What are the main factors behind recent deindustrialisation ?

Auteur : Marganne, Pierre
Promoteur(s) : Artige, Lionel
Faculté : HEC-Ecole de gestion de l'Université de Liège
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Supervisor:	**Pierre Marganne**
Artige Lionel	To obtain the degree of
Readers :	Master in Economics
Barnabé Walheer	with a specialization in
Joseph Tharakan	Macroeconomics and Finance
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Contents

List of Abbreviations

East E : Eastern Europe

GDP : Gross domestic product

ISIC : International Standard Industrial Classification

NACE : Nomenclature statistique des Activités économiques dans la Communauté Européenne

PYP : Previous Year Prices

SCC : Spatial Correlation Consistent

UNSD : United Nations Statistics Division

VA : Value Added

VIF : Variance Inflation Factor

West E : Western Europe

WIOD : World Input-Output Database

1 Introduction

The manufacturing sector has long been a central pillar of economic development, driving growth, innovation and the creation of skilled jobs. Historically, it has played a decisive role in transforming production structures, raising living standards and boosting international competitiveness (Szirmai, 2012). However, for several decades now, most economies at different levels of development have seen a steady decline in the share of manufacturing in total employment and gross domestic product (Rodrik, 2016). This phenomenon, known as deindustrialisation, has been accompanied by profound sectoral transformations: the rise of services, the reorganisation of production chains and international dependence.

This development is sparking heated debate in economic and political circles. The Draghi report (2024) highlights that deindustrialisation raises major strategic issues for Europe, particularly in terms of economic sovereignty, supply chain resilience and the ability to support the ecological transition. In economic literature, there are multiple interpretations of the causes of this phenomenon. Some see it as a 'natural' development linked to tertiarisation and changes in consumer preferences as income rises. Others highlight exogenous factors, such as international trade, competition from low-wage countries, the outsourcing of certain productive functions, and technological progress (Rowthorn & Ramaswamy, 1997).

This thesis proposes to address recent deindustrialisation from a specific angle, combining two dimensions of analysis that are rarely studied together. Firstly, it distinguishes manufacturing sectors according to their technological level, low technology on the one hand, Medium to High technology on the other, in order to identify whether the causes and extent of deindustrialisation differ according to production sophistication. Second, it adopts a comparative perspective between Eastern and Western Europe, two geographical areas with distinct industrial trajectories but integrated into the same economic space. The analysis covers the period 1996–2014, chosen to cover a recent phase of deindustrialisation, while avoiding the major disruptions linked to the COVID-19 health crisis and benefiting from the availability of homogeneous data for all the countries studied.

The central question that this thesis seeks to answer is: What are the determinants of recent deindustrialisation in developed economies, and how do their effects differ between sectoral technology levels and between Eastern and Western Europe over the period 1996–2014?

The first section presents the literature review, outlining the main theoretical and empirical approaches to deindustrialisation. The second section sets out the methodology, describing the data used and the strategy adopted to analyse changes in manufacturing employment.The third section provides a descriptive analysis, highlighting recent trends and structural changes observed. The fourth section introduces the model, i.e. the decomposition method used to identify the various effects behind the phenomenon. The fifth section presents the results, i.e. the econometric estimates and their interpretation. Finally, the sixth section provides the conclusion, which summarises the main findings, discusses their economic implications and highlights the limitations of the study.

2 Literature review

Deindustrialisation is a major structural phenomenon that has affected advanced economies for several decades. Although the concept seems intuitive, it remains broad. Economic literature has developed several approaches to measure it, identify its causes and analyse its consequences.

2.1 The importance of the industry

Part of the economic literature recognises the fundamental role of the manufacturing sector in the growth dynamics of economies. Contrary to the neoclassical view, which considers growth to be sectorally neutral, the Kaldorian perspective (Kaldor, 1968) attributes particular properties to manufacturing as a driver of long-term growth.

According to this approach, the manufacturing sector benefits from both static and dynamic economies of scale (Thirlwall, 1983), reflected in increasing returns, learning by doing, and a greater ability to accumulate productivity gains. In addition, it generates positive externalities that spread throughout the economy: improved skills, infrastructure development, and above all technological innovation, which has historically been more concentrated in industry and then spreads to other sectors.

Several empirical studies have validated Kaldorian logic within developed economies. Fingleton and McCombie (1998) identify robust evidence of increasing returns in the manufacturing sector based on European regional data. Their study confirms the existence of a significant link between industrial production growth and productivity growth in the form of Verdoorn's law[1], supplemented by an estimate of innovation diffusion.

In this context, deindustrialisation can be a cause for concern. It suggests not only a sectoral restructuring of the economy, but also the loss of a crucial lever for productive transformation, innovation and sustainable growth. This justifies efforts by public authorities to understand and address this phenomenon.

2.2 Measuring deindustrialisation

It is important to distinguish between the concepts of industrial sector and manufacturing sector, which are often used interchangeably but have varying definitions depending on the source. In general, the manufacturing sector corresponds to activities involving the transformation of raw materials into finished or semi-finished goods, as defined in international classifications (NACE section C, or ISIC Rev. 4 section D[2]). This is the scope used

[1] Verdoorn's law, derived from Verdoorn (1949), applies that labour productivity growth is positively related to output growth, particularly in the manufacturing sector. This relationship reflects the presence of increasing returns to scale, and underpins the strategic importance of industrial activity in long-term growth dynamics and economic welfare.

[2] NACE (Nomenclature statistique des activités économiques dans la Communauté européenne) and ISIC (International Standard Industrial Classification of All Economic Activities) are standard international classification systems used to categorize economic activities. In their current versions (NACE Rev. 2 and ISIC Rev. 4), manufacturing is defined in section C and section D, respectively.

in most recent empirical studies on deindustrialisation, such as Rowthorn & Ramaswamy, (1999) or Demmou, (2010).

Conversely, the industrial sector can include a broader field, encompassing not only manufacturing but also extractive industries, energy, construction, and certain technical services related to production. Some authors adopt broad or alternative definitions: for example, Herrendorf considers "the term manufacturing in this context to refer to all activity that falls outside of agriculture and services"(Herrendorf et al., 2014,p. 4). Or Fingleton & McCombie (1998), who include energy. These differences in scope have implications for measures of deindustrialisation: an analysis based solely on manufacturing tends to reveal more marked declines than those observed for the industrial sector as a whole. It is therefore essential to specify the scope used in each study, particularly from a comparative perspective.

2.3 Causes identified in the literature

The explanations put forward in economic literature are numerous and often complementary.

Non-homothetic preferences : Non-homothetic preferences are often cited as a factor explaining deindustrialisation, particularly in high-income countries. Derived from Engel's law, this concept refers to the fact that the structure of household expenditure changes disproportionately to increases in income. For example, the proportion of income spent on food decreases as living standards rise (Houthakker, 1957).

This logic also applies to manufactured goods, but with an inverted U-shaped pattern: the share of expenditure devoted to these goods increases at the beginning of the development and industrialisation process, then decreases beyond a certain income threshold, in favour of services. This transition was highlighted by Herrendorf et al (2014) for several economies over a period spanning the 19th and 20th centuries. According to Rowthorn & Ramaswamy (1999), this structural change in consumption preferences is one of the main determinants of deindustrialisation in advanced economies.

Foellmi and Zweimüller (2008) formalise this mechanism in a theoretical framework that links Engel-type demand shifts to long-run growth patterns. Their model shows that as income rises, consumers progressively substitute towards higher-quality and more diverse goods, and eventually towards services, generating what they call “Engel's consumption cycles” .

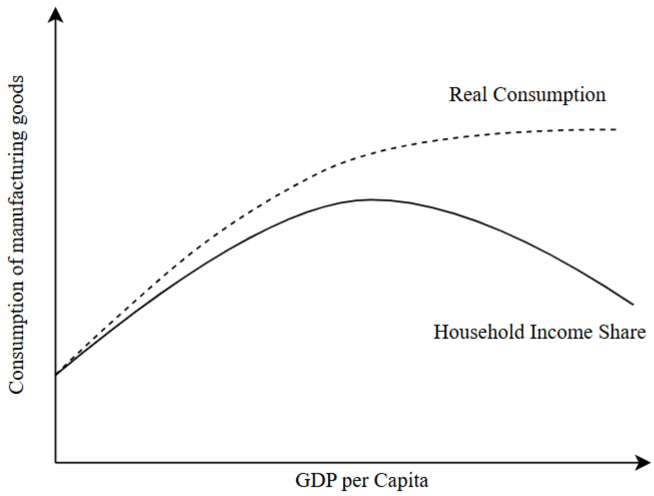


Figure 1: Non-homothetic preferences for manufacturing

Source: Own diagram based on Engel's law

Technology: Technical progress, which is faster in the industrial sector than in the service sector, paradoxically leads to a decline in industrial employment. Indeed, productivity gains in industry make it possible to produce more with less labour. But if demand for industrial goods does not increase at the same rate, this translates into a reduction in labour requirements in the sector. Furthermore, these productivity gains support wage increases in industry. The service sectors, faced with stagnant productivity, must nevertheless align themselves with these wages in order to remain attractive, without being able to compensate through efficiency gains. They must therefore increase their relative prices. This is the mechanism at the heart of Baumol's cost disease (Baumol, 1967).

This dynamic contributes, in the long term, to a reallocation of employment towards services. As a result, economic growth gradually becomes dependent on sectors with low productivity gains, which can slow down the overall growth rate of the economy. Rowthorn & Ramaswamy (1999) also quantify part of this mechanism in several industrialised countries by analysing the comparative evolution of price levels, productivity gains and the sectoral structure of production.

These two causes of deindustrialisation ,technology and preferences, linked to factors internal to economies, are identified in the literature as the main causes of deindustrialisation. Rowthorn & Ramaswamy (1999) estimate that between half and two-thirds of the decline in manufacturing employment can be explained by these internal causes for 17 of the 18 countries studied between 1963 and 1994.

Outsourcing: In addition to these structural factors, there is the role of outsourcing. certain functions historically performed internally by industrial companies (maintenance, logistics, IT services, etc.) are subcontracted to companies classified in service sectors. This organisational change alters the sectoral distribution of employment, without reflecting a real loss of productive activity.

In a study on the decline in industrial employment in France, Demmou (2010) estimates that this 'fictitious job loss' accounts for 20 to 25% of the total decline in industrial employment, thus highlighting the importance of this statistical effect in the analysis of deindustrialisation.

More generally, Berlingieri (2013) shows that this reconfiguration of distribution of activities explains a significant part of the rise of services in OECD countries: the outsourcing of intermediate functions by manufacturing companies contributes to apparent deindustrialisation, without an equivalent decline in real manufacturing output and workers strictly assigned manufacturing production.

Globalisation: Another cause identified in the literature, and often mistakenly taken by the general public as the main source of industrial job losses, is the increase in international trade driven by globalisation. The effects of international trade on deindustrialisation are nuanced. In a study covering 15 advanced countries, Van Neuss (2018) distinguishes between the effects of domestic demand, productivity gains and integration into global value chains. He shows that while globalisation, particularly through imports of goods, does contribute to the decline in industrial employment, its effects remain nuanced. The extent of the effects of international trade on industrial employment varies greatly depending on whether trade is between developed countries or with developing countries, certainly due to differences in factor intensity between economies. This approach allows globalisation to be seen as one factor among others, rather than the sole or main cause of deindustrialisation.

2.4 Methodologies used in the literature

The diversity of empirical methods used reflects the multidimensional complexity of the phenomenon of deindustrialisation. One approach is based on general equilibrium models that simulate the effects of technological or commercial shocks on the sectoral structure of the economy (Herrendorf et al., 2014). Although rigorous, these models are complex and often require a great deal of data and structural assumptions.

Other studies adopt an accounting approach, using national accounting statistics to break down changes in employment or industrial value added into different explanatory components. For example, Demmou (2010) uses it to estimate the 'fictitious job loss' and deindustrialisation due to the other causes mentioned above or Tregenna, (2009). This type of approach, often used in applied studies, remains limited in formally identifying causal relationships.

Finally, much of the literature relies on econometric methods to quantify the influence of structural and cyclical determinants. For example, Rowthorn & Ramaswamy (1999) and Van Neuss (2018) use multi-country regressions to isolate the respective effects of productivity, consumption preferences and international trade. Fingleton and McCombie (1998), meanwhile, apply a regional econometric approach to test the validity of Verdoorn's law at the European Union level. Other authors, such as Alderson (1999), also explore the dynamic dimensions of the link between industry and growth through panel models.

This methodological diversity is essential for capturing the multiple facets of the deindustrialisation process, but it also contributes to the dispersion of empirical results and the difficulty of formulating unambiguous diagnoses.

3 Methodology

3.1 WIOD databases

In this thesis, some of the data used is derived from input-output tables. These tables provide a detailed representation of economic flows between sectors of an economy and are essential for estimating macroeconomic aggregates such as value added or intermediate consumption. Since deindustrialisation is a long-term phenomenon, it is crucial to have long, structured time series in order to analyse sectoral transformations over time.

To do this,data from the World Input-Output Database (WIOD), developed by the University of Groningen are used. This database has the advantage of providing globally harmonised inter-industry tables, coupled with detailed socio-economic data, for a wide range of countries and sectors. It is particularly well suited to the analysis of global value chains, sectoral productivity and structural change.

However, due to methodological changes (notably the transition from ISIC Rev.3 to Rev.4 classification) and statistical improvements, Groningen has made two separate versions of the WIOD available: a first version published in 2013, and a second in 2016. These two versions differ in terms of the period covered, the number of countries and sectoral disaggregation.

