0.605
	(1.897)	(-1.968)	(-0.796)	(-1.604)	(0.912)	(1.662)	(-3.061)	(2.059)	(4.293)	(2.080)	(-2.482)	(-0.815)
Medium Skilled												
Partner = South	0.528	-1.191*	0.663	-0.252	0.312	-0.0604	0.887***	-0.426**	-0.460**	1.199	-1.539	0.340
	(0.674)	(-1.815)	(1.201)	(-0.636)	(0.998)	(-0.214)	(3.906)	(-2.282)	(-2.369)	(0.786)	(-1.324)	(0.390)
Partner = Similar	0.660	-0.568	-0.0913	-0.728	0.639*	0.0888	-0.346	0.0904	0.255	0.474	-0.501	0.0272
	(0.637)	(-1.118)	(-0.109)	(-1.619)	(1.872)	(0.288)	(-1.481)	(0.510)	(1.390)	(0.316)	(-0.582)	(0.0225)
Partner = North	1.719	-1.191	-0.528	-0.599	0.331	0.268	-0.867***	0.298**	0.569***	2.113	-1.456	-0.657
	(1.564)	(-1.354)	(-0.946)	(-1.228)	(0.920)	(1.135)	(-3.665)	(2.326)	(2.982)	(1.229)	(-0.987)	(-1.022)
High skilled												
Partner = South	-1.504***	0.463	1.042***	0.600***	-0.172	-0.429**	0.533***	-0.376***	-0.157	-1.066	0.409	0.657
	(-2.970)	(0.777)	(2.681)	(2.888)	(-0.871)	(-2.411)	(2.676)	(-3.021)	(-1.142)	(-1.190)	(0.568)	(0.699)
Partner = Similar	-0.503	0.112	0.391	-0.188	0.227	-0.0388	-0.0331	0.0679	-0.0348	0.459	-0.419	-0.0401

	(-0.768)	(0.223)	(0.787)	(-0.407)	(0.754)	(-0.174)	(-0.201)	(0.483)	(-0.365)	(0.506)	(-0.607)	(-0.0560)
Partner = North	0.404	-0.254	-0.150	-0.655***	0.555***	0.100	-0.546***	0.278**	0.268***	2.427***	-1.225*	-1.202**
	(0.893)	(-0.721)	(-0.318)	(-3.665)	(3.506)	(0.715)	(-3.885)	(2.324)	(3.470)	(2.754)	(-1.704)	(-2.284)
Service industries:												
Low Skilled												
Partner = South	-1.559	0.493	1.066*	1.148**	-0.860*	-0.288	0.694**	-0.716**	0.0228	-5.607***	5.191**	0.416
	(-1.143)	(0.412)	(1.787)	(2.051)	(-1.892)	(-0.981)	(2.054)	(-2.141)	(0.105)	(-2.612)	(2.533)	(0.450)
Partner = Similar	0.548	-0.265	-0.283	0.0117	0.0357	-0.0474	-0.0956	-0.0469	0.143	0.0516	0.215	-0.267
	(1.195)	(-0.495)	(-0.710)	(0.0555)	(0.160)	(-0.319)	(-0.697)	(-0.505)	(1.538)	(0.0675)	(0.234)	(-0.459)
Partner = North	0.911	0.445	-1.356*	-0.309	-0.0859	0.395	-0.152	0.105	0.0472	0.254	1.490	-1.744
	(1.078)	(0.661)	(-1.851)	(-0.498)	(-0.160)	(1.008)	(-0.966)	(0.812)	(0.559)	(0.126)	(0.928)	(-1.334)
Medium skilled												
Partner = South	-1.536**	1.558**	-0.0216	1.407***	-1.227***	-0.180	1.216***	-0.909***	-0.307**	-3.809**	2.514*	1.296
	(-2.036)	(2.220)	(-0.0667)	(2.823)	(-3.108)	(-0.714)	(5.349)	(-5.073)	(-2.445)	(-1.984)	(1.687)	(1.114)
Partner = Similar	0.0798	0.847*	-0.926*	0.160	-0.180	0.0196	-0.367	0.240	0.127	-0.289	-0.855	1.144
	(0.163)	(1.896)	(-1.868)	(0.339)	(-0.530)	(0.0742)	(-1.335)	(1.265)	(0.780)	(-0.180)	(-0.845)	(1.204)
Partner = North	0.409	0.550	-0.960**	-0.473	0.125	0.348	-0.455*	0.190	0.265**	0.670	-0.965	0.295
	(0.889)	(1.193)	(-2.324)	(-1.416)	(0.353)	(1.028)	(-1.951)	(0.891)	(2.023)	(0.862)	(-1.238)	(0.469)
High skilled												
Partner = South	-0.164	0.140	0.0245	-0.178	0.183	-0.00458	0.621**	-0.434**	-0.186**	-0.0619	-0.412	0.474
	(-0.331)	(0.269)	(0.0941)	(-0.681)	(0.626)	(-0.0354)	(2.277)	(-2.028)	(-2.280)	(-0.0664)	(-0.519)	(1.049)
Partner = Similar	-0.0799	0.262	-0.183	0.178	-0.187	0.00849	0.0347	-0.0103	-0.0243	-0.524	0.406	0.118
	(-0.208)	(0.836)	(-0.958)	(1.089)	(-1.141)	(0.103)	(0.270)	(-0.113)	(-0.292)	(-0.751)	(0.718)	(0.348)
Partner = North	-0.718	0.757	-0.0396	0.220	-0.0518	-0.168	-0.353	0.340	0.0135	-2.486*	1.531	0.954*

	(-1.097)	(1.373)	(-0.166)	(0.893)	(-0.302)	(-1.163)	(-1.424)	(1.482)	(0.208)	(-1.883)	(1.613)	(1.926)
Ln(Capital)	-0.401	0.408	-0.00761	-0.392	0.396	-0.00446	-0.421*	0.402	0.0185	-0.422*	0.422	-0.000487
	(-1.508)	(0.980)	(-0.0182)	(-1.566)	(0.986)	(-0.0107)	(-1.691)	(1.014)	(0.0434)	(-1.712)	(1.049)	(-0.00117)
Ln(Sales)	-0.0327	0.0968	-0.0641	-0.00611	0.0278	-0.0217	0.0488	0.0129	-0.0617	-0.0689	0.00880	0.0601
	(-0.0245)	(0.0781)	(-0.0511)	(-0.00443)	(0.0225)	(-0.0176)	(0.0364)	(0.0107)	(-0.0495)	(-0.0495)	(0.00714)	(0.0482)
Ln(Wage premium High:Low skilled)	6.663***	5.484***	-12.15***	6.642***	5.452***	-12.09***	6.624***	5.468***	-12.09***	6.690***	5.456***	-12.15***
	(4.814)	(4.801)	(-7.872)	(4.759)	(4.768)	(-7.860)	(4.851)	(4.846)	(-7.866)	(4.831)	(4.755)	(-7.891)
Ln(Wage premium High:Medium skilled)	7.143***	-14.52***	7.378***	7.155***	-14.47***	7.318***	7.148***	-14.49***	7.339***	7.076***	-14.45***	7.378***
	(4.256)	(-9.082)	(5.623)	(4.183)	(-8.958)	(5.554)	(4.270)	(-9.149)	(5.561)	(4.183)	(-8.974)	(5.608)
Constant	0.0237	0.811***	-0.835***	0.0392	0.802***	-0.842***	0.0288	0.811***	-0.840***	0.0392	0.797***	-0.836***
	(0.240)	(6.652)	(-6.766)	(0.392)	(6.758)	(-6.964)	(0.298)	(6.892)	(-6.967)	(0.388)	(6.538)	(-6.904)
	1.372***	1.292***	0.949***	1.371***	1.292***	0.947***	1.357***	1.286***	0.944***	1.368***	1.290***	0.949***
	(7.059)	(7.566)	(6.315)	(7.020)	(7.538)	(6.297)	(7.104)	(7.647)	(6.277)	(7.087)	(7.583)	(6.335)
Observations	35,284	35,284	35,284	35,281	35,281	35,281	35,281	35,281	35,281	35,296	35,296	35,296

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 4

How do NTMs affect countries' participation in global value chains?

Loe Franssen[♦] Olga Solleder[Φ]

Abstract

This Chapter examines the effects of NTMs on global value chain participation, using a large cross sectional database compiled by the International Trade Centre (ITC) and UNCTAD that identifies various NTMs on the product level. Using this data, we firstly present NTM indices such as the frequency, coverage and prevalence ratio. We then separate goods into intermediate and final products and consequently analyse the relationship between NTMs levied on *imported* intermediates and *export* values of final goods within the same value chain. The rationale for doing so is that GVCs are composed of both an import and an export component and we are interested whether intervention on the import side has "knock-on" effects on the export component in the value chain. After properly accounting for unobserved heterogeneity with country and industry fixed effects, only the prevalence ratio shows some evidence of such an effect. However, when we instrument for the prevalence ratio with the trade union density of a particular country-industry, this relationship becomes insignificant as well, suggesting that NTMs levied on the source of a GVC do not affect countries' forward GVC participation.

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4.0. Introduction

Recent technological advancements and reductions in trade tariffs have made it increasingly profitable for firms to separate their production chain into individual tasks. These tasks can then be sourced internationally to firms in countries which have a comparative advantage in executing this specific task, giving rise to global value chains. However, as trade tariffs are being reduced, non-tariff measures are becoming more important and prevalent. Indeed, the number of NTMs reported to the WTO has tripled from 1995 to 2010 and has quadrupled until 2012 (Grubler et al., 2015). This does not only affect trade in final goods but also in intermediate goods and can therefore affect countries' participation in global value chains. Namely, if a country that imports metal to produce car engines finds it harder to import this critical input due to a NTM, this might affect how many engines it can export and therefore reduce its participation in the global value chain of automobiles.

