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Master in Economic Development and Growth

Assessing the Environmental Impact of Process Automation in German Manufacturing GVCs

by

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Abstract

Both automation and climate change are important topics on today's policy agenda. Automation is often argued to have environmental benefits in terms of energy efficiency, however, no attempt has yet been made to empirically address the relation between automation and energy consumption. Therefore this paper aims to fill this gap by exploring whether automation and energy intensity developments follow similar trends and tests for the existence of a correlation. Another contribution of this paper is the evaluation of energy intensity developments and automation in global value chains, as this accounts for the effect of offshoring and enables the incorporation of the rebound effect commonly discussed in the ICT-energy intensity literature. The first part of the analysis is focused on deriving labor income shares, which serve as a proxy for automation, and energy intensity levels in German GVCs. In order to do so, a multi-region input-output model is employed in combination with data from the WIOD. Subsequently, the existence of a relationship between labor income share and energy intensity developments is examined based on a simple regression model. The main findings show that (i) automation was present in all GVCs as labor income shares declined and were not found to be related to offshoring; (ii) energy intensity initially increased, but started to fall after 2000; (iii) overall automation was associated with a small reduction in energy intensity; and (iv) automation in foreign production stages was accompanied by a rise in energy intensity.

Key words: automation, environmental degradation, energy intensity, global value chains, IO-analysis

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1. Introduction

Approximately ten years ago, Stern (2007: pp 1) referred to climate change as ‘the greatest and widest-ranging market failure ever seen’. Throughout the last decade, increased awareness for the need to drastically reduce our greenhouse gas (GHG) emissions has been raised. The most prominent example is the Paris Agreement, which is the first internationally coordinated and legally binding framework designed to tackle climate change on a global scale (Climate Focus, 2015). By the end of 2016, the Paris Agreement entered into force as 55 countries that are responsible for at least 55 percent of the global GHG emissions had adopted the agreement and this list is still growing (United Nations, 2017). Executing the ambitious plans of the agreement requires a deeper understanding of where and how emissions in our global economy are generated.

Technological change has raised the efficiency of production processes and thereby reduced the amount of inputs required to produce a particular level of output. According to Schwab (2016) the new technologies of the ‘fourth industrial revolution’, which are characterized by connecting things (products, services or places) with people, yield the capability to reduce negative externalities that accompany economic, such as carbon emissions. Several studies have found that technological progress has indeed been the main driver of reduced energy intensity over the last few decades (Henriques and Kander, 2010; Groot and Mulder, 2012; Voigt et al., 2014). Energy intensity is commonly used as a proxy for energy efficiency and refers to the amount of energy consumed per unit of GDP. According to Bonavita (2013), process automation is one of the most important drivers of raising energy efficiency in industrial production plants. Moreover, automation through for example cloud computing can also reduce energy consumption in non-industrial occupations (Schwab, 2016). A recent study has concluded that almost fifty percent of all jobs are susceptible to automation and in fourteen percent of the jobs more than two-thirds of the tasks are easily automated (Nedelkoska and Quintini, 2018). The authors show that in Germany, there has already been a transition towards jobs less exposed to automation enabled by training that requalifies workers for such occupations. As argued by Autor (2015), continuous restructuring of jobs will take place due to technological progress. If the new task sets carried out by workers consist of less energy consuming activities, automation can contribute to emission abatement in the overall economy.

As outlined by Barnett et al. (2017), the application of robots in production processes can affect energy consumption in several ways. In example, energy savings can be realized by substituting traditional machine tasks with robots that are more efficient or the use of completely automated dark factories that do not require light and heating. However, increased application of robots can also expand energy intensity as automation instead of manual assembly in manufacturing processes can raise the energy inputs used in production processes (Barnett et al., 2017). Consequently, it is still uncertain whether process automation relieves the pressure on the environment or has a less beneficial impact than is generally assumed by proponents of automation, such as Gurney (2014). To my knowledge, no previous attempts have been made to quantify the environmental impact of automation. Hence, this paper is the first to explore the question whether automation can relieve environmental degradation through a reduction in energy intensity. Due to data limitations, changes in the labor income share will serve as a proxy to identify the presence of automation. Moreover, in order to account for energy intensity changes related to offshoring and include the energy consumption related to the production of automation equipment, complete value chains are analyzed. Consequently, an input-output model is appropriate to derive labor income share and energy intensity developments. Finally, this paper focuses at German manufacturing value chains, because the country is associated with high levels of automation.

The remainder of this paper is structured as follows. Section 2 will discuss all the relevant literature related to automation and environmental degradation. Based on the literature, the following propositions are derived: (i) declining labor income shares are present in German manufacturing GVCs; (ii) the former is related to offshoring; and (iii) GVCs that conform to only proposition (i) are characterized by reduction in energy intensity. Section 3 explains the decision to focus on German GVCs into more detail and provides some background information regarding automation and energy intensity in the German economy. Moreover, section 4 describes the data used in the analysis and illustrates the interpretation of multi-region input-output tables. All data is extracted from the World Input-Output Database. Subsequently, section 5 will introduce the input-output methodology based on Los et al (2015) and explains how the labor income shares and energy intensity levels are derived. Additionally, a simple regression model is introduced which serves to examine the existence of a correlation between labor income share and energy intensity developments. Section 6 and 7, present and discusses the results from the input-output model and the regression analysis and the main results are as follows: (i) labor income share declined in nearly all GVCs and was not related to offshoring; (ii) energy intensity initially increased in all GVCs, but followed a steep downward trend after 2000; (iii) automation, proxied by labor income share, was on average found to reduce energy intensity to a small extend; (iv) automation in foreign GVC stages was accompanied by a rise in energy. Finally, section 8 provides some concluding remarks, limitations and suggestions for future research.

2. Theory and Previous Research

As discussed above, the objective of this study is to provide a link between the literatures on automation and the field of environmental economics. Automation has been a widely discussed topic in terms of its impact on the labor force, however, its environmental implications have received very little attention so far. On the other hand, the energy economics literature has tried to quantify the impact of information and communication technologies (ICT) on energy and electricity consumption (amongst others Romm, 2002; Cho et al, 2007; Bernstein and Madlener, 2010; Saidi et al, 2015). Since automation technologies such as industrial robots and labor-saving software rely heavily on the use of ICT, evaluating empirical research from this field can provide useful insights into the expected effect of automation on energy use in production processes. Moreover, it is important to discuss the literature on international fragmentation of production processes as offshoring can affect the proxy for automation, which is the labor income share, in global value chains (GVCs) and as such it is difficult to disentangle the effect related to automation and international trade in intermediates.

As such, this section will start by reviewing the theory and existing empirical work on automation. Hereafter, I will touch upon the literature on international fragmentation due to its capability to affect the measurement of automation, which is followed by a discussion regarding the presence of automation in the German economy. Finally, a review of the literature on the environmental impact of technological progress should provide a better understanding of how the adoption of ICT in production processes affects the environment, with a special focus on energy intensity.

2.1 Automation

Automation anxiety has been a topic of discussion since the first industrial revolution, as workers actively resisted against the employment of new machines that were designed to replace tasks previously carried out by manual labor (Brynjolfsson and Mcafee, 2012; Economist, 2015). Although the body of literature on automation is still relatively new, the recent developments in the field of artificial intelligence (AI) have increasingly attracted the interest of economists and rekindled the discussion about the impact of automation on the labor force. Before starting to review this strand of literature, it is important to clarify what the term automation comprises. First of all, the Cambridge dictionary defines automation as follows: ‘to make a process in a factory or office operate by machines or computers in order to reduce the amount of work done by humans and the time taken to do the work’. Another definition describes industrial automation as ‘the control of machinery and processes used in various industries by autonomous systems through the use of technologies like robotics and computer software’ (Rouse, n.d.). In other words, automation is adopted with the aim to raise the productivity of production processes and thereby replaces labor by capital in the form of machines and software. According to the International Society of Automation (n.d.), the application of automation technologies can benefit virtually all industries and names the transport equipment, food and pharmaceutical, chemical and petroleum, pulp and paper industries as some examples were automation is successfully applied.

2.1.1 Measuring the Presence of Automation

Even though automation technologies take over tasks previously performed by human labor, it has remained unclear whether it displaces or expands employment in the overall economy. As such, most of the existing literature on automation has mainly focused on answering this question. In mainstream economics, it is generally believed that there is a factor saving bias to technical change, meaning that less factor inputs are required to produce the same amount of output, which affects the relative factor prices and shares (Blaug, 1997). Consequently, how the prices and shares of labor and capital develop with respect to each other depends on which factor is saved. In turn, this implies that technical change can either expand the amount of labor embodied in the production process (labor augmenting) or raise the capital input component of the final output value of a good or service (capital augmenting). However, it should be noted that both labor- and capital augmenting technical change can occur at the same time and hence the direction of the change in labor income share is determined by the net effect of the change in capital and labor employed (see Lawrence, 2015). Based on this rationale, machine learning can thus be perceived as a form of capital augmenting technical change, since it raises the share of capital income by being a close substitute for human labor.

A recent study by Acemoglu and Restrepo (2017) has investigated the relationship between automation and the local labor markets in the US. By the development of a model that allows robots to compete with workers, the authors show that automation can reduce the level of both employment and wages. Furthermore, regressing the change of employment and wages in local labor markets on their respective exposure to industrial robots reveals that wages and employment levels are negatively affected by automation (Acemoglu and Restrepo, 2017). Since competition between man and machine reduces the price of labor and in addition replaces part of the human labor inputs with capital inputs, the labor income share in the total output value of a product or service is expected to decline. 30 years earlier, Leontief and Duchin (1986) already studied the impact of automation on employment over the period 1963 – 2000. Based on their input-output model they estimated that the increased adoption of automation could result in labor savings of 10 percent over the upcoming 20 years. However, they predicted that due to the increased demand for investment in capital goods, at least during the initial stages of automation, the share of production workers in the labor force would remain stable. Most of the labor savings were expected to occur in middle-skilled clerical jobs. The existence of such skill biased technical change has later been confirmed by several studies (amongst others Goldin and Kats, 2007; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos et al 2011, 2014; Michaels et al 2014; Frey and Osborne, 2017). As argued in these papers, a substantial part of displaced middle-skilled workers seek employment in lower-skilled professions, which drives down the low skilled wages due to increased competition. If this is the case, the labor income share in the economy can fall as the price of labor declines relative to the price of capital.

Multiple scholars have argued that recent technological developments, especially within the field of AI, have increased the amount of jobs that are at risk of being automated (amongst others Brynjolfsson and McAffee, 2011, 2012; Schwab, 2016). This is due to the development of machines, software and robots that provide close to perfect substitutes for labor at different skill levels and the fear of automation is thus no longer restricted to the middle- and low-skilled routine based tasks (Economist, 2016; Prettner, 2016; Acemoglu and Restrepo, 2017; Manyika et al., 2017). Hence, increased application of automation technologies throughout the entire economy yields the capability to replace labor without generating sufficient new tasks for the displaced workers as the autonomously operating technologies do no longer require the involvement of human labor (Prettner, 2016). Put differently, 'automation competes with labor and therefore its widespread adoption reduces wages, while, at the same time, the income that automation generates is channeled to the capital owners' (Prettner, 2016: pp 9). As such, the growing application of robots and ICT in production processes is expected to increase the economy wide share of capital income at the expense of labor income, which is according to Prettner consistent with the declining labor income shares observed in most developed countries throughout the last decades.

As outlined above, the phenomenon of automation has been measured by economists in various ways. First of all, Acemoglu and Restrepo (2017) and Dauth et al (2017) include a direct measure by employing a model that accounts for automation based on the exposure of local labor markets in the U.S. to industrial robots. Unfortunately, the required data is not publicly accessible and displacement of jobs can also occur with the introduction of automated software and as such fails to capture the entire automation effect. Apart from the aforementioned studies, automation is usually accounted for by indirect measures. In example, the literature on skill-biased technical change uses a Routine Task Intensity (RTI) index as a proxy for automatability of particular occupations. Moreover, Prettner (2016) argues that a declining labor income share can serve as a proxy for automation. The theoretical foundation of the relationship between automation and a declining labor income share discussed in the previous paragraph has been empirically investigated by multiple scholars. For example, Karabarbounis and Neiman (2013: pp 3) find that the net and gross labor shares declined in most countries around the world during the last four decades and show that the simultaneous reduction in both labor share measures is pointing towards 'technology-driven changes in the relative price of investment goods'. Such investment goods can thus include capital augmenting ICT and industrial robots. Furthermore, Prettner (2016) has incorporated automation in the form of industrial robots into a standard Solow growth model and consequently shows that amongst others a unique share of savings is invested in automation, which in turn maximizes the long-run growth of the economy. Moreover, this model shows that an increase in the stock of robots reduces the labor income share of the economy. Using parameter values obtained from the existing literature and the World Bank, plus the assumption that between 1970 and 2007 share of industrial robots in the capital stock of advanced countries has risen from zero to 2.25 percent, the model estimates a 5.5 percentage point decline in the US labor income share, which is similar to the observed labor income share reductions in the the data. This is only 14 percent of the effect found by Karabarounis and Neiman, but Prettner acknowledges that this estimate is likely to be a lower bound since industrial robots comprise only a fraction of the automation technologies employed in the economy. Finally, Graetz and Michaels (2015) confirm that the period 1993-2007 was characterized by an intensification in the use of industrial robots, which was found to be negatively related to the labor income share.

In contrast, Lawrence (2015) states that the previously mentioned studies assume that labor and capital are gross substitutes and as such result in capital deepening. However, he argues that the elasticity of substitution between capital and labor in the US was actually lower than one, which would mean that on average capital increases have a labor-augmenting rather than declining effect. In contrast, he finds that in the US the labor income share declined due to the complementary nature of the two factors, which occurs when a 1 dollar reduction in capital is accompanied by a decline in labor that is larger than 1 dollar. Hence, explaining the labor income share changes depends on the elasticity of substitution between labor and capital. Mućk (2017) confirms that this elasticity of substitution in developed economies usually takes a value below one, which means that on average labor and capital are gross complements. Consequently, it is difficult to identify whether labor income share reductions should be attributed to automation or a decrease in the capital inputs employed.

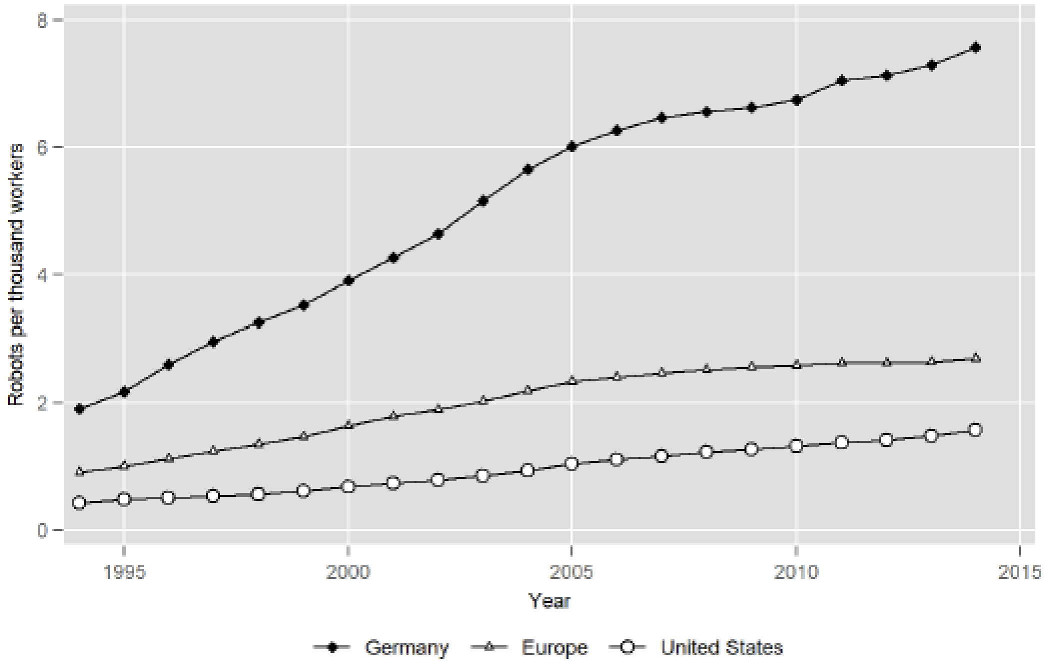
2.1.2 International Production Fragmentation

In the previous subsection the literature on automation in the field of economics has been reviewed. However, these studies have mainly focused on measuring automation and its impact on the labor force at the country or state level. As outlined before capital and labor can be gross complements or substitutes, which is dependent on the nature of the capital good. However, declining labor income shares in GVCs can also relate to offshoring of production stages to low wage economies. The basic intuition behind this is as follows. Baldwin and Evenett (2011) argue that the ICT revolution has enabled companies to perform different stages of a production process in distinct geographical locations and consequently value chains have become increasingly internationally fragmented. The existence of such fragmentation has been confirmed by Los et al. (2015) as they show a rise in the value added generated outside the country-of-completion for most manufacturing production chains since 1995. The decision to offshore certain stages is often related to the lower production costs associated with the foreign location. Due to the low wages in developing countries, low-skilled labor intensive processes are increasingly performed overseas, whereas the higher value added stages that generally require more skilled workers remain within the home country (Baldwin and Evenett, 2011). Hereby, the labor income share in an entire value chain can decline when the average labor compensation falls as a result of offshoring.

However, Fröhm et al. (2008) state that increased competition from low wage economies has given rise to the adoption of automation technologies within advanced economies. In similar vein, Bloom et al (2011) find that trade induced technical change, particularly caused by import competition from China, has stimulated innovation and raised total factor productivity in surviving European firms. If companies decide to keep their routine based, low-skilled tasks within the home country and replace human labor by industrial robots, the labor income share in domestic stages of a production chain reduces as well. In example, both the US and Europe have seen a substantial rise in robot density (the amount of industrial robots per thousand workers) between 1993 and 2008 (see figure 2.1). Hence, labor income share reductions in the overall GVC can reflect the presence of automation for these countries. Turning to Germany, a country characterized by a very high robot density and a large manufacturing employment share compared to other developed countries (with the exception of Asia), displacement of workers seems to be less of a worry than for the US (Restrepo and Acemoglu, 2016; Dauth et al, 2017; IFR, 2017). However, Dauth et al (2017) show that this is mainly due to the fact that new entrants in the labor market find jobs in services rather than in manufacturing and even though the currently employed manufacturing workers are not fired, they will see their wages decline. Finally, based on the adoption of a model similar to that of Acemoglu and Restrepo (2017) the authors conclude that ‘robots seem to have contributed to the declining labor income share, which has been noted in many countries and which is perhaps among the most important economic challenges for the future’ (Dauth et al, 2017: pp 42).

Hence, focusing on the production chains of manufacturing industries is likely to reveal a declining labor income share over the period 1995-2008. However, we do need to consider that the effects can be partially canceled out as for example activities related to management functions are included within these manufacturing supply chains, which are complemented by technology and thus can raise income in the presence of automation. This is in line with the earlier mentioned simultaneous occurrence of labor-augmenting and capital-augmenting technological change that was proposed by Lawrence (2015) and as such the magnitude of the impact of automation on the labor income share might be understated.

Figure 2.1 - Industrial Robot Density in Europe, Germany and the US



Source: Dauth et al, 2017

The above discussion of the literature on automation and international fragmentation of production processes has shown that it is difficult to identify the decline in labor income share specifically related to automation since other factors such as offshoring can also affect labor income shares in GVCs. Direct measurement of this automation effect is only possible for the part of automation related to industrial robots as ICT capital has heterogeneous effects on the labor income share (Dauth et al, 2017). However, the IFR data on industrial robot exposure is not publicly available and as such the labor income share will serve as a proxy for automation, although the automation effect might be understated. Using a multiregional Input-Output model can, however, provide insights whether the labor income share adjustments in a GVC are possibly related to offshoring to low wage countries. In such a situation we will observe a rise of value added generated by foreign stages in the GVC, but at the same time the labor income share of the foreign stages will fall as a result of lower prices of the factor input labor. In contrast, when the foreign value added share of the GVC remains more or less stable, but the labor income share of the entire production chain falls, this provides a strong indication for the presence of automation. Because Germany serves as a good example of a developed country with a large manufacturing sector which is highly exposed to automation, the analysis in this paper will be focused on German manufacturing industries.