Feature	**WIOD 2013**	**WIOD 2016**
Period covered	1995 to 2011	2000 to 2014
Countries included	27 EU countries (excluding Croatia) + 13 other major world economies	28 EU countries (including Croatia) + 15 other economies
Total number of countries	40	43
Sectoral breakdown	35 sectors (ISIC Rev.3 classification)	56 sectors (ISIC Rev.4 classification)

Methodological differences between the 2013 and 2016 versions

The two datasets differ in several methodological aspects of their construction. However, these differences do not prevent them from being merged for the purposes of sectoral aggregate analysis. As Timmer points out in the introduction to the 2016 version of the WIOD, both versions are based on the same type of data and follow a similar basic methodology. The main differences concern the transition from the ESA 95 to ESA 2010 accounting framework[3] and the adoption of the ISIC Rev.4 sector classification instead of

[3]Methodological transition from the ESA 95 to the ESA 2010 accounting framework, reflecting revisions in the European System of Accounts. This change, implemented progressively across countries,

Rev.3 (Timmer et al., 2016). Despite these adjustments, the merger of the two databases remains methodologically consistent and relevant for studying the evolution of industry's share of value added and employment over time.

3.2 Merger of the two datasets

To build a consistent database over a long period, the two versions of the WIOD datasets (2013 and 2016) have been merged. This merger is based on a series of methodological choices aimed at ensuring the temporal and sectoral comparability of the data.

First, only countries present in both versions were retained in order to ensure consistent coverage over the entire period. Second, the period from 2001 to 2014 is covered by data from the 2016 version, while the years 1996 to 2000 are taken from the 2013 version. The junction between the two series requires consistency checks. As shown in the graphs below, long-term trends, particularly the share of manufacturing employment and the share of manufacturing value added, are broadly similar over the overlap period (2001–2011). However, slight differences can be observed for certain countries, such as Germany for employment and England for value added. These differences are linked to national revisions included in the 2016 version, as mentioned by the Groningen team. This change in the data set will therefore need to be controlled for by introducing a control variable or dummy at the point of transition to ensure the consistency of the results.

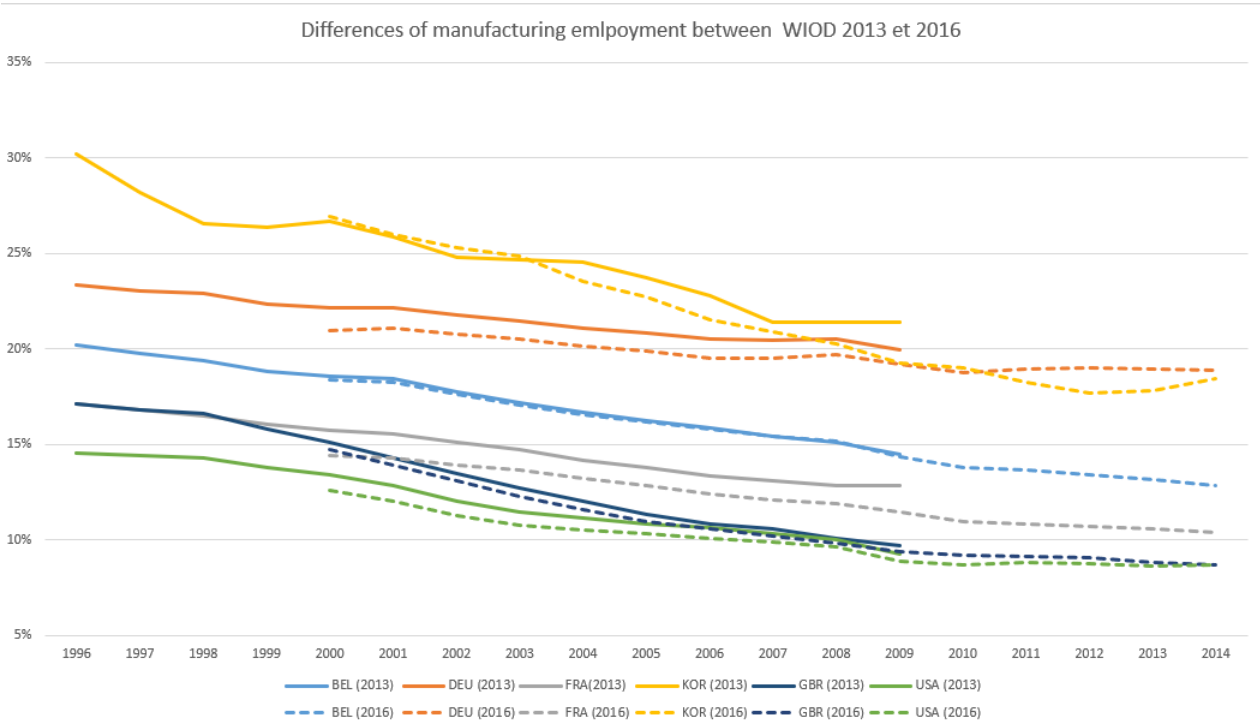


Figure 2: Part of manufacturing employment

Source: WIOD Database, 2013 and 2016 versions

affects sectoral classifications and the treatment of certain transactions (e.g., R&D as investment), which may introduce minor discontinuities in time series.

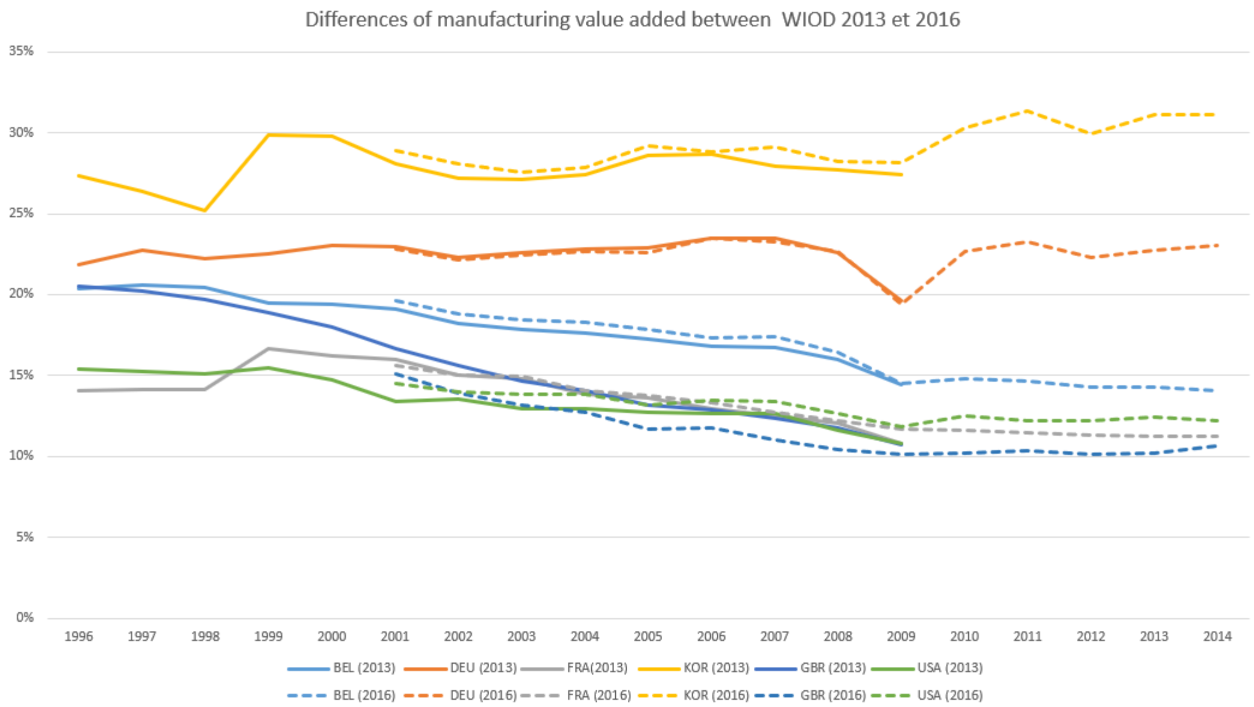


Figure 3: Part of manufacturing value added

Source: WIOD Database, 2013 and 2016 versions

The main technical difficulty lies in the divergence of sector classifications. The 2013 version uses the ISIC Rev.3 classification, while the 2016 version adopts ISIC Rev.4. In order to ensure sectoral consistency, harmonising of the aggregation of the manufacturing sector according to two levels of technological intensity: Low-Tech, Medium to High-Tech, as well as other major non-manufacturing sectors have been done. This classification is based on the typology proposed by the OECD for ISIC Rev.3. The ISIC Rev.4 sectors were then matched to those of ISIC Rev.3 using the correspondence tables published by the United Nations (UNSD) while taking into account the sectoral division carried out by WIOD.

This approach allows for a structured and consistent reading of the manufacturing sector over the entire period analysed. From the WIOD tables, the real value added calculated in previous year prices (PYP) is aggregated, as well as intermediate consumption and gross output. In connection with the Input-Output tables, the University of Groningen provides several data sets in its 'Socio Economic Accounts', including employment by sector. Using employment data from WIOD ensures that employment is directly linked to each sector, minimizing the risk of misclassification errors due to categorization methods.

Table 2: Sector Aggregation Summary

Group	**Description**	**ISIC Rev.3**	**ISIC Rev.4**
Agriculture		A, B	A01-A03
Non-manufacturing industry	Mining and Quarrying	C	B
	Electricity, Gas and Water Supply	E	D35, E36-E39
	Construction	F	F
Low-tech nology manufacturing	Food, Beverages and Tobacco	D15, D16	C10-C12
	Textiles and Leather Products	D17-D19	C13-C15
	Wood and Products of Wood	D20-D22	C16-C18
	Manufacturing, Nec; Recycling	D36, D37	C31-C33
Medium to High technology manufacturing	Coke, Refined Petroleum and Nuclear Fuel	D23	C19
	Rubber and Plastics	D25	C22
	Other Non-Metallic Mineral	D26	C23
	Basic Metals and Fabricated Metal	D27, D28	C24, C25
	Chemicals and Chemical Products	D24	C20, C21
	Machinery, Electrical and Optical Equipment	D29-D33	C26-C28
	Transport Equipment	D34, D35	C29, C30
Services	Market Services	G, H, I, J, K	G, H, I, J, K, L, M, N,
	Non-market services	L, M, N, O, P, Q	O, P, Q, R, S, T ,U

To take into account the level of wealth of the countries analysed, the study includes GDP per capita in purchasing power parity (PPP), expressed in constant 2021 international dollars. This measure allows for a more relevant comparison of living standards than nominal data. The data comes from the Our World in Data database (Roser et al., 2023), which compiles information from reference sources such as Eurostat, the OECD and the World Bank.

To assess the degree of openness of countries to globalisation, the 'Trade as a share of GDP' indicator is also available on the Our World in Data platform (2025). These data, taken from the national accounts of the World Bank and the OECD, have been harmonised by Our World in Data to ensure comparability both over time and between countries.

To compare structural trends between Eastern and Western Europe, the countries in the dataset were grouped into two broad aggregates, each representing a distinct regional profile. This classification follows historical, economic, and institutional divides[4]. The full composition of each group is presented in the table below.

Table 3: Country Aggregations: Western and Eastern Europe

Group	**Countries**
Western Europe	Austria, Belgium, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Sweden
Eastern Europe	Czech Republic, Hungary, Poland, Romania, Slovakia, Bulgaria, Lithuania, Latvia, Estonia, Slovenia

4 Descriptive analysis

4.1 Trends in manufacturing employment

Over the period studied, the average share of manufacturing employment in the various countries studied declined, both in the Low-tech and Medium to High-tech sectors. The Medium to High-tech sector fell from 11.4% of total employment in 1996 to 8.5% in 2014. A sharp decline in the sector can be seen in 2001 when the database changed (WIOD 2013 to WIOD 2016). The downward trend in the Low-tech sector is much clearer and smoother, falling from 10.5% to 6.9% of employment.

Low Tech Employment

Over the period studied, almost all countries, with the notable exception of India, experienced a decline in the share of manufacturing employment in Low-tech sectors. This deindustrialisation is reflected in a general trend towards a reduction in the weight of

[4]Eastern Europe includes the Central and Eastern European countries (CEECs) while Western Europe is composed of Northern Europe, Southern Europe and Western Europe.

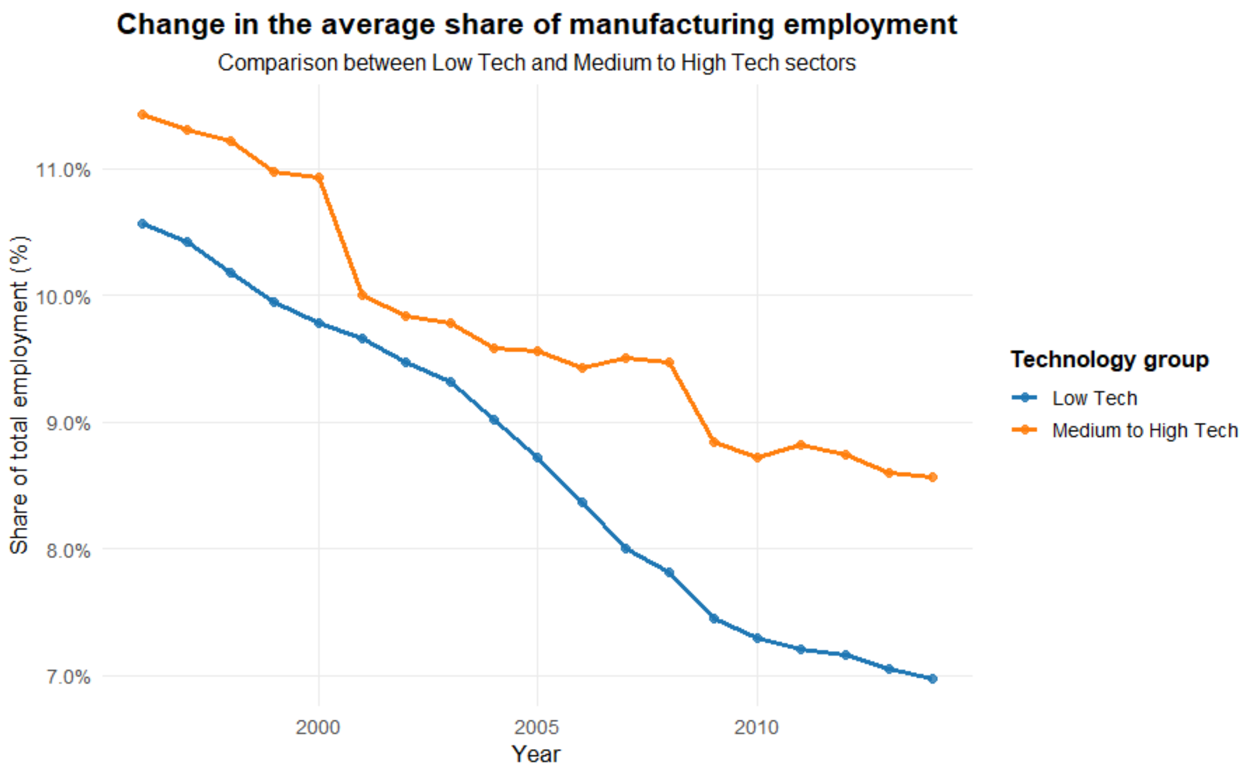


Figure 4: Change in share of manufacturing employment

Source: WIOD Database, 2013 and 2016 versions

these jobs in the economy, although the scale and pace of this change varies from country to country.