This effect does not necessarily need to be negative however. The hypothesized effect depends critically on the motive for installing the NTM. There is a literature that argues that NTMs are used merely as substitutes for formal tariffs (Ghodsi, 2015; Moore and Zanardi, 2011; Tudela-Marco et al., 2014) or policy retaliation (de Almeida et al., 2012; Vandenbussche and Zanardi, 2008). In this case, it is most likely that NTMs will negatively affect trade values and GVC engagement, as found for example by Kee, Nicita, Olareagga (2009) and Disdier, Fontagné and Mimouni (2008). However, there can be more legitimate reasons behind the installation of NTMs as well. For example, voluntary sustainability standards (VSS) that are used to satisfy quality, safety, social and environmental norms can not only positively affect trade values in the long run, but also improve financial outcomes for participating producers (von Hagen and Alvarez, 2011). In addition, NTMs can facilitate and therefore increase trade by reducing informational asymmetries, enhancing consumer trust and decreasing transaction costs (Beghin et al., 2014; Blind et al., 2013; Bratt, 2014).

An interesting finding in the literature is that SPS and TBT requirements, which is the focus of this Chapter as well, tend to decrease trade on the extensive margin, but increase trade on the intensive margin (Bao and Qiu, 2012; Crivelli and Gröschl, 2012) and even the overall performance of industries (Ghodsi and Stehrer, 2016). This makes sense from the perspective that NTMs can act as a barrier to enter foreign markets, but once a firm complies with the standard, the positive quality signal can ensure increase trade values (Beghin et al., 2012).

This Chapter contributes to this small but growing literature on the effects of NTMs on global value chains by using a large and novel cross sectional dataset, compiled by the ITC and UNCTAD, on 57 countries[36] in the year 2014[37]. We proxy for NTMs by using three indices as outlined by Gourdon (2014) which are the frequency, coverage and prevalence ratio. Besides this novel dataset, a second original contribution comes in the way we link these NTMs to GVCs. Namely, the product level data allows us to focus specifically on NTMs levied on imported intermediate goods, which can be identified with the Broad Economic Classifications (BECs). This variable is then included in a gravity model which allows us to examine its effect on the *export* values of final goods. The reason we look at this linkage comes from following the definition of vertical specialisation (Hummels, Ishii and Yi, 2001) or import to export (i2e (Baldwin and Lopez-Gonzalez, 2015)) who state that GVCs necessarily include both an import and an export component. Further, this relationship allows us to examine whether there is a potential "knock-on" effect of NTMs levied on imported intermediates, on the subsequent exports of products within that same value chain[38]. As said earlier, this knock-on effect can be positive or negative. The baseline estimation in this Chapter finds no significant correlation between the coverage and frequency ratio on imported intermediates and the export value of final goods, once we correctly control for unobserved heterogeneity via the inclusion of country and industry fixed effects. However, we do find initial evidence that the prevalence ratio on imported intermediates tends to be positively related with export values. This finding suggests that trade policy levied on the source of GVCs, in the form of the average number of NTMs per imported intermediate product, can serve as a quality signal and boost the subsequent export values of goods within the same value chain.

However, this relationship could be the reverse as well, i.e. higher exports could lead to increased quality demands for foreign intermediates resulting in a higher average number of NTMs per product. Such reverse causality would lead to endogeneity for which we should control. Therefore, we will apply an IV strategy that not only controls for endogeneity, but also investigates the direction of the baseline correlation, which is the third contribution of this Chapter. Specifically, we instrument for NTMs with trade union

[36] Treating the European Union as 1 country, as they have identical trade regulations.

[37] See Appendix 4.1 for a full overview of the data dimensions

[38] One key challenge is how to identify that imports and exports belong to the same value chain. For now, we take the industry as a proxy for the value chain, ignoring indirect value added from one industry to another.

densities at the country-industry level. Here we find that the positive correlation that we found for the prevalence ratio disappears, leading us to conclude that there is no significant effect of NTMs levied on the import component of a GVC, on the export values of the same chain.

This Chapter will first explain our empirical methodology which starts from a gravity setup but amends it in various ways. After that, we present descriptive NTM statistics in the form of the coverage, prevalence and frequency ratio for the countries in our dataset. We specify these ratios by the type of product that they are levied on as well, to get more insights in their influence on global value chains. After that, we empirically relate these indices to export values before applying an IV to control for possible endogeneity while the final section provides some concluding remarks.

4.1. Empirical section

This section will outline the data used and empirical methodology followed, some descriptive statistics on the extent of NTMs in various countries and the empirical results of how NTMs affect trade in global value chains.

4.1.1. Empirical methodology

We start our model from a gravity framework[39] to estimate the effect of trade barriers on trade flows where imports X_{cj} from partner *j* to country *c* depend on the following factors:

$$X_{cj} = GS_j M_c \emptyset_{cj} \tag{4.1}$$

Where G is a variable that does not depend on *c* or *j* such as the level of world liberalization while $\emptyset_{cj}$ represents the ease of exporter j access to the market of *c*. M_c denotes all importer specific factors that make up the total importers demand (such as importer GDP) while S_j comprises exporter specific factors that represent the total amount they are willing or able to supply (such as exporter GDP)[40].

This is then estimated in the following linear way:

[39] For the purpose of this thesis, we provide a somewhat elementary explanation of the gravity model. The informed reader can start from equation (4.4).

[40] When applying this standard gravity model to bilateral trade flows where trade in intermediate goods is significant, these mass variables do not accurately proxy for supply and demand. We will elaborate on this later.

$$lnX_{cj} = lnG + lnS_j + lnM_c + ln\emptyset_{cj} \tag{4.2}$$

Note that trade costs $\emptyset_{cj}$ are typically proxies with bilateral distance, complemented by dummies for islands, landlocked countries, common borders as well as common language, adjacency or other relevant cultural features to capture information costs.

This method was improved by the notable contribution of Anderson and van Wincoop (2004) by stating that the *relative* trade costs should also be taken into account in this model, i.e. the propensity of country *c* to import from country *j* is determined by country *c*'s trade costs toward *j* relative to its overall resistance to imports and to the average resistance facing exporters in country *j*, not simply by the absolute trade costs between countries *c* and *j*. These are called multilateral trade resistance MTR terms.

$$X_{cj} = \frac{Y_c Y_j}{Y}\left(\frac{t_{cj}}{\Delta_j P_c}\right)^{1-\sigma} \tag{4.3}$$

Where Y denotes world GDP, t_{cj} (one plus the tariff equivalent of overall trade costs) is the costs in *c* of importing a good from *j*, which depends for example on physical distance, or whether a country is landlocked, share common borders, language or other cultural factors. Sigma is the elasticity of substitution and $\Delta_j P_c$ represent country *j* and *c* multilateral resistance terms i.e. their ease of market access. These terms not only include physical distance but also more subtle factors such as NTMs or other trade costs. This then breaks down to the following familiar linear form:

$$lnX_{cj} = a_o + a_1 lnY_c + a_2 lnY_j + a_3 lnt_{cj} + a_4 ln\Delta_j + a_5 lnP_c + \varepsilon_{cj} \tag{4.4}$$

Note that a_3 = 1- σ

When applying (4.4) to our data, we make four important modifications concerning the identification of the multilateral resistance terms, the specification of the mass variables, the treatment of zero trade flows and, finally, the level of analysis.

Firstly, the problem with estimating (4.4) is that the multilateral resistance terms MTRs captured by a_4 and a_5 can not be observed directly. There are multiple ways to deal with this, but the easiest is to use fixed effects. Since MTRs, including NTMs that do not originate in time t_0 are difficult to observe, we follow the popular approach of using fixed effects for import and export countries[41]. Note that these fixed effects would also control for $a_3 lnt_{cj}$, such as physical distance between countries as well as other geographical and cultural factors, which should not change over time. Therefore, we can simplify (4.4) to:

$$lnX_{cj} = a_0 + a_1 lnY_c + a_2 lnY_j + a_3 lnNTM_{cj} + \varphi_{cj} + \varepsilon_{cj} \tag{4.5}$$

Where φ_{cj} indicates importer and exporter fixed effects[42], which have replaced the MTRs formerly captured by a_4 and a_5. Following Gourdon (2014), we will use three proxies for the presence of NTMs which are the frequency, coverage and prevalence ratio, as explained in the next section.

In terms of the NTMs, we control for NTMs levied on the *imports* of intermediate goods. The rationale is that, following the definitions by Hummels, Yi and Isshi (2001) and Baldwin and Lopez-Gonzalez (2015) GVCs crucially involve both an import and an export component. We are interested in the effects of protection on the import side, which can be seen as backward GVC participation, on the export values of final goods, which can be seen as forward participation in the value chain. Noting NTMs on imported intermediates as NTM(II), we can describe our regression function as:

$$lnX_{cj} = a_0 + a_1 lnY_c + a_2 lnY_j + a_3 ln(NTM(II))_{cj} + \varphi_{cj} + \varepsilon_{cj} \tag{4.6}$$

Secondly, as explained by Baldwin and Taglioni (2011, 2006) the use of home and partner country GDP as a proxy for their demand and supply, respectively, becomes inaccurate when a significant proportion of trade flows via global value chains. Trade via GVCs can be characterized as trade in parts and components used for intermediate consumption, rather than final goods used for final consumption. When considering the imports of a country that is strongly involved in global production networks, what determines its demand will not so much be dependent on its domestic demand, but more so on foreign demand. Following Baldwin and Taglioni (2011, p. 2), consider the determinants of Thai imports of auto parts from the Philippines. Rather than using a mass variable such as Thai GDP to proxy for Thai demand of cars, we should really proxy for the demand for cars by the Philippines. The easiest way to circumvent this problem is by dropping the mass variables

[41] As explained in Head and Mayer (2013), using fixed effects to control for MTRs became widely accepted within the literature because of Feenstra (2004) and Redding and Venables (2004).

[42] We estimate each equation with 1) no fixed effects, 2) country fixed effects only, 3) industry specific effects only and finally 4) country and industry fixed effects using the Stata command reghdfe by Correia (2016).