2.2 The Environmental Impact of Automation

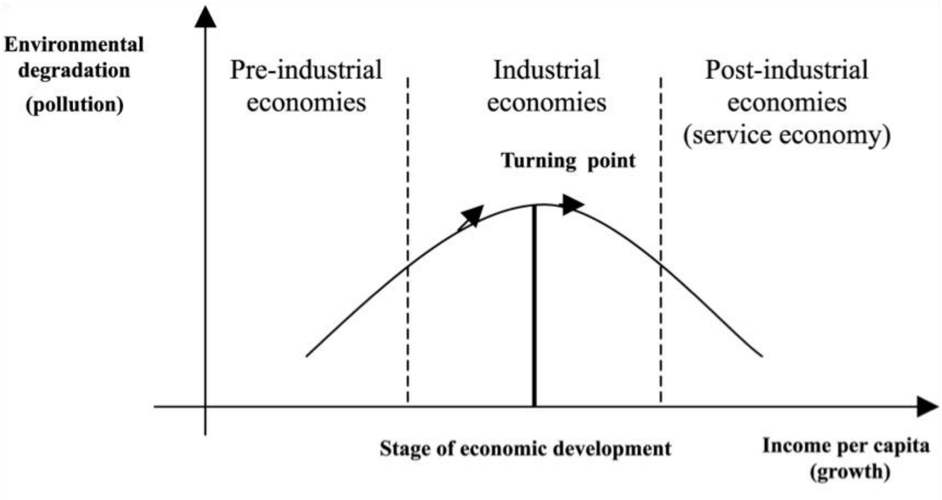
Now that the literature on automation has been reviewed, it is time to turn to the theory and empirical research from the field of environmental economics. As was briefly touched upon in the first section of this paper, it has generally been assumed that technological progress yields the capability of reducing environmental degradation. As explained by Mäler (2011), an economy without technological progress cannot produce beyond the point where natural resources are depleted. Since natural resources are scarce, extending this horizon is only possible by technical progress through (i) innovations related to new ways of producing energy at low constant cost and that enable the use of waste as a source of energy or (ii) innovations that reduce the amount of resources that are embodied in goods and services. The latter can be related to the impact of automation as the use of industrial robots can have beneficial environmental effects due to increased efficiency in production processes (IFR, 2017). This section will further explore the relation between technological development in the form of ICT capital and energy consumption in order to get a better understanding regarding the expected direction of the environmental impact of automation.

2.2.1 Environmental Kuznets Curve

First of all, the Environmental Kuznets Curve (EKC) hypothesis refers to relationship between economic development and environmental degradation and proposes that environmental pressure in terms of quantity and intensity rises from early stages of development until a certain level of income per capita is reached, after which the pressure on the environment starts to follow a downward sloping trend (Panayotou, 1993; Stern et al, 1996; Dinda, 2004). This inverted-U-shaped relationship is based on the by Kuznets (1955) proposed relationship between income inequality and economic development, which proposes a rise in income inequality up to a certain income level after which income inequality starts to fall.

According to Panayotou (1993) there are multiple theoretical explanations underlying the in relationship presented in figure 2.2. First of all, the following five factors determine ‘the state of natural resources and the environment: (i) the level of economic activity and the size of the economy; (ii) the sectoral structure of the economy; (iii) the vintage of technology; (iv) the demand for environmental amenities; and (v) the conservation and environmental expenditures and their effectiveness’ (Panayotou, 1993: pp 2). With respect to the subsequent analysis, factor (ii) is relevant for hypothesizing the environmental impact of automation as it depends on the sectoral structure how much room there is for technological progress to reduce environmental pressure. In example, an industrial economy can realize large environmental improvements as heavy manufacturing is often characterized by high energy intensity, whereas a service economy is already performing less energy intense activities. Additionally, factor (iii) is relevant as automation technologies are at forefront of technological progress and as such manufacturing industries that adopt industrial robots at an increasing rate are expected to see substantial improvements in energy intensity levels compared to the ones that are operating below the technological frontier.

Figure 2.2 - Environmental Kuznets Curve



Source: Panayotou (1993)

Although several studies have shown that the EKC shape holds for some pollutants at the country level, there has been widespread criticism that questions the empirical relevance of this theory [see Lieb (2003) for a survey]. One very important limitation is the failure to account for international trade and as such offshoring of energy intense manufacturing activities can be a major reason of the reduced environmental degradation in developed economies. Of course this does not make a difference on the global level and as such this paper considers the developments for complete production chains, which means that rises in environmental degradation through offshoring are incorporated.

2.2.2 Energy Intensity

Turning to the evaluation of the environmental impact of automation, I will first define the concept of energy intensity and then discuss why this will serve as the unit of measurement in the subsequent analysis. First of all, the term energy intensity refers to the quantity of energy required to produce one unit of output (Kander et al., 2013). As such energy intensity *(i)* is obtained by the following equation where E_i represents total energy input and Y is GDP:

$$i = \frac{E_i}{Y} \quad (1)$$

Energy intensity is the inverse of energy productivity, meaning that a more energy intense economy is characterized by lower energy productivity. According to Kander et al. (2013), adjustments in energy productivity can take place due to the following three, not mutually exclusive, developments: (i) technological progress; (ii) changes in general knowledge and competence; and (iii) structural change. It has often been argued that the decline in energy intensity observed in for example the European Union (see Figure 2) is caused by a transition towards a more service oriented economy. However, based on a shift-share and logarithmic mean Divisia index (LMDI) decomposition analysis Henriques and Kander (2010) found that this assumption is invalid as structural change only accounts for a small share of the reductions in energy intensity. Instead, they conclude that particularly in developed OECD countries the manufacturing sector delivered the largest contribution to the decline in energy intensity. Earlier, Kander (2005) argued that the observed downward pressure on energy intensity in the Swedish manufacturing sector was enabled by ICT developments as (i) industrial structures have become lighter due to the application of microelectronics; (ii) microelectronics in the form of process computers have raised the efficiency of material and energy flows; and (iii) microelectronics have reduced the energy consumption of households. The last reason can of course be questioned as ICT has probably raised the amount of electricity consuming appliances within households. Later on, I will return to the importance of ICT for automation of production processes and their expected effect on energy intensity.

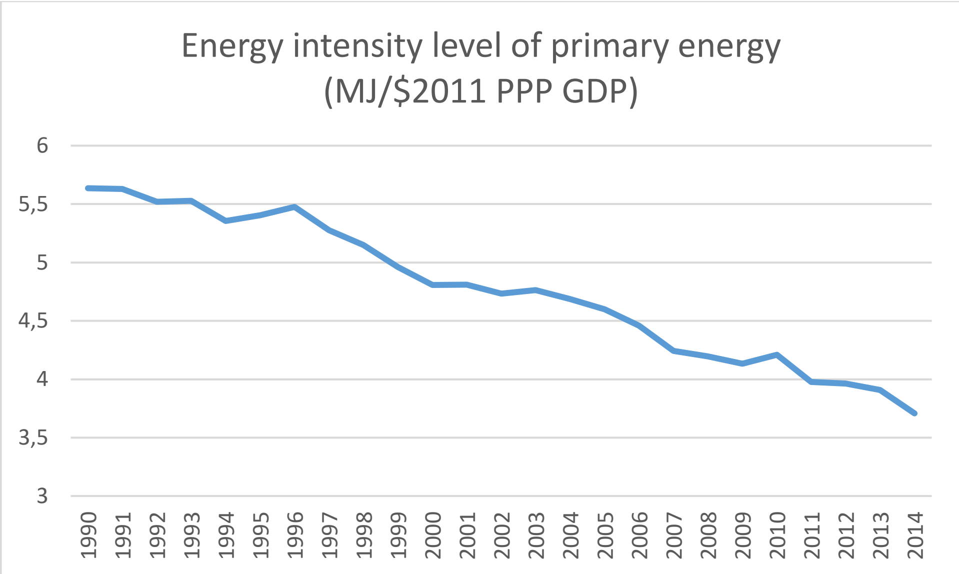
Apart from energy intensity, the level of $\mathrm{CO_2}$ emissions produced in the economy is driven by population and income per capita growth, which both affect the output level, and changes in $\mathrm{CO_2}$ intensity due to fuel switching (Henriques and Borowiecki, 2017). Hence, changes in the level of $\mathrm{CO_2}$ emissions can be decomposed according to the Kaya-identity in order to determine the drivers of $\mathrm{CO_2}$emissions (Kaya, 1989; Kander et al, 2013; Henriques and Borowiecki, 2017):

$$CO_2 = \frac{Y}{P} * P * \frac{E}{Y} * \frac{CO_2}{E} \quad (2)$$

Here, the first two terms reflect the scale effects related to changes in income per capita and population, respectively. Moreover, the third term is the energy intensity effect as presented in equation (1) and finally the last term represents the carbon intensity of energy measured as the emissions per unit of energy consumed. Kander et al. (2013) show that over the period 1870-

2008 both scale effects have contributed to an increase in carbon emissions in Europe. Especially the impact of income per capita growth was an important determinant as it accounted for a 1.71 percent rise in CO_2 emissions annually, whereas the population growth effect was slightly less than a third of this figure. In contrast, the energy intensity effect accounted for a reduction in CO_2 emissions of 0.85 percent per year, whereas the carbon intensity effect reduced CO_2 emission by a negligible amount (0.032 percent). Consequently, it can be argued that energy intensity has been the most important driver of CO_2 reductions in Europe.

Figure 2.3 - Energy Intensity in the European Union 1990 – 2014



Source: Worldbank Data (2018)

As discussed earlier, Henriques and Kander (2010) found that energy intensity reductions were not substantially driven by structural change. Hence, it can be assumed that technological change within sectors, manufacturing in particular, has been the main source of this observation. However, it should be noted that sub-sectoral structural changes, such as shifts towards the production of different manufactured goods, are not separately accounted for as all industrial sectors are aggregated. A decomposition with greater sectoral detail by Groot and Mulder (2012) shows that the larger extent of energy intensity reductions between 1970 and 2005 are indeed related to (technology-driven) efficiency improvements within sectors. However, due to further disaggregation of the manufacturing and service sectors that were used by Henriques and Kander (2010), structural shifts that otherwise would have been attributed to within sector efficiency improvements are now accounted for. Hence, they find that for the most recent period structural changes have become increasingly important as they explained 42 percent of the energy efficiency reductions over 1995-2005 compared to just 22 percent over 1980-2005. In similar vein, Voigt et al. (2014) make use of the 34 different sectors contained in the World Input-Output Database to show that in most of the 40 countries under evaluation, energy intensity reductions were indeed driven by technological change rather than structural change. Especially in the case of Canada, Germany, France, Spain, China, India and Poland reductions in energy intensity were strongly related to the employment of more efficient production technologies. However, the US, Japan and Italy saw their energy intensity decline based on shifts toward less energy intensive sectors.

However, one important drawback of the above mentioned papers is that they do not account for international trade. As a consequence, the identified intra-industry efficiency gains could also be related to specialization of industries in less energy intense stages of production processes, whereas the ones with high levels of energy consumption per unit of output are outsourced to developing countries. A large strand of literature has aimed to answer the question where emissions are generated by examining the emissions embodied in trade based on different types of input-output models (for a review see Wiedmann et al, 2007). On the one hand, such models allow for the determination of emissions embodied in production processes in a particular country, whereas on the other hand they can account for the emissions produced globally to satisfy the consumption of final goods in that same country. Comparing the production- and consumption-based perspectives can then identify whether countries are net importers or exporters of emissions. Hence, the consumption based perspective can reveal if a reduction in carbon emissions produced locally is offset by a rise in emissions produced elsewhere, which is referred to as 'carbon leakage' (Botier, 2012). This is important in the light of the climate change debate, because the decline in energy intensity observed for most developed countries could thus be partially caused by offshoring 'dirty' production stages, which is empirically supported by several studies (see Davis and Caldeira, 2010; Knight and Schor, 2014).

2.2.3 ICT and Energy Intensity

Now that we have established that most of the energy intensity reductions observed in Europe over the past decades were to the largest extend explained by technological progress, I will devote some attention to the relationship between technological change in the form of ICT capital and energy consumption. Since ICT is an important component of automation technologies [see Schwab (2016) for an overview of ICT applications], the literature on the relationship between ICT and the environment can help us to gain useful insights into the expected impact of automation on energy intensity.

It is important to acknowledge that the increased application of ICT can both be energy expanding and energy saving and hence, the net effect is determined by the balance between these contrasting forces (Mattern et al, 2010; Kander, 2013). According to Kander (2013), the former effect is said to occur through the large amount of resources required to produce ICT equipment such as micro-chips. Moreover, expansion of energy consumption can arise as the wide application of electrical appliances in the economy raises the aggregate energy consumption. As such, production processes may become more energy intense as they require more electricity to power their equipment. On the other hand, Kander (2013) argues that energy savings arise through more energy efficiency created by the application of ICT in production processes. A rise in overall energy consumption even though technological progress has made production more energy efficient is more commonly referred to as the rebound effect (Plepys, 2002; Gossart, 2015). As outlined by Gossart (2015) the price reductions of ICT have increased its application as an intermediate input in production processes and since ICT is energy consuming, this could increase the total level of energy consumption in the economy. We can extend this reasoning to automation technology. Consequently, we cannot simply assume that increased adoption of automated processes always contributes to a decline in energy intensity. It might be the case in sectors that are initially characterized by high energy intensity, but could be the opposite when workers are replaced by machines in less energy intense sectors.

Thus far empirical investigations of the relationship between ICT and energy consumption have not reached consensus on the direction of the effect. In example, Cho et al. (2007) show that for most manufacturing sectors in South Korea ICT investments have increased energy consumption in the form of electricity by increased use of electricity at the expense of labor. Moreover, Bernstein and Madlener (2010) investigated the electricity intensity in five of the largest manufacturing industries (chemical, food, metal, pulp & paper and textile) in 8 European countries, including Germany. Their overall findings imply that ICT capital diffusion reduced the electricity intensity of production in all sectors, but for computers and software systems the direction of the effect was different across industries. On the other hand, increased ICT applications are found to reduce energy intensity in the US (Romm, 2002; Laitner and Ehrhardt-Martinez, 2008). Moreover, Rexhaueser et al. (2014) evaluated the environmental impact of ICT for 27 industries in 10 OECD countries and find that ICT capital significantly reduces energy demand.

However, these empirical studies do not account for trade and as such, a rise in energy consumption through the production of ICT equipment might not show up in the effect when ICT capital is imported. Similarly, the previously mentioned structural change towards less energy intensive production sectors in advanced economies is usually accompanied by offshoring of more energy intensive production to developing countries (Bernstein and Madlener, 2010). Such measurement issues can be illustrated by the following example. According the IFR (2017), Germany ranks as the fifth robot dense country and as such is one of the largest buyers of industrial robots in the world. If these robots or parts of them are produced abroad, looking at the energy intensity of manufacturing industries within Germany does not include the potential increases in energy consumption related to the production of this equipment. Now consider the automotive industry which employs large amounts of industrial robots. If we would only look at the energy intensity of production stages that are using automated equipment, such as the assembly of a car, we fail to account for the upstream stages of the supply chain that deliver robots to the car manufacturer. Consequently, evaluating the energy intensity changes of the entire GVC is a better way to evaluate whether automation is in net energy expanding or saving. An Input-Output model can be used to derive the energy consumption levels required by all production stages to produce a particular level of final goods from any country-industry combination. This method will be further explained in sections 3 and 4.

2.3 Propositions: Automation and Energy Intensity in GVCs

Since the aim of this paper is to provide a link between the literature on automation and environmental economics, the above reviewed theory and empirical research is used to hypothesize the relationship between automation an energy intensity. In order to do so, I will first evaluate whether the following two propositions hold to identify the presence of automation.

Proposition 1: The labor income share of German manufacturing GVCs has decreased over the period 1995 – 2008.

Proposition 2: Labor income share reductions of German GVCs can be explained by offshoring to low wage economies.

If only proposition 1 is confirmed, the reductions in the labor income share are most likely caused by capital deepening and hence point towards the presence of automation. However, if both proposition 1 and 2 are confirmed, the labor income share reductions can also relate to lower labor costs associated with offshoring and as such the automation measure might be biased.

After the first two propositions have been evaluated, I will turn to the environmental aspect of the analysis by evaluating the changes in energy intensity observed in German manufacturing GVCs. Since the theory and empirical research on the effect of ICT on energy intensity is divided, the final proposition takes the position of the positivist side.

Proposition 3: For the GVCs that conform to only proposition 1, the energy intensity of the GVC will decline.

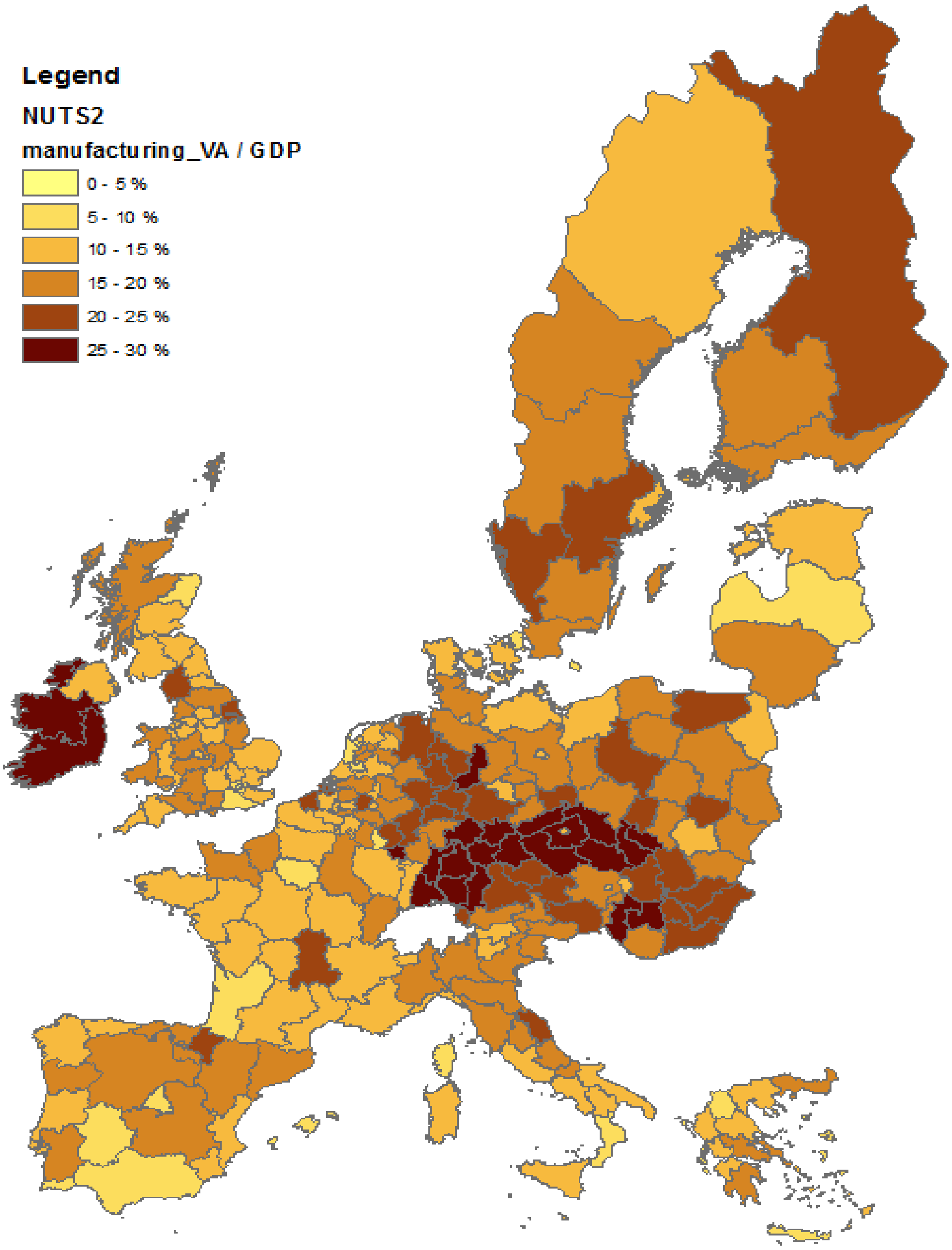
However, due to the rebound effect it might well be that the findings will show opposite effects. The subsequent analysis will reveal the direction of the net effect.