A noticeable jump in 2001 in the series for certain countries (notably the United Kingdom, Germany and France) reflects the change in the database between WIOD 2013 and WIOD 2016. Despite this one-off discrepancy, the underlying trend remains broadly consistent, with a persistent decline in most cases.

The countries in the sample did not start the period with the same levels of industrial employment, nor did they end up with identical rates at the end of the period. Nevertheless, a common trend of decline in the Low-tech manufacturing sector emerged for most of them.

However, a few exceptions are worth noting. India, in particular, experienced significant growth in Low-tech employment, rising from 6.7% to around 9% of total employment. This reflects a phase of ongoing industrialisation during the period observed. Brazil, meanwhile, experienced an increase in industrial employment between 2000 and 2009, before losing all of these gains over the following decade, illustrating a delayed but marked process of deindustrialisation.

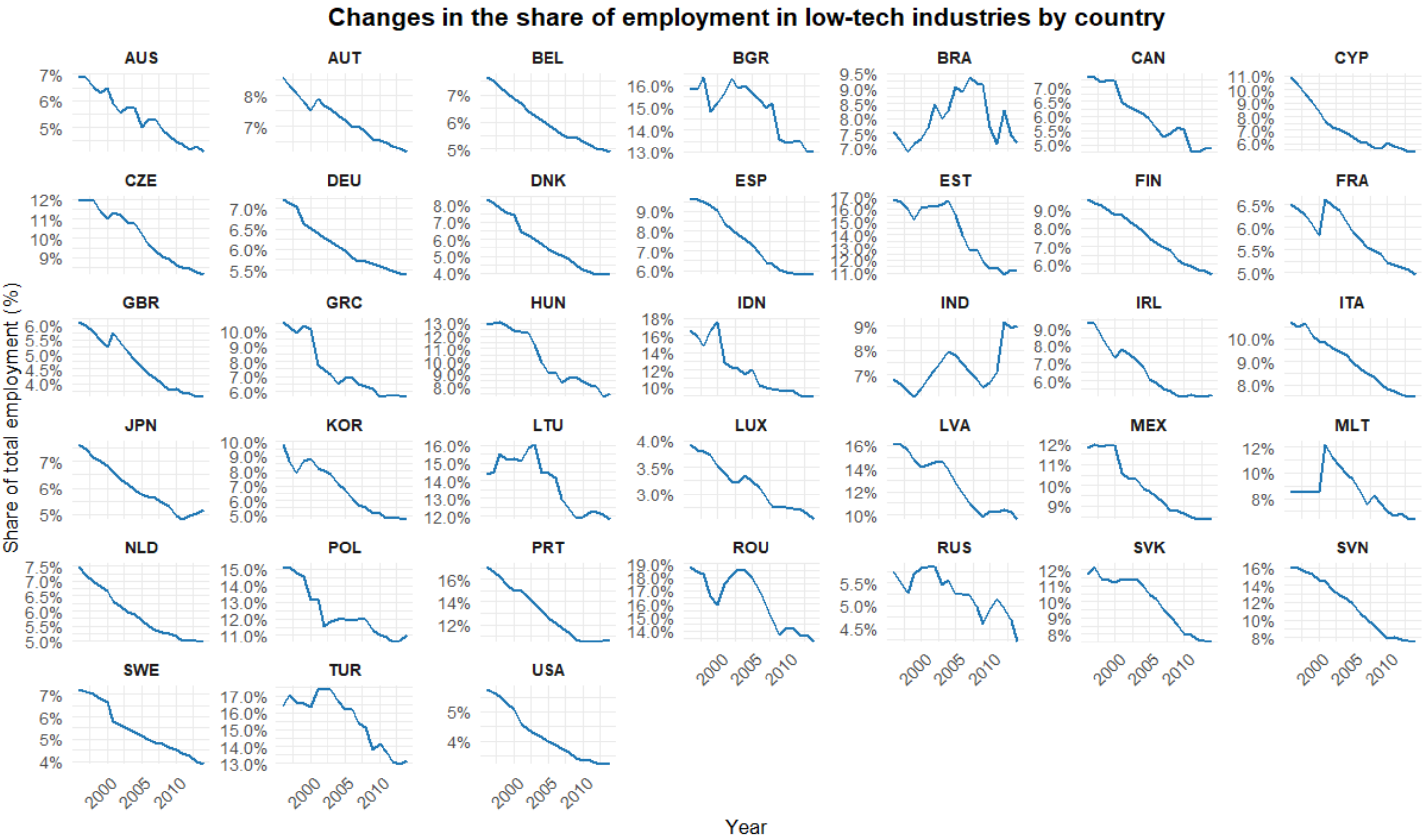


Figure 5: Change in share of manufacturing employment in Low Tech by country

Source: WIOD Database, 2013 and 2016 versions

Medium to High-Tech Employment

The evolution of employment in Medium to High-tech sectors is more heterogeneous than in Low-tech sectors. While most countries show a downward trend over the entire period studied, several economies, notably Estonia, the Czech Republic, India, Hungary and Turkey, show significant growth in employment in these more technology-intensive sectors.

The starting and ending levels are much more dispersed between countries: while Slovakia had an initial rate of over 16%, Brazil started with less than 5% of jobs in Medium to High-tech sectors. This initial heterogeneity reflects profound differences in the industrial specialisation of national economies.Furthermore, in several cases, the series show high volatility and less clear trends, which may reflect different industrial paths or measurement effects.

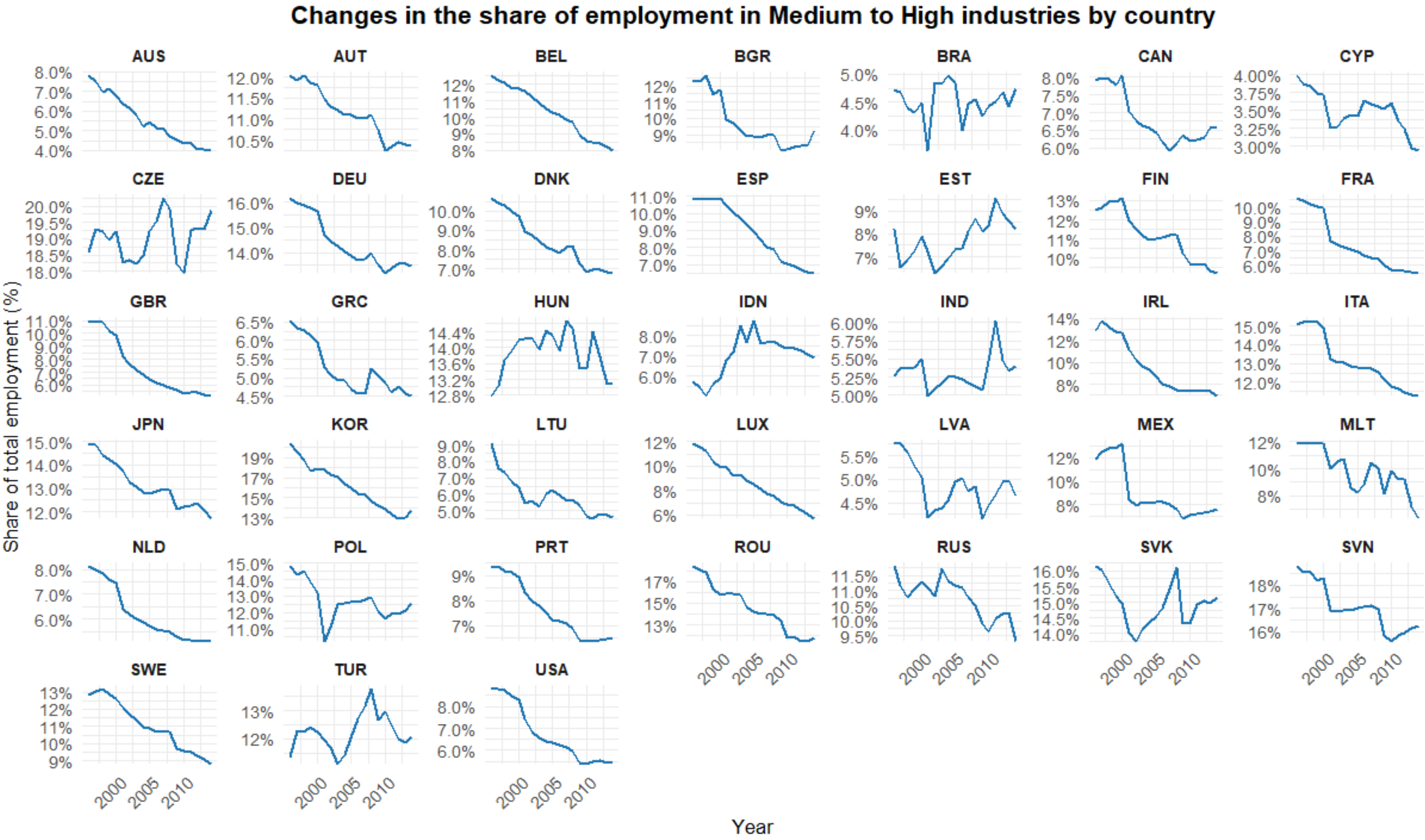


Figure 6: Change in share of manufacturing employment in Low Tech by country

Source: WIOD Database, 2013 and 2016 versions

Eastern Europe – Western Europe

A comparative analysis between Eastern and Western European countries highlights distinct yet interconnected industrial dynamics. Eastern European countries began the period with a proportionally larger industrial base, accounting for around 30% of total employment in the manufacturing sector in 2001 (including 15% in Low-tech sectors and 15% in Medium to High-tech sectors). This share declined significantly over time, reaching around 22% in 2014, divided between 10% for Low-tech and 12% for Medium to High-tech, reflecting a notable but less marked deindustrialisation than that observed in the West.

This distinction refers to a common interpretation on European productive integration, according to which Eastern European countries have been gradually integrated into the value chains of Western European economies, particularly Germany (Baldwin & Lopez-Gonzalez, 2015), by specialising in segments with lower added value. This pattern would imply an industrial composition dominated by Low-tech in the East and Medium to High-tech in the West. However, the data show that this polarisation is not so clear-cut: Eastern Europe has a high proportion of manufacturing jobs in both technology groups, including in the more advanced segments.

However, this observation must be qualified. The typology used here is based on a binary classification between Low-tech and Medium to High-tech. It is likely that national specialisations are in fact more refined, with Western Europe concentrating its industrial employment more in the most technological sectors within the Medium to High-tech group (e.g. electronic equipment, pharmaceuticals, aeronautics), while Eastern Europe remains more oriented towards intermediate or assembly activities within the same group. These nuances are not captured by this aggregate analysis.