$a_1 \ln Y_c$, $a_2 \ln Y_j$ specified in (4.6) and include them in the fixed effects, assuming that the demand and supply capacities do not vary significantly over time.

$$lnX_{cj} = a_0 + a_1 ln(NTM(II))_{cj} + \varphi_{cj} + \varepsilon_{cj} \tag{4.7}$$

Thirdly, an often cited problem in using gravity techniques to analyse trade patterns is the existence of zero trade flows. Due to the nature of the gravity estimation, taking the log of such zero trade values would drop them out. Various different approaches have therefore been developed and applied to deal with this problem, such as dropping the observations with zero trade flows, adding a small constant to the value of trade before taking logs or estimating the model in levels, along the line of a Poisson Pseudo Maximum Likelihood (PPML) estimator. This Chapter will follow the literature in dealing with zero trade flows as follows.

We add a small value to the zero trade flows. However, rather than taking a uniform constant of say, $1, to each trade flow, we follow Eaton and Kortum (2001) by applying the minimum observed level of trade between country *c* and its partners for product *p*[43]. The approach is intuitive as the minimum trade flow for a specific product and importer can reflect differences in market size, competition, trade barriers, as well as reporting and measurement issues.

Besides this method, we will also make use of the PPML estimator, developed by Silva and Tenreyro (2006), where the dependent variable is in levels rather than in log differences. By not log-linearizing trade flows, zero trade flows will not drop out. A second reason why the PPML estimator is better than the method above is that the previous method leads to inconsistent estimates in the presence of heteroscedasticity. This is because the expected value of the logarithm of a random variable depends on higher order moments of its distribution so that the transformed errors will be correlated with the covariates (Silva and Tenreyro, p.653). Further, Westerlund and Wilhelmsson (2011) recommended Poisson fixed effects estimator over OLS on the basis of experiments with simulated and real data with a panel structure. The PPML estimation in our case can be expressed as:

$$X_{cj} = \exp(a_0 + a_1 ln(NTM(II))_{cj} + \varphi_{cj} + \varepsilon_{cj}) \tag{4.8}$$

[43] i.e. the lowest value of trade per good between different partners

Where the dependent variable is in levels, rather than in logs[44].

The final modification concerns the level of analysis. So far, we have followed the standard gravity format which is at the country-partner level. However, we aggregate trade values across partners to take a broader measure of global value chains. Note that if we would use the partner-disaggregated values, we would really be measuring re-exports of specific products. Secondly, although we have product level data, we will aggregate this to the industry level, noted i, in order to proxy for the value chain, so that our main estimation will be:

$$lnX_{ci} = a_0 + a_1 ln(NTM(II))_{ci} + \varphi_{ci} + \varepsilon_{ci} \tag{4.9}$$

Which, in Poisson looks like:

$$X_{ci} = exp\left(a_0 + a_1 ln\big(NTM(II)\big)_{ci} + \varphi_{ci} + \varepsilon_{ci}\right) \tag{4.10}$$

4.1.1.1. Endogeneity

When examining the relationship between trade barriers and export values, there is the often-cited problem of endogeneity. Besides obvious causes such as omitted variables, endogeneity can come in the form of reverse causality. While NTMs are likely to affect trade in one way or another, it is also possible that those goods that are imported become subject to trade barriers if the home country wants to protect its domestic industry. This reverse causality is likely to create bias in the empirical results.

In our case, where we are interested in the "knock-on" effect of NTMs levied on intermediates imported on the trade values of goods exported within the same industry, this reverse causality might be present as well. That is, while increased protection on backward participation within the value chain might decrease a countries' forward participation, it is also possible that the level of a country's forward participation might affect its protection on backward participation. For example, if a country feels that its exports of a particular GVC are relatively low, it may try to boost them by improving its access to foreign inputs by lowering NTMs. Therefore, we have to control for this somehow.

[44] To control for the high dimensional fixed effects φ_{cjp}, we use the poi2hdfe estimation technique in Stata developed by Guimarães and Portugal (2010) which allows for the inclusion of two higher dimensional fixed effects. Therefore, we include origin country and time fixed effects as dummies, while partner and product codes can be absorbed.

We choose to do so via an instrumental variable technique which can be used to filter the exogenous variation in the endogenous variable (NTMs on the import of intermediates in this case) and relate that to the dependent variable (export values of final goods), creating unbiased coefficients. We follow Kelleher (2015) by instrumenting for the potential endogenous NTM variable by looking at the presence of trade unions. The rationale is straightforward: trade unions might put pressure on its government to protect domestic industries from foreign competition and thus install trade barriers (Kono, 2006). Kelleher (2015) finds evidence of this, by showing that both the presence and the number of such industry organisations significantly influences the decision to introduce NTMs and can therefore act as a useful instrument. We will regress this variable on the logged NTM proxies in a first stage regression, to test its relevance. Then, in a second stage, we use the predicted values of the first stage and regress them on the export values as done before. This way, we can make stronger inferences about the effect of NTMs levied on intermediate inputs on the export values of final goods within the same industry.

4.1.1.2. IV Specification

We can formalize the use of the instrumental variable more specifically. To test the relevance requirement, i.e. to see whether the instrument is sufficiently correlated with our potentially endogenous NTM variable, we run the first stage regression as:

$$\ln(\widehat{NTM}(II))_{ci} = \alpha_0 + \alpha_1 \ln(Trade\ Union\ Density)_{ci} + \varphi_{ci} + u_{ci} \tag{4.11}$$

Here, it is assumed that the instrumental variable is uncorrelated with ε_{ci} in (4.9). Since we have an exactly identified model, i.e. as many instruments as endogenous variables, we cannot formally test this validity requirement as was done in Chapter 2. Instead, passing this test can only be done on a qualitative basis and here we refer to Kelleher (2015) who found that the presence of trade unions can serve as a valid proxy for the presence of NTMs.

In the next step, we regress the fitted values from the first stage equation (4.11) on the variable of interest, giving our causal relation of interest as:

$$\ln X_{ci} = \alpha_0 + \alpha_1 \ln(\widehat{NTM}(II))_{ci} + \varphi_{ci} + \varepsilon_{ci} \tag{4.12}$$

By regressing the exogenous variation in intermediate import NTMs on export values, we make sure that GVCs are not correlated with any other confounding variables that might affect export values. If we find here that the predicted NTM(II) values, which are based on trade union densities, are significantly correlated with export values, we can infer that it's NTMs that affect export values, rather than the other way around. This is because trade unions can only affect export values by installing either formal or informal protection and since we control for the former via industry and country fixed effects, we could argue that informal protection in the form of NTMs is the only factor that can explain this positive correlation.

4.1.2. Data used

This Chapter makes use of a large dataset compiled by the International Trade Centre (ITC), the United Nations Conference on Trade and Development (UNCTAD) and the World Bank. The database identifies countries' regulatory laws that could potentially have an effect on trade. Besides a "world" category, it also specifies NTMs that are only apply to specific partner countries. This regulatory dataset is therefore different from, for example, the WTO Integrated Trade Intelligence Portal (I-TIP) database which consists of data on notifications by WTO members on other countries applying NTMs to their exports. The WTO I-TIP database is therefore biased in that the NTMs faced will have a negative effect, as they are notified by the country as being detrimental to trade. As discussed in the literature review, NTMs can actually also facilitate trade. Such NTMs are less likely to be notified by WTO members and therefore omitted in I-TIP. After compiling data from both UNCTAD and the ITC, we have data on 57 countries in the year 2014 (see Appendix 4.1). This is merged with trade data, also on the product level, to make inferences about the effect of NTMs on trade via value chains. The next section will provide some descriptive statistics of this data.

For the IV estimation, we need data on the presence or lobbying power of trade unions. We proxy for the power of trade unions by using data on trade union densities coming from Visser's (2015) Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, 1960-2014 (ICTWSS). Trade union density is calculated as the proportion of paid workers who are union members. The rationale is that the higher the trade union density, the more lobbying power the trade union has for installing trade protection. The novelty of this database comes from the fact that the data for trade union density is available on the industry level, allowing for a more detailed examination than most data sources that only provide trade union densities on a national level. Appendix 4.2 shows those countries and industries which we can match with our data on NTMs and trade.

The next section shows how we measure our NTM variable, for which we proxy by using a frequency, coverage and prevalence ratio. We show how these are defined and apply them to our data immediately for some descriptive statistics. After that, we will outline our specific research questions and present the results of the empirical estimation.

4.2. NTM proxies and descriptive statistics

Before going to the empirical estimation, we can exploit the nature of our data by showing the type of goods that are traded, freely or under an NTM. Firstly, Figure 4.1 gives a breakdown of the type of goods that are traded per ITC defined regions[45]. By breaking both gross imports and exports down to the Broad Economic Classification (BEC) of UNCTAD, we can get some indication to the extent that those regions are engaged in global value chains. BEC classifications provide a rough breakdown whether traded goods are used by industries for further production, or by households for final consumption[46]. This breakdown into intermediate vs final products can provide us with some measure of countries' involvement in global value chains as the former is often used as a proxy for this (Feenstra and Hanson, 1996; Hijzen, 2005; Hummels et al., 2001). Here we see that the trade in intermediate goods is very close to those numbers found by Johnson and Noguera (2012) for example, who estimate that trade in intermediates is roughly 65 percent. Clear deviations from these numbers are only found in the developed economies, which is largely the European Union, and developing Asia-Pacific, which is largely made up of China and India (Appendix 4.1). We see that in the former group, the average import and export of intermediates is 10 percentage points higher than this average, which implies that the EU is more significantly engaged in global value chains. The developing Asia-Pacific region is potentially more interesting, as it tends to import the most but export the least intermediates than any other region. This is indicative of this region's role in global value chains, where countries such as China and India often specialise in the assembly activity of a value chain, which implies importing intermediates, assembling them into a final good and then export the final good.

[45] See Appendix 4.1 for a full breakdown of the countries included per region.

[46] Note that in this analysis, we grouped capital goods along with intermediate goods.