3. Background Information on the German Economy

3.1 Sectoral Structure

As mentioned earlier, international fragmentation of production processes has led to the emergence of global value chains (GVCs). Consequently, the production of a particular final good does not only generate labor and capital income in the country-of-completion, but also abroad. According to a study by the OECD (2015), German value chains are mostly fragmented across European countries, but have started to incorporate upstream suppliers from China to an increasing extend as well. One of the key findings from this study is that 'German manufacturing drives Germany's integration within global value-chains, with the highest export orientation of manufacturing among the G7 and BRIICS economies, but services play an important role too, contributing 37.5% to the value of all manufactured exports in 2011' (OECD, 2015:pp.1). Besides high foreign demand for manufactured goods from German industries, the country also has access to a large domestic market.

Figure 3.1 - Manufacturing VA share of GDP in Europe (2010)



Source: Author's calculations based on World Input-Output Database, June 2017

Looking at figure 3.1 reveals that manufacturing industries are still very important for the German economy as most of the Southern regions are characterized by a manufacturing value added share of more than 25 percent, which is exceptionally high compared to other European countries (with the exception of Ireland and some Central European countries). These high shares are especially visible in Baden-Württemberg and Bayern, which are both seen as one of Europe's most competitive industrial regions which is mainly related to the importance of the following manufacturing industries: automotive, electrical engineering, mechanical engineering, automation and robotics (European Commission, 2018). This manufacturing value added can be either generated by labor or capital income. According to the Economist (2017), Germany has been able to maintain its position as a large manufacturer through ‘innovative engineering’, which has brought off-shored production stages back to the country. Due to such developments, it is likely that the capital income share of value added has increased with respect to the labor income share. As argued before, this can affect the energy efficiency of production chains in two ways through process optimization on the one hand and the increased application of energy consuming equipment on the other. Therefore, it is interesting to evaluate how the labor income share and the energy intensity in German manufacturing GVCs have developed over time.

3.2 Automation in German Industries

The previously discussed fourth industrial revolution, also referred to as ‘Industry 4.0’, has recently gained support of an increasing amount of organizations, which include the World Economic Forum, the European Parliament, McKinsey and Deloitte (Prakash, 2017). The developments in the field of artificial intelligence will be the driving force in this ‘next era of industrialization’ and Germany is expected to take a leading position in the transformation of industrial production since it has been at the forefront of both production and adoption of automated technologies (Prakash, 2017; Dauth et al., 2017). Dachs et al. (2017) have found a significant positive correlation between the application of Industry 4.0 enabling technologies and the probability of reshoring in German manufacturing firms, which they attribute to the rise in factory site automation and productivity levels associated with these technologies. In turn, this implies that re-shored production stages are becoming more capital intense.

According to a report by the International Federation of Robotics (2017), Germany is the third most automated country in the world, ranking behind the Republic of Korea and Singapore. The German robot density, measured as the amount of industrial robot installations per 10,000 manufacturing workers, has reached 309 units in 2016, which is more than 4 times as large as the global average of 74 units (IFR, 2017). Additionally, the IFR (2017) states that compared to Asia and the Americas, Europe was the region with the highest average robot density in 2016. Since German manufacturing GVCs were found to be mostly dispersed across European countries (see Los et al., 2015; OECD, 2015), increased automation might not only have taken place within domestic production stages, but also in the upstream stages performed abroad. Most of the worldwide robot installations in 2016 were attributed to process automation in the automotive industry, which accounted for 1,131 robot installations per 10,000 workers in the German car manufacturing industry. Additionally, general industry in Germany saw their robot density rise to 181 units per 10,000 workers. Dauth et al. (2017) indicate based on data from the IFR that the following German manufacturing industries saw the largest increases in robot density per 1,000 workers over the period 1994-2014:

- Leather, Leather and Footwear with an average increase of about 35 robots;
- Pulp, Paper and Paper Products with an average increase of about 15 robots;

- Rubber and Plastics with an average increase of about 15 robots;
- Electrical Equipment with an average increase of about 20 robots;
- Transport Equipment with an average increase of about 80 robots;
- Manufacturing, Nec. with an average increase of about 40 robots.

It should be noted that the above rise in industrial robots does not include automation of processes related to ICT enabled software and does not account for increased automation in foreign production stages of German manufacturing firms, which will both be incorporated in the subsequent analysis.

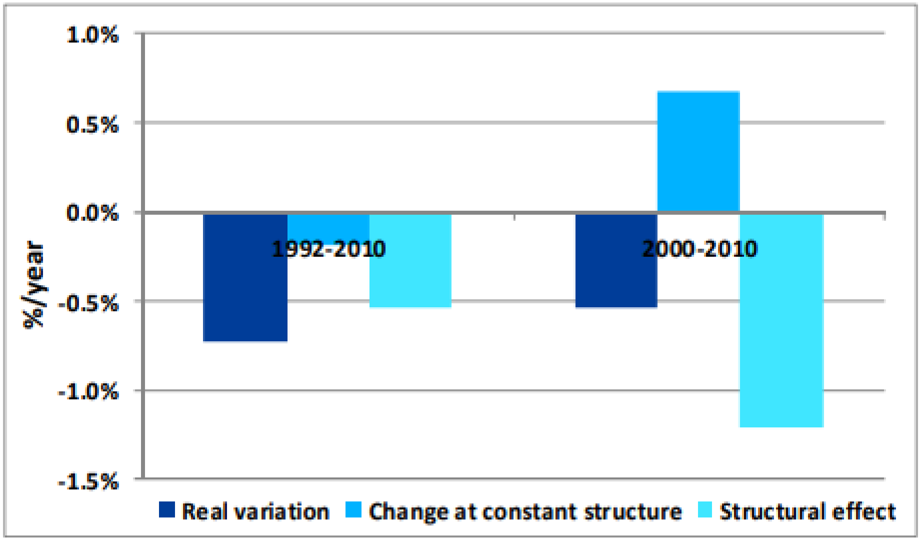
3.3 Energy Intensity Developments

Since 1995 there has been a voluntary agreement between the German industrial sector and the federal government with the aim to substantially reduce CO_2 emissions. In order to realize this goal, policies such as promoting energy efficiency improving investments have entered into force (IEA, 2013). Based on these efforts, a reduction in energy intensity in German manufacturing over the period 1995-2008 can be expected. Turning to the developments in energy consumption, the German Federal Statistical Office shows that domestic primary energy consumption was by far the largest in manufacturing sectors and has on average increased by 0.6 percent between 2005 and 2015 whereas energy consumption in service activities declined by 0.8 percent over the same period (Destatis, 2018). This was mainly caused by large rises of energy consumption in the following industries: wood and products of wood and cork, coke and refined petroleum products, rubber and plastics and other non-metallic mineral. However, large reductions are observed for textiles, paper and paper products, and other transport equipment.

However, a rise in energy consumption can also be related to a rise in output produced by an industry and as such energy intensity reveals more about rising efficiency of production processes with respect to the use of energy inputs. Martínez (2009) shows that between 1990 and 2005 energy consumption in the German industrial sector grew by 2.3 percent, while simultaneously energy intensity declined by 12 percent. Based on a decomposition analysis she finds that German industry is overall more capital intensive than Colombian industry, whereas energy intensity in the former is lower. Hence, this implies that the adoption of more advanced technologies reflected by higher capital intensity is an important driver of energy intensity. On the other hand, more capital intensive industries within Germany were found to be more energy intensive than less capital intensive ones. However, this could be explained by the fact that energy intense manufacturing industries, initially require more capital goods in their production processes. In this case, capital deepening does not necessarily result in rising energy intensities.

Schlomann et al. (2015a) show that the energy efficiency improvements in German manufacturing after 2000 were mainly related to structural changes towards less energy intense manufacturing, such as transport equipment production. Similar results are presented in the report on German energy efficiency by ABB (2012). Furthermore, between 1992 and 2010 an annual reduction in energy intensity of only 0.2 percent was due to within sector improvements and that for the latter part of the period the non-structural element was even positive (see figure 3.2). As argued by Schlomann et al. (2015b), this rise in energy intensity within sectors could have been an effect of underutilization of production facilities after 2007.

Figure 3.2 - Trends in the energy intensity of manufacturing and structural effect



Source: ABB energy efficiency report (2012)

Moreover, it should be noted that these statistics only account for energy intensity of manufacturing activities itself, whereas the subsequent analysis looks into the energy intensity of an entire value chain in order to account for the energy efficiency changes of upstream linkages that produce automation equipment and to prevent overstating of efficiency improvements in the country-of-completion related to off-shoring of energy intense stages. Considering the previously discussed rise in foreign value added by other European countries identified by Los et al (2015), efficiency developments in the rest of the EU can also affect energy intensity in German GVCs. Schlomann et al. (2015b) show that the EU average energy intensity reduction of manufacturing at constant structure (so within sector improvements) between 2000 and 2007 was just below 2 percent, whereas the structural change component amounted to approximately 0.6 percent. Consequently, the energy efficiency of German manufacturing GVCs might decline due to less energy intense production of intermediate inputs in other EU countries.

4. Data

As outlined before, the imperative of this paper is to examine the environmental impact of automation in German manufacturing GVCs, meaning that Germany is the country-of-completion. Due to the data limitations, direct measurement of automation is not possible. Instead, labor income share developments will serve as a proxy for automation, since both theory and empirical evidence suggest that automation affects the labor income share. Moreover, the environmental impact of automation will be measured by changes in energy intensity as this was found to be the main driver of CO_2 reductions in Europe

In order to determine the changes in labor income share of value added and energy intensity for the GVCs of 14 German manufacturing industries over the period 1995-2008, I make use of the world input-output tables (WIOTs) from the 2013 release of the World Input-Output Database (Timmer et al., 2015). The WIOD also covers the years 2009 - 2011, but these are not considered in the analysis as the start of the Great Recession might bias the results through underutilization of production facilities, which can cause energy intensity to rise. The WIOTs contain bilateral trade data on 35 different industries in 40 different countries and an additional region that is called 'rest of the world', which contains estimated data for the remaining part of the world economy. Most of the industries are at the two-digit ISIC rev.3 level and include agriculture, mining, construction, utilities, 14 manufacturing industries, telecom, finance, business services, personal services, eight trade and transport services industries and three public services (see Appendix A).

Since the WIOTs only contain data on trade flows and value added expressed in millions of current US dollars, additional information is needed to determine the changes in labor compensation and energy consumption. Data on labor compensation is drawn from the socio-economic satellite accounts (Timmer et al., 2015) and data on energy use is taken from the environmental satellite accounts, which are also constructed for the WIOD (Genty, 2012). The dataset contains information on both gross energy use and emission relevant energy use. The difference between the two indicators is that gross energy use includes the total amount of energy inputs required to produce a particular level of output, which means that when we look at the final production stage all energy inputs of the upstream stages are included and that emission relevant energy use only accounts for the energy inputs related to a particular production stage. Using the former measure to evaluate the energy use of an entire GVC results in double counting of emissions. Consequently, the subsequent analysis uses the emissions relevant energy use. Such data is available for all regions including ‘rest of the world’ and is expressed in terajoules (TJ), which can be directly used in combination with the WIOTs expressed in millions of US$.

On the other hand, the labor compensation is initially expressed in millions of local currency units and as such is not directly compatible with the WIOTs. The WIOD provides a supplementary document containing the exchange rates that have been used to transform all bilateral trade data in the WIOTs into their respective US$ values. Consequently, I have applied these exchange rates to express the labor compensation data in millions of US$. Another problem for the subsequent input-output analysis is that there is no labor compensation data available for the ‘rest of the world’ region (RoW). To counter this issue, I have estimated the values for RoW as follows. First, I took the average labor compensation and value added levels over all country-industry combinations other than RoW. Subsequently, dividing the average labor compensation by the average value added provides the average labor income share. Now the labor compensation in the 35 RoW industries are determined by multiplying the value added levels with the average labor income share for each year.

Table 4.1 - A Stylized World Input-Output Table (adapted from Los et al., 2015)

	Intermediate Inputs (*n* columns per country)	Final Demand (one column per country)	Total Output
	1 … N	1 … N	
n industries, country 1 ... *n* industries, country *N*	$\mathbf{Z}^{11}$ $\mathbf{Z}^{1\cdot}$ $\mathbf{Z}^{1N}$ $\mathbf{Z}^{\cdot 1}$ $\mathbf{Z}^{\cdot\cdot}$ $\mathbf{Z}^{1N}$ $\mathbf{Z}^{N1}$ $\mathbf{Z}^{N\cdot}$ $\mathbf{Z}^{NN}$	$\mathbf{y}^{11}$ $\mathbf{y}^{1\cdot}$ $\mathbf{y}^{1N}$ $\mathbf{y}^{\cdot 1}$ $\mathbf{y}^{\cdot\cdot}$ $\mathbf{y}^{\cdot N}$ $\mathbf{y}^{N1}$ $\mathbf{y}^{N\cdot}$ $\mathbf{y}^{NN}$	$\mathbf{x}^{\mathbf{1}}$ $\mathbf{x}^{\cdot}$ $\mathbf{x}^{\boldsymbol{N}}$
Value Added	$(\mathbf{w}^{1})'$ $(\mathbf{w}^{\cdot})'$ $(\mathbf{w}^{N})'$		
Total Output	$(\mathbf{x}^{1})'$ $(\mathbf{x}^{\cdot})'$ $(\mathbf{x}^{N})'$		

A stylized example of a WIOT is presented in table 4.1 in order to provide some intuition of how these tables can be employed for the determination of value added, labor compensation and energy use in GVCs. First of all, it can be observed that a distinction is made between demand for intermediate inputs (presented by matrix **Z**) and final goods and services (presented by matrix **Y**). This separation is characteristic to input-output models, as it allows for the determination of domestic value added versus foreign value added generated in a

GVC, since the total value added embodied in final goods cannot be fully attributed to the country-of-completion. The most important feature of such a method is the incorporation of value added generated by upstream suppliers through input-output linkages. Consequently, the use of WIOTs enables the determination of the labor income share of value added in all stages of the production process. Moreover, the ability to identify the location where intermediate inputs are produced, at home or abroad, can reveal useful information about the causes of labor income share changes as has been discussed in the previous section.

To further clarify the difference between intermediate inputs and final demand, I will now provide an illustration of how the elements in Figure 3.1 should be interpreted. Both the intermediate and final demand matrices $\mathbf{Z}$ and $\mathbf{Y}$ consist of multiple smaller 'blocks' that contain matrices and vectors, respectively.[1] For example, matrix $\mathbf{Z}^{1N}$ represents an *n x n* matrix and its typical element z_{ij}^{1N} indicates the delivery of intermediate inputs from industry *i* in country 1 to industry *j* in country *N*. In example, z_{ij}^{1N} can thus refer to the inputs used by the 'Transport Equipment' industry in Germany, which are produced by the 'Electrical and Optical Equipment' industry in Japan. It is important to keep in mind that *i,j* = 1,..., *n*, where *n* identifies the number of industries. As previously mentioned, the WIOTs used for the subsequent analysis have 35 industries, so *i,j* = 1,…,35 throughout the remainder of this paper. Because matrix $\mathbf{Z}^{1N}$ represents the intermediate inputs used by the industries in country *N* that are produced by industries located in country 1, this matrix consists of the exports from country 1 to country *N*. Moreover, matrix $\mathbf{Z}^{11}$ refers to the intermediate inputs used by industries in country 1 that were also produced in this particular country, so that typical element z_{ij}^{11} represents the inputs produced by industry i in country 1 used by industry j in country 1.

Now shifting focus to the final demand matrix, $\mathbf{y}^{1N}$ represents an *n*-element vector and its typical element y_i^{1N} indicates the consumption in country *N* of final goods and services produced by industry i in country 1. Note that n will refer to the number of industries throughout the remainder of this paper. Included in the final demand vector $\mathbf{y}$ are the following four final use categories: final consumption expenditure by households and non-profit organizations; final consumption expenditure by the government; net capital formation; and inventory adjustments. To illustrate, y_i^{1N} can thus refer to the total German demand for

[1] Matrices are indicated by bold capital letters, whereas bold lower case letters represent vectors. All scalars that represent a specific matrix or vector element are identified by italicized lower case letters.

final goods produced in the 'Mining and Quarrying' industry in Sweden. Also here applies that $\mathbf{y}^{1N}$ represents the demand in country N for imported final goods and services from the industries in country 1. Moreover, $\mathbf{y}^{11}$ indicates the final demand by country 1 for domestically produced goods and services.

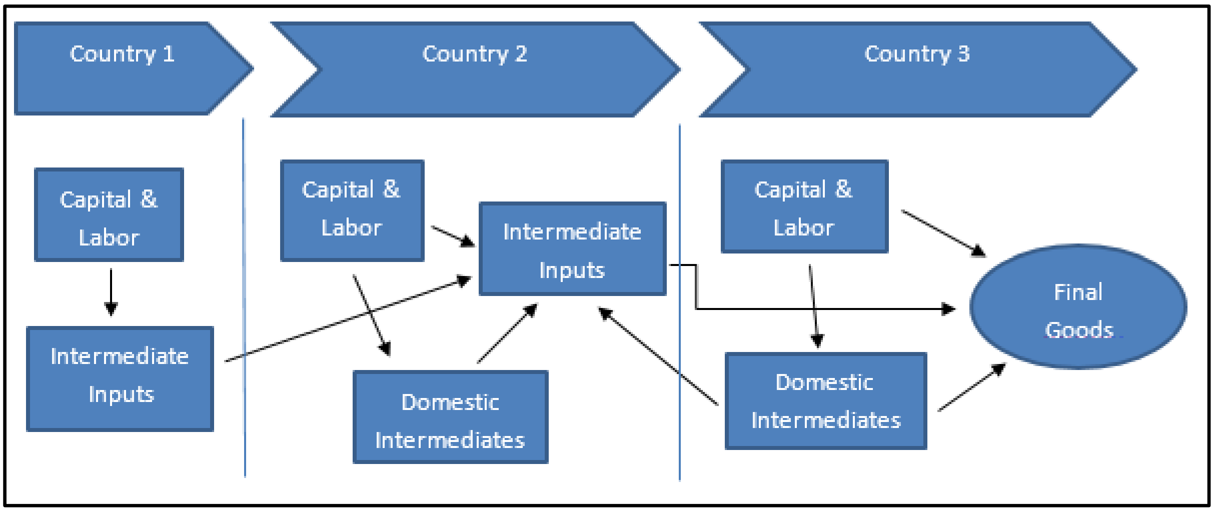
Besides, $\mathbf{x}^{N}$ represents an n-element vector containing total output levels, which corresponds to the intermediate input use and value added (sum over the rows) or the intermediate inputs plus final demand (sum over the columns) of country N. Here the typical element x_i^N indicates the total output of industry i in country N. Additionally, vector $\mathbf{w}^{N}$ represents total value added for country N and its typical element w_i^N thus refers to the value added generated in industry i of country N. Moreover, this vector can be further disaggregated into a labor compensation and other value added vector which also consist of n-elements. In addition, the energy consumption levels can be determined by replacing the value added vector **w** by vector **em**, which contains the amount of emission relevant energy use (in TJ).

As previously touched upon, the domestic labor income and value added levels obtained from the input-output analysis will be used to determine the change in labor income shares over the period 1995 – 2008 in order to identify the presence of automation. Hereafter, the energy intensity will be obtained by dividing the emission relevant energy use levels by GDP (equals value added) as was suggested in equation (1). These series will then be used as variables in the regression equation.