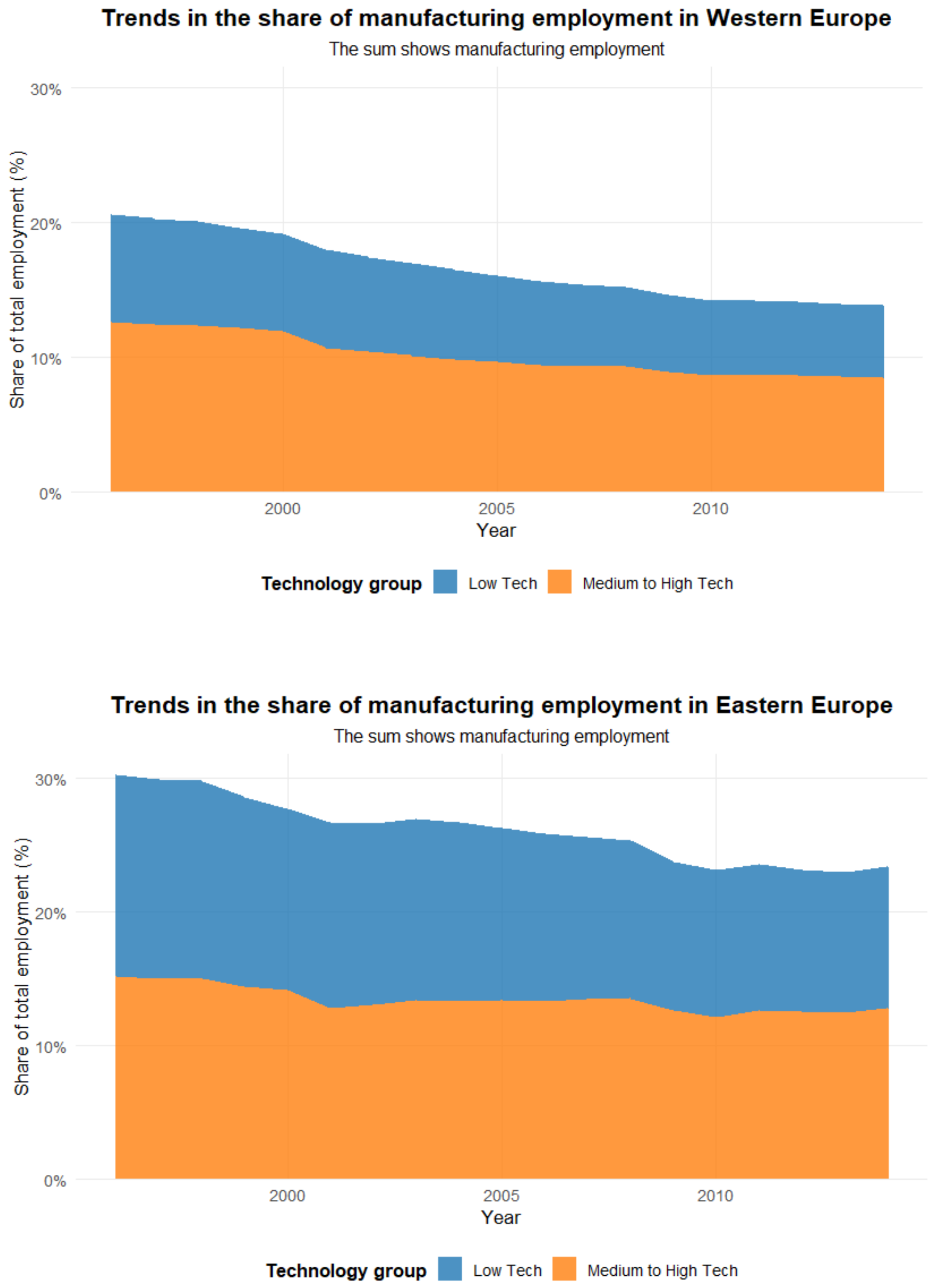


Figure 7: Western and Eastern Europe Employment

Source: WIOD Database, 2013 and 2016 versions

4.2 Link between manufacturing employment and GDP per capita

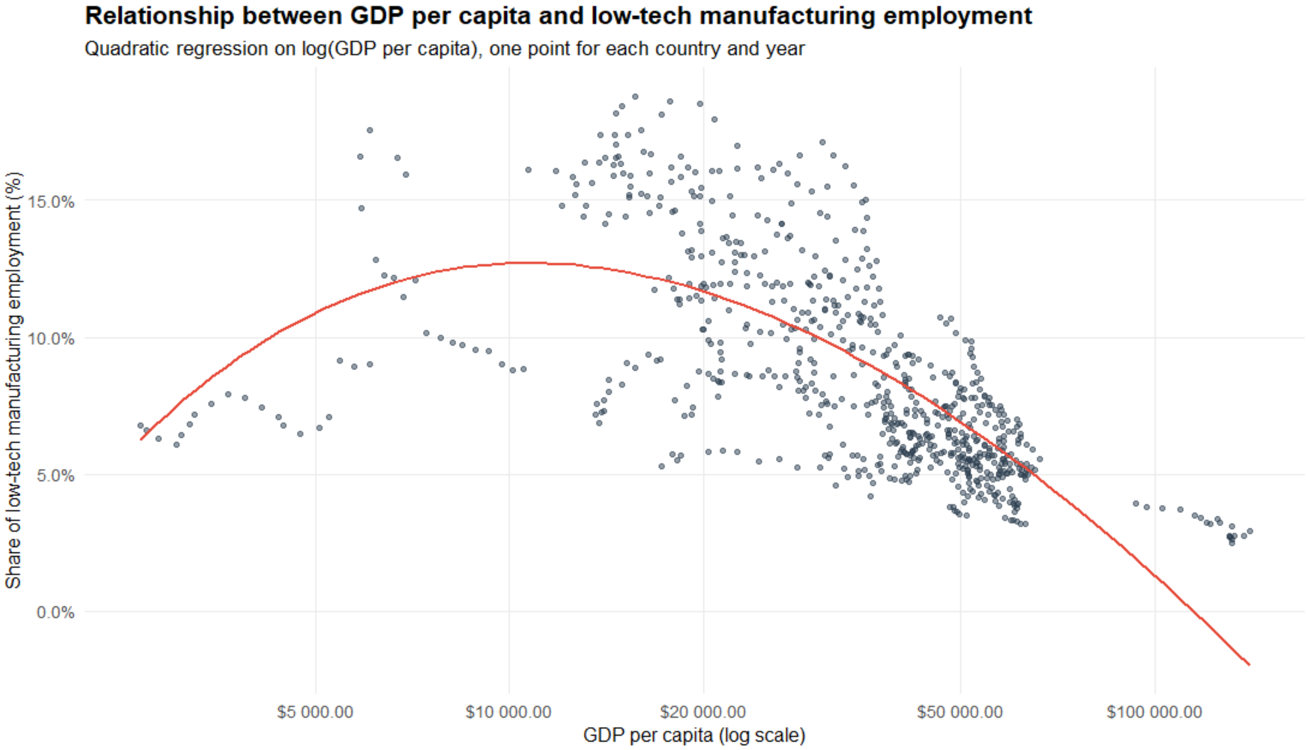
The inverted U-shaped relationship between the level of economic development (measured by GDP per capita) and the share of employment in the manufacturing sector is well documented in the literature, particularly through Engel's law applied to sectoral structure. This relationship is one of the major theoretical foundations of deindustrialisation. Herrendorf et al.(2014) highlighted this relationship using long historical series covering several advanced economies, some dating back to the early 19th century.

In this study, the data covers the period from 1996 to 2014 and focuses on economies that are already largely industrialised. The sample therefore mainly covers the downward part of the inverted 'U', where the increase in GDP per capita is accompanied by a gradual decline in the share of manufacturing employment. This suggests that the observed deindustrialisation is partly the result of a natural shift in the structure of demand in mature economies towards services.

However, it is important to differentiate the effect of GDP per capita according to the technological level of manufacturing sectors, as these do not produce the same types of goods or respond to the same consumption dynamics. The Low-Tech group is mainly composed of traditional industries such as agri-food, textiles and basic necessities, which are highly exposed to the effects of demand saturation described by Engel's law. Conversely, the Medium to High-tech group includes industries with higher added value, such as mechanical engineering, electronics, transport equipment, and chemicals and pharmaceuticals. These goods may meet more inelastic, renewable or specific needs of advanced economies, which could mitigate the declining relationship between GDP per capita and employment in these sectors (Tregenna & Andreoni, 2020).

This distinction is reflected empirically in the data: the decreasing relationship between GDP per capita and manufacturing employment is visible[5], although imperfectly, for Low-tech sectors, in line with theoretical predictions. On the other hand, no clear relationship appears to emerge for Medium to High-tech sectors, probably due to the diversity of activities grouped under this category. The relationship between level of development and industrial employment therefore appears more heterogeneous in the more technology-intensive sectors.

[5]The trend curves are significant but remain indicative, due to the lack of more in-depth analysis of the unique relationship between GDP and employment.



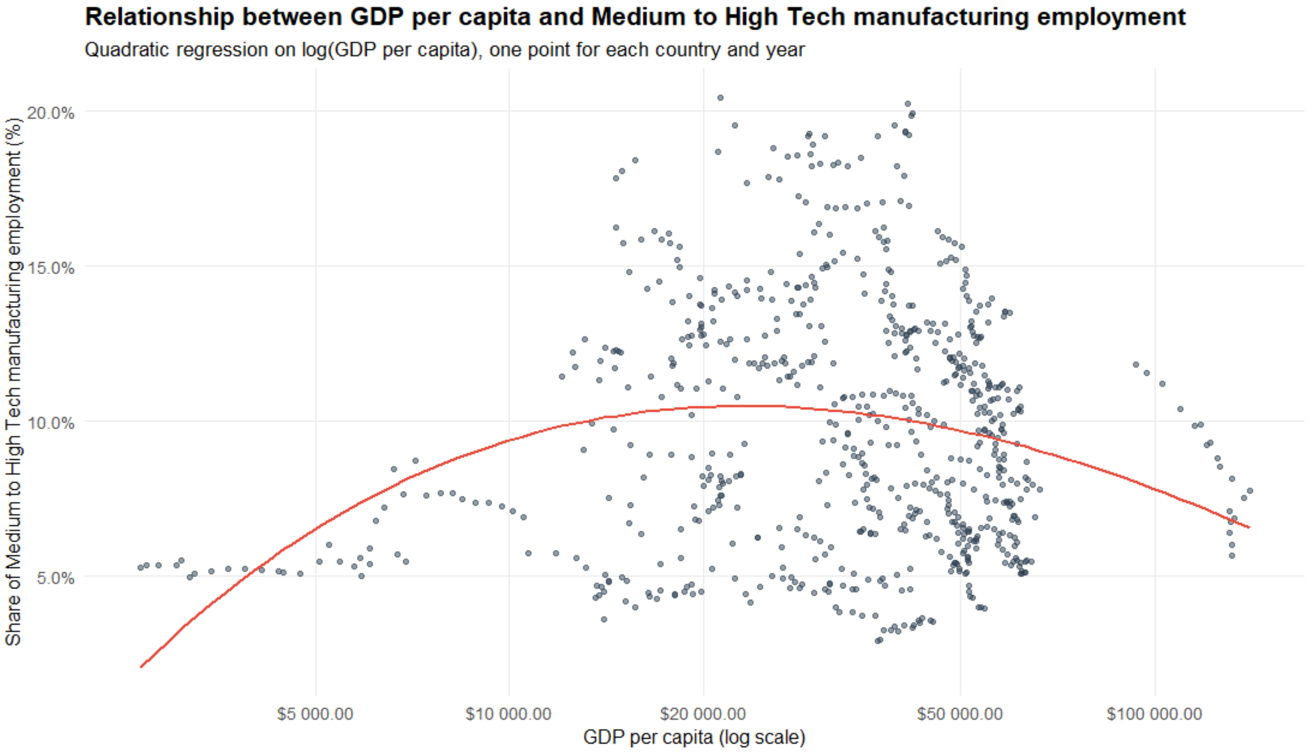


Figure 8: Link between Employment and GDP per capita

Source: WIOD Database, 2013 and 2016 versions

4.3 Productivity differential

The technological explanation for deindustrialisation, based on Baumol's cost disease, is founded on the assumption that productivity gains are structurally higher in manufacturing sectors than in services. This growing productivity gap between the two sectors leads, in the long term, to a gradual reallocation of employment from manufacturing to services, as explained in the previous literature review.

To measure this differential, a relative productivity ratio is used, defined as the ratio between labour productivity in manufacturing sectors (by technology group) and that in services. A constant ratio over time would suggest that productivity gains are comparable between the two sectors, while an increasing ratio would indicate a faster acceleration in manufacturing productivity, in line with Baumol's hypothesis. The graph below illustrates the evolution of this average ratio for all the countries studied, separately for the Low-tech and Medium to High-tech sectors. Two main observations emerge.

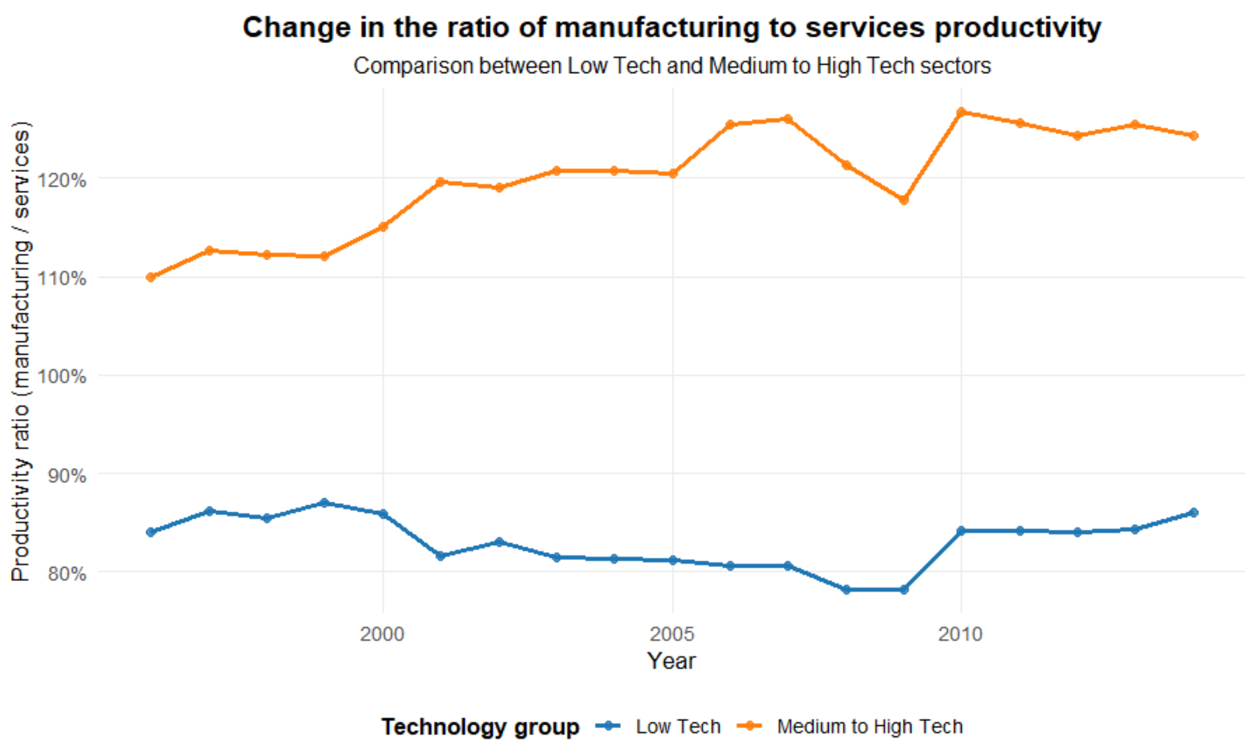


Figure 9: Productivity gain's differential

Source: WIOD Database, 2013 and 2016 versions

Firstly, the relative productivity of Medium to High-tech sectors is consistently higher than that of Low-tech sectors. This is consistent with the more capital-intensive and higher value-added nature of Medium to High-tech sectors, which tend to have higher labour productivity.