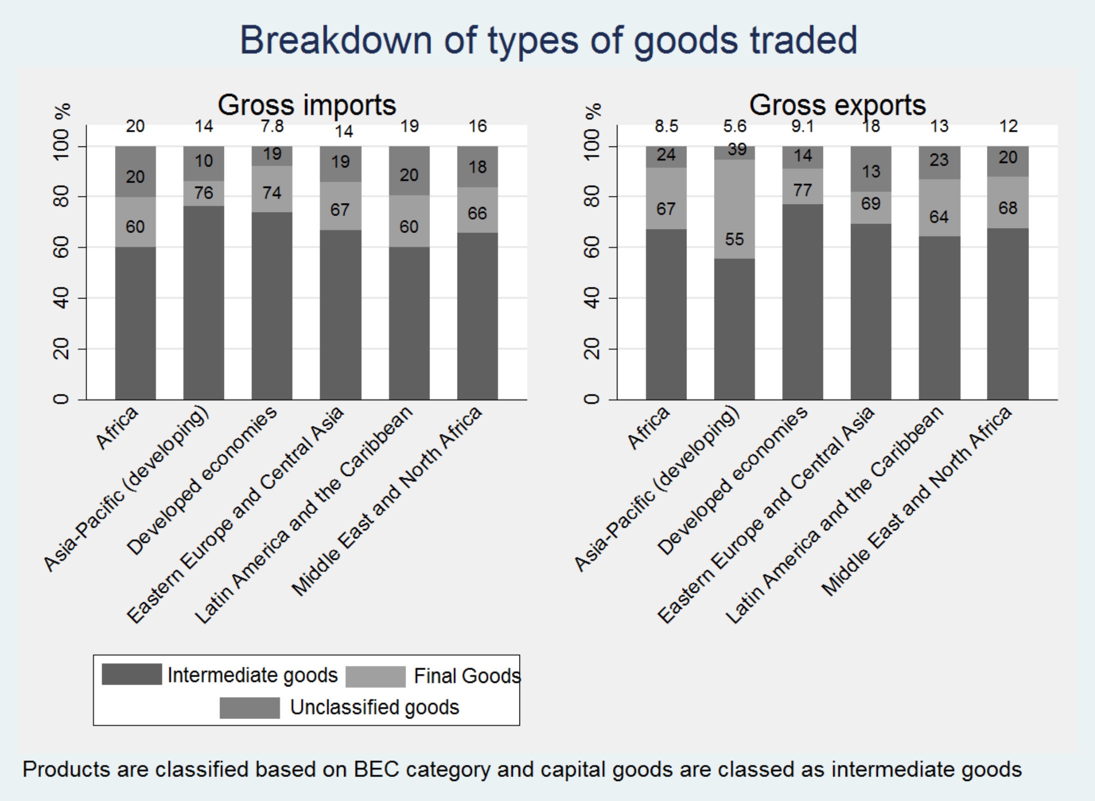


Figure 4.1 A breakdown of Gross Exports according to Broad Economic Classifications (BEC)

Having a rough idea of the type of goods countries trade, we can investigate the NTMs that they levy upon this. Following the proxies in Gourdon (2014), we can show frequency, coverage and prevalence ratio of NTMs.

Frequency ratio:

The frequency ratio summarizes the percentage of products *p* to which one or more NTMs are applied by country *c*, or:

$$F_c = \left[\frac{\sum D_p M_p}{\sum M_p}\right] * 100 \tag{4.13}$$

Where D_p is a dummy variable representing whether good *p* is NTMed or not and *Mp* indicates whether the good is imported or not. Since this Chapter investigates the NTM coverage per type of good, we can specify F_c on the product BEC classification *b*, which can be in an intermediate or final form:

$$F_c = \left[\frac{\sum_{b=1}^{3}(\sum D_{pb} M_{pb})}{\sum M_p}\right] * 100 \tag{4.14}$$

Where $\sum D_{pb}M_{pb}$ represents the total number of goods M_{pb} that experience at least 1 NTM, per type of good *b*. F_c then represents this total as a share of all goods imported. Using this measure, however, would overstate the NTMs levied on this type of goods that are heavily traded. Therefore, we should adjust the denominator to become BEC class specific as in:

$$F_{cb} = \left[\frac{\sum D_{pb}M_{pb}}{\sum M_{pb}}\right] * 100 \tag{4.15}$$

Doing so, Figure 4.2 shows that final goods tend to have a higher percentage of goods that experience an NTM, across all regions[47]. We further see that the developed economies, notably the EU, has the highest frequency ratio for both final and intermediate goods, while Africa has the lowest. This is in line with various research that there seems to be a correlation between regulation and development (UNCTAD, 2016).

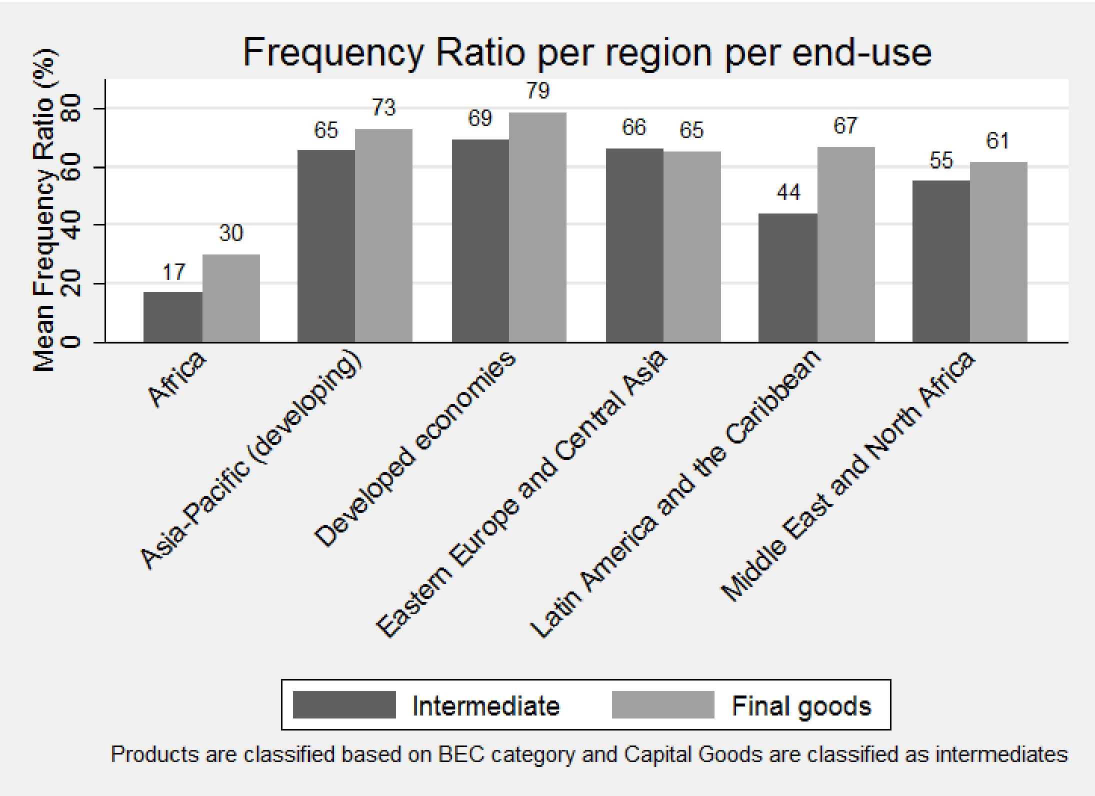


Figure 4.2 Frequency ratio

[47] Further note that we grouped capital goods under intermediate goods and left unclassified goods out of the calculations.

Coverage ratio:

Unlike the frequency ratio, the coverage ratio gives some indication of the importance of NTMs on overall imports as it measures the percentage of trade that is subject to NTMs for the importing country c, or:

$$C_c = \left[\frac{\sum D_p V_p}{\sum V_p}\right] * 100 \tag{4.16}$$

Where *V* is the value of the imported product *p*. We modify this percentage again slightly to look specifically at the coverage ratio per type of good *c* as:

$$C_c = \left[\frac{\sum_{b=1}^{3}(\sum D_{pb} V_{pb})}{\sum V_p}\right] * 100 \tag{4.17}$$

However, using this measure would overstate the NTMs used in that type of goods that are heavily traded. Therefore, as before, we should correct the measure and look at the coverage of NTMs per type of good along the lines of:

$$C_{cb} = \left[\frac{\sum D_{pb} V_{pb}}{\sum V_{pb}}\right] * 100 \tag{4.18}$$

Doing so, Figure 4.3 below shows that the earlier seen Figure 4.2 for the frequency ratio is largely confirmed with the coverage ratio. That is, final goods are once again regulated heavier than intermediate goods and the developed economies exhibits strongest forms of regulation while Africa the least. In fact, 87 percent of the value of final goods that developed economies import is subject to an NTM. In Africa, only 29 % of the value of imported intermediates is subject to such regulation.