5. Methodology

Since the previous section explained into more detail how all elements in a WIOT should be interpreted, I will now proceed with a discussion of the methodological approach adopted in this paper. In order to determine the total value added and labor compensation required for the production final output of industry i in country N, all intermediate input linkages should be considered. The upstream suppliers of this industry can both be located within the country-of-completion, but also abroad. A stylized example of such an internationally fragmented value chain is presented below to illustrate the relevance of the input-output framework.

Figure 5.1 - A stylized example of a Global Value Chain (adapted from Los et al., 2015)



If we consider figure 5.1 to present the production process of a car in the German transport equipment industry, it can be observed that the production process is geographically dispersed across three countries. Here country 3 represents Germany, which is the country-of-completion, whereas country 2 delivers intermediate inputs such as steel sheets and tires. In turn, the inputs used to produce these steel sheets and tires are delivered by either domestic industries in country 2, or imported from industries in country 1. All these production stages contribute to final output value of the German car as they add value in the form of labor and capital inputs. International fragmentation allows the German car manufacturer to structure the value chain in such a way that each of the stages is performed in the most cost effective location. If intermediate inputs that were previously produced in country 3 are now offshored to country 2 due to lower labor costs, this can affect the share of labor compensation with respect to value added in the overall GVC. Moreover, automation of stages in any of the three countries will result in a reduction of value added in the form of labor compensation and a rise in the value added generated by capital inputs. As such, making use of input-output (IO) models enables us to track the changes in total value added and labor compensation embodied in the production of final goods in the German transport equipment sector over time. Additionally, an IO model enables the decomposition of value added and labor compensation into a domestic and foreign component. In similar vein, the above rationale can also be applied to determine the total energy consumption related to the production of final output in the German transport equipment sector.

As was outlined in section 2, it is important to account for the possibility of declining labor income shares and changes in energy intensity being related to offshoring. Consequently, analyzing the developments in entire GVCs instead of evaluating the developments in industries at the country level will enable us to gain more insights into the actual source of labor income share changes. Moreover, examining the energy intensity developments of the entire production chain captures the earlier discussed rebound effect related to the production of automation technology in more upstream stages of a GVC.

5.1 Deriving the Labor Income Share

First of all, I will start by explaining how the total value added and labor compensation levels of GVCs can be derived through the use of an IO-model. Subsequently, the obtained value added and labor compensation levels will be used to obtain the labor income (LI) share of a particular GVC.

The matrices below represent a simplified example of a WIOT including two regions, where *s* represents the country under evaluation and *r* represents all remaining countries. As outlined in section 3, matrix **Z** contains the data on intermediate goods or services produced in industries in either country s or r and are used by industries in country s or r. Hence, $\mathbf{Z}^{sr}$ identifies the intermediates produced by region s that are used in the production processes in region *r*. In similar vein, matrix **Y** represents the production of final goods and services in country s and *r*, that are consumed by both s and *r*, such that $\mathbf{y}^{sr}$ represents the final output produced in country *s* in order to satisfy final demand in country *r*.

$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_{ss} & \mathbf{Z}_{sr} \\ \mathbf{Z}_{rs} & \mathbf{Z}_{rr} \end{bmatrix}, \qquad \mathbf{Y} = \begin{bmatrix} \mathbf{y}_{ss} & \mathbf{y}_{sr} \\ \mathbf{y}_{rs} & \mathbf{y}_{rr} \end{bmatrix} \qquad and \qquad \mathbf{A} = \begin{bmatrix} \mathbf{A}_{ss} & \mathbf{A}_{sr} \\ \mathbf{A}_{rs} & \mathbf{A}_{rr} \end{bmatrix}$$

Matrix **Z** can thus be further decomposed into four smaller *n* x *n* matrices, where matrix $\mathbf{Z}_{ss}$ refers to the domestically produced intermediate inputs consumed by domestic industries. The intermediate inputs produced in *s* that are used by foreign industries are represented by $\mathbf{Z}_{sr}$. Furthermore, matrix **Y** consists of four *n*-element vectors, where $\mathbf{y}_{ss}$ contains the demand levels in country *s* for domestically produced final goods and services. Hence, $\mathbf{y}_{rs}$ represents the demand in region *s* for final goods and services produced abroad. Dividing each element in matrix **Z** by the corresponding element of the gross output vector **x**, such that typical element $a_{ij}^{sr} = z_{ij}^{sr}/x_j^r$, creates the direct input coefficients matrix **A**. Here typical element a_{ij}^{ss} in $\mathbf{A}^{ss}$represents the amount of inputs from industry *i* in country *s* required to produce one unit of gross output in industry *j* in country *s*.

Additionally, the value added coefficients are contained in an *n* x *k*-element vector labeled **v**, where *k* indicates the amount of countries in the model and is constructed by dividing the elements in **w** by the corresponding elements of **x**. Hence, typical element v_i^s refers to the amount of value added created per unit of gross output of industry i in country s ($v_i^s = w_i^s/x_i^s$). In order to determine the value added created by each industry i in country j related to the final demand for goods of industry i in country s, which is reflected by $\mathbf{y}_i^{ss} + \mathbf{y}_i^{sr}$, the methodology adopted in Los et al. (2015) is followed.[2]

$$\mathbf{g} = \mathbf{v}'(\mathbf{I}-\mathbf{A})^{-1}\mathbf{Yi} \tag{3}$$

In this equation, vector **g** contains the value added generated in each of the country-industry combinations involved in the entire GVC. Furthermore, the GVC under consideration is determined by **Y** in the sense that only the elements of **Y** that relate to a particular country-industry combination take their original values, whereas all other elements are set to zero. As such, the adjusted **Y** matrix will look as follows if we consider the GVC of industry 1 in country s:

$$\mathbf{Y}^* = \begin{bmatrix} \mathbf{y}_{ss}^* & \mathbf{y}_{sr}^* \\ 0 & 0 \end{bmatrix} \qquad \text{with} \qquad \mathbf{y}_{ss}^* = \begin{pmatrix} y_i^{ss} \\ 0 \\ \vdots \\ 0 \end{pmatrix} \quad \text{and} \quad \mathbf{y}_{sr}^* = \begin{pmatrix} y_i^{sr} \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

Additionally, recall that **A** contains the direct inputs needed to fulfill one unit of total output. However, the production of these intermediate inputs also requires inputs and in a similar vein the production processes of those inputs again use inputs. Therefore $(\mathbf{I}-\mathbf{A})^{-1}$ in equation (3) represents the Leontief inverse (**L**), which specifies the total value of intermediate inputs (so from first-, second-, third-tier suppliers, and so forth) needed to produce one unit of final demand. Furthermore **i** represents a summation vector consisting of ones, for which the number of rows is equal to the amount of columns in **Y**. As such, equation (3) can be written in matrix notation as follows:

$$\mathbf{g} = \mathbf{v}' \begin{bmatrix} \mathbf{L}^{ss} & \mathbf{L}^{sr} \\ \mathbf{L}^{rs} & \mathbf{L}^{rr} \end{bmatrix} \begin{bmatrix} \mathbf{y}_{ss}^* & \mathbf{y}_{sr}^* \\ 0 & 0 \end{bmatrix} \mathbf{i} \tag{4}$$

Hence, the final output value of goods produced by industry i in country j, denoted by FINO(i,j), consists of the sum of value added in industries i in all countries k required for production of good (i, j). Vector **g** contains the corresponding VA(k)(i, j) levels for each (i, j) such that:

$$FINO(i,j) = \textstyle\sum_k VA(k)(i,j) \tag{5}$$

---

[2] This methodological approach has been commonly used in input-output analysis for a long time. A more detailed explanation can be found in Miller and Blair (2009).

Since the value added vector **w** can be further decomposed into labor income and capital income, the above methodology can also be employed to derive the labor compensation embodied in a particular GVC. In order to do so, vector **w** is replaced by a vector of the same dimensions, which contains labor compensation levels per for each industry *i* in country *j*. Similar to the derivation of **v**, the vector with labor income coefficients called **l** is obtained by dividing the elements of the labor compensation vector by the corresponding elements of **x**. Vector **li** contains the labor income generated in each of the country-industry combinations involved in the entire GVC and is derived by the following equation:

$$\mathbf{li} = \mathbf{l}'(\mathbf{I}-\mathbf{A})^{-1}\mathbf{Yi} \tag{6}$$

Since **li** contains the corresponding LI(*k*)(*i*, *j*) levels for each (*i*, *j*) the labor income related to the production of final good (*i*, *j*), denoted by LIFINO (*i*, *j*), is derived as follows:

$$LIFINO(i,j) = \sum_k LI(k)(i,j) \tag{7}$$

After the labor compensation and value added levels for each GVC are computed, it is now possible to determine the labor income share ratio as follows:

$$LI\ share\ (i,j) = \frac{LIFINO(i,j)}{FINO(i,j)} \tag{8}$$

For the ease of notation the above equations do not incorporate a time indicator. However, the equations are executed for each year of the period under evaluation. As such, it can be evaluated how the labor income share of a particular GVC has developed over time.

5.2 Accounting for Offshoring

In order to evaluate whether offshoring might have affected the LI share, I will continue to follow the approach of Los et al. (2015) by deriving the foreign value added of a GVC, which is denoted by FVA (*i*, *j*). It contains all value added outside country-of-completion *j* and is obtained by the following equation:

$$FVA(i,j) = \sum_{k\neq j} VA(k)(i,j) = FINO(i,j) - VA(j)(i,j) \tag{9}$$

Moreover, this can be expressed as a share of total value added in the production of good (*i*, *j*) in order to measure whether foreign stages became more important throughout the period of interest:

$$FVAS(i,j) = \frac{FVA(i,j)}{FINO(i,j)} \tag{10}$$

First a visual inspection of the developments in LI share and FVA share will be carried out to see whether there seems to be a relation between the two variables. In addition, a simple regression model will be employed to identify whether it is plausible that the LI share is affected by a rise in offshoring. Since the results obtained from the IO-analysis contain data on the years 1995 until 2008 for 14 German GVCs, a fixed effects model is employed to account for unobserved heterogeneity that might arise due to unobserved characteristics related to each individual GVC. It should be noted that the model is only used to detect whether the LI share is significantly affected by a rise in the FVA share and is limited as there are no control variables included. Moreover the percentage change in LI share and FVA share with respect to the year before are used instead of the levels, which leads to the following regression equation:

$$\Delta LI\ share_{i,j\ t} = \beta_0 + \beta_1 \Delta FVAS_{i,j\ t} + \alpha_{i,j} + u_{i,j\ t} \qquad (11)$$

Here $\Delta LI\ share_{i,j\ t}$ represents the percentage change in LI share of GVC (i, j) at time *t* and $\Delta FVAS_{i,J\ t}$ the percentage change in FVA share of GVC (i, j) at time *t*. Moreover, $\alpha_{i,j}$ is the unobserved GVC heterogeneity effect and $u_{i,j\ t}$ is the normal error term.

5.3 Deriving Energy Intensity

Now the methodology used to derive value added and labor compensation levels of a value chain will be adapted in order to determine the energy use of a particular GVC. In order to do so, vector **w** is replaced by vector **em**, which contains emission relevant energy use data for each industry *i* in country *j*. Similar to the derivation of **v** and **l**, the vector with energy use coefficients called **ec** is obtained by dividing the elements of the labor compensation vector by the corresponding elements of **x**. Vector **e** contains the energy use levels in each of the country-industry combinations involved in the entire GVC and is derived by the following equation:

$$\mathbf{e} = \mathbf{ec}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{Yi} \qquad (12)$$

Here vector **e** contains the corresponding Energy Use (*k*)(*i*, *j*) levels for each (*i*, *j*) related to the production of final good (*i*, *j*). As such, the sum over the vector denoted by E (*i*, *j*) presents the total energy use embodied in the production of (*i*, *j*), which is derived as follows:

$$E\ (i,j) = \sum_k EU(k)(i,j) \qquad (13)$$

Consequently, energy intensity will be derived in accordance with equation (1) introduced in section 2, which means that energy input levels will be divided by GDP. The total value added generated in a

GVC represents the contribution of this value chain to GDP levels across the countries where the stages are located. As such, equation (14) provides the energy use related to the creation of one US$ of value added in the GVC under evaluation.

$$Energy\ Intensity\ (i,j) = \frac{E\ (i,j)}{FINO(i,j)} \tag{14}$$

Note that also here the equations (12) – (14) do not include a time indicator. However, they will be repeated for each year of the period under evaluation to track the energy intensity development over time.

5.4 Automation and Energy Intensity

Again, a visual inspection of the developments in energy intensity and LI share will be carried out to see whether there seems to be a relation between the two variables. Hereafter, a simple regression model similar to equation (11) will be used to assess whether energy intensity is positively or negatively correlated with LI share. Furthermore, the percentage change in energy intensity and LI share with respect to the previous year are used instead of the levels, which leads to the following regression equation:

$$\Delta E_{i,j\ t} = \beta_0 + \beta_1 \Delta LI\ share_{i,j\ t} + \alpha_{i,j} + u_{i,j\ t} \tag{15}$$

Here $\Delta LI\ share_{i,j\ t}$ represents the percentage change in LI share of GVC (i, j) at time *t* and $\Delta E_{i,j\ t}$ the percentage change in energy intensity of GVC (i, j) at time *t*. Moreover, $\alpha_{i,j}$ is the unobserved GVC heterogeneity effect and $u_{i,j\ t}$ is the normal error term.

6. Results

This section will explore if automation seems to have affected environmental degradation and if so, whether the effect was positive or negative. For the ease of the analysis, each proposition will be evaluated independently. As such, the results for the labor income share developments in the 14 German manufacturing GVCs are presented first. Hereafter, the developments of foreign value added (FVA) shares are presented and linked to the labor income share developments. Subsequently, the energy intensity developments are presented, after which they are compared to the developments of the labor income share in order to answer the question whether labor income shares are correlated with energy intensity.

6.1 Labor Income Share

Table 6.1 presents the developments of the labor income share in all 14 German manufacturing GVCs. It can be observed that the labor income share in 2008 was substantially lower than in 1995 for all GVCs under consideration, which provides a strong indication that production processes have indeed been subject to automation during this period. However, it is interesting to note that the labor income share has increased for nearly all GVCs between 2007 and 2008. An explanation for this observation could be the rising labor productivity and corresponding wage increases that occurred at the outset of the crisis (Mulligan, 2011).

Comparing the labor income share developments of different GVCs shows that the initially more capital intense sectors, characterized by a labor income share below 0.7 in 1995, maintained this position over the period under evaluation. This observation was particularly evident for 'coke, refined petroleum and nuclear fuel', 'pulp, paper, printing and publishing' and 'chemicals and chemical products' GVCs, which all saw their labor income share fall below 0.6 in 2008. Even though, 'rubber and plastics' and 'other non-metallic minerals' still belonged to the bottom 6 in terms of their labor income share in 2008, their labor income share did not show a declining trend prior to 2001. In contrast, the initially most labor intense GVCs were 'manufacturing', 'wood and products of wood and cork', electrical and optical equipment' and 'basic and fabricated metals'. The latter joined the most capital intense sectors at the end of the period as its labor income share fell dramatically. Additionally, large labor income share reductions are observed for the other 3 most labor intense GVCs, meaning that most automation took place in the rather capital intense sectors and very labor intense sectors.

Table 6.1 - Labor Income share developments German manufacturing GVCs 1995-2008

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Food, Beverages & Tobacco														
LI share	0.708	0.705	0.692	0.693	0.697	0.694	0.686	0.688	0.703	0.678	0.688	0.672	0.656	0.670
Δ LI share (%)	n.a.	-0.39	-1.90	0.15	0.69	-0.53	-1.11	0.36	2.15	-3.58	1.48	-2.34	-2.30	2.13
Textiles and Textile Products														
LI share	0.734	0.738	0.720	0.705	0.708	0.701	0.696	0.695	0.694	0.674	0.673	0.650	0.635	0.649
Δ LI share (%)	n.a.	0.61	-2.49	-2.07	0.48	-1.03	-0.74	-0.13	-0.06	-2.89	-0.21	-3.39	-2.39	2.27
Leather, Leather & Footwear														
LI share	0.738	0.741	0.729	0.735	0.710	0.733	0.712	0.673	0.691	0.655	0.658	0.651	0.650	0.673
Δ LI share (%)	n.a	0.40	-1.60	0.70	-3.30	3.21	-2.90	-5.45	2.74	-5.33	0.54	-1.12	-0.11	3.56
Wood and Products of Wood and Cork														
LI share	0.779	0.797	0.746	0.740	0.743	0.732	0.736	0.736	0.727	0.722	0.694	0.661	0.647	0.646
Δ LI share (%)	n.a.	2.36	-6.40	-0.86	0.48	-1.47	0.53	0.02	-1.22	-0.71	-3.90	-4.80	-2.05	-0.10
Pulp, Paper, Paper , Printing and Publishing														
LI share	0.682	0.670	0.673	0.668	0.603	0.608	0.608	0.617	0.624	0.605	0.588	0.575	0.576	0.565
Δ LI share (%)	n.a.	-1.70	0.42	-0.70	-9.75	0.77	0.11	1.36	1.26	-3.04	-2.80	-2.34	0.25	-1.99
Coke, Refined Petroleum and Nuclear Fuel														
LI share	0.622	0.621	0.595	0.553	0.623	0.536	0.531	0.574	0.564	0.542	0.522	0.514	0.530	0.534
Δ LI share (%)	n.a.	-0.09	-4.29	-7.02	12.67	-14.05	-0.91	8.12	-1.71	-3.91	-3.72	-1.38	3.02	0.75
Chemicals & Chemical Prod.														
LI share	0.652	0.651	0.635	0.639	0.640	0.641	0.633	0.618	0.626	0.600	0.586	0.577	0.571	0.583
Δ LI share (%)	n.a.	-0.16	-2.40	0.60	0.19	0.01	-1.26	-2.33	1.40	-4.30	-2.25	-1.55	-1.03	2.15

Table 6.1 (continued) - Labor Income share developments German manufacturing GVCs 1995-2008

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Rubber and Plastics														
LI share	0.668	0.668	0.662	0.661	0.657	0.675	0.682	0.658	0.660	0.646	0.633	0.615	0.615	0.634
Δ LI share (%)	n.a.	-0.05	-0.92	-0.16	-0.62	2.73	1.05	-3.52	0.37	-2.16	-2.02	-2.84	0.09	2.95
Other Non-Metallic Mineral														
LI share	0.652	0.673	0.669	0.668	0.666	0.684	0.700	0.695	0.694	0.662	0.676	0.637	0.612	0.625
Δ LI share (%)	n.a.	3.22	-0.66	-0.13	-0.23	2.62	2.38	-0.69	-0.13	-4.59	2.03	-5.70	-3.96	2.09
Basic Metals and Fabricated Metal														
LI share	0.750	0.758	0.738	0.717	0.728	0.711	0.722	0.709	0.700	0.670	0.657	0.629	0.612	0.627
Δ LI share (%)	n.a.	1.16	-2.69	-2.84	1.48	-2.31	1.57	-1.73	-1.34	-4.24	-2.04	-4.20	-2.78	2.55
Machinery, Nec														
LI share	0.740	0.740	0.722	0.709	0.727	0.721	0.725	0.720	0.719	0.703	0.673	0.655	0.637	0.659
Δ LI share (%)	n.a	0.06	-2.50	-1.81	2.58	-0.91	0.61	-0.69	-0.14	-2.23	-4.19	-2.75	-2.79	3.53
Electrical and Optical Equipment														
LI share	0.762	0.748	0.725	0.719	0.707	0.697	0.728	0.743	0.716	0.691	0.676	0.662	0.634	0.675
Δ LI share (%)	n.a.	-1.83	-3.05	-0.82	-1.70	-1.45	4.57	2.02	-3.63	-3.46	-2.21	-2.07	-4.26	6.53
Transport Equipment														
LI share	0.716	0.736	0.708	0.698	0.715	0.734	0.710	0.708	0.693	0.691	0.677	0.662	0.638	0.674
Δ LI share (%)	n.a.	2.80	-3.76	-1.46	2.53	2.65	-3.26	-0.38	-2.02	-0.31	-2.00	-2.31	-3.66	5.75
Manufacturing, Nec; Recycling														
LI share	0.802	0.801	0.774	0.760	0.756	0.749	0.738	0.747	0.736	0.718	0.710	0.672	0.675	0.686
Δ LI share (%)	n.a.	-0.07	-3.40	-1.82	-0.51	-0.88	-1.48	1.21	-1.57	-2.40	-1.06	-5.44	0.53	1.61