Secondly, the trends in these ratios differ:

- The ratio of Low-tech sectors has remained stable overall over time, suggesting that productivity gains in these sectors are evolving at the same pace as in services.

- Conversely, the ratio for Medium to High-tech sectors shows a slight increase, rising from around 1.1 to 1.25 over the period studied. This means that productivity in these sectors is growing faster than in services, confirming the theoretical scenario of Baumol's cost disease.

This growing productivity gap between Medium to High-tech sectors and services is therefore likely to cause pressure in the long term to reallocate employment away from the manufacturing sector, particularly its more technology-intensive segments.

4.4 Globalisation and industrial employment

Openness to international trade is a key structural determinant of manufacturing employment dynamics. It is measured here using a standard indicator of 'openness to trade', defined as the sum of exports and imports relative to GDP. This composite ratio captures a country's degree of integration into global trade without distinguishing between exports and imports or analysing the trade balance, although these dimensions may offer more detailed insights in some cases (Rowthorn & Ramaswamy, 1999; Van Neuss, 2018).

The impact of trade liberalisation on manufacturing employment is theoretically ambiguous. On the one hand, greater openness can stimulate competitiveness and promote the expansion of export sectors, particularly in the more capital-intensive Medium- to high-tech segments, which can be an advantage for northern countries (Van Neuss, 2018). On the other hand, it can also lead to increased competition in the most vulnerable segments (particularly low-tech), encourage outsourcing and result in a contraction of local manufacturing employment (Rowthorn & Ramaswamy, 1999). Moreover, globalization is linked to an outflow of investment from North to South countries which also impacts employment capabilities (Alderson, 1999).The impact of trade liberalisation on manufacturing employment is therefore empirically uncertain and likely to vary depending on the type of sector (Low-tech or Medium to High-tech). This uncertainty justifies the introduction of this variable as a control in the regression in order to assess its net effect.

Over the period studied, trade openness increased overall for most countries in the sample, with the notable exceptions of Russia and Turkey. The 2008–2009 financial crisis caused a sharp decline in the openness ratio in most economies, reflecting the temporary decline in global trade. It is also important to note the wide variation in openness levels between countries: small, highly integrated economies such as Belgium, Ireland and Luxembourg have much higher ratios than large economies with significant domestic markets such as the United States, India and even France.

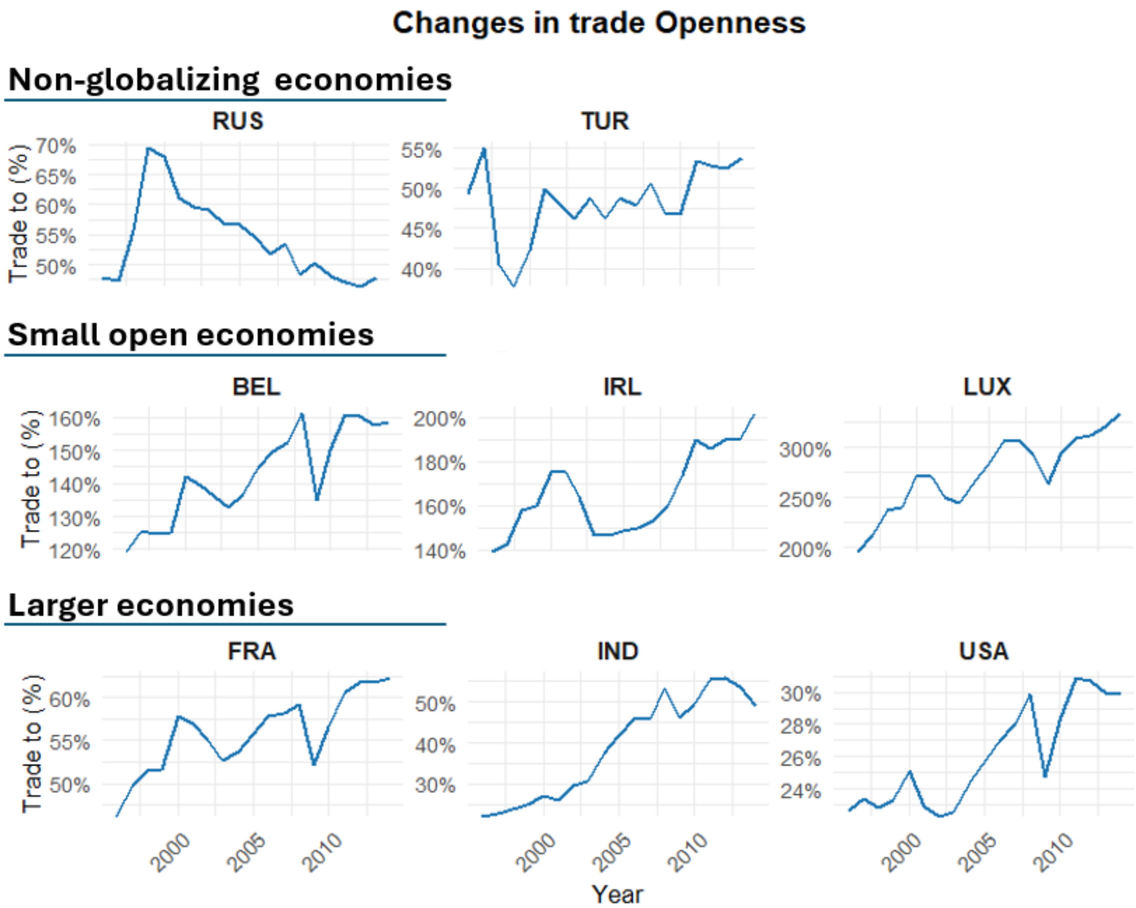


Figure 10: Changes in trade Openness

Source: Our World in Data

4.5 Outsourcing and intermediate consumption

In analysing the causes of deindustrialisation, internal outsourcing, i.e. the outsourcing of certain functions previously carried out internally in manufacturing companies, plays a key role. As Demmou (2010) points out, this phenomenon can lead to an apparent decline in manufacturing employment without any real loss of productive capacity. This type of reallocation is often referred to as a 'fictitious loss' of industrial jobs.

The intermediate consumption rate allows to empirically approach this phenomenon, which measures the share of intermediate consumption in total production. A high or rising level of this ratio may reflect greater dependence on services or inputs provided by other sectors, reflecting the intensification of outsourcing. This ratio may also capture, more broadly, an increased breakdown of the value chain, whether at the national or international level, even if the variable does not allow for a precise distinction between the nature and origin of inputs.

Over the period studied, the evolution of this ratio varies greatly from country to country. Some countries, such as South Korea, Germany, and Canada, show a gradual increase, indicating a growing reliance on external inputs and, potentially, the outsourcing of certain tasks, partly services formerly performed in-house. In contrast, countries such as Romania, Portugal, and Mexico exhibit a downward trend, which may point to a reintegration of previously outsourced activities or shifts in industrial structure reducing the use of intermediate inputs. In general, most countries have rates between 60% and 70%, indicating a structurally high level of use of intermediate consumption in manufacturing production.

4.6 Summary of key stylised facts

The descriptive analysis conducted in the previous sections has highlighted several common structural trends, while emphasising the diversity of national trajectories. In particular, there is more widespread deindustrialisation in some countries than in others, as well as heterogeneity in the evolution of explanatory variables such as GDP per capita, trade openness, intermediate consumption levels and sectoral specialisation.

However, this approach is limited in terms of identifying the mechanisms underlying deindustrialisation. The correlations observed do not allow us to isolate the specific effect of each variable, nor to distinguish the dynamics specific to each technological group (low tech vs. Medium to high tech). This is why a more formal approach is needed.

The objective is therefore to quantify the respective roles of the different variables identified in the literature and presented in the descriptive section in order to better understand the structural factors behind the decline in manufacturing employment, while taking into account sectoral and temporal specificities.

5 Employment deindustrialisation model

Model formalisation

In this thesis, the focus is on deindustrialisation in terms of employment, defined as the decline in the share of manufacturing jobs in total employment. Therefore, the breakdown of the change in the share of manufacturing jobs proposed by Tragenna (2009) is applied. To decompose the changes in the share of manufacturing in total employment, the sectoral share of employment σ_{ijt} is set up as the following identity :

$$\sigma_{ijt} = \frac{L_{ijt}}{L_{jt}} \; = \; \phi_{ijt}\,\delta_{ijt}\,\theta_{jt} \tag{1}$$

σ_{ijt} being the share of employment in sector i, in country j at time t. L is the number of employes. $\phi_{ijt}$is the labour intensity of sector i compute as employment divides by the value-added in the sector. δ_{ijt} is the share of value added of sector i. θ_{jt} is the economy wide productivity.

This breakdown allows changes in a sector's share of employment over a period of time h to be divided into three effects[6].

[6]The decomposition demonstration carried out by Tregenna (2009) is presented in the appendix.

Labour intensity effect

$$= \frac{1}{6}\ (\phi_{ijt} - \phi_{ijt-h})\{(\delta_{ijt-h}\theta_{jt-h} + \delta_{ijt}\theta_{jt}) + (\theta_{jt-h} + \theta_{jt})(\delta_{ijt-h}\delta_{ijt})\} \tag{2}$$

Sector share effect

$$= \frac{1}{6}\ (\delta_{ijt} - \delta_{ijt-h})\{(\phi_{ijt-h}\theta_{jt-h} + \phi_{ijt}\theta_{jt}) + (\theta_{jt-h} + \theta_{jt})(\phi_{ijt-h} + \phi_{ijt})\} \tag{3}$$

Labour productivity effect

$$= \frac{1}{6}\ (\theta_{jt-h} - \theta_{jt-h})\{(\phi_{ijt-h}\delta_{ijt-h} + \phi_{ijt}\delta_{ijt}) + (\delta_{ijt-h} + \delta_{ijt})(\phi_{ijt-h} + \phi_{ijt})\} \tag{4}$$

- The "*labour intensity effect*" is the change in employment in a sector associated with the change in labour intensity in that sector.
- The "*sector share effect*" measures the change in employment in a sector associated with the change in the sector's share of the country's total value added.
- The "*labour productivity effect*" measures the change in employment in a sector associated with changes in productivity in the economy as a whole.

Results

Tregenna's results, covering periods varying from country to country between 1980 and 2003, highlight the predominantly negative effects of the 'sector share' and 'labour intensity' components on the share of manufacturing employment. The labour intensity effect generally appears to be greater than that of sector share, suggesting that changes in sectoral productivity have a more pronounced impact on employment. The third effect, that of labour productivity, is generally positive. However, Tregenna does not interpret this in detail, as it is not the focus of her analysis.

My results concerning Low-tech sectors over the period 1996–2014 are broadly consistent with those obtained by Tregenna (2009). However, they appear to be much more consistent in terms of the behaviour of the various effects analysed. This consistency can be explained in part by the fact that Tregenna studied a more unstable period, marked in particular by the collapse of the USSR, which led to very contrasting economic dynamics among Eastern European countries.

Over the period studied, all countries except India experienced a decline in the share of industrial employment. This decline correlates with a reduction in the share of value added by the Low-tech sector in the economy, as well as a decrease in labour intensity in this sector .On the other hand, the effect linked to labour productivity is positive in almost all countries, and comparable in magnitude to that of labour intensity, except in the case of Japan. This can be explained by the conceptual proximity between these two effects: labour intensity is inversely related to productivity.

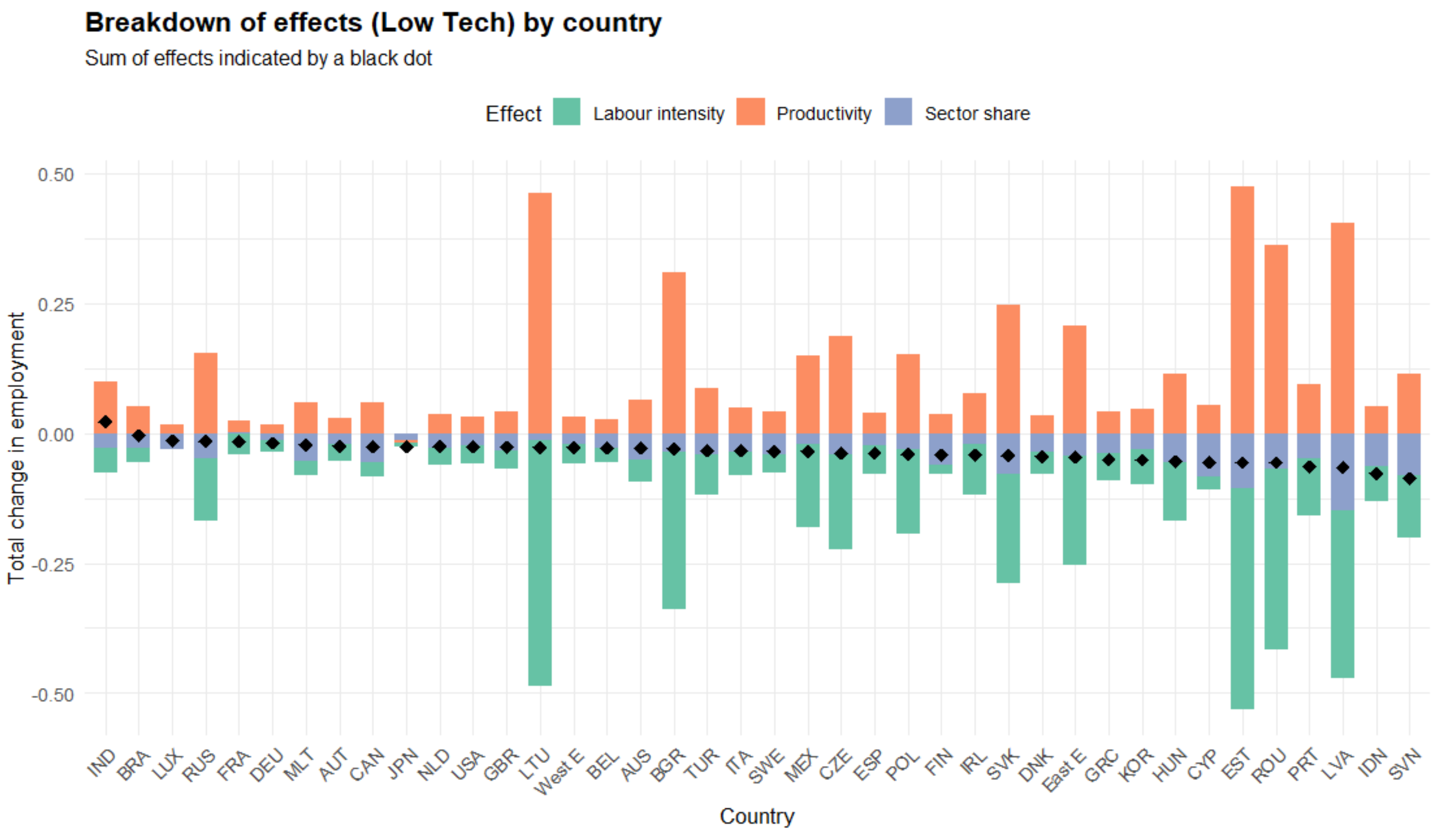


Figure 11: Low Tech employment losses decomposition

Source: WIOD Database, 2013 and 2016 versions

The results for Medium- to high-tech sectors are more mixed than those observed for Low-tech sectors. In most countries, the decline in manufacturing employment in these sectors is mainly due to a decrease in the sector's share of value added in the economy, as well as a decline in labour intensity. However, there are some notable exceptions. In South Korea and Lithuania, for example, the share of value added in the Medium- to high-tech sector increased, thereby contributing positively to industrial employment trends. Similarly, in Turkey, labour intensity had a positive effect on employment, indicating that during the period studied, the number of jobs per unit of value added in this sector increased, thereby increasing labour intensity.