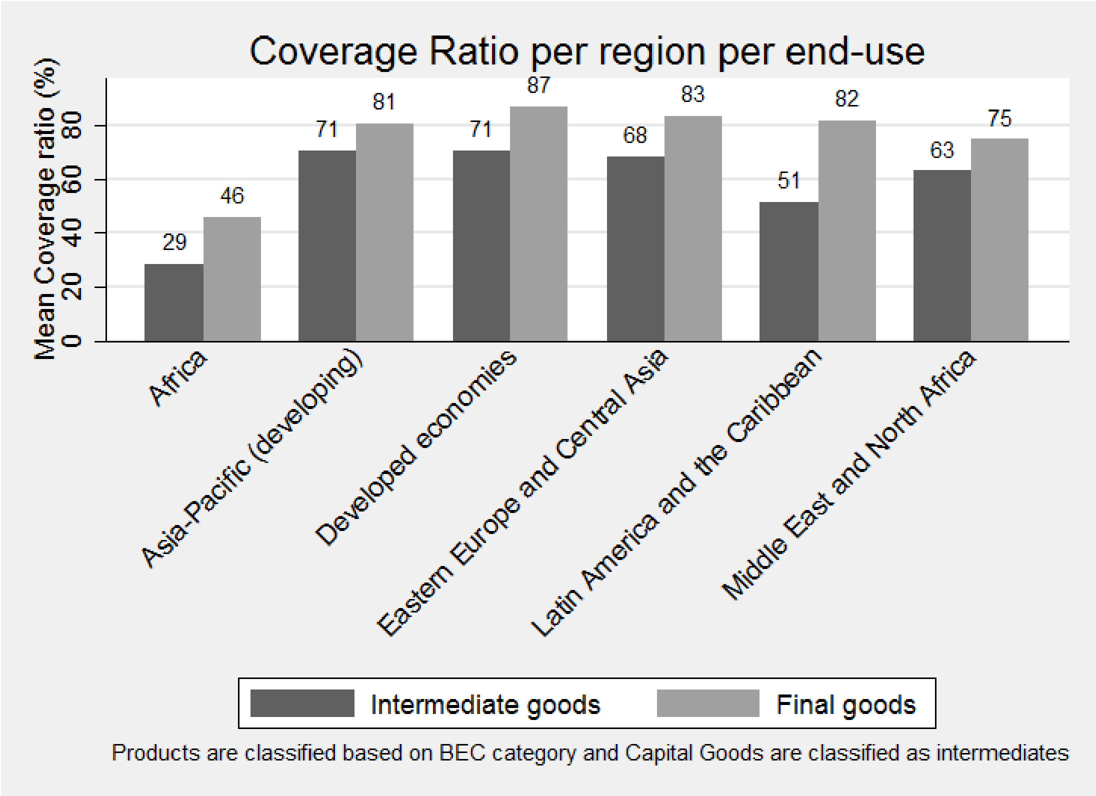


Figure 4.3 Coverage Ratio

Prevalence ratio

Unlike the frequency and coverage ratio, the prevalence ratio takes into account whether a good has more than 1 NTM levied on it, which is often the case. We find the prevalence ratio as the average number of NTMs on an imported product, or:

$$P_c = \left[\frac{\sum N_p M_p}{\sum M_p}\right] \tag{4.19}$$

Which, when applied to specific good classifications *b* can be specified as:

$$P_{cb} = \left[\frac{\sum_{b=1}^{3}(\sum N_{pb} M_{pb})}{\sum M_p}\right] \tag{4.20}$$

And the results are shown in the Figure below (Figure 4.4). Once again, we see that final goods are heavier regulated than intermediate goods, ranging from an average of 18 NTMs per final good in the MENA region to 1.1 NTMs in Africa. In comparison, intermediate goods only experience an average maximum of 6.4 NTMs in developing Asia-Pacific and 0.47 in Africa. We further see that this is the only proxy where the developed economies do not come out on top. Instead, it's the MENA region that levy most NTMs per final goods and Asian countries that protect intermediate goods most often.

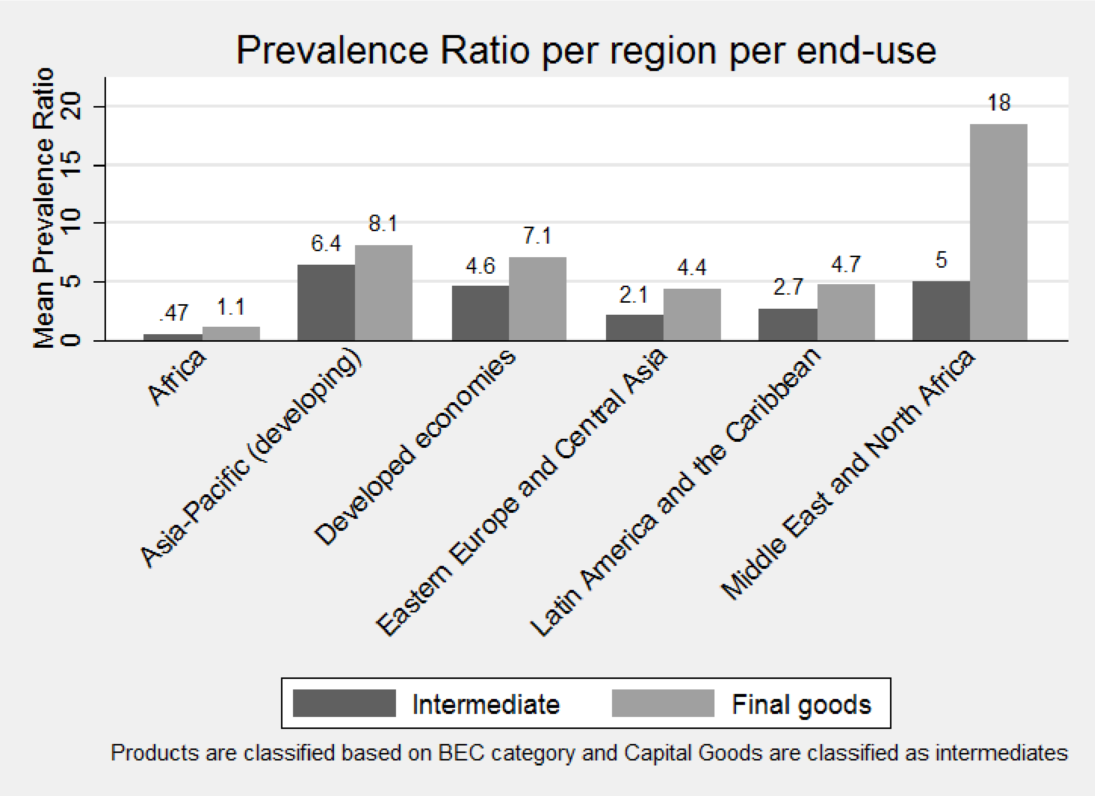


Figure 4.4 Prevalence Ratio

4.3. Results

4.3.1. Baseline estimation

The results of the baseline regression specified in (4.9) and (4.10), using all 3 proxies for NTMs as described in the previous section can be found in Appendix 4.3. Remember we are interested in the effect of NTMs levied on the import of intermediates, on the export value of goods from the same industry, with the rationale being that protection on backward participation in the value chain can have knock on effects on forward participation. Figure 4.5 summarizes the empirical output using the PPML method which we believe is the most effective way to deal with zero trade flows. Further note that the boxplots shown represent a 99% confidence interval, with the little vertical bars representing a 95% cut off.

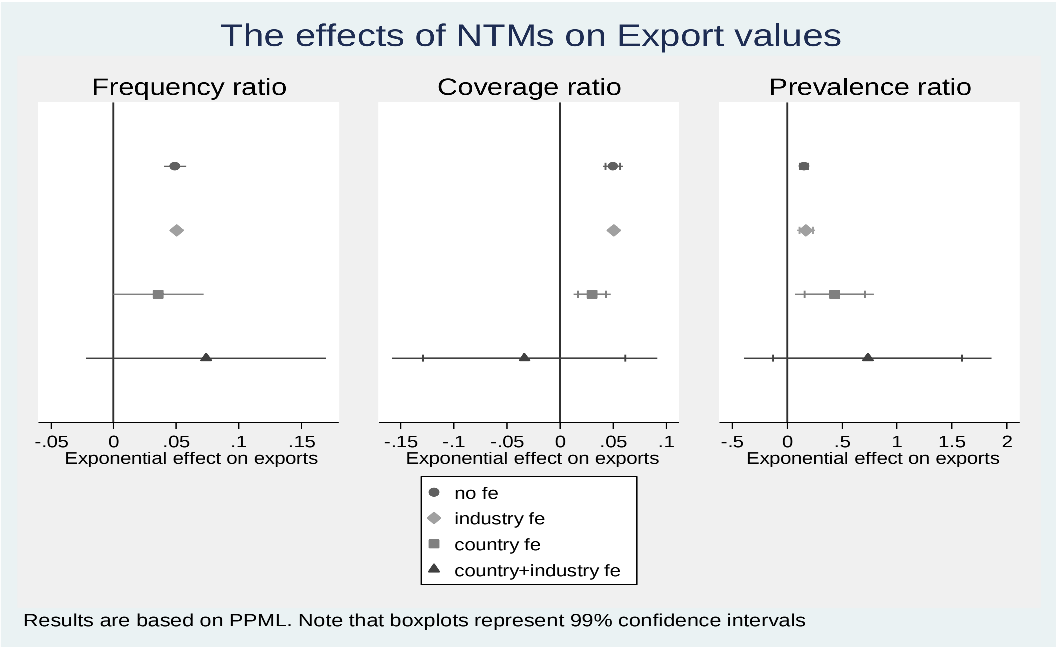


Figure 4.5 Graphical output of equation (4.10). For full tabular output, see Appendix 4.3

Figure 4.5 shows that the inclusion of fixed effects has a crucial effect on the results. Namely, while controlling for country and industry fixed effects individually shows a significant and positive correlation between NTMs and export values, controlling for them simultaneously shows an insignificant correlation. These findings, that are based on the PPML estimator, are representative for the other methods as well, i.e. where we ignore zero trade values and where we replace them with a minimum value (See Appendix 4.3). It further applies equally for the coverage (Table 4.5), frequency (Table 4.4) and prevalence ratio (Table 4.6). There is only one small exception that becomes apparent once we decrease the significance level to 90 percent. In that case, the prevalence ratio shows a significantly positive relationship with the dependent variable, robust to all three methods of dealing with zero trade values (Table 4.6).

Following the PPML approach, Table 4.6 shows that the specific coefficient on the effect of the prevalence ratio on export values is 0.734 which means that a 1 unit increase in the prevalence ratio raises the export of final goods by a factor of $e^{0.734} = 2.08$. In percentage terms, this is equivalent to a 1% increase in the prevalence ratio leading to a ((0.734-1)*100) = 108 percent increase in the export values of final goods. This is significantly more than the results from the other two methods suggest. Namely, when we ignore zero trade values or replace them with a minimum value, we see that a 1 percent increase in the prevalence ratio would lead to a 1.5% increase in trade (Table 4.6).

This positive correlation could be interpreted by referring to the role of NTMs as a signal of quality. That is, foreign intermediates of higher quality tend to boost exports. The relationship could also be the reverse. That is, sectors that export a lot of goods might want to improve the quality of their foreign inputs and thus install NTMs. Besides this ambiguous direction of the result, the result itself is quite weak as well, as it is only significant at a 90% level when following the PPML method or when ignoring zero trade values. For these reasons, the relationship between the prevalence ratio on imported inputs and export values of the same value chain deserves further attention. In the next section, we apply the instrumental variable as outlined in section 4.1.1.2 to see if the positive correlation holds and whether the direction is such that it is the NTM that affect export values, rather than the other way around. Since the Eaton-Kortum method of dealing with zero trade values displayed the most significant relationship between the prevalence ratio and the export values – i.e. significant at 95% (Table 4.6) – we apply the IV to this method specifically. This is done in Stata by using the *"ivtobit"* command and left censoring at zero.