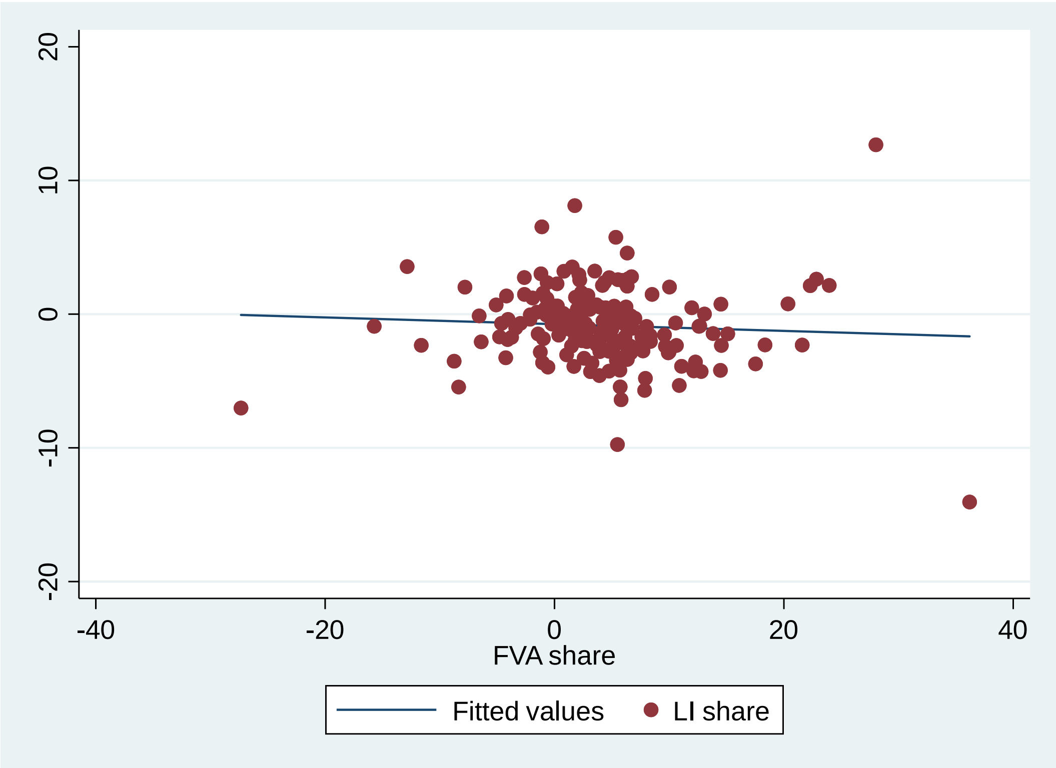
Based on the previously discussed number of robot installations between 1994 and 2014 identified by Dauth et al. (2017), the transport equipment sector is expected to show a substantial decline in labor income share. Interestingly, this is not observed for the period before the turn of the century. However, from 2000 onwards the labor income share indeed fell sharply. This could mean that initially automation was labor complementing or that displaced workers were assigned other tasks within the production process, but eventually led to the inability to absorb excess labor within this GVC. Moreover, the German manufacturing, nec. sector saw a large rise in industrial robot installations, which is in line with the results. In addition, large labor income share declines in the electrical and optical equipment and pulp, paper and paper products GVCs also coincide with the increased amount of industrial robots within these industries. On the contrary, leather and footwear has seen a considerable increase in industrial robot adoption, whereas this did not translate into large labor income share reductions. This might be caused by structural changes within the GVC towards other related industries, such increased employment in the production of automation equipment as was predicted by Leontief and Duchin (1986). Similarly, rubber and plastics were characterized by an above average rise in industrial robot installations, while the labor income share reductions did not materialize until 2001. Hereafter the labor income share started to decline, which could again mean that throughout the first phase of automation excess labor was absorbed elsewhere in the GVC, whereas the amount of newly created jobs within the sector or in related industries was eventually not sufficient.

Based on the aforementioned results, we can confirm proposition 1 for most GVCs as the developments exhibit a downward sloping trend in labor income shares for twelve out of fourteen industries. However, for most industries this trend was more pronounced after the turn of the century. The two exceptions are the ‘food, beverages and tobacco’ and ‘basic and fabricated metal’ industries, which both seem to stagnate around their initial labor income share levels between 1995 and 2008.

6.2 Offshoring

Now that we have confirmed the presence of labor income share declines in most GVCs, I will turn to the evaluation of proposition 2 in order to determine whether offshoring has played a role in the labor income share reductions. In line with the findings of Los et al. (2015), the FVA shares have increased substantially over the period 1995-2008 for all German GVCs, which means that the value added created outside of the country-of-completion has risen (the results are presented in appendix B.1). Consequently, we might worry that the declining labor income shares are partially determined by lower labor costs within the entire GVC due to offshoring. However, Los et al. (2015) showed that a large share of the trade in intermediate inputs in German manufacturing GVCs takes place within the European Union. Since the IFR (2017) showed that Europe was the most robot dense region in the world, it is unrealistic to assume that declining labor income shares are solely related to lower wages in foreign production locations. In contrast, the OECD (2015) found that Chinese suppliers were to a rising extend involved in German GVCs. However, even though lower labor costs could have affected the labor income share, it should be noted that for example the German transport equipment sector generated only 4.3 percent of its total value added in East Asia (Los et al., 2015). Hence, the impact of lower wages is likely to be limited.

Figure 6.1 - Scatterplot foreign value added shares and labor income shares 1995-2008 (% changes)

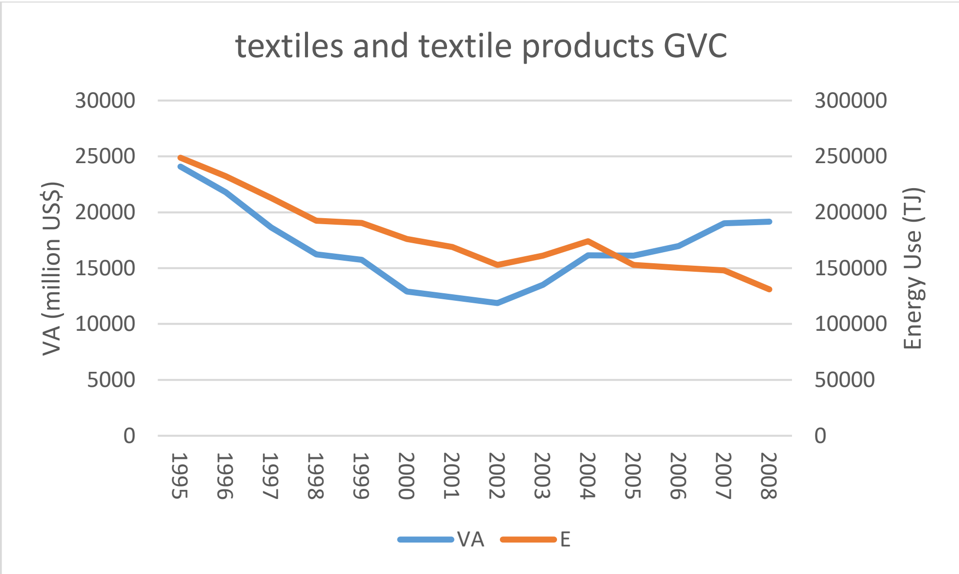


The relationship between the labor income share and FVA share changes is presented in figure 6.1 and does indicate a strong correlation between the two series. In order to ensure that labor income shares are not determined by offshoring, the simple fixed effects model introduced as equation (11) is employed. The regression results are presented in Appendix B.1 and show that a rise in FVA share reduces the labor income share by a negligible amount and the effect is not significant. Based on this sample, there is no statistical evidence in favor of proposition 2, which means that the observed labor income share reductions were probably not related to increased offshoring of production stages.

6.3 Energy Intensity

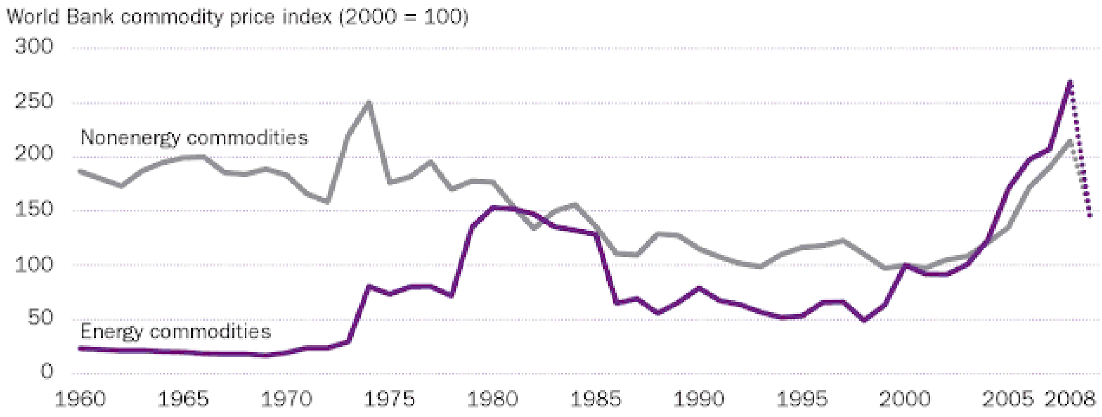
Now that the presence of automation in German GVCs has been examined, the energy intensity developments over the period 1995-2008 are presented. As was discussed in section 3, between 2005 and 2015 large reductions in energy consumption were observed for the German textiles industry, which could have been driven by either a drop in final output or less energy intensive production processes. Figure 6.2 shows that until 2004, the changes in energy consumption seemed to be related to changes in the output level. However, after 2004 the GVC income continued to rise, whereas the energy consumption level dropped below its 2002 value. As such, energy efficiency improvements were an important driver of energy consumption reductions from 2004 onwards. Looking at table 6.4 confirms that energy intensity indeed started to decline after 2001, implying that more output could be produced with less energy inputs.

Figure 6.2 - VA and Energy Use developments 1995-2008



Similar trends are visible for all other GVCs, as the energy intensity levels rose during the first years of the period under evaluation, reaching their highest values around the turn of the century (see table 6.2). Hereafter, they started to decline rapidly and eventually the energy intensity levels in 2008 were substantially lower than the initial levels in 1995 (with the exception of ‘wood and products of wood and cork’). Since energy efficiency is partially determined by energy prices, energy intensity is likely to be higher in regions or periods with low energy prices (IEA, 2008). As can be observed from figure 6.3, the energy commodity prices were relatively low in the period 1995-1999, after which they started to rise rapidly. Hence, this commodity price boom is likely to have raised incentives to adopt more energy efficient technologies, which would explain the observed similarity of energy intensity trends across different GVCs.

Figure 6.3 - Global Commodity Price Developments 1960-2008



Source: World Development Indicators, 2009

In turn, the commodity price boom also provides an explanation for the fact that the most pronounced energy intensity reductions took place within GVCs characterized by high energy intensity levels. In example the German other non-metallic mineral, basic and fabricated metals, chemicals, chemical products and coke, refined petroleum and nuclear fuel industries and textiles and textile products saw the largest absolute declines, resulting in convergence of the energy intensity disparities across GVCs. These industries are both relatively energy and capital intense, which is in line with the findings from Martínez (2009). The commodity price boom probably raised the production costs of the aforementioned industries to such a large extend that they were forced to become more energy efficient. However, looking at the energy intensity reductions as a percentage of their highest value, many of the less energy intense sectors show energy efficiency improvements of almost the same magnitude. This is especially evident for the machinery, nec., electrical and optical equipment and transport equipment GVCs.

Table 6.2 - Energy Intensity developments German manufacturing GVCs 1995-2008

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Food, Beverages & Tobacco														
Energy Intensity	8.56	8.95	9.51	9.85	10.00	11.29	11.09	10.65	9.78	8.63	8.37	7.89	6.64	6.18
Δ Energy Intensity (%)	n.a.	4.54	6.21	3.58	1.49	12.97	-1.74	-4.02	-8.14	-11.75	-3.06	-5.67	-15.90	-6.87
Textiles and Textile Products														
Energy Intensity	10.33	10.66	11.41	11.84	12.08	13.63	13.65	12.88	11.93	10.78	9.50	8.85	7.78	6.84
Δ Energy Intensity (%)	n.a.	3.24	7.00	3.82	2.00	12.80	0.13	-5.65	-7.38	-9.61	-11.91	-6.80	-12.08	-12.12
Leather, Leather & Footwear														
Energy Intensity	9.14	8.44	8.93	9.65	9.95	11.65	12.16	11.19	9.81	8.95	8.05	7.48	6.55	5.31
Δ Energy Intensity (%)	n.a.	-7.67	5.81	8.07	3.10	17.03	4.35	-7.95	-12.35	-8.74	-10.03	-7.14	-12.45	-18.92
Wood and Products of Wood and Cork														
Energy Intensity	8.04	8.21	8.70	9.23	9.72	11.65	11.89	11.76	11.41	10.12	9.32	8.80	8.66	8.29
Δ Energy Intensity (%)	n.a.	2.09	6.03	6.08	5.32	19.85	1.99	-1.08	-2.97	-11.31	-7.91	-5.53	-1.64	-4.22
Pulp, Paper, Paper , Printing and Publishing														
Energy Intensity	8.53	8.53	9.24	9.37	9.82	11.65	11.63	11.06	10.76	9.82	8.98	8.82	8.03	7.34
Δ Energy Intensity (%)	n.a.	-0.02	8.33	1.44	4.85	18.55	-0.16	-4.93	-2.64	-8.75	-8.53	-1.81	-8.97	-8.64
Coke, Refined Petroleum and Nuclear Fuel														
Energy Intensity	63.69	62.62	69.72	69.45	76.61	71.55	55.99	54.15	50.17	39.49	33.66	27.49	26.32	20.27
Δ Energy Intensity (%)	n.a.	-1.67	11.33	-0.39	10.31	-6.61	-21.75	-3.28	-7.36	-21.29	-14.75	-18.34	-4.24	-23.00
Chemicals & Chemical Prod.														
Energy Intensity	12.10	13.58	14.98	14.53	15.10	16.62	16.27	15.16	13.59	11.82	10.99	10.23	9.16	8.35
Δ Energy Intensity (%)	n.a.	12.24	10.31	-3.01	3.92	10.08	-2.15	-6.78	-10.39	-13.01	-7.03	-6.88	-10.54	-8.84

Table 6.2 (continued) - Energy Intensity developments German manufacturing GVCs 1995-2008

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Rubber and Plastics														
Energy Intensity	8.84	9.73	10.76	10.73	11.43	11.71	11.57	11.07	10.46	9.65	8.53	8.20	7.39	6.72
Δ Energy Intensity (%)	n.a.	10.02	10.57	-0.25	6.47	2.52	-1.19	-4.37	-5.45	-7.78	-11.67	-3.87	-9.78	-9.06
Other Non-Metallic Mineral														
Energy Intensity	14.31	15.69	17.68	17.92	17.81	21.04	20.85	20.01	18.03	15.68	14.48	13.44	12.60	11.45
Δ Energy Intensity (%)	n.a.	9.62	12.67	1.39	-0.63	18.15	-0.90	-4.02	-9.92	-13.02	-7.63	-7.19	-6.26	-9.10
Basic Metals and Fabricated Metal														
Energy Intensity	15.74	16.34	17.78	17.91	18.02	20.18	19.32	18.46	16.34	15.20	13.45	12.88	10.98	9.79
Δ Energy Intensity (%)	n.a.	3.83	8.83	0.74	0.61	11.96	-4.25	-4.42	-11.51	-6.99	-11.50	-4.23	-14.77	-10.84
Machinery, Nec														
Energy Intensity	6.80	6.82	7.16	7.46	7.85	8.78	8.51	7.79	7.20	6.60	6.11	5.93	5.27	4.71
Δ Energy Intensity (%)	n.a.	0.26	5.07	4.12	5.25	11.85	-3.08	-8.43	-7.62	-8.29	-7.44	-3.01	-11.13	-10.60
Electrical and Optical Equipment														
Energy Intensity	6.20	6.39	6.76	7.08	7.42	7.96	8.44	7.71	6.99	6.43	6.07	5.87	5.20	4.53
Δ Energy Intensity (%)	n.a.	3.08	5.83	4.73	4.76	7.22	6.12	-8.71	-9.32	-8.00	-5.68	-3.15	-11.43	-12.92
Transport Equipment														
Energy Intensity	7.83	8.09	8.37	8.84	9.29	10.46	9.72	9.04	8.13	7.61	7.15	6.76	5.97	5.60
Δ Energy Intensity (%)	n.a.	3.32	3.35	5.62	5.19	12.55	-7.06	-6.99	-10.12	-6.33	-6.10	-5.48	-11.73	-6.12
Manufacturing, Nec; Recycling														
Energy Intensity	7.03	7.83	8.32	8.28	8.98	9.50	9.30	8.99	8.27	7.64	6.89	6.53	5.93	5.97
Δ Energy Intensity (%)	n.a.	11.32	6.28	-0.44	8.45	5.82	-2.12	-3.40	-7.94	-7.65	-9.87	-5.10	-9.28	0.66

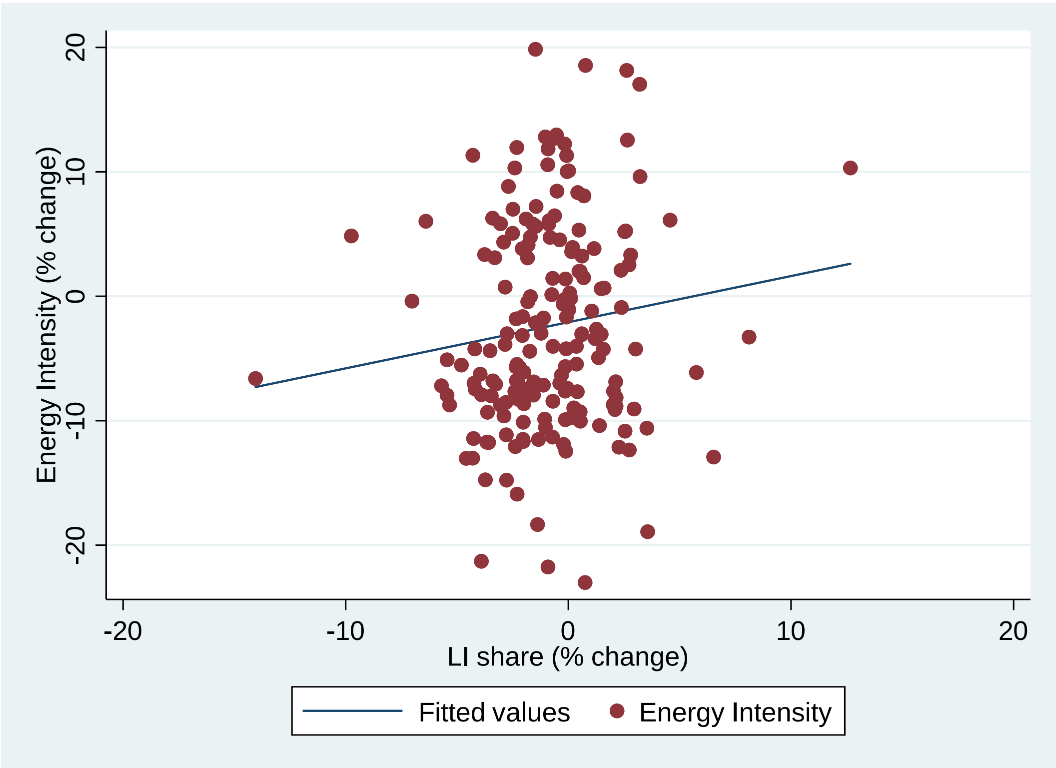
Recall that energy intensity in Europe has declined substantially since the 1970s (see figure 2.3). From the results presented here, it becomes clear that this was not the case for German manufacturing GVCs during the period 1995-2000. There are multiple possible reasons for this contrasting observation. First of all, structural changes towards services or less energy intense manufacturing industries are not of major importance when we look at the developments within a particular GVC as the production of final output in such value chains requires the performance of certain production activities. These activities can become more energy efficient as a result of technological change, but structural chance is only relevant when looking at the domestic stages versus the foreign stages as the former may specialize in less energy intense activities, while the more energy intense activities are moved abroad. Since this analysis evaluates the overall GVC developments with respect to energy intensity levels, offshoring of dirty production stages should not reduce the energy intensity of the entire value chain. Secondly, Dauth et al (2017) argued that an increasing amount of the people entering the labor force find employment in the service industry. This analysis focuses on energy intensity developments within GVCs and as such does not consider the relative importance of more and less energy intense GVCs for the energy intensity of the overall German economy.