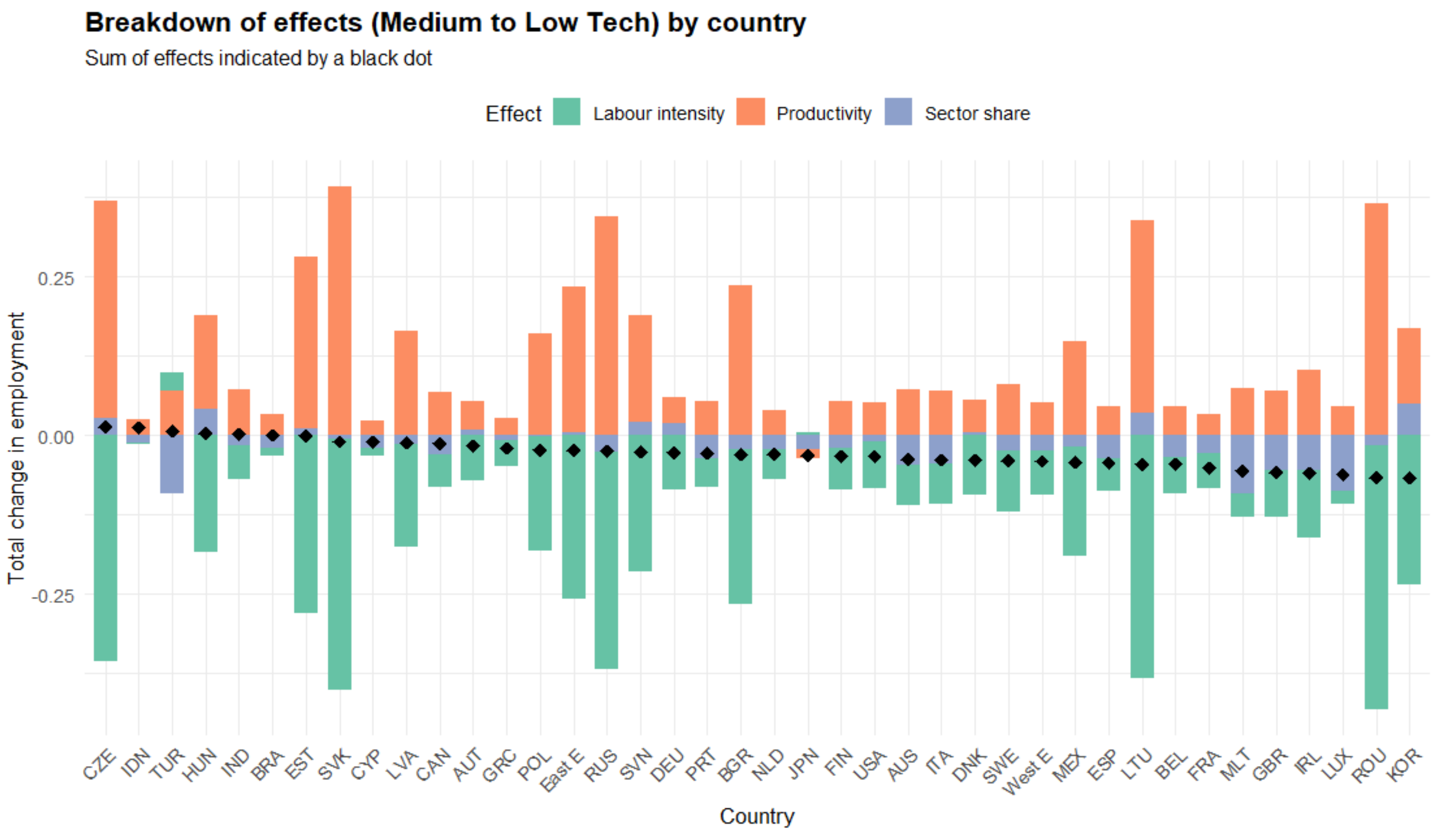


Figure 12: Medium to High Tech employment losses decomposition

Source: WIOD Database, 2013 and 2016 versions

Comparison between Eastern Europe and Western Europe

In the Low Tech group, Eastern Europe recorded a greater decline in the share of manufacturing employment than Western Europe. This decline is mainly explained by the sector share effect, while the productivity and labour intensity effects offset each other. For Western Europe, the dynamic is similar, but the labour intensity effect also played a significant role in the reduction of manufacturing employment, indicating greater labour substitution.

In the Medium to High Tech group, the trend is reversed. Western Europe has seen a more marked reduction in the share of employment in these sectors, due to negative labour intensity and sector share effects. For Eastern Europe, the sector share effect is slightly positive, which means that the group's share of value added has increased, positively impacting employment. The decline in employment in Eastern Europe is explained solely by the labour intensity effect.

6 Results

6.1 General econometric framework

The objective of this section is to empirically assess the impact of the various causes identified in the economic literature on deindustrialisation, taking into account the heterogeneity between technological sectors. The approach is based on the logic of the third decomposition proposed by Tregenna (2009), while adapting it to a usable econometric framework.

The dependent variable chosen is the share of manufacturing employment in total employment. This choice makes it possible to neutralise purely demographic effects (such as the increase in the working population), which are not directly linked to the process of deindustrialisation.

In accordance with Tregenna's model, three main explanatory effects are considered: The "*Sector Share Effect*" is measured by the share of manufacturing value added in GDP. It reflects the relative importance of the manufacturing sector in the economy. The effects of Labour Productivity and Labour Intensity are, in practice, difficult to separate due to their structural interdependence. Their joint contribution is therefore approximated by a variable of labour productivity in the manufacturing sector.

Several additional explanatory variables are added to this basis in order to capture the mechanisms mentioned in the literature:

- Changes in consumer preferences are approximated by GDP per capita, as used in the literature.
- Differentiated sectoral technical progress is captured by the ratio between labour productivity in the manufacturing sector and that in the services sector. This ratio measures the relative productivity gap between sectors.
- The phenomenon of outsourcing is measured by the ratio of intermediate consumption in the manufacturing sector, as suggested by Demmou (2010).
- Finally, globalisation is taken into account through the degree of trade openness (exports + imports relative to GDP).

This specification allows for an analysis of the economic and structural determinants of deindustrialisation, while assessing how their effects vary according to the technological level of manufacturing sectors. The aim is to determine whether the various factors of deindustrialisation affect the entire manufacturing sector uniformly, or whether their impact differs depending on the technological intensity of the activities.

Variable construction and transformations

With regard to the construction of explanatory variables, several of them are formulated as relative annual variations, according to the formula :

$$\Delta = (X_t - X_{t-1})/X_{t-1} \tag{5}$$

This transformation is applied to ratios such as the share of manufacturing value added, the share of industrial employment, the productivity ratio between sectors, the intermediate consumption ratio and the trade openness ratio. This choice makes it possible to capture the dynamics of changes, rather than their absolute level, and to neutralise the effects of structural trends or persistent intersectoral heterogeneity. Variables expressed in monetary terms, such as labour productivity and GDP per capita, are transformed into differentiated logarithms :

$$\Delta = ln(X_t) - ln(X_{t-1}) \tag{6}$$

This operation is econometrically equivalent to a relative percentage change, while allowing for a more direct interpretation of the coefficients as elasticities. Furthermore, taking logarithms helps to reduce dispersion and approximate the normality of the variables, thereby improving the robustness of the estimates.

6.2 Preliminary tests

VIF

In order to ensure that there was no problematic multicollinearity between the explanatory variables, a VIF (Variance Inflation Factor) test was carried out for both specifications (Low-Tech and Medium to High-Tech). The results show that all VIFs are well below the critical threshold of 10. In both cases, the highest VIFs relate to the variables of manufacturing value added share and relative productivity, with values around 3[7], which is still acceptable. These results therefore allow it to be concluded that there is no serious multicollinearity in the estimated models, which reinforces the robustness of the estimated coefficients and the validity of the associated economic interpretations.

Hausman test

In order to determine the most appropriate econometric specification, a Hausman test was performed to compare fixed-effects and random-effects models. This test assesses whether individual effects (sectoral in this case) are correlated with the explanatory variables. If there is correlation, the random-effects estimator is biased, and the fixed-effects model is therefore preferable. The results of the Hausman test indicate p-values of 5.6% for Low-tech sectors and 0.1% for Medium to High-tech sectors, leading to the rejection of the null hypothesis that random effects estimators are consistent. Consequently, the fixed-effects model is used for the estimation. This choice is also consistent with current practice in the literature on applied macroeconomics and sectoral economics, where unobserved specific effects (sectoral or country) are generally assumed to be correlated with the explanatory variables, justifying the use of a fixed-effects model.

Heteroscedasticity

A Breusch-Pagan test was performed to detect the possible presence of heteroscedasticity in the model residuals. The results show p-values below 0.1% for the Medium to High-Tech and Low-Tech sectors. These results lead to the rejection of the null hypothesis of homoscedasticity of errors. This indicates the presence of significant heteroscedasticity, which must be corrected in order to obtain robust estimates and valid inferences.

[7]The different test's results are summurize in the appendix

Error autocorrelation
A Wooldridge test for autocorrelation in panels was performed to check for the presence of first-order autocorrelation errors. The results indicate very low p-values (less than 0.1%), leading to the rejection of the null hypothesis of no autocorrelation. These results reveal the presence of significant autocorrelation of the residuals in the data, which constitutes a violation of the classical assumptions of the regression model. It is therefore necessary to correct the standard errors accordingly.

Cross-Section Dependence
A cross-dependence test was performed using the Pesaran test to assess the possible presence of correlation between the errors of the different units in the panel (in this case, countries). This test verifies the validity of the hypothesis of independence of residuals between entities, which is essential to ensure the robustness of estimates in a classic panel model. The p-values obtained in this test, which are very close to zero, lead to the rejection of the null hypothesis of no cross-dependence, thus indicating a significant correlation between errors across countries. This result suggests the existence of unobserved common shocks affecting several economies simultaneously. In a context of global economic interdependence, this phenomenon is consistent with the nature of the macroeconomic data used. These common shocks may be linked in particular to global economic crises, technological developments or political dynamics.

Spatial Correlation Consistent (SCC)
In order to ensure the robustness of the estimates in the face of major violations of the classical assumptions of panel models, particular attention was paid to the treatment of errors. Indeed, econometric tests revealed the presence of heteroscedasticity, first-order autocorrelation of errors, and cross-dependence between units. If these phenomena are not taken into account, they can lead to biased standard errors and compromise the validity of statistical inferences.

To correct these different forms of structural dependence in the residuals, the estimates were made using robust SCC (Spatial Correlation Consistent) standard errors, as proposed by Driscoll and Kraay (1998). This method produces standard errors that are robust to heteroscedasticity, temporal autocorrelation and cross-dependence in panels of moderate to large size. It is a particularly relevant tool in a macroeconomic context where countries are interdependent and exposed to common global shocks as in this study.

Time fixed effects
In order to take into account common shocks that may simultaneously affect all countries over time (such as global crises, global technological developments or international reforms), a Fisher test (F-test) was performed to assess the relevance of including fixed time effects in the model. The results of the test lead to a significant rejection of the null hypothesis, indicating that adding these time effects significantly improves the statistical quality of the specification.

Consequently, fixed time effects are included in the final model. This specification also has the advantage of neutralizing methodological breaks related to the change in database (from WIOD 2013 to WIOD 2016 from 2001 onwards). This type of discontinuity affecting all units at the same time is absorbed by the fixed year effects, thus making it unnecessary to introduce a specific control variable for this change.