4.3.2. IV results

Table 4.1 shows the results of applying equation (4.12) to our data and using the prevalence ratio as our proxy for NTMs on imported intermediates.

Table 4.1 IV output for the Prevalence ratio

VARIABLES	(1) No fe	(2) Industry fe	(3) Country fe	(4) Country+industry fe
Ln (Prevalence ratio)	1.093	3.225	3.779	-142.1
	(0.287)	(1.355)	(0.115)	(-0.218)
Constant	12.75**	11.62***	4.081	281.1
	(2.344)	(3.236)	(0.0682)	(0.228)
	Results from first stage test			
Correlation of instrument (trade union density) with prevalence ratio	0.264**	0.297**	-0.035	-0.007
	(2.54)	(2.07)	(-1.05)	(-0.23)
Durbin-Wu-Hausman test	0.076	1.847	1.042	5.178*
P value	0.7901	0.211	0.337	0.052
Observations	36	36	36	36

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To test the validity of the instrument, we checked the correlation of the instrument with the potentially endogenous prevalence ratio, controlling for the exogenous variables captured by φ_{ci} as outlined in equation (4.11). Here, we find that the relevance test is passed as long as we do not include country fixed effects. That is, the instrument chosen, the trade union density in a particular country-industry, is significantly correlated with our predictor variable of interest as long as we exclude country fixed effects. However, when we include country fixed effects, this relationship breaks down. The Durbin-Wu-Hausman test of endogeneity is significant at a 10 % level when including country and industry fixed effects. This indicates that our model as specified in equation (4.9) does indeed suffer from endogeneity when we include country and industry fixed effects. Finally, remember we are unable to execute the validity test, as our model is exactly identified.

Looking at the coefficient of the prevalence ratio, we see that the positive correlation identified in Table 4.6 breaks down. This suggests that those baseline findings in Table 4.6 suffered from endogeneity, most likely in the form of reverse causality, which is represented by the Durbin-Wu-Hausman test as well. By correcting for that with an instrumental variable, the positive correlations found earlier no longer hold so that NTMs levied on imported intermediates do not seem to affect countries' participation in global value chains. Further remember that we applied the IV to that method of dealing with zero trade values that showed the most significant correlation between the prevalence ratio and export values. The fact that even this most significant relationship breaks down when using the IV method provides further evidence that NTMs on imported intermediates do not significantly affect export values.

4.4. Concluding remarks

Both non-tariff measures, as well as global value chains have expanded rapidly in recent years. NTMs can affect GVCs both by interfering on the import and the export side of a global value chain. This Chapter has looked specifically at the relationship between NTMs levied on imported intermediates and exports of final goods within the same value chain, for which we used the industry as a proxy. While we might have expected a protectionist effect of NTMs, in the sense that an NTM levied on the import of intermediates would have a negative knock on effect on export values of goods within the same value chain, we did not find this to be the case. In fact, initial correlations suggested a positive correlation between import NTMs and export values. This can best be interpreted by referring to NTMs as having a positive quality signalling effect in the sense that better intermediates are correlated with higher export values. However, after properly accounting for unobserved heterogeneity by including both country and industry fixed effects, only the prevalence ratio remained as having a positive impact on export values of the same value chain. This correlation was strongest when zero trade values were replaced with a minimum trade value as in Eaton and Kortum (2001). We then tested the robustness of this specific finding by instrumenting for the prevalence ratio with trade union densities of industries within specific countries, and found that this statistic relationship no longer holds. This can be explained by endogeneity in the original estimation, either from omitted variable bias or from reverse causality. For these reasons, this Chapter concludes that NTMs levied on the import of intermediates do not affect countries' participation in global value chains.

However, the methodology has certain limitations, of which we would like to point out three. Firstly, our GVC identification strategy is limiting on two accounts. Firstly, by linking imported intermediates to exported final goods of the same industry only, does not allow for indirect contributions of various industries to each other. For example, while it would correctly identify the value chain "cars" by linking the import of tires to the export of final cars, it would not identify the provision of electronics into the car as being part of the same value chain. Secondly, forward participation can occur by the export of intermediate goods too. By identifying a value chain specifically by linking imported intermediates to exporting final goods, we are targeting a more downstream part of the production like the assembly stage. While this is still a GVC activity, it is only a subset of the total trade that happens via global value chains.

The second limitation of this Chapter refers to the instrument used for the robustness check, with the main problem being the data availability. After matching our NTM data with the trade union density data, we only had 36 observations left from the initial 1197[48] so that it is uncertain whether our finding applies to all the observations. The instrument further fails to sufficiently proxy for the prevalence ratio once we include country fixed effects. However, the fact that it shows an insignificant correlation with final goods' export values when the relevance test is passed, i.e. when controlling only for industry fixed effects, suggests that the conclusion that NTMs do not affect countries' participation in GVCs, holds.

[48] As we only have trade union density data for 9 out of 57 countries, and for 4 out of 21 industries.

The third and final limitation refers to our proxy for NTMs. While we used an absolute proxy, in the form of the coverage, frequency and prevalence ratio, recent research on the impact of NTMs on trade states that relative proxies of NTMs might be more appropriate (Cadot et al., 2015). This claim dates back to Kox and Lejour (2005) who present a model that states that trade policies levied by a trade partner are no barrier to trade if they are identical to the policies of the home country. In this case, the firm in the home country has already complied with the (domestic) regulation, and the foreign regulation should therefore not provide a barrier anymore. To this extent, Rau et al. (2010) and Cadot et al. (2015) construct a regulatory heterogeneity index that measures the extent to which the domestic trade policy is identical to the trade partners' trade policy. Such a measure for NTMs could be used in the future to measure its effect on trade via global value chains.

Appendix 4.1: Overview of included countries per region

The following table shows all the countries in the dataset, ordered per region. We use these dimensions to calculate the descriptive statistics.

Table 4.2. Overview of included countries per region

Middle East and North Africa (13)	**Asia-Pacific (developing) (6)**	**Eastern Europe and Central Asia (EECA) (3)**	**Developed Economies (4)**	**Latin America (21)**	**Africa (10)**
Jordan	China	Turkey	European Union	Argentina	Burkina Faso
Bahrain	India	Russia	Israel	Bolivia	Cote d'Ivoire
Kuwait	Sri Lanka	Kazakhstan	Japan	Brazil	Cameroon
Lebanon	Pakistan		Hong Kong	Costa Rica	Senegal
Morocco	Nepal			Chile	Madagascar
Oman	Philippines			Colombia	Malawi
Qatar				Ecuador	Rwanda
Saudi Arabia				Guatemala	Tanzania
Egypt				Guyana	Namibia
Algeria				Suriname	Mauritius
Mauritania				Mexico	
Tunisia				Peru	
Palestinian Territory				Uruguay	
				Venezuela	
				Paraguay	
				Antigua and Barbuda	
				Bahamas	
				Barbados	
				Jamaica	
				Trinidad and Tobago	
				Dominica	

Appendix 4.2: Overview of data dimensions in IV estimation

Table 4.3 shows the dimensions of the database used in the IV estimation. The reason that several countries have dropped out is due to the fact that the ICTWSS did not have data on all the countries in our sample. In other words, we were only able to merge our NTM database with the ICTWSS for the following countries:

Table 4.3 An overview of the data used

Country	Sector matched	Year used
Argentina	• Agriculture • Manufacturing • Mining • Public admin & defence	2008
Brazil	• Agriculture • Manufacturing • Mining • Public admin & defence	2013
Chile	National average only	2005
China	National average only	2009
European Union	We use weighted member country-industry trade union densities from the UK (2013), Sweden (2009), Spain (2010), Netherlands (2010), Denmark (2008), Hungary (2009), Ireland (2009), France (2004), Greece (2004) and Italy (2006). Weights are the share of the country-industry contribution to the total EU GDP. We construct these weighted averages for the following industries: • Agriculture • Manufacturing • Mining • Public admin & defence	
India	• Agriculture • Manufacturing • Mining • Public admin & defence	2012
Israel	National average only	2012
Japan	• Agriculture • Manufacturing • Mining • Public admin & defence	2012
Mexico	National average only	2012

Appendix 4.3: Baseline Regression Output

Table 4.4 Empirical output using the Frequency Ratio as an NTM proxy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ignoring zeros				PPML				Eaton - Kortum			
	No fe	Country fe	Industry fe	Country + industry fe	No fe	Country fe	Industry fe	Country + industry fe	No fe	Country fe	Industry fe	Country + industry fe
Frequency	1.095**	7.336***	1.037**	2.592**	0.0491***	0.0359*	0.0505***	0.0739	0.996**	6.540***	0.908*	2.227*
	(2.539)	(5.373)	(2.297)	(2.065)	(10.61)	(1.951)	(18.58)	(1.510)	(2.098)	(4.056)	(1.913)	(1.678)
Constant	5.625***				11.65***				5.010***	-25.04***	8.434***	-2.734
	(4.197)				(46.14)				(3.376)	(-3.408)	(5.551)	(-0.440)
Observations	946	946	946	946	1,132	1,053	1,075	1,000	1,053	1,053	1,053	1,053
R-squared	0.053	0.589	0.258	0.813								
Number of countries						53						
Number of industries							19					

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5 Empirical output, using the Coverage ratio as an NTM proxy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ignoring zeros				PPML				Eaton Kortum			
	No fe	Country fe	Industry fe	Country + industry fe	No fe	Country fe	Industry fe	Country + industry fe	No fe	Country fe	Industry fe	Country + industry fe
Coverage	1.765**	5.535***	1.644**	0.780	0.0497***	0.0302***	0.0505***	-0.0336	1.706**	6.479***	1.455*	0.752
	(2.463)	(5.006)	(2.199)	(1.183)	(13.66)	(4.465)	(30.66)	(-0.691)	(2.185)	(4.678)	(1.858)	(1.037)
Constant	2.715				11.41***				1.980	-24.99***	6.064**	4.087
	(1.075)				(61.44)				(0.717)	(-3.929)	(2.177)	(1.219)
Observations	946	946	946	946	1,132	1,053	1,075	1,000	1,053	1,053	1,053	1,053
R-squared	0.054	0.582	0.257	0.812								
Number of countries						53						
Number of industries							19					