Decomposing the energy intensity developments into changes in foreign and domestic production stages reveals that initially energy intensity was much higher in foreign production stages, but these levels started to converge after 2000 (results presented in Appendix B.3). This implies that offshored stages during the period 1995-1999 were more energy intense than the production stages that remained within the home country, whereas the higher energy costs after 2000 resulted in substantial energy efficiency improvements at home as well as abroad. As such, energy prices are likely to have affected the rate of technological progress in the overall value chain. Even though the domestic stages were overall less energy intense, some GVCs still saw energy intensity reductions of up to 50 percent. Consequently, it can be argued that in the domestic stages both structural change towards less energy intense value chain activities and technological advance could have contributed to energy intensity reductions. However, the domestic energy intensity reductions were not matched by a rise in energy intensity abroad, which implies that the overall production process has become more energy efficient due to technological progress.

6.4 The Environmental Impact of Automation

As has become clear from the results presented earlier, labor income shares in nearly all GVCs have shown a downward trend over the period 1995-2008 and energy intensity levels have initially increased, but fell sharply after 2000. Consequently, regression results following from equation (15) will be evaluated in order to determine whether energy intensity and labor income share developments might be correlated. Hereafter, I will zoom in on the developments within specific GVCs as it is interesting to examine whether the industries with the strongest labor income reductions also saw the largest reductions in energy intensity. Due to space limitations, not all individual GVCs are discussed. However, the remaining GVC specific developments can be found in Appendix B.4.

Figure 6.4 - Scatterplot labor income shares and energy intensity developments 1995-2008



First of all, figure 6.4 shows that there might be a small positive correlation between the labor income share and energy intensity developments. Labor income share increases (decreases) seem to coincide with a rise (decline) in energy intensity. The fixed effects regression results are presented in table 6.4 and column 1 confirms that over the entire sample period, there is statistical support for the existence of a small positive correlation between labor income share changes and energy intensity changes. On average, a one percent rise in the labor income share is associated with a 0.386 percent reduction in energy intensity. However, the rising labor income shares in the year 2008, which were as previously mentioned likely related to wage increases caused by the macroeconomic conditions at the time, might have suppressed the effect that automation had on labor income shares. Hence, column 2 presents the results for the restricted sample period of 1995-2007 and shows that excluding 2008 almost doubles the size of the coefficient. Moreover, energy intensity was found to have increased in all GVCs until the years around the turn of the century. Therefore, column 3 presents the results for the years 2000-2008, which reveals that the relationship between labor income shares and energy intensity was indeed somewhat stronger after the year 2000. However, the coefficient is loses some significance and the increase is only 0.44 percentage point.

Table 6.3 - Fixed Effects regression of the changes in energy intensity and labor income shares for German manufacturing GVCs 1995-2008

VARIABLES	(1) Energy Int. (% change)	(2) Energy Int. (% change)	(3) Energy Int. (% change)	(4) Foreign Energy Int. (% change)	(5) Domestic Energy Int. (% change)
Sample	full sample	excluding 2008	2000-2008	full sample	full sample
LI share (% change)	0.386***	0.768***	0.430**		
	(0.120)	(0.185)	(0.156)		
Foreign LI share (% change)				-0.669***	
				(0.203)	
Domestic LI share (% change)					0.502***
					(0.110)
Constant	-2.068***	-0.897***	-5.129***	-4.776***	-1.898***
	(0.102)	(0.208)	(0.139)	(0.116)	(0.077)
Observations	182	168	126	182	182
R-squared	0.018	0.068	0.068	0.018	0.186
Number of Industry_ID	14	14	14	14	14

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

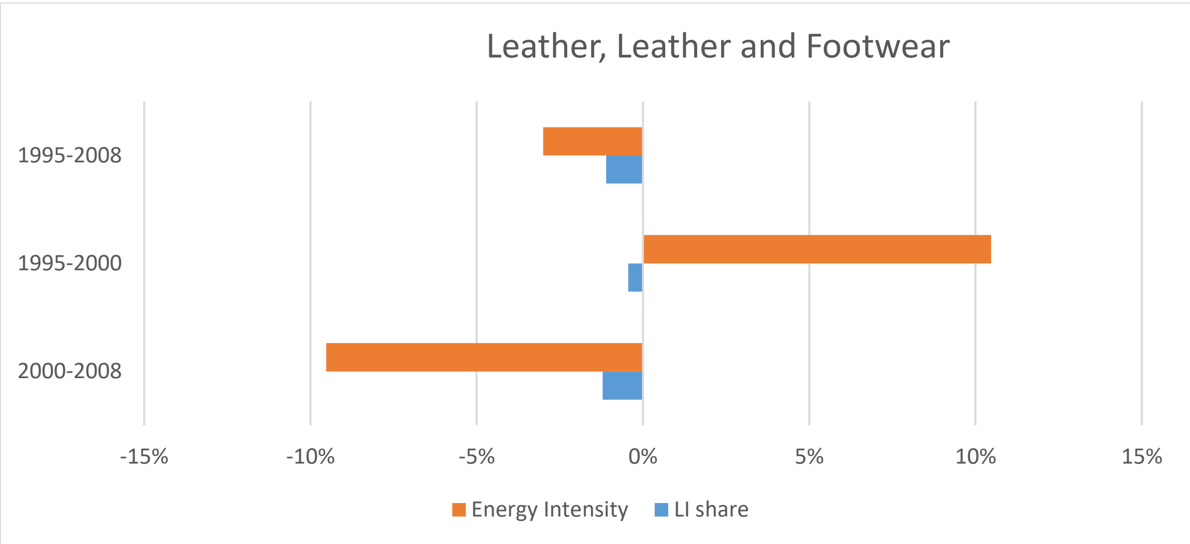
Finally, the regression has been performed for both foreign and domestic stages only.[3] Based on the literature presented in section 2, we might expect that foreign stages exhibit a negative correlation between labor income shares and energy intensity as offshoring to low wage economies suppresses the labor income share in foreign stages, while energy intensity in those locations is assumed to be relatively high. In contrast, labor income share reductions in the

[3] The domestic and foreign labor income share results are not presented, but available upon author's request.

domestic stages were assumed to be related to automation and as such expected to have environmental benefits in terms of their energy intensity. Column 4 indeed exhibits a significant negative correlation as on average a one percent decrease in foreign labor income share is associated with a rise in energy intensity of 0.669 percent. Turning to the results for the domestic stages in column 5, it can be seen that there is a highly significant positive correlation that implies a decline in energy intensity of 0.502 percent when the labor income share falls by one percent. As such it can be argued that the energy efficiency improvements associated with automation only observed in production activities performed in the German stages of the value chain.

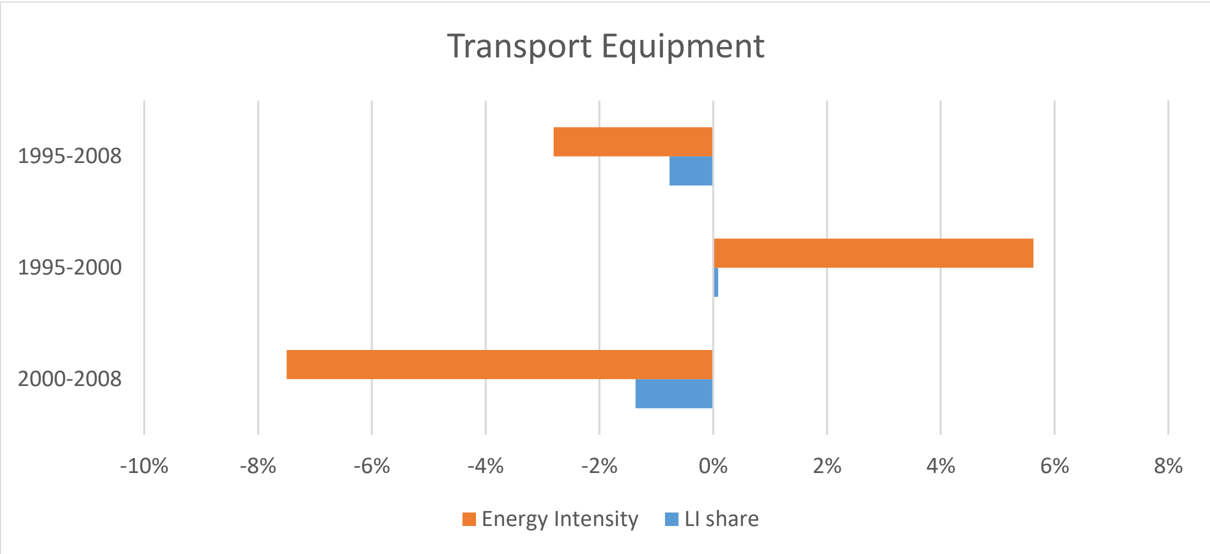
In order to gain some more insights about which GVCs conform to the aforementioned relationship between energy intensity levels and labor income shares, the developments over the entire period under evaluation and the years before and after the turn of the century are analyzed. First of all, the German leather and footwear industry has seen a large increase in industrial robot installations between 1994 and 2014 (Dauth et al., 2017). Hence, it is interesting to examine the changes in the labor income share and energy intensity of this GVC into more detail. Figure 6.5 shows that over the entire period under evaluation, average annual growth rates of -1.1 percent and -3 percent are observed for labor income share and energy intensity, respectively. However, the period before the turn of the century exhibits a large increase in energy intensity combined with a small reduction in labor income shares. In contrast, for the period 2000-2008 a positive correlation between labor income shares and energy intensity levels seems to exist.

Figure 6.5 – Annual Growth Rates of Labor Income Share and Energy Intensity: Leather & Footwear GVC



Turning to the transport equipment sector, which saw the largest rise in industrial robot installations and is the most automated industry in terms of robot density, shows that energy intensity and labor incomes shares indeed followed similar trends. Figure 6.6 presents the coexistence of labor income share reductions (increases) and declining (rising) energy intensity levels for the entire period under evaluation and both subsamples. This exact pattern is also visible for the other non-metallic mineral GVC even though this industry was not identified as having a sharp rise in industrial robot installations and contributed substantially to the overall energy consumption rise in the German industrial sector (see figure 6.7). The latter can be explained by the large decline in energy intensity of observed in the foreign stages of this GVC, while the domestic energy intensity levels remained more or less stable. Consequently, automation might have played a more prominent role for upstream supply linkages located abroad.

Figure 6.6 - Labor Income Share and Energy Intensity Developments in Transport Equipment GVC



Finally, the German manufacturing industry has seen a large rise in industrial robots over the period 1994-2014 (Dauth et al., 2017). Consequently, it would have been expected to see patterns similar to those observed for the transport equipment sector. However, the labor income share declined at an annual rate of 1.5 percent before the turn of the century, whereas this was slightly lower between 2000 and 2008 (see figure 6.8). Interestingly, energy intensity rose considerably during the former period and declined in the latter, which indicates that the initial phase of automation might have actually put a larger pressure on the environment. Moreover, it should be pointed out that the magnitude of the labor income share reductions before 2000 was quite large compared to other industries, which could mean that large scale automation occurred relatively early. Since the energy prices were rather low during this period, these early automation technologies might have been focused on improving labor productivity, but not on reducing the amount of energy inputs.

Figure 6.7 - Labor Income Share and Energy Intensity Developments in Other Non-Metallic Mineral GVC

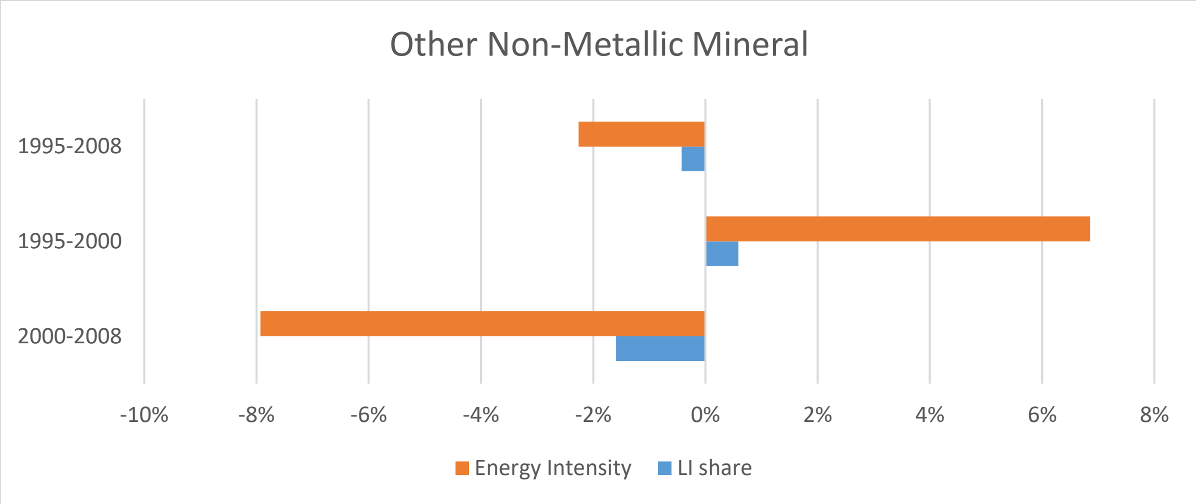
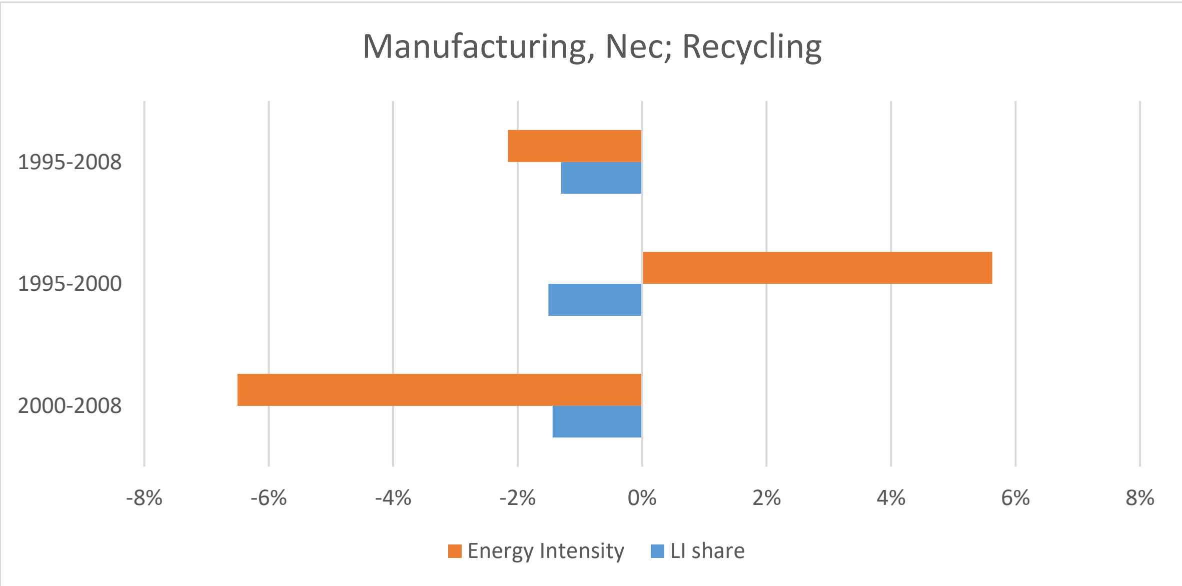


Figure 6.8 - Labor Income Share and Energy Intensity Developments in Electrical & Optical Equipment GVC



7. Discussion

The aim of this paper is to gain insights in the relationship between automation and environmental degradation. In light of the results presented in the previous section, the first proposition regarding the presence of labor income share reductions can be confirmed as all German manufacturing GVCs show substantial declines over the period 1995-2008.

Moreover, no statistical support in favor of the second proposition is found. Hence, it is inferred that relocating production stages to low wage economies did not sufficiently affect labor income shares in the GVCs under evaluation. Consequently, the observed reductions in the labor income share are at least partially related to process automation. Finally, the third proposition hypothesized that automation positively affects environmental degradation as most of the existing literature advocates the energy efficiency benefits arising from these technologies. The analysis reveals the existence of a statistically significant correlation between labor income share changes and energy intensity changes, which is particularly pronounced for the domestic production stages within the GVCs. Therefore, it can be concluded that within Germany the increased adoption of automation technologies has contributed to declining energy intensity levels.

However, the largest declines in energy intensity are observed in the foreign production stages, which has led to conversion of energy intensity levels between domestic and foreign stages over the period under evaluation. In contrast, it is interesting to note that on average a one percent reduction in the labor income share of foreign production stages has actually been accompanied by a rise in energy intensity of 0.669 percent. Consequently, the significant negative correlation implies that on average years characterized by a reduction in the foreign labor income share which can be related to offshoring to low wage countries or automation exhibited a rise in energy intensity. If the former was the reason for the labor income share reductions, it can be inferred that energy intensity in developing economies was relatively high, which is in line with the literature on consumption versus production based emissions. Alternatively, if the labor income share reductions are related to automation, it could be the case that more energy intense production stages, such as manufacturing of microchips used in automation equipment, were located abroad. Since the electronics clusters that employ great amounts of industrial robots in their production processes are mainly located in (South-) East Asia, automation in these upstream stages could have raised energy intensity (IFR, 2017). Hence, the observed energy intensity reductions in offshored stages after 2000 are likely to be related to other types of technological progress rather than to automation. A possible explanation for this observation could be the presence of so called ‘technological leapfrogging’, which refers to the idea that ‘today’s developing countries have access to a set of efficient technologies that was not available to rich countries in the past, when they were at similar stages of economic development’ (van Benthem, 2015: pp.94). In other words, when a developing country imports cleaner technologies from advanced economies, the production is usually perceived to become less energy intense. Relating this to the EKZ hypothesis discussed in section 2, this would imply that developing economies peak at a lower level of energy intensity (Reddy and Goldemberg, 1990). Since energy intensity level in foreign production stages started to fall at the same time as the emergence of the commodity price boom, it could be the case that the German firms exported new technologies to their off-shored production sites in order to suppress severe increases in production costs. Moreover, the accession of China to WTO in 2001 may have raised the ease with which Chinese producers could import technologies from abroad. Since China has become increasingly integrated in German GVCs over the last two decades, this might have contributed to the rise in energy efficiency within foreign production stages (Los et al., 2015; OECD, 2015).