6.3 Model and results

The econometric model is therefore as follows:

$$\Delta Employment_{it}\ Rate = \alpha_i + \lambda_t + \beta_1 .\Delta part\ VA_{it} + \beta_2 .\Delta \ln(prod)_{it} \quad + \beta_3 .\Delta Prod\ Ratio_{it} + \beta_4 .\Delta IC_{it} + \beta_5 .\Delta \ln(GDP/Cap)_{it} \quad + \beta_6 .\Delta \ln(GDP/Cap)^2_{it} + \beta_7 .\Delta Trade_{it} + \epsilon_{it} \tag{7}$$

$\Delta Employment_{it}$	Change in the employment rate of country i at time t. It measures the year-to-year variation in employment share.
α_i	Country fixed effects, captures time-invariant characteristics specific to i.
λ_t	Time fixed effects, captures shocks or changes common to all countries in year t.
$\Delta part\ VA_{it}$	Measures the year-to-year variation in the value-added share of the sector group.
$\Delta \ln(prod)_{it}$	Measures the year-to-year logarithmic difference of the in labour productivity (value-added per worker).
$\Delta Prod\ Ratio_{it}$	Measures the year-to-year variation in the ratio of manufacturing productivity to services productivity
ΔIC_{it}	Measures the year-to-year variation in intermediate consumption ratio.
$\Delta \ln(GDP/Cap)_{it}$	Measures the year-to-year logarithmic difference of GDP per capita in constant \$.
$\Delta \ln(GDP/Cap)^2_{it}$	Square of the logged GDP per capita change, allows for quadratic effects.
$\Delta Trade_{it}$	Measures the year-to-year variation in trade openness, measured as the ratio of (exports + imports) to GDP.
ϵ_{it}	The idiosyncratic error term, represents random shocks and omitted variables not captured by the fixed effects or included regressors.

Interpretation of results

The model has a strong explanatory power, with high adjusted coefficients of determination for both technology groups: 0.812 for the low-technology sector and 0.857 for the Medium- to high-technology sector. This indicates that the variables included explain a substantial portion of the variations in manufacturing employment in each group.

The first coefficient, measuring the 'Sector Share Effect', is positive and highly significant in both cases. A 1% increase in the sector's share of value added is associated with an increase of more than 0.8% in the share of employment in that sector. This result is consistent with theoretical predictions and the findings of Tregenna 2009, namely that employment in a sector is strongly linked to its size in the economy.

The second coefficient, reflecting both labour intensity and labour productivity effects, is negative and significant for both groups. This confirms that an increase in productivity is accompanied by a reduction in employment, all other things being equal. The effect is more pronounced in the low-technology sector, suggesting that productivity gains are less offset by upmarket expansion or increased production.

The third coefficient, associated with the relative productivity of the sector compared to services *Prod Ratio*, is also negative and significant in both groups. This result confirms the hypothesis of differentiated sectoral technical progress: when productivity in the manufacturing sector grows faster than in services, this leads to a reallocation of manufacturing jobs to the services sector, in line with Baumol's cost disease. The coefficients are similar (-0.65 and -0.66), which means that changes in the productivity differential have the same impact on both sectors. However, as seen in the descriptive section, productivity gains are much higher in the Medium to High sector. This group was therefore more broadly impacted by Baumol's cost disease.

The coefficient relating to intermediate consumption, used here as a proxy for outsourcing, is only marginally significant ($p < 0.1$) in the Low Technology group. It is negative, indicating that an increase in intermediate consumption, reflecting greater outsourcing of certain tasks, tends to reduce employment in these sectors, consistent with the findings of Demmou (2010) for France. Part of the deindustrialisation stems from the 'fictitious job loss' induced by the way employment is allocated to each sector. However, this effect is not significant in the Medium to High Tech sectors, which could reflect a different dynamic or stem from a lack of variation in the sample.

With regard to trade openness, no significant effect was observed. This result is unsatisfactory but consistent with the literature. It highlights the complex, differentiated and sometimes non-linear nature of the effects of international trade on manufacturing employment.

Per capita GDP does not appear to be significant in the regressions, either for the Low-tech or the Medium to-High-tech sectors. This result contrasts with the conclusions of Rowthorn & Ramaswamy (1999) and Herrendorf (2014), who identify a robust relationship between a country's level of wealth and the share of manufacturing employment, interpreted as a structural effect of deindustrialisation linked to rising income.

When allowing for a non-linear relationship, the quadratic term is weakly significant (p-value < 0.1) in the case of Low-tech sectors. However, its positive sign indicates a convex relationship in the short-run dynamics: periods of stronger income growth are associated with stronger increases decreases in Low-tech manufacturing employment. To capture the inverted U-shaped relationship between income and manufacturing employment as stated in the literature, the regression has to be done in levels rather than in variations.

Table 5: Estimation Results
Dependent variable: Employment part

	Low Technology Manufacturing	Medium to High Technology Manufacturing
$\Delta part\ VA$	0.8429 ***	0.8692 ***
	(0.0431)	*(0.0244)*
$\Delta \ln(prod)$	-0.0801 ***	-0.0603 ***
	(0.0107)	*(0.0136)*
$\Delta Prod\ Ratio$	-0.6525 ***	-0.6650 ***
	(0.0432)	*(0.0327)*
ΔIC	-0.0518 .	0.003
	(0.0297)	*(0.0295)*
$\Delta \ln(GDP/Cap)$	0.0224	0.0157
	(0.0524)	*(0.0609)*
$\Delta \ln(GDP/Cap)^2$	0.7996 .	0.4218
	(0.4847)	*(0.4134)*
$\Delta Trade$	-0.0038	0.0008
	(0.0135)	*(0.0137)*
N = 684	T = 18	n = 38
R^2	0.829	0.869
Adjusted R^2	**0.812**	**0.856**

Notes: Robust standard errors in parentheses.
* P-values : *** <0.001, ** <0.01, * <0.05 , . < 0,1

6.4 Robustness

In order to verify the stability of the results, two alternative estimates were made for comparison with the main fixed effects model.

First, a pooled OLS regression was estimated, incorporating a control variable capturing the change in database (from WIOD 2013 to WIOD 2016). Although this specification does not take into account individual or temporal heterogeneity, it provides a simplified initial comparison. The results confirm the same direction of the main coefficients, which is an encouraging sign of the robustness of the identified effects.

Secondly, a level estimation was carried out, keeping the explanatory variables in their initial form (rather than as variations). The coefficient of determination is slightly lower in this version of the model (Adj.$R^2 = 0.752$ for Low-Tech and Adj.$R^2 = 0.624$ for Medium to High-Tech), but remains at an acceptable level.

Major differences:

Firstly, the coefficient associated with trade openness become significant for Low-Tech, with a negative sign. This result suggests that an increase in a country's economic integration into global value chains is associated with a decrease in the share of manufacturing employment, partly confirming the concerns raised in the literature about the potentially deindustrialising effects of globalisation on Low-Tech for advanced economies.

Second, the non-linear relationship between GDP per capita and manufacturing employment (captured by the square of GDP per capita) is significant and negative for the regression in levels. This confirms the inverted U-shaped relationship discussed in the literature between wealth levels and manufacturing employment. Furthermore, the magnitude of the coefficient differs across technology groups: it is larger (in absolute value) for the Low-tech group than for the Medium to High-tech group (respectively -0.0065 and -0.0026). This result suggests that Low-tech manufacturing sectors are more sensitive to income-driven structural change, in line with Engel's law. As households' income rises, the relative demand for Low-tech manufactured goods declines more rapidly, leading to stronger employment losses in these sectors. By contrast, medium- to high-tech sectors are less affected, as their products are possibly more income-elastic.

Finally, the coefficients relating to intermediate consumption also become significant, but their sign is positive for the regression in levels. This result contradicts the conventional interpretation of outsourcing as a factor directly reducing manufacturing employment. This can be explained by the fact that this ratio captures not only outsourcing, but also the level of integration of the manufacturing sector into the rest of the economy, which can sometimes be associated with stable or even rising employment.

Table 6: Estimation Results
Dependent variable: Employment part

	Low Technology		Medium to High Technology	
	OLS	Variables in Level	OLS	Variables in Level
$\Delta part\ VA$	0.8449 ***	1.0273 ***	0.8941 ***	0.5999 ***
	(0.0169)	*(0.0245)*	*(0.0138)*	*(0.0344)*
$\Delta \ln(prod)$	-0.0621 ***	-0.0106 ***	-0.0399 ***	-0.0047 .
	(0.0070)	*(0.0022)*	*(0.0066)*	*(0.0025)*
$\Delta Prod\ Ratio$	-0.6775 ***	-0.0592 ***	-0.7062 ***	-0.0429 ***
	(0.0151)	*(0.0028)*	*(0.0120)*	*(0.0033)*
ΔIC	-0.0413	0.0163	0.0051	0.0230 *
	(0.0265)	*(0.0169)*	*(0.0169)*	*(0.0111)*
$\Delta \ln(GDP/Cap)$	0.0380 .	0.1451 ***	0.0155 ***	0.0674
	(0.0210)	*(0.0132)*	*(0.0204)*	*(0.0168)*
$\Delta \ln(GDP/Cap)^2$	0.8036 ***	-0.0065 ***	0.5557 *	-0.0026 **
	(0.2338)	*(0.0006)*	*(0.2199)*	*(0.0009)*
$\Delta Trade$	0.0039	-0.0055 ***	0.0071	-0.0006
	(0.0100)	*(0.0013)*	*(0.0098)*	*(0.0017)*
$WIOD\ Change$	0.0058 **		0.0044 *	
	(0.0018)		*(0.0017)*	
R^2	0.825	0.774	0.888	0.657
Adjusted R^2	**0.823**	**0.752**	**0.887**	**0.624**

Notes: Robust standard errors in parentheses.
* P-values : *** <0.001, ** <0.01, * <0.05 , . < 0.1

7 Conclusion

7.1 Summary

The analysis conducted over the period 1996–2014 shows that deindustrialisation, measured by the decline in the share of manufacturing employment, affected all countries in the sample with the notable exception of India. This decline is particularly marked in Low-tech sectors, where the dynamics observed are relatively consistent across countries, in line with the results obtained by Tregenna (2009), although the latter studied a more unstable period. The decline in employment in these sectors is mainly explained by the contraction in the sector's relative value added and a decrease in labour intensity. The productivity effect, which is inversely related to labour intensity, is positive in most cases.

In Medium- to high-tech sectors, the results are more mixed. While the general trend remains one of declining employment, some countries, such as South Korea and Lithuania, have seen an increase in the share of industrial value added, contributing positively to employment. Others, such as Turkey, have seen labour intensity increase. These cases suggest that different trajectories remain, linked to industrial policies or economic shocks.

A comparison between Eastern and Western Europe reveals contrasting dynamics: in the Low Tech group, deindustrialisation is more pronounced in Eastern Europe, mainly due to the decline in manufacturing value added. Conversely, in the Medium to High Tech group, Western Europe is experiencing the sharpest decline.

In econometric terms, the model has a strong explanatory power, with adjusted R^2 values of 0.812 for the Low Tech sectors and 0.856 for the Medium to High Tech sectors. The sector share effect is positively and strongly linked to employment, confirming that the relative size of the sector remains a key determinant of its capacity to employ. The combined effect of productivity and labour intensity is negative, reflecting the substitution of labour by efficiency gains, particularly in Low-tech sectors.

Relative productivity compared to services also has a significant negative effect, supporting Baumol's cost disease hypothesis: an industrial sector that becomes more productive than the service sector tends to see its share of employment decline. This dynamic has had a greater impact on Medium- to high-tech sectors, where productivity gains have been most pronounced.

The outsourcing indicator, measured by the share of intermediate consumption, has a modest but significant effect in Low-tech sectors, highlighting the impact of organisational reconfigurations on the decline in employment. The effects of trade liberalisation are not significantly apparent, reflecting the complexity of its impacts, which are often indirect or differentiated according to national contexts.

Finally, GDP per capita, which is supposed to capture the structural effects of non-homothetic preferences, is not significant in the main regressions in variations. However, when estimated in levels, the relationship becomes significant and supports the inverted U-shaped curve described by Rowthorn & Ramaswamy (1999). This result is consistent with the idea that most countries in the sample are already advanced economies, located on the downward part of the curve.

7.2 Limitations

Despite the methodological efforts made, several limitations must be highlighted regarding the scope and interpretation of the results presented in this thesis.

Limited sector granularity
One of the methodological choices was to group manufacturing activities according to two broad technological levels: Low Tech and Medium to High Tech. While this distinction makes it possible to capture important structural differences, it remains relatively aggregated. A more detailed breakdown, particularly by distinguishing between high-tech and intermediate sectors, would have made it possible to identify specific behaviours. This limitation is mainly due to constraints in matching the sector classifications between the 2013 and 2016 versions of WIOD.

Imperfect measurement of international trade interactions
The trade openness variable used, measured by the sum of imports and exports relative to GDP, is too general to capture the complexity of the effects of international trade on manufacturing employment. Studies such as those by Van Neuss (2018) differentiate flows according to their origin (North/South) and nature (imports vs. exports), which makes it easier to identify the mechanisms at play. Other approaches, such as that of Demmou (2010), use the manufacturing trade balance, which is more directly linked to the competitiveness of the sector.

Relatively short but relevant study period
The analysis covers the period 1996–2014, i.e. 19 years. This choice may seem restrictive in view of more recent industrial developments, but it has several methodological advantages. On the one hand, this period makes it possible to capture the structural dynamics of contemporary deindustrialisation, particularly in advanced economies, while avoiding extreme disruptions. It excludes the COVID-19 health crisis and its unprecedented economic consequences, which could have obscured the structural signals observable in the data. In this sense, this period provides a coherent and stable analytical window, well suited to the long-term study of industrial transformations, while benefiting from good data homogeneity thanks to the WIOD databases.

Proxies may be imperfect for the phenomena studied
Some variables used in this study, notably the ratio of intermediate consumption as a proxy for outsourcing, only imperfectly capture the mechanisms at work. This ratio may also reflect internal technological developments or changes in production structures, without it always being possible to attribute them to outsourcing in the strict sense. More generally, several key variables are based on aggregated data.

Absence of endogeneity treatment
The econometric model is based on a fixed-effects panel specification with exogenous explanatory variables. However, it is likely that some relationships are bidirectional: for example, productivity can influence employment, but the structure of employment can

also affect productivity. In the absence of valid instruments, this issue could not be addressed, but could be the subject of future research.

Absence of institutional or qualitative dimension
Finally, the analytical framework remains deliberately quantitative and comparative. It does not take into account institutional, political or social factors that may play an important role in countries' industrial trajectories (labour regulations, innovation support policies, integration into global value chains, etc.). A case study-type analysis, or the introduction of qualitative variables, would complement the current approach.