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6 Empirical output, using the Prevalence ratio as an NTM proxy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ignoring zeros				PPML				Eaton Kortum			
	No fe	Country fe	Industry fe	Country + industry fe	No fe	Country fe	Industry fe	Country + industry fe	No fe	Country fe	Industry fe	Country + industry fe
Prevalence	0.761***	4.505***	0.721**	1.481*	0.153***	0.431***	0.172***	0.734*	0.737**	4.009***	0.673**	1.544**
	(2.832)	(4.000)	(2.564)	(2.003)	(8.153)	(3.090)	(5.407)	(1.678)	(2.356)	(3.226)	(2.166)	(1.974)
Constant	9.084***				13.99***				8.139***	-0.424	11.24***	5.315***
	(26.52)				(62.78)				(21.00)	(-0.264)	(27.50)	(4.387)
Observations	946	946	946	946	1,132	1,053	1,075	1,000	1,053	1,053	1,053	1,053
R-squared	0.060	0.597	0.264	0.813								
Number of countries						53						
Number of industries							19					

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5
Summary and Conclusions

This Ph.D. thesis, titled "Essays on Global Value Chains", has sought to answer the question of how global value chains affect the relative demand for skilled labour. As highlighted in the introduction, both global value chains and within-country inequality have increased significantly in recent decades and continue to do so. Since the former can affect the latter via the relative demand for skilled labour, it is of economic, political and social interest to better understand the interplay between global value chains and the relative demand for skilled labour. This thesis shed fresh light on these issues by providing various theoretical and empirical contributions. In short, these contributions can be grouped as follows:

1. An all-encompassing conceptual framework
2. The sector versus factor bias debate
3. Empirical evidence regarding the research question
4. Data and GVC proxies
5. Drivers and obstacles to GVCs

This section will discuss those contributions one-by-one, before providing some suggestions for future research.

5.1. An all-encompassing conceptual framework

Chapter 1 sought to answer to the identified a review of the literature in search for a theoretical answer to the research question. However, in doing so, it quickly became apparent that there is no such one unambiguous answer. This research gap is well known in the literature (Kohler, 2002; Feenstra, 2008; Amador and Cabral (2015)) and can be attributed to crucial modelling differences between key theoretical models that can explain what happens in one specific case, but cannot provide an all-encompassing answer. Chapter 1 managed to synthesize these conflicting theories into one all-encompassing figure, with a large explanatory power. Firstly, it can summarize a wide range of theoretical contributions in an intuitive and visual manner. Secondly, it can illustrate how small modifications to various micro-economic assumptions can have crucial implications on the model's prediction. Thirdly, it provides a visual summary of the key channels by which GVCs affect the relative demand for skilled labour. Fourthly, it can be used as a guide in understanding the ambiguous literature regarding the factor and sector bias of a productivity change. Fifthly, it can be used as a conceptual framework for empirical analysis of the research question. For these reasons, the figure ultimately serves as a pedagogical tool for (under)graduate students and policy makers to understand the interplay between GVCs and the relative labour market without the need to understand complex algebra.

5.2. The sector versus factor bias debate

Edward Leamer (1994; 1998) and Paul Krugman (2000) sparked a big debate about whether it is the sector bias or the factor bias of a productivity change that determines what happens to relative factor demands. Here, the sector (factor) bias refers to the skill intensity of the sector (factor of production) that experiences the productivity change. While various contributions, e.g. Xu (2001), have explained under which conditions one or the other might dominate, an intuitive explanation was still missing. As their relative magnitudes depend ultimately on the elasticities of factor and goods substitution (Xu, 2001), one can use the Figure of Chapter 1 – by changing the slopes of the relative demand curves in quadrants 1 and 3 respectively (See Section 1.4.2.3 from page 46 onwards) – to illustrate which effect will dominate, significantly simplifying the analysis. Besides this qualitative contribution, Chapters 2 and 3 provided empirical contributions to this issue. Here, evidence was found that is in line with the argument by Krugman (2000) that in a large open and integrated world economy, the sector bias of a productivity increase should not affect relative factor demands. Krugman explained that Leamer's (1994; 1998) theory, which assumes that the productivity change occurs in a small open economy, is nothing more than a useful classroom example that is not in line with real world observations. Indeed, Chapters 2 and 3 have found that conditioning empirical exercises on the factor bias of the GVC activity, in which a firm (Chapter 2) or country (Chapter 3) engages, crucially affects the outcome. In contrast, conditioning on the sector bias did not significantly affect the outcome. What this means for answering the research question is discussed next.

5.3. Empirical evidence regarding the research question

The factor bias of global value chains refers to the skill intensity of the intermediate good that a country specialises in, via the GVC. Since this, and not the skill intensity of the sector that engages in GVC (i.e. the sector bias), ultimately affects how GVCs influence the relative demand for skilled labour, the empirical answer to the research question can be thought of as follows. Simply put, GVCs allow (firms within) countries to specialise in their comparative advantage at an even more granular level than before, i.e. in the production of intermediate rather than final goods. Low (high) skilled abundant countries will be able to specialise even more in low (high) skilled intensive tasks, decreasing (increasing) the relative demand for skilled labour. Both Chapters 2 and 3 found evidence of this, as summarized in Figure 5.1 and 5.2, respectively.

Specifically, Figure 5.1. clearly shows that those firms that engage and specialise in the high (low) skilled intensive part of a global value chain (i.e. FB=high(low)) tend to have a significantly more (less) skilled workforce. The only deviation from this finding is apparent in the bottom right diagram of Figure 5.1, which shows that firms in high skilled industries engaging in the relatively low skilled activities of a GVC actually tend to hire relatively more skilled personnel than firms that do not engage in GVCs, as can be seen in the bottom right diagram of Figure 5.1. This can be explained, however, by referring to Feenstra and Hanson (1996) who argue that what might seem low skilled intensive for one country, can be seen as high skilled intensive for another country. This is likely the case here, as we only observe this effect in high skilled industries where the low skilled intensive tasks might actually be relatively high skilled. To our knowledge, this is the first Chapter that empirically examines the effect of GVCs, conditional on its sector and factor bias, on the relative skill employment of firms in developing countries.

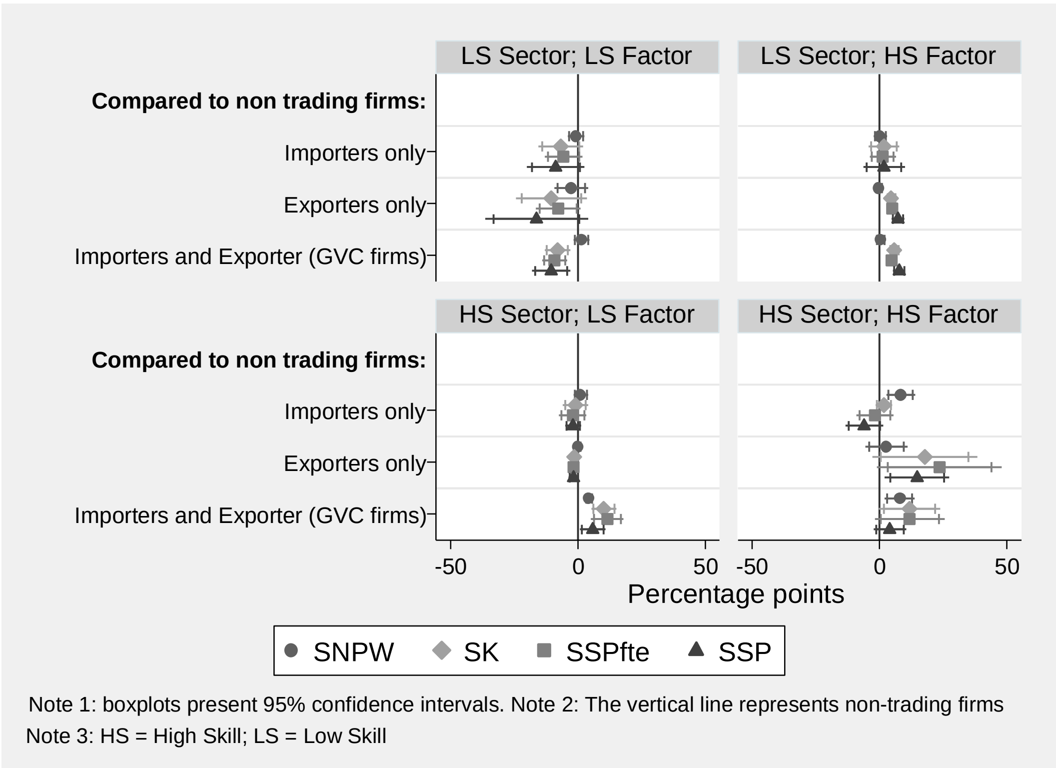
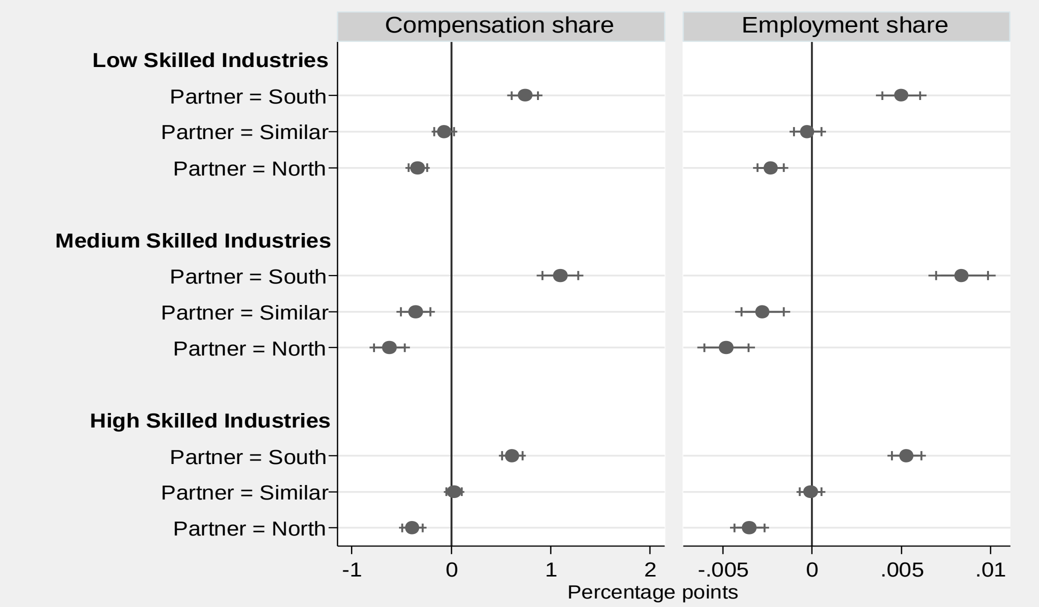