Even though a significant positive correlation between labor income shares and energy intensity is found for the overall GVCs and domestic stages, the size of the coefficients are not particularly large considering the tremendous reduction in energy intensity observed after the year 2000. As mentioned before, a one percent decrease in the overall GVC labor income share was estimated to reduce energy intensity by less than 0.5 percent between 2000 and 2008. Furthermore, the estimated coefficient for the domestic stages over the entire period under evaluation was slightly larger, but still small. Therefore, other forms of technological progress are likely to be responsible for the larger share of the observed energy intensity declines. An additional explanation for these results could be related to the rebound effect (see section 2.2.3). On the one hand, the production of ICT related equipment, such as microchips, was argued to be considerably energy consuming and decreasing prices of ICT equipment have resulted in more widespread application of these energy using technologies (Kander, 2013). On the other hand, the application of ICT can raise energy efficiency through process optimization and better coordination of production activities. In similar vein, increased adoption of automation technologies in production processes can simultaneously improve energy efficiency within GVCs and raise energy intensity due to a higher amount of electrical equipment embodied in the production of final output. Consequently, the energy efficiency improvements realized through automation probably created energy intensity reductions in certain parts of the GVCs, which in turn are partially offset by a rise in energy consumption in order to power and produce the automation equipment. Since the results presented in columns 1-3 of table 6.3 incorporate all upstream supply linkages, the rebound effect is captured and as such the estimated relationship between labor income share and energy intensity developments represents the net effect.

Turning to the period prior to 2000, all GVCs under evaluation exhibited a substantial rise in energy intensity levels in both foreign and domestic operations, while labor income share reductions were present in nearly all of them. As such, this could mean that labor income share reductions were not caused by automation, but occurred due to a decline in capital investments in the presence of a complementary relation between labor and capital (Lawrence, 2015). Even though it is beyond the scope of the model to determine whether automation or lower levels of capital were the main driver of labor income share reductions, most GVCs saw a reduction in value added during this period. This provides an indication that reduced capital investments may have played a role. Another possible explanation could be that during the initial phase of automation, the rebound effect was larger than the energy efficiency improvements obtained from process automation.

Finally, the results from this study show that although the effects might not be exceptional, automation can potentially contribute to emission abatement, especially with respect to German GVC stages. As such, the generally negative attitude towards automation held by society might need to be reconsidered. The current developments in the field of AI may augment the potential of reducing energy efficiency through the adoption of industrial robots or automated software systems. However, it should be noted that the impact of energy efficiency gains in technologies that complement rather than substitute labor is probably more powerful, as a large share of the energy intensity reductions cannot be explained by declining labor income shares. Consequently, the relationship between different types of technological progress and energy consumption should be investigated into more detail in order to identify where the largest potential of further reductions in energy intensity resides. Moreover, climate change is not a local, but a global phenomenon. The finding that labor income share declines were associated with a rise in energy intensity confirms that environmental regulations and policies aimed at reducing energy intensity should reach beyond the borders of the country-of-completion. As such, policy makers will need to provide incentives to raise energy efficiency in all stages of the value chain in order to maintain and accelerate the downward trend that has set in at the start of the new millennium.

8. Conclusion

Over the past decades, increased awareness with respect to the importance of combatting climate change has resulted in a considerable amount of initiatives aimed at understanding the nature of energy consumption within the global economy. In mainstream economics, technological progress is generally considered to be factor saving and as such has the capability of reducing both labor and energy inputs. Therefore it is interesting to examine whether automation, which is usually characterized as labor saving technological change, has reduced the amount of energy inputs embodied in the production of final output. If this is indeed the case, stimulating automation could provide a fruitful policy tool in reducing energy intensity levels.

Multiple empirical studies have investigated the impact of ICT on energy intensity, however, no consensus has yet been reached. Some outcomes show that increased application of these technologies has raised energy intensity as ICT consumes more energy than it saves, whereas other studies have found that process optimization through the employment of ICT has reduced energy intensity within production processes. Since, automation technologies are heavily integrated with ICT, the aforementioned studies can be extended to explore the environmental impact of automation.

8.1 Main Results

This study aims to examine whether automation improves or deteriorates the energy intensity levels in German manufacturing value chains. The decision to focus on German GVCs is related to its prominent role in the adoption and productions of automation technology, such as industrial robots. Due to data limitations, automation is a difficult topic to address empirically and to my knowledge this paper is the first one to evaluate whether process automation could have implications for climate change. Additionally, the analysis accounts for the so-called rebound effect by evaluating complete value chains instead of focusing on domestic industries. Hereby, it is prevented that energy intensity reductions related to offshoring of energy intense production stages are interpreted as energy efficiency improvements related to automation. As such, the central question in this paper is:

Does automation seem to affect energy intensity levels in German GVCs and if so, what is the direction of the effect?

The findings show that on average, labor income share reductions of one percent are associated with a decline in energy intensity of less than 0.5 percent. Energy intensity levels declined to a much larger extend than the labor income shares over the period 2000-2008 and as such the largest part of energy efficiency improvements cannot be explained by automation. Similar to the simultaneous energy expanding as well as reducing effect of ICT, automation can simultaneously increase or reduce energy intensity. Hence, the small correlation between the two variables could be related to the presence of such as rebound effect. Turning to the developments in domestic stages also reveals a positive correlation between labor income share and energy intensity developments, which is slightly more pronounced than that for the overall GVC. However, if energy intense production of for example microchips used in automation technologies takes place abroad, this rebound effect is not incorporated.

Another interesting finding is related to the developments within the foreign production stages. The results show that energy intensity was initially much higher for these stages, but that over the period under evaluation they have converged considerably relative to the energy intensity levels in domestic stages. However, a negative correlation between labor income share and energy intensity developments is found, which implies that automation did not contribute to the observed energy intensity reductions. An explanation could be that the rebound effect entirely offsets the energy efficiency gains. Other forms of technological progress thus played a more prominent role in the energy intensity decline abroad.

8.2 Limitations and Future Research

As outlined before, this study is the first one to investigate the relationship between automation and energy intensity. The lack of publicly available data on automation made it impossible to employ a direct measure of automation. Hence, the labor income share served as a proxy because most of the literature assumes that labor and capital are gross substitutes. However, a major limitation lies in the fact that capital and labor can also be gross complements (Lawrence, 2015). If this is indeed the case, the labor income share reductions provide an imperfect measure for automation as they could be related to a reduction in capital inputs. For the first 5 years of the period under evaluation, this might indeed have been the case as total value added declined in nearly all GVCs. On the other hand, value added levels rose sharply after the turn of the century, which makes it unlikely that reduced capital investments were a problem for the period 2000-2008.

Moreover, the energy intensity is defined as the amount of energy inputs (in TJ) required to create one million US$ of value added. However, value added is measured in current instead of constant prices and therefore might have overstated the actual energy intensity reductions. Nevertheless, between 1995 and 2008 the European Union was characterized by low inflation rates (about two percent per year). Since most of the total value added of German GVCs is generated within this region, using constant prices is not expected to alter the results to a large extend.

Finally, this paper is aimed at exploring whether automation could be related to energy intensity. As a consequence, no causal inferences can be made based on this analysis. Additionally, the regression model used to evaluate the existence of a correlation between the two variables is very limited as there was no data for control variables. Energy intensity can for example be determined by other types of technological change that are labor complementing or fuel switching. Hence, omitted variable bias is probably an issue, which should be considered when interpreting the results.

Since significant correlations are found between energy intensity and labor income share developments, it is interesting to further explore the relationship between the two variables. First of all, the development of a more robust methodology could greatly improve the accuracy of the results. In example, the construction of a satellite account containing data on robot density per industry would give better insights in how large of a role automation actually plays in individual GVCs. Such data would allow for a derivation of the number of robots engaged in the production of a particular level of final goods in any country-industry combination. Comparing this to emission levels can then reveal whether robot intense GVCs are indeed more or less energy intense, which would greatly enhance our understanding of the environmental impact of automation technologies.

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Appendices

A. Industry Aggregation

Table A.1 - Sectoral Coverage WIOD 2013 release

Industry No.	Code	Name
c1	AtB	Agriculture, Hunting, Forestry and Fishing
c2	C	Mining and Quarrying
c3	15t16	Food, Beverages and Tobacco
c4	17t18	Textiles and Textile Products
c5	19	Leather, Leather and Footwear
c6	20	Wood and Products of Wood and Cork
c7	21t22	Pulp, Paper, Paper , Printing and Publishing
c8	23	Coke, Refined Petroleum and Nuclear Fuel
c9	24	Chemicals and Chemical Products
c10	25	Rubber and Plastics
c11	26	Other Non-Metallic Mineral
c12	27t28	Basic Metals and Fabricated Metal
c13	29	Machinery, Nec
c14	30t33	Electrical and Optical Equipment
c15	34t35	Transport Equipment
c16	36t37	Manufacturing, Nec; Recycling
c17	E	Electricity, Gas and Water Supply
c18	F	Construction
c19	50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
c20	51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
c21	52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
c22	H	Hotels and Restaurants
c23	60	Inland Transport
c24	61	Water Transport
c25	62	Air Transport
c26	63	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
c27	64	Post and Telecommunications
c28	J	Financial Intermediation
c29	70	Real Estate Activities
c30	71t74	Renting of M&Eq and Other Business Activities
c31	L	Public Admin and Defence; Compulsory Social Security
c32	M	Education
c33	N	Health and Social Work
c34	O	Other Community, Social and Personal Services
c35	P	Private Households with Employed Persons

B. Additional Results

B.1 Foreign Value Added Shares

Table B.1 - Foreign value added share developments German manufacturing GVCs 1995-2008

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Food, Beverages & Tobacco														
Foregin VA share	0.148	0.149	0.161	0.163	0.159	0.179	0.176	0.172	0.179	0.180	0.197	0.215	0.224	0.245
Δ Foreign VA share (%)	n.a.	1.28	8.04	0.83	-2.33	12.51	-1.84	-2.00	4.05	0.44	9.31	9.28	4.26	9.17
Textiles and Textile Products														
Foregin VA share	0.242	0.243	0.259	0.242	0.272	0.262	0.262	0.245	0.245	0.269	0.284	0.302	0.307	0.307
Δ Foreign VA share (%)	n.a.	0.25	6.79	-6.39	11.97	-3.38	-0.22	-6.57	0.22	9.92	5.49	6.35	1.48	0.22
Leather, Leather & Footwear														
Foregin VA share	0.235	0.233	0.253	0.262	0.269	0.271	0.289	0.265	0.258	0.286	0.304	0.319	0.340	0.296
Δ Foreign VA share (%)	n.a	-0.83	8.34	3.66	2.58	0.82	6.65	-8.36	-2.63	10.88	6.24	5.00	6.62	-12.85
Wood and Products of Wood and Cork														
Foregin VA share	0.147	0.146	0.154	0.164	0.171	0.197	0.203	0.202	0.206	0.207	0.230	0.249	0.256	0.255
Δ Foreign VA share (%)	n.a.	-0.64	5.81	6.25	4.46	15.11	3.16	-0.62	1.97	0.73	11.08	7.93	2.82	-0.27
Pulp, Paper, Paper , Printing and Publishing														
Foregin VA share	0.141	0.135	0.142	0.145	0.153	0.185	0.183	0.176	0.179	0.181	0.188	0.208	0.212	0.217
Δ Foreign VA share (%)	n.a.	-4.79	5.15	2.69	5.49	20.36	-0.71	-4.19	1.83	1.06	3.95	10.63	2.13	2.40
Coke, Refined Petroleum and Nuclear Fuel														
Foregin VA share	0.373	0.382	0.431	0.313	0.401	0.546	0.460	0.468	0.504	0.512	0.602	0.627	0.619	0.709
Δ Foreign VA share (%)	n.a.	2.31	12.79	-27.34	28.03	36.20	-15.72	1.77	7.62	1.69	17.53	4.03	-1.18	14.51
Chemicals & Chemical Prod.														
Foregin VA share	0.173	0.175	0.192	0.202	0.212	0.240	0.245	0.216	0.223	0.230	0.244	0.267	0.275	0.287
Δ Foreign VA share (%)	n.a.	0.95	9.67	5.21	5.32	13.08	1.88	-11.62	2.91	3.14	6.18	9.59	3.01	4.18

Table B.1 (continued) – Foreign value added share developments German manufacturing GVCs 1995-2008

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Rubber and Plastics														
Foregin VA share	0.181	0.177	0.192	0.204	0.216	0.227	0.232	0.211	0.216	0.227	0.245	0.270	0.276	0.281
Δ Foreign VA share (%)	n.a.	-2.11	8.03	6.70	5.84	4.77	2.18	-8.75	1.99	5.50	7.91	9.99	2.07	2.13
Other Non-Metallic Mineral														
Foregin VA share	0.110	0.114	0.126	0.127	0.133	0.164	0.171	0.166	0.169	0.176	0.194	0.209	0.208	0.221
Δ Foreign VA share (%)	n.a.	3.51	10.56	1.11	4.92	22.84	4.37	-2.97	2.17	3.92	10.03	7.86	-0.57	6.34
Basic Metals and Fabricated Metal														
Foregin VA share	0.208	0.206	0.215	0.213	0.207	0.252	0.250	0.240	0.244	0.274	0.297	0.340	0.356	0.364
Δ Foreign VA share (%)	n.a.	-0.66	4.47	-1.24	-2.62	21.60	-1.00	-3.74	1.67	12.14	8.37	14.47	4.76	2.20
Machinery, Nec														
Foregin VA share	0.163	0.164	0.172	0.177	0.187	0.211	0.210	0.201	0.204	0.217	0.230	0.248	0.260	0.264
Δ Foreign VA share (%)	n.a	0.76	5.12	2.85	5.53	12.60	-0.02	-4.62	1.83	6.33	5.70	7.72	5.08	1.55
Electrical and Optical Equipment														
Foregin VA share	0.184	0.182	0.194	0.197	0.209	0.238	0.253	0.233	0.231	0.243	0.256	0.265	0.278	0.275
Δ Foreign VA share (%)	n.a.	-0.97	6.27	1.74	6.15	13.83	6.34	-7.81	-1.04	5.40	5.18	3.49	4.76	-1.10
Transport Equipment														
Foregin VA share	0.211	0.226	0.238	0.249	0.263	0.280	0.268	0.262	0.267	0.286	0.301	0.312	0.322	0.340
Δ Foreign VA share (%)	n.a.	6.72	5.50	4.41	5.89	6.43	-4.25	-2.13	1.77	7.01	5.33	3.70	3.27	5.35
Manufacturing, Nec; Recycling														
Foregin VA share	0.155	0.154	0.163	0.169	0.177	0.199	0.196	0.192	0.193	0.206	0.220	0.233	0.242	0.247
Δ Foreign VA share (%)	n.a.	-0.71	5.89	3.99	4.23	12.67	-1.43	-1.91	0.37	6.64	6.80	5.73	3.96	2.34

B.2 Regression Results Foreign Value Added and Labor Income Share

Table B.2 - Fixed Effects regression of the changes in foreign value added shares and labor income shares for German manufacturing GVCs 1995-2008

Dependent var: LI share (% change)	Fixed Effects
FVAshare (% change)	-0.0281
	(0.0254)
Constant	-0.736***
	(0.105)
Observations	182
Number of industries	14
R-squared	0.005
Industry FE	YES

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

B.3 Foreign versus Domestic Energy Intensity Developments

Table B.3- Domestic and Foreign Energy Intensity in German GVCs 1995-2008

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Food, Beverages & Tobacco														
Energy Intensity Domestic	6.86	7.33	7.91	8.05	7.89	8.89	8.88	8.52	7.82	6.93	6.61	6.30	5.16	4.84
Energy Intensity Foreign	18.37	18.20	17.80	19.07	21.14	22.32	21.48	20.89	18.77	16.40	15.54	13.70	11.77	10.33
Textiles and Textile Products														
Energy Intensity Domestic	8.12	8.72	9.44	9.36	9.49	10.60	10.83	10.22	9.37	8.27	6.60	5.98	5.10	4.51
Energy Intensity Foreign	17.26	16.72	17.05	19.60	19.03	22.15	21.58	21.07	19.79	17.59	16.80	15.48	13.85	12.09
Leather, Leather & Footwear														
Energy Intensity Domestic	6.90	6.20	6.60	7.08	7.03	8.61	9.36	8.41	7.24	6.26	5.14	4.61	3.85	3.11
Energy Intensity Foreign	16.45	15.81	15.83	16.90	17.92	19.82	19.03	18.91	17.21	15.67	14.74	13.59	11.77	10.53
Wood and Products of Wood and Cork														
Energy Intensity Domestic	5.75	6.11	6.48	6.70	6.86	8.35	8.82	8.72	8.59	7.75	6.84	6.45	6.94	6.98
Energy Intensity Foreign	21.36	20.52	20.92	22.15	23.60	25.14	23.91	23.78	22.30	19.18	17.60	15.93	13.67	12.14
Pulp, Paper, Paper , Printing and Publishing														
Energy Intensity Domestic	6.48	6.66	7.27	7.16	7.37	8.67	8.89	8.41	8.45	7.85	6.98	6.87	6.32	5.86
Energy Intensity Foreign	20.98	20.54	21.13	22.33	23.39	24.81	23.84	23.46	21.38	18.78	17.64	16.25	14.38	12.66
Coke, Refined Petroleum and Nuclear Fuel														
Energy Intensity Domestic	71.18	72.87	89.67	76.02	83.09	80.15	65.45	66.79	61.34	48.26	46.51	42.72	40.60	37.01
Energy Intensity Foreign	51.11	46.05	43.37	55.04	66.92	64.40	44.88	39.80	39.18	31.14	25.18	18.42	17.54	13.40
Chemicals & Chemical Prod.														
Energy Intensity Domestic	9.46	11.47	13.00	12.08	12.19	12.79	13.28	12.36	10.84	9.43	8.58	8.02	7.20	6.61
Energy Intensity Foreign	24.71	23.58	23.34	24.24	25.90	28.74	25.50	25.33	23.20	19.85	18.46	16.30	14.32	12.66

Table B.4 (continued) - Domestic and Foreign Energy Intensity in German GVCs 1995-2008

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Rubber and Plastics														
Energy Intensity Domestic	5.82	7.15	8.26	7.76	8.19	7.74	7.91	7.62	7.20	6.75	5.35	5.13	4.70	4.27
Energy Intensity Foreign	22.52	21.71	21.28	22.29	23.13	25.27	23.74	23.91	22.35	19.52	18.29	16.49	14.49	12.99
Other Non-Metallic Mineral														
Energy Intensity Domestic	12.86	14.51	16.61	16.55	16.11	19.12	19.41	18.61	16.50	14.40	13.21	12.42	11.91	11.00
Energy Intensity Foreign	26.12	24.88	25.12	27.33	28.84	30.87	27.86	27.06	25.54	21.66	19.77	17.33	15.25	13.07
Basic Metals and Fabricated Metal														
Energy Intensity Domestic	12.50	13.76	15.27	14.87	14.91	16.93	16.43	15.71	13.62	12.80	11.05	10.42	8.79	8.12
Energy Intensity Foreign	28.07	26.25	26.93	29.17	29.92	29.82	28.01	27.17	24.75	21.55	19.15	17.67	14.93	12.71
Machinery, Nec														
Energy Intensity Domestic	4.10	4.35	4.71	4.65	4.66	5.27	5.16	4.68	4.28	3.86	3.41	3.20	2.76	2.51
Energy Intensity Foreign	20.68	19.40	18.94	20.49	21.70	21.95	21.06	20.18	18.56	16.47	15.16	14.20	12.40	10.83
Electrical and Optical Equipment														
Energy Intensity Domestic	3.66	4.06	4.42	4.41	4.46	4.59	5.06	4.54	4.02	3.54	3.22	3.08	2.58	2.21
Energy Intensity Foreign	17.48	16.86	16.51	18.00	18.63	18.74	18.43	18.11	16.88	15.40	14.33	13.64	12.03	10.67
Transport Equipment														
Energy Intensity Domestic	4.85	5.30	5.59	5.61	5.70	6.62	6.20	5.72	4.97	4.64	4.23	3.84	3.31	3.23
Energy Intensity Foreign	18.97	17.68	17.24	18.59	19.35	20.35	19.35	18.39	16.78	15.05	13.94	13.18	11.54	10.21
Manufacturing, Nec; Recycling														
Energy Intensity Domestic	4.39	5.52	5.96	5.50	5.98	5.79	5.87	5.72	5.21	4.89	4.13	3.89	3.53	4.07
Energy Intensity Foreign	21.40	20.50	20.44	21.94	22.95	24.47	23.35	22.70	21.07	18.25	16.67	15.25	13.44	11.75

B.4 Annual Energy Intensity and Labor Income Share Growth Rates

The figures below present the annual growth rates of the labor income share and energy intensity in German manufacturing GVCs over the period 1995-2008, with a further decomposition of the effect between 1995-2000 and 2000-2008, respectively.

Figure B.1 - Labor Income Share and Energy Intensity Developments: Food, Beverages & Tobacco GVC

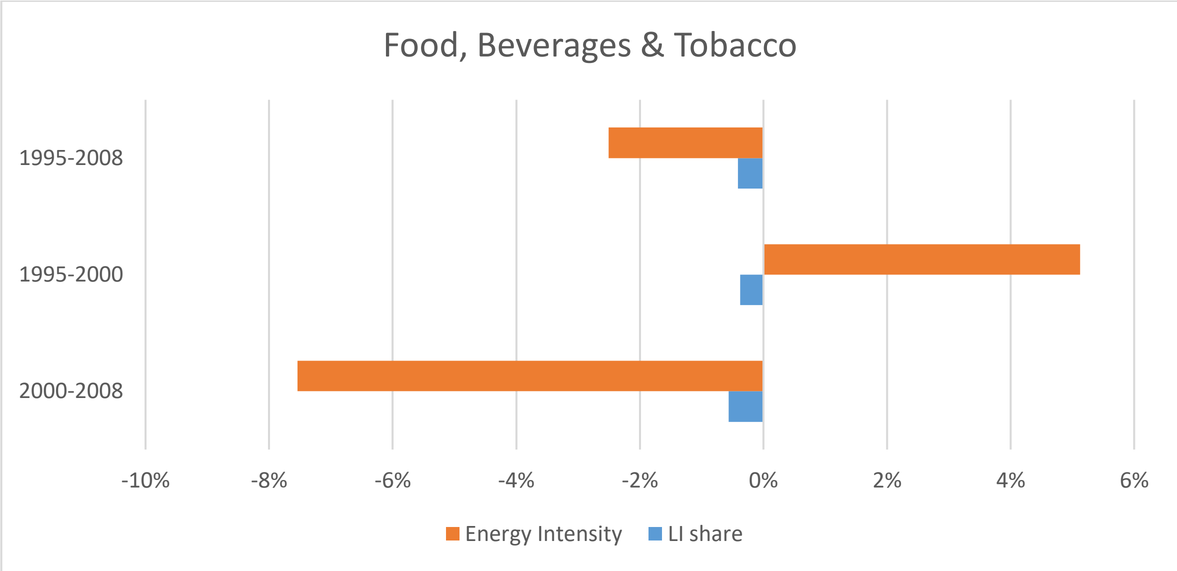

Figure B.2 - Labor Income Share and Energy Intensity Developments: Textiles & Textile Products GVC

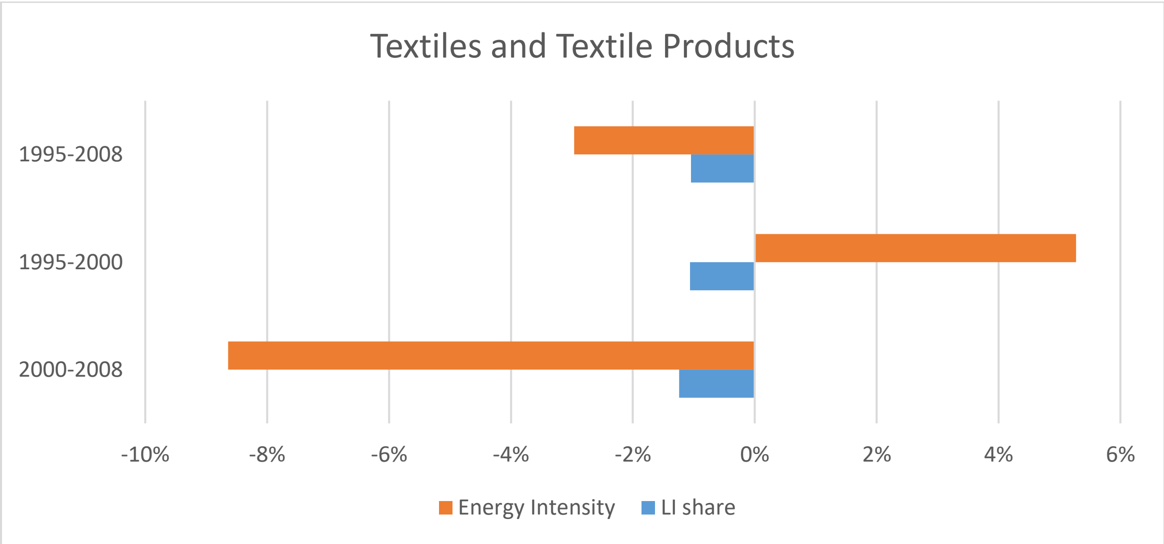

Figure B.3 - Labor Income Share and Energy Intensity Developments: Wood & Products of Wood and Cork GVC

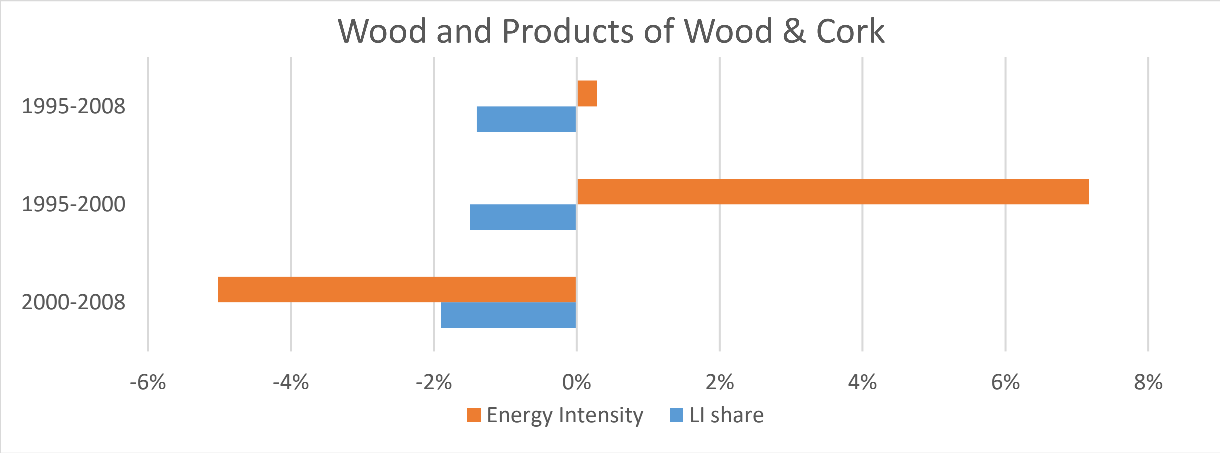

Figure B.4 -Labor Income Share and Energy Intensity Developments: Pulp, Paper, Printing & Pusblishing GVC

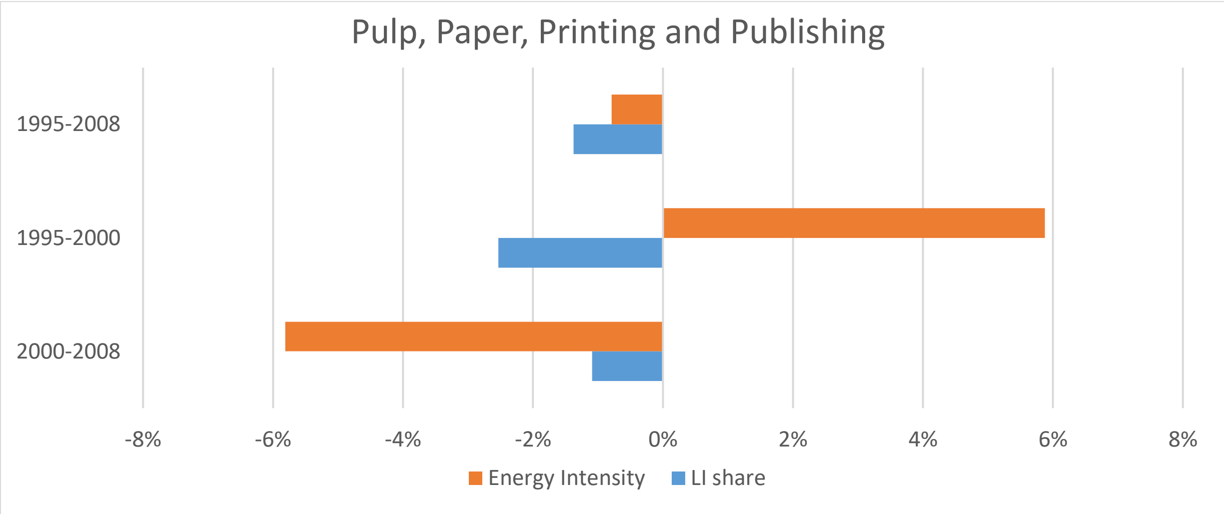

Figure B.5 - Labor Income Share and Energy Intensity Developments: Coke, Refined Petroleum & Nuclear Fuel GVC

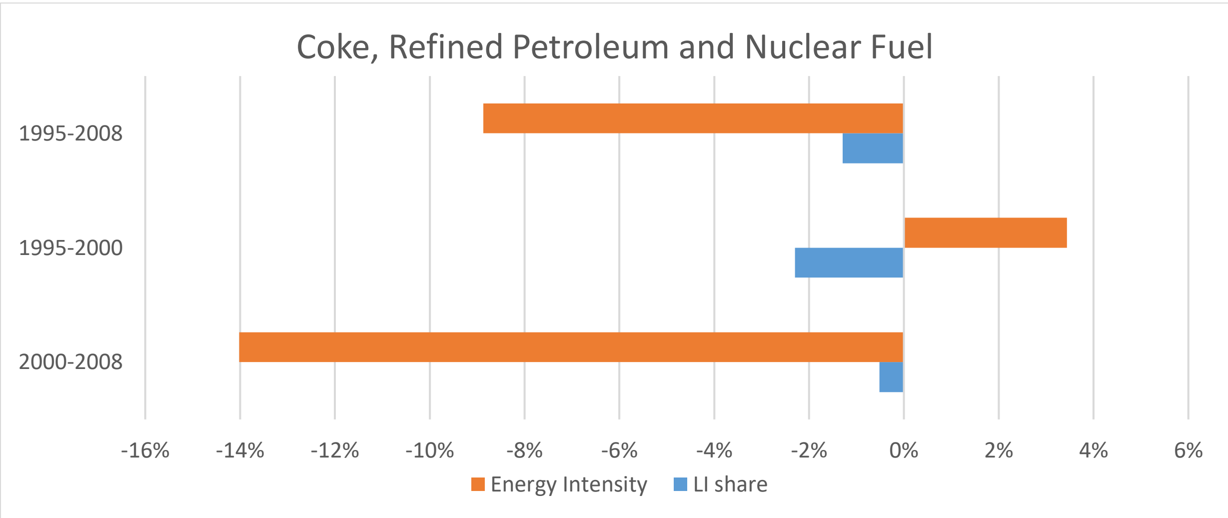

Figure B.6 - Labor Income Share and Energy Intensity Developments: Rubber & Plastics GVC

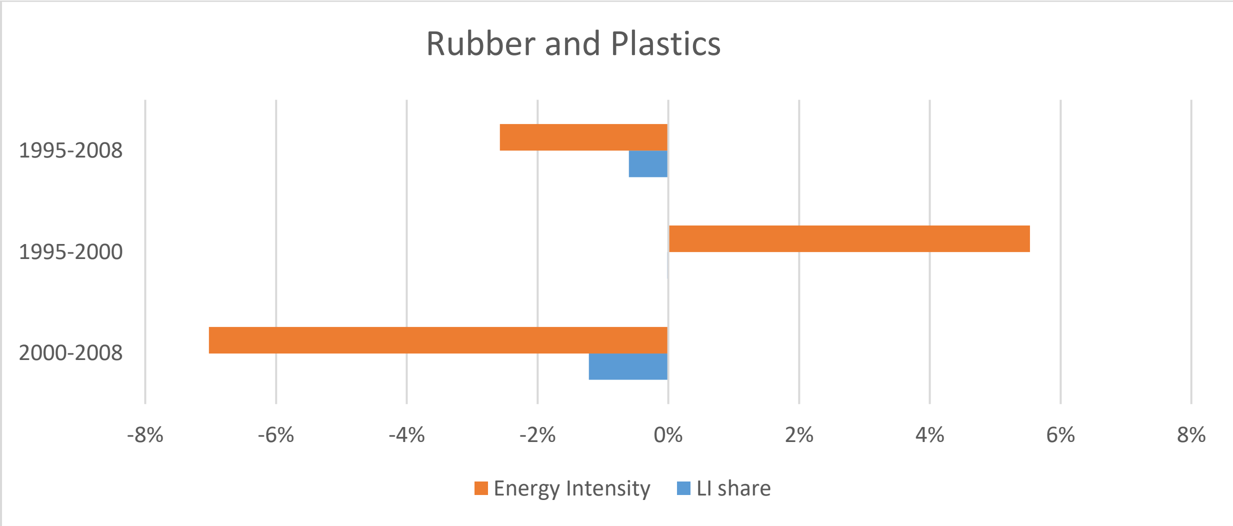

Figure B.7- Labor Income Share and Energy Intensity Developments: Chemicals and Chemical Products GVC

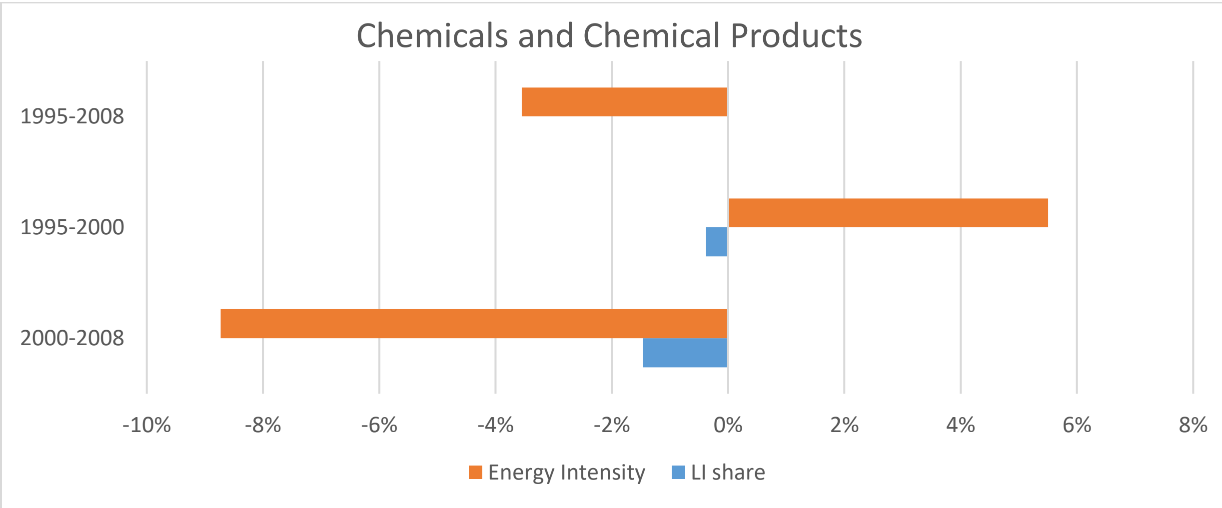

Figure B.8 - Labor Income Share and Energy Intensity Developments: Basic Metal and Fabricated Metal GVC

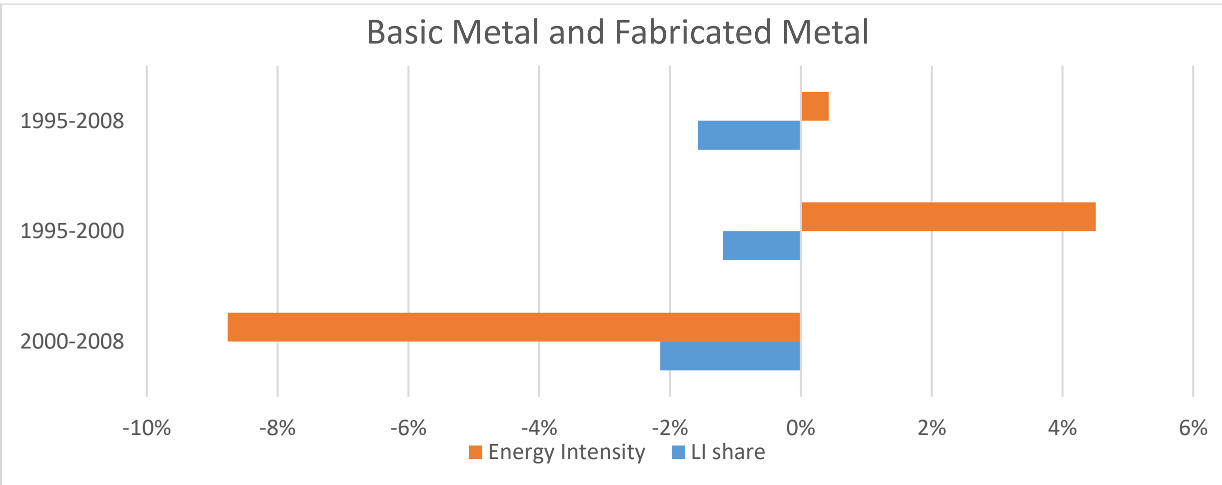

Figure B.9 - Labor Income Share and Energy Intensity Developments: Machinery, Nec. GVC

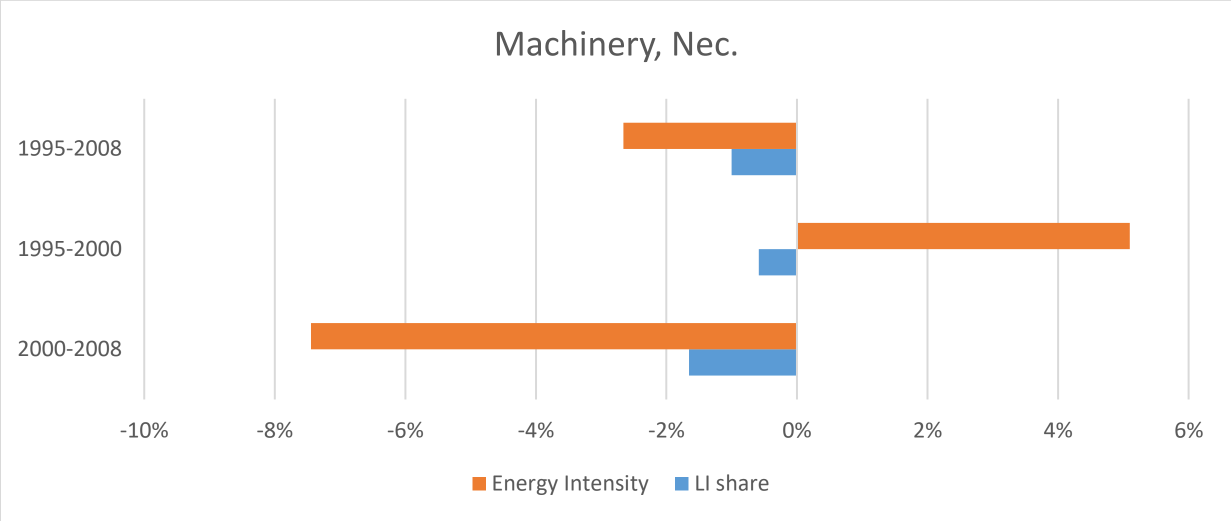

Figure B.10 - Labor Income Share and Energy Intensity Developments: Electrical & Optical Equipment GVC