7.3 Implications

The findings of this thesis suggest that the deindustrialisation observed in advanced economies during the period 1996–2014 is mainly the result of two structural dynamics: the reduction in the relative size of the manufacturing sector in the economy (sectoral composition effect) and the sustained increase in labour productivity in this sector. These effects appear to be the common drivers of deindustrialisation, regardless of the technological levels of the sectors considered.

This suggests that economic policies seeking to prevent deindustrialisation or encourage reindustrialisation face a fundamental tension: on the one hand, support for industry relies largely on strengthening its competitiveness; on the other hand, improving competitiveness often requires productivity gains, which can paradoxically lead to a decline in manufacturing employment.

The homogeneity of effects between the Low-tech and Medium-to high-tech sectors also suggests that there is no obvious sectoral lever that can preserve employment in one without affecting the other. In other words, any policy aimed at changing the industrial trajectory and acting at a broad macroeconomic level will find it difficult to discriminate between the types of sectors developed without resorting to more appropriate tools: sectoral taxation, trade policy or demand structure.

Finally, the results remind us that reindustrialisation, as currently promoted by many governments, cannot be reduced to moving upmarket or supporting innovation. In the absence of real growth in demand for manufactured goods or a change in the geographical distribution of production, policies to support productivity could even accelerate the decline in industrial employment by reinforcing labour substitution.

The link between industrial upgrading and European integration appears to be more complex than a simple pattern of geographical specialisation, in which Eastern Europe would be confined to low value-added activities, while Western Europe would focus on advanced technology segments. The enlargement of the European Union, which took place largely during the period under review, did not lead to any visible compensation: the decline in employment in Low-tech sectors in Western Europe was not accompanied by an equivalent increase in Eastern Europe, and the reverse is also true for Medium-to high-tech sectors. This suggests that European manufacturing integration has not resulted in a simple shift in industrial employment, but reflects deeper dynamics.

The econometric approach adopted in this thesis, although effective in isolating the statistical determinants of deindustrialisation, is based on a relatively aggregated and sectoral modelling of the phenomenon. By focusing on observable variations in employment, this approach does not pay attention to the deeper structural transformations at work. A complementary analysis, based on the logic of global value chains, would better capture these dynamics, which are invisible to traditional econometric tools, by highlighting the functional reorganisation of industrial production beyond sectoral and national boundaries.

7.4 Closing remarks

Ultimately, this thesis has shed empirical light on recent mechanisms of deindustrialisation in advanced economies, highlighting the central role of productivity and the relative contraction of the manufacturing sector, regardless of technological level. While the analysis deliberately relies on an econometric approach focused on employment, it shows that the trajectories observed are part of profound structural dynamics shared by most of the countries studied.

Beyond its specific contributions, this work illustrates the complexity of a phenomenon in which technological developments and changes in demand overlap. Understanding these interactions remains a crucial issue, both for research and for public policy, at a time when reindustrialisation has once again become a stated priority.

Finally, although the period studied ends in 2014, the trends identified here provide a useful point of comparison for assessing the industrial transformations of recent years, marked by new economic and geopolitical shocks. Continuing this analysis over a longer period, and incorporating the dimension of global value chains, would be a logical step towards gaining a better understanding of the contours of deindustrialisation in the contemporary era.

A Appendix

A.1 Correlation matrices

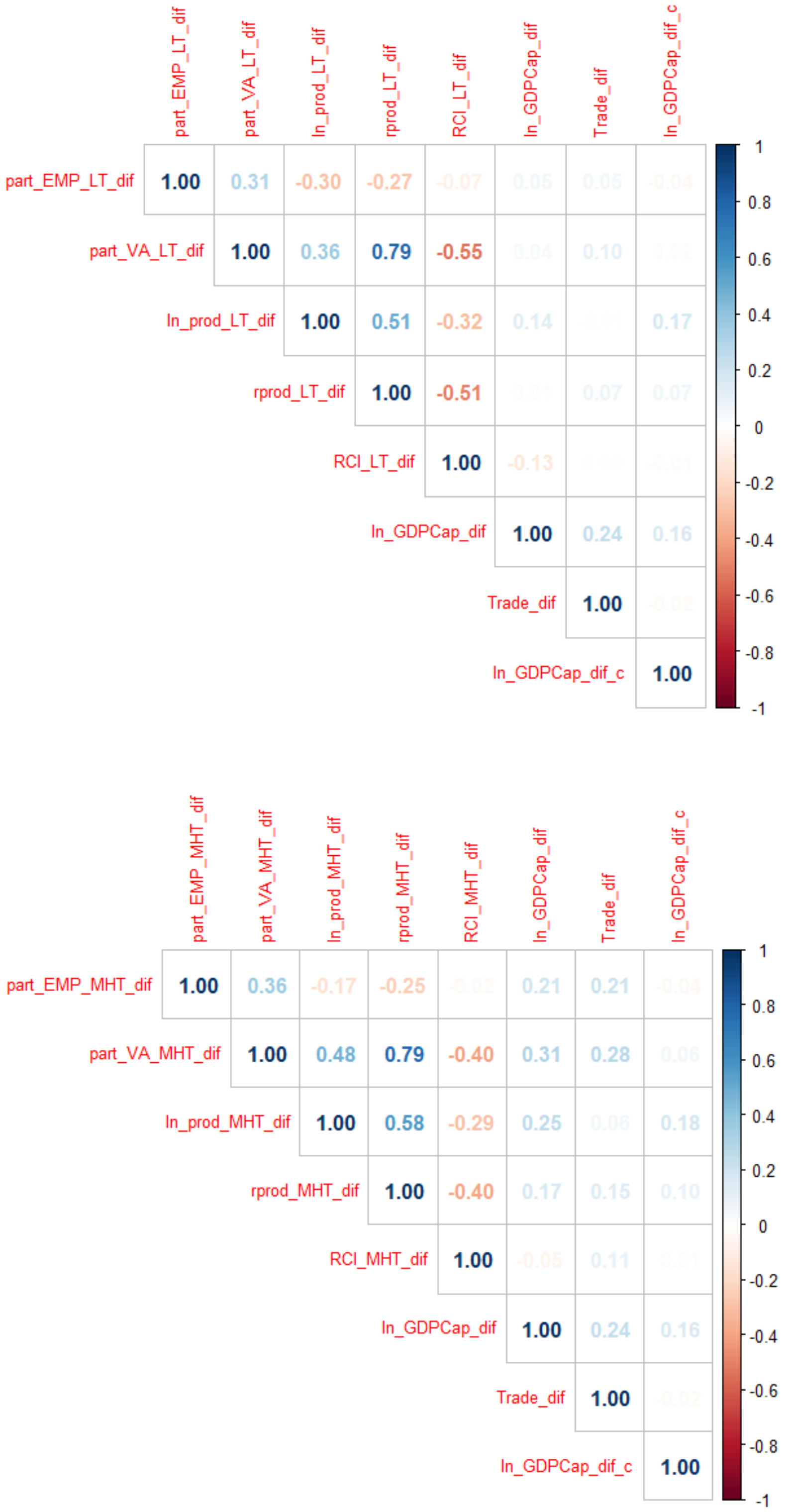


Figure 13: Low Tech and Medium to High Tech Variables Correlation matrices

Source: Own computation based mentioned databases

A.2 Use of AI

Transparency regarding the use of AI
This dissertation benefited from the use of AI-assisted tools for drafting and language refinement, including ChatGPT for structuring, and DeepL for translation. All research, data analysis, interpretation, and conclusions are the author's own. In respect with *ULiège Charter for the use of generative artificial intelligence in academic work.*

A.3 Tests Summary

Table 7: Summary of Econometric Tests

Test	Purpose	Statistic	p-value / Decision
Breusch-Pagan Test	Detect heteroskedasticity		(***reject H_0)
Low Tech		37.7	8.298e-06
Medium to High Tech		39.9	3.311e-06
Wooldridge Test for Autocorrelation	Detect serial correlation		(***reject H_0)
Low Tech		79.5	1.044e-09
Medium to High Tech		69.5	5.468e-08
Hausman Test	Choose between FE and RE models		(reject H_0, FE preferred)
Low Tech		15.1	0.0558
Medium to High Tech		46.4	1.956e-07
Pesaran CD Test	Cross-sectional dependence		(***reject H_0)
Low Tech		7.7	9.381e-15
Medium to High Tech		9.0	2.2e-16
Variance Inflation Factor (VIF)	Detect multicollinearity	Higher VIF	No concern ($<$ 5)
Low Tech		3.21	
Medium to High Tech		3.23	

A.4 Employment loss decomposition

The employment decomposition comes from (Tregenna, F.2009, p.466).

$$\sigma_{ijt} = \phi_{ijt}\,\delta_{ijt}\,\theta_{jt} \tag{8}$$

Hence

$$\Delta\sigma_{ijt} = \phi_{ijt}\,\delta_{ijt}\,\theta_{jt} - \phi_{ijt-h}\,\delta_{ijt-h}\,\theta_{jt-h} \tag{9}$$

By a Three-way decomposition

$$\Delta\sigma_{ijt} = \underbrace{(\phi_{ijt} - \phi_{ijt-h})\left(\frac{\delta_{ijt-h}\,\theta_{jt-h} + \delta_{ijt}\,\theta_{jt}}{2}\right)}_{\text{labour Intensity Effect 1}} + \underbrace{(\delta_{ijt} - \delta_{ijt-h})\left(\frac{\theta_{jt-h} + \theta_{jt}}{2}\right)\left(\frac{\phi_{ijt-h} + \phi_{ijt}}{2}\right)}_{\text{Sector Share Effect 1}}$$
$$+ \underbrace{(\theta_{jt} - \theta_{jt-h})\left(\frac{\delta_{ijt-h} + \delta_{ijt}}{2}\right)\left(\frac{\phi_{ijt-h} + \phi_{ijt}}{2}\right)}_{\text{labour Productivity Effect 1}}$$

$$\Delta\sigma_{ijt} = \underbrace{(\phi_{ijt} - \phi_{ijt-h})\left(\frac{\delta_{ijt-h} + \delta_{ijt}}{2}\right)\left(\frac{\theta_{jt-h} + \theta_{jt}}{2}\right)}_{\text{labour Intensity Effect 2}} + \underbrace{(\delta_{ijt} - \delta_{ijt-h})\left(\frac{\theta_{jt-h}\,\phi_{ijt-h} + \theta_{jt}\,\phi_{ijt}}{2}\right)}_{\text{Sector Share Effect 2}}$$
$$+ \underbrace{(\theta_{jt} - \theta_{jt-h})\left(\frac{\delta_{ijt-h} + \delta_{ijt}}{2}\right)\left(\frac{\phi_{ijt-h} + \phi_{ijt}}{2}\right)}_{\text{labour Productivity Effect 2}}$$

$$\Delta\sigma_{ijt} = \underbrace{(\phi_{ijt} - \phi_{ijt-h})\left(\frac{\delta_{ijt-h} + \delta_{ijt}}{2}\right)\left(\frac{\theta_{jt-h} + \theta_{jt}}{2}\right)}_{\text{labour Intensity Effect 3}} + \underbrace{(\delta_{ijt} - \delta_{ijt-h})\left(\frac{\theta_{jt-h} + \theta_{jt}}{2}\right)\left(\frac{\phi_{ijt-h} + \phi_{ijt}}{2}\right)}_{\text{Sector Share Effect 3}}$$
$$+ \underbrace{(\theta_{jt} - \theta_{jt-h})\left(\frac{\delta_{ijt-h}\,\phi_{ijt-h} + \delta_{ijt}\,\phi_{ijt}}{2}\right)}_{\text{labour Productivity Effect 3}}$$

Taking the means of each of the three terms from the three alternative formulations :
Labour intensity effect

$$= \frac{1}{6}\,(\phi_{ijt} - \phi_{ijt-h})\{(\delta_{ijt-h}\theta_{jt-h} + \delta_{ijt}\theta_{jt}) + (\theta_{jt-h} + \theta_{jt})(\delta_{ijt-h}\delta_{ijt})\} \tag{2}$$

Sector share effect

$$= \frac{1}{6}\,(\delta_{ijt} - \delta_{ijt-h})\{(\phi_{ijt-h}\theta_{jt-h} + \phi_{ijt}\theta_{jt}) + (\theta_{jt-h} + \theta_{jt})(\phi_{ijt-h} + \phi_{ijt})\} \tag{3}$$

Labour productivity effect

$$= \frac{1}{6}\,(\theta_{jt-h} - \theta_{jt-h})\{(\phi_{ijt-h}\delta_{ijt-h} + \phi_{ijt}\delta_{ijt}) + (\delta_{ijt-h} + \delta_{ijt})(\phi_{ijt-h} + \phi_{ijt})\} \tag{4}$$

List of Resource Persons

- Artige Lionel — Supervisor, HEC
- Barnabé Walheer — Jury Member, HEC
- Joseph Tharakan — Jury Member, HEC

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EXECUTIVE SUMMARY

This thesis investigates the determinants of recent deindustrialisation mainly in developed economies, focusing on differences between Low Technology and Medium to High Technology manufacturing sectors and between Eastern and Western Europe over the period 1996 to 2014. Using a decomposition model inspired by Tregenna (2009), the analysis separates the changes in employment share into sector share, labour intensity and productivity effects. Results show that in Low Technology sectors, most countries experienced a decline in employment driven by shrinking manufactoring sector shares and rising productivity, with Eastern Europe affected more severely. Medium to High Technology sectors display greater heterogeneity. Some countries, such as South Korea and Lithuania, recorded positive sector share effects, while Turkey saw gains from higher manufacturing labour intensity. Econometric estimates confirm the sector share effect as one of the most significant driver of employment deindustrialisation, productivity gains and higher relative productivity compared to services also have an impact. Outsourcing effects are found only for Low Technology sectors. Trade openness and GDP per capita do not show robust impact. Findings highlight a structural tension: policies that raise productivity may inadvertently accelerate manufacturing job losses, underscoring the need for balanced reindustrialisation strategies.

Key Words : Deindustrialisation, Manufacturing employment, Sectoral technology levels

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