Figure 5.1 The key findings from Chapter 2

These conclusions were in line with the findings from Chapter 3, which used macro level data from the World Input Output Database (WIOD) and decomposing it along the Wang, Wei and Zhu's (2013) decomposition method. Applying this decomposition provided several commonly used GVC proxies which were correlated with the wage and employment share of different skill types of workers. To the best of our knowledge, this is the first time that this decomposition method has been used to estimate the effect of GVCs on the relative demand for skilled labour.

As was argued in this Chapter, VS1*, which measures the share of gross exports that is domestically produced and returns home via a third country, provided the best measure for GVCs (see the next section). Therefore, Figure 5.2 summarizes the correlation between VS1* as a proxy for GVCs with the compensation and employment share of high skilled labour, conditioned on the sector and factor bias of the GVC. It shows strong evidence in line with a factor bias effect, as domestic value added exported to a less (more) skilled abundant country was correlated with increased (decreased) high skill labour compensation and employment shares. Once again, this can be interpreted by thinking of GVCs as allowing countries to specialise in their comparative advantage at an even more granular level, i.e. the intermediate input or task level, rather than the final good.



Note 1: Boxplots represent 99 % confidence intervals. Note 2: Partner = South implies high skilled factor bias

Figure 5.2 An excerpt of the key findings from Chapter 3 that shows the effect of GVCs, measured via VS1 on the compensation and employment share of high skilled labour*

5.4. Data and GVC proxies

Measuring international production sharing is an extremely difficult concept since offshoring refers to management decisions made at the micro level that cannot be easily linked to macro-economic trade statistics (WTO, 2005). Therefore, micro data is typically preferred, as it allows policy makers and others not only to improve their aggregate assessments of competitiveness and GVC participation, but also to identify the drivers and the reaction of the real economy to policy interventions (Taglioni and Winkler, 2016 p. 112). Unfortunately, however, micro or firm level data is typically difficult to obtain. Chapter 2 of this thesis, however, used World Bank data which provides a rich source of firm level data. This data, specifically the information regarding firms' import of intermediates and export of final goods allowed the construction of a GVC proxy. However, a trade off was identified between ensuring that a firm is actually engaged in a GVC, by increasing the cut-off level of imports and exports, versus preventing the identification of a specific type of GVC engagement, as firms that import nearly all of their intermediates and export all of their outputs are most likely assembly firms.

Chapters 3 and 4 used macro level data. More specifically, Chapter 3 made use of an initiative launched in 2011 by the "Global Forum on Trade Statistics" that sparked a number of contributions regarding the measurement of trade in value added in the format of inter-country input output tables. In addition, it used a decomposition method by Wang Wei and Zhu (2015) that decomposes such value added flows into a set of well-known macro-level proxies for a country's engagement in GVCs. Out of those flows, that were depicted in Figure 3.1, Chapter 3 concluded, based on theoretical and empirical arguments, that the so called VS1* proxy is the most appropriate measure for GVC engagement. This proxy specifically measures the share of domestic value added exported that returns home. Note that this is very close to the idea of offshoring, where a country or a firm also exports a particular product for further processing to a third country and then re-imports it again.

Chapter 4 also used macro level data, but of a less specific GVC nature than the data used in Chapter 3. Namely, it used product level trade data and identified GVC engagement as the import of intermediates and the export of final goods. The challenge, as it was in Chapter 2, is to link these two, i.e. to make sure that the imported intermediates are used in subsequent exports, according to Baldwin and Lopez-Gonzalez' (2015) concept of import to export. While Chapter 2 dealt with this by taking the firm as the connecting factor, and subsequently by increasing the cut-off levels of importing and exporting to ensure that the former is used in the latter, Chapter 4 dealt with it by taking the industry as the connecting factor, i.e. it identified imports of intermediates and exports of final goods by the same industry as a GVC connection. This is, however, clearly limiting as it ignores any indirect international contributions from one industry to another. The final section of this Chapter provides some suggestions for further research, that depend largely on the availability and quality of future data collections.

5.5. Drivers and obstacles to GVCs

Finally, this thesis investigated the drivers and obstacles to global value chains. Figures 0.1 and 0.2 in the introduction explained that information and communication technologies and decreased trade tariffs contributed significantly to the spread of GVCs. However, as pointed out in Chapter 4, while formal tariffs are coming down, non-tariff barriers to trade are on the rise. Chapter 4 investigated whether those non-tariff measures (NTMs) act as substitutes to tariffs, or whether they might in fact be trade enhancing by serving as quality signals. A baseline regression found initial evidence that the prevalence ratio, i.e. the average number of regulations per imported intermediate product, was positively correlated with export values suggesting NTMs can act as a quality signal to foreign buyers. However, after properly controlling for unobserved heterogeneity with an instrumental variables method, it was concluded that NTMs, either measured by their frequency, coverage or prevalence ratio levied on the import of intermediates, did not significantly affect the export values of final goods.

5.6. Suggestions for future research

Suggestions for future work can be broken down into empirical and theoretical suggestions. On the empirical side, various suggestions have already been mentioned as each empirical Chapter (2-4) provided suggestions regarding the measurement of the critical independent variable. For example, Chapter 2 discussed the challenge of linking imported intermediates to subsequent exports; Chapter 3 discussed the importance of further research into the role of the final destination of value added, and; Chapter 4 referred to measuring NTMs by looking at their regulatory heterogeneity (Cadot et al., 2015), rather than their absolute presence.

Indeed, it seems that empirical research has the best prospects of making additional contributions to the literature, as it can benefit from recent contributions on improved data collection on GVC activity (See Section 3.2 on page 122). While significant contributions have been made in recent years regarding the measurement of GVCs on the macro level, i.e. by measuring value added in inter country input output tables, data on the micro level is arguably more important, as it allows for a more precise measurement of GVC participation along with its drivers and consequences (Taglioni and Winkler, 2016, p. 112; WTO, 2005). Examples of such micro level databases do exist, particularly for Denmark and Belgium, where publicly available datasets have matched individual workers to Danish and Belgian firms respectively, whose trade flows can be broken down by product as well as origin and destination countries. Such detailed analysis would allow for three additional empirical contributions in the future.

Firstly, it would allow for a better identification of trade via GVCs by linking imported intermediates to subsequent exports which would improve the estimations of how much trade happens via global value chains. As outlined in Chapter 2, this could be done simply by including a question in enterprise surveys whether a firm uses imported intermediates in the goods that it exports. Secondly, more detailed data would allow to empirically assess the relative magnitudes of the productivity, price and labour supply effect, as outlined in Chapter 1. So far, Hummels, Jørgensen, Munch and Xiang (2014) are one example of a paper that has attempted to specifically identify the productivity effect by using the detailed Danish firm level data. Future work could extend on this by also looking at the price and labour supply effect. Doing so would answer the call for more empirical research on these effects' relative magnitudes by Grossman and Rossi-Hansberg (2008, p. 1997).

The third and final suggestion for future research is also related to Grossman and Rossi-Hansberg (2008). Namely, one of their main points was that the literature should focus more on trade in tasks as opposed to trade in final goods. The findings in this thesis are in line with that, as we found that the factor bias, which can be thought of as a trade in tasks[49], rather than the sector bias, which can be thought of as trade in the final good, crucially affected the empirical outcomes. More detailed data would allow us to identify at an even more granular level what is being traded via GVCs. Besides more detailed firm level data, future research could also use datasets such as the O*Net database which classifies employment based on specific occupational tasks, as shown for example by Lanz, Miroudot and Nordås (Lanz et al., 2011).

[49] Grossman and Rossi-Hansberg (2008) agree on this point as they say the difference between trade in intermediate goods or trade in tasks is largely "semantic" (p. 1997)

On the theoretical side, future research could further expand the figure developed in Chapter 1. While the figure's intention was to side step theoretical ambiguity by not formulating a theoretical model, future research might assess whether the models by Xu (2001) and Grossman and Rossi-Hansberg (2008) can be used to develop a formal model underlying this figure after all. Doing so would provide more theoretical justification and therefore academic credibility to the figure, which can then still be used as a pedagogical tool to understand the effects of GVCs on the relative demand for skilled labour, without the need to understand complex models. Secondly, the figure is currently only synthesizing well known neoclassical theories. One could look into expanding this figure by incorporating models that are based on non-neoclassical assumptions such as labour market imperfections and frictions.

Such future research is much needed to enhance our understanding of the momentous effects of economic globalization on societies at large. This is most necessary in a todays' period characterized by growing anti-globalization sentiment, partly caused by growing within-country inequality. This thesis has contributed to this understanding but further work remains necessary, as highlighted in this section. While GVCs have many positive effects, as embodied by the productivity effect, some workers can lose out. It is therefore important to understand exactly how GVCs affect economies, so that those who might be affected negatively can be compensated with the overall gains from economic globalization. While this discussion refers back to a well-known argument within the literature – i.e. that while international trade may negatively affect some people, it increases the overall pie of economic welfare – it is now more relevant than ever.